ISSN 0429-9345

FAO FISHERIES TECHNICAL PAPER

487

Stock assessment for fishery management

A framework guide to the stock assessment tools of the Fisheries Management Science Programme

Cover:
Illustration/photo collage by Emanuela D'Antoni using photographs by A. Conti (FAO/17789) and R. Sozzani.

Stock assessment for fishery management

FAO
FISHERIES
TECHNICAL
PAPER
487

A framework guide to the stock assessment tools of the Fisheries Management Science Programme

by
Daniel D. Hoggarth
Savitri Abeyasekera
Robert I. Arthur
John R. Beddington
Robert W. Burn
Ashley S. Halls
Geoffrey P. Kirkwood
Murdoch McAllister
Paul Medley
Christopher C. Mees
Graeme B. Parkes
Graham M. Pilling
Robert C. Wakeford
Robin L. Welcomme

FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS
Rome, 2006

ISBN 92-5-105503-3

Regrettably, while this volume was in press, we heard of the death of Dr Geoff Kirkwood. Geoff had been instrumental in developing many of the techniques that are outlined in this document and his friends and colleagues, as well as fisheries science in general, will miss him greatly.

Preparation of this document

These guidelines are intended to assist fishery scientists in using a set of stock-assessment computer programs, developed as part of efforts of the UK Department for International Development (DFID, previously ODA) and the Fisheries Department of the Food and Agriculture Organization of the United Nations (FAO) to disseminate appropriate methodologies to the developing world. The software and this supporting documentation are the outcome of a series of studies funded by DFID under its Fisheries Management Science Programme (FMSP). The collation and publication of this document in English, by FAO, was supported by FMSP project R8360.

The CD-ROM included with this paper provides the installation files for each of the four FMSP software programs for fish stock assessment:

1. Length Frequency Distribution Analysis (LFDA);
2. Catch and Effort Data Analysis (CEDA);
3. Yield; and
4. Participatory Fisheries Stock Assessment (ParFish), including toolkit.

These installation files are also available on the FMSP Web site at:
http://www.fmsp.org.uk.

Abstract

This paper provides guidelines for fish stock assessment and fishery management using the software tools and other outputs developed by the UK Department for International Development's Fisheries Management Science Programme (FMSP) in the years 1992 to 2004. Part 1 describes some key elements of the precautionary approach to fisheries management. A stock assessment process is also outlined that can provide the information needed for such precautionary management. The management process summarized in Chapter 2 is based on recent FAO guidance, including the Code of Conduct for Responsible Fisheries. It emphasizes the need for setting goals and operational objectives; for defining these explicitly as reference points for a range of fishery indicators; for adopting decision control rules that include precautionary thresholds allowing for uncertainties and risk tolerances, and that drive fishery management using a set of measures that are pre-agreed with stakeholders. Chapter 2 also stresses the need to integrate use rights and co-management arrangements into the management framework, where appropriate, as key elements for success.

Chapter 3 presents the process of stock assessment, underlining the need for quantitative assessment of uncertainties and risks and the provision of advice based on the various goals of the fishery and considering both short- and long-term impacts of management strategies. Methods are given to estimate the current status of the fishery either as the stock size, the fishing mortality rate or other ecological or goal-based indicators. Methods are also described for estimating maximum sustainable yield (MSY) and other yield-based reference points, as well as some aimed at protecting the spawning capacity of the stock and avoiding recruitment overfishing. For sustainable exploitation, it is recommended that yield-based reference points are used as targets while spawning capacity reference points are used as limits and given the higher precedence. Precautionary thresholds should be set to prevent the limits being exceeded.

Chapter 4 provides information on the FMSP stock assessment tools and guidelines, including four FMSP software packages – LFDA, CEDA, Yield and ParFish – by which intermediate parameters, indicators and reference points may be estimated. The inputs and outputs and the relative advantages and potential uses of the tools are described. The four chapters in Part 2 further describe these four software tools, providing guidelines on their use and the fitting of models. Full technical details and tutorials are available in the software help files provided on the accompanying CD-ROM.

Part 3 then summarizes the guidelines produced by a number of other FMSP projects relating to stock assessment and management approaches that were introduced in Chapter 4. Chapter 10 uses simulation models to compare the performance of length-based and age-based approaches for two tropical fish species. The analysis demonstrates the benefits of using age based approaches where possible, but it is noted that results may differ for other species and their particular life history strategies. Chapter 11 develops simple relationships for the estimation of potential yield and maximum sustainable fishing mortality based on the Beverton and Holt "life-history invariants". These relationships allow sustainable yields and fishing capacity to be estimated from sparse data, which may either be already available, or can be relatively easily obtained. Chapter 12 derives guidelines for the management of multispecies demersal bank and deep reef slope fisheries exploited principally with hooks and lines. Chapter 13 presents a Bayesian stock assessment applied to the Namibian orange roughy fishery. This case study illustrates the benefits and some of the difficulties found in applying the Bayesian approach and draws out some lessons learnt. Chapter 14 describes a number

of empirical modelling approaches that can be used to support fisheries management, ranging in complexity from simple methods that only require historical catches through to complex multivariate models based on General Linear Modelling and Bayesian network approaches. These approaches may suit data poor circumstances, or when among fishery comparisons are possible, for example under adaptive approaches to (co-) management.

Throughout the framework, the use of adaptive learning and feedback approaches are promoted within the general principle of precaution. Complementary use of these approaches should enable uncertainties to be reduced and long-term benefits to be maximized with reduced risks to the resource base.

Hoggarth, D.D.; Abeyasekera, S.; Arthur, R.I.; Beddington, J.R.; Burn, R.W.; Halls, A.S.; Kirkwood, G.P.; McAllister, M.; Medley, P.; Mees, C.C.; Parkes, G.B.; Pilling, G.M.; Wakeford, R.C.; Welcomme, R.L.
Stock assessment for fishery management – A framework guide to the stock assessment tools of the Fisheries Management Science Programme (FMSP).
FAO Fisheries Technical Paper. No. 487. Rome, FAO. 2006. 261p. Includes a CD-ROM

Acknowledgements

Part 1 of this document – the framework for using the FMSP stock assessment tools – was crafted around the outputs of various FMSP projects and studies, mainly by project manager Dan Hoggarth. Thanks are due to Robert Arthur, Ashley Halls, Geoff Kirkwood, Paul Medley, Chris Mees, Catherine O'Neill and Graeme Parkes for their help in defining the framework used in Part 1. Robert Arthur drafted sections 2.3 and 2.4 and contributed to other parts of Chapters 2 and 3; Graham Pilling drafted section 3.6.5; Chris Mees drafted section 4.4. Material for Parts 2 and 3 of the document were mostly drafted by the original researchers of the different FMSP projects, as listed at the start of each section.

The authors are grateful to the participants of the September 2004 FMSP Stock Assessment Tools training workshop held in Mangalore, India, for their useful comments on an early draft of the document; and to John Munro, Kevin Stokes and Catherine O'Neill, as well as Serge Garcia and Kevern Cochrane of FAO for their edits and suggestions on the draft text.

CREDITS

The LFDA and CEDA packages were designed by Dr Geoff Kirkwood, Richard Auckland and Simon Holden and programmed by Richard Auckland, Steve Zara, Mark Bravington and Simon Holden. "Yield" was designed by Dr Geoff Kirkwood and Trevor Branch and programmed by Trevor Branch, Simon Nicholson, Steve Zara and Brian Lawlor. The ParFish software was designed and programmed by Paul Medley. The ParFish toolkit was designed by Paul Medley, Suzannah Walmsley and Charlotte Howard.

AUTHORS' ADDRESSES

Daniel D. HOGGARTH
Scales Inc., No. 3, C3-12 Graeme Hall Park, Christ Church, Barbados

Savitri ABEYASEKERA and Robert W. BURN
Statistical Services Centre, University of Reading, PO Box 240, Reading RG6 6FN, United Kingdom of Great Britain and Northern Ireland

Robert I. ARTHUR, Ashley S. HALLS, Christopher C. MEES, Graeme B. PARKES and Robert C. WAKEFORD
MRAG Ltd, 18 Queen Street, London W1J 5PN, United Kingdom of Great Britain and Northern Ireland

John R. BEDDINGTON
Division of Biology, Faculty of Life Sciences, Imperial College, South Kensington campus, London SW7 2AZ, United Kingdom of Great Britain and Northern Ireland

Geoffrey P. KIRKWOOD, Murdoch McALLISTER and Robin L. WELCOMME
Renewable Resources Assessment Group (RRAG), Imperial College (as above)

Paul MEDLEY
Sunny View, Main Street, Alne, North Yorkshire YO61 1RT, United Kingdom of Great Britain and Northern Ireland

Graham M. PILLING
Centre for Environment, Fisheries and Aquaculture Science (CEFAS), Pakefield Road, Lowestoft, Suffolk NR33 0HT, United Kingdom of Great Britain and Northern Ireland

Contents

Foreword

Fishery analysts require stock assessment tools to provide advice to managers but may be constrained in choosing the best tools by the difficulty in identifying the real benefits and costs of the alternative options. This guide attempts to help stock assessment advisors (and in some countries the managers themselves) to choose appropriate tools for their needs. It focuses particularly on a suite of products developed by the Fisheries Management Science Programme (FMSP) of the UK Department for International Development (DFID, previously known as ODA).

The FMSP was established by DFID to generate improved livelihood benefits for poor people through the application of new knowledge in both capture and enhancement fisheries. Since its creation in 1992, the FMSP has produced a series of outputs on the assessment and management of exploited fish stocks. These outputs range from new methods and software for assessing fish stocks and providing guidance to fishery managers, to applied research on specific country fisheries. The first FMSP software packages (LFDA and CEDA) were developed in the early 1990s and have already been used by an estimated 150 fishery scientists in developing countries. FMSP projects have been undertaken by many different scientists, usually involving collaborations between United Kingdom and developing country researchers and managers. Much of the output has already been disseminated by the individual projects, e.g. at symposia, in journal papers, via collaborating country institutions and so on. Many of the technical reports and papers from the projects are available on the FMSP web site (http://www.fmsp.org.uk/), maintained by the programme manager MRAG Ltd.

This document attempts to synthesize the various FMSP tools, guidelines and other outputs into a single, integrated guide about stock assessment as it relates to fishery management. The materials included in the document originate from over twenty FMSP projects (see list below), out of the total of 48 carried out since 1992. Other FMSP projects have focused on a range of topics including floodplain river and reservoir fisheries ecology; fish aggregating devices; economics and management of foreign fisheries in Exclusive Economic Zones (EEZs); prawn fisheries enhancement; and the understanding of fisheries livelihoods.

The framework presented here integrates the need for precautionary and adaptive management processes and, as such is compatible with (and partly derived from) the management framework currently promoted by FAO (FAO, 1997; Cochrane, 2002a). Much of the same terminology is deliberately adopted. It is designed to support the new paradigm of precautionary management as described in the Code of Conduct for Responsible Fisheries (FAO, 1995a, 1996) and the 1995 UN "Fish Stocks Agreement", which entered into force in 2001. This guide attempts to facilitate and support the implementation of these instruments by describing the range of possible stock assessment approaches that may be used to feed information into the management process, and by providing some tested tools for their application.

While attempts are made to describe the alternative possible routes that stock assessments may follow, it is stressed that fish stock assessment is a complex and much studied field, with many variants of the different models available and in use around the world. This manual does not attempt to describe all the possible approaches, but instead aims to describe the FMSP tools that have been developed within an overall framework of the options available. Elementary comparisons are made with some of the other software packages that have been produced. The details of the mathematics involved in different approaches is mostly left to the help files available for each of the different FMSP software, included on the companion CD-ROM. It is assumed therefore that readers will have at least a basic understanding of the alternative stock assessment techniques and fisheries models and their operation. Further details on the mathematics and assumptions behind the different methods may be found in fisheries textbooks such as Gulland (1983), Hilborn and Walters (1992), Sparre and Venema (1998), Quinn and Deriso (1999) and Cadima (2003).

List of FMSP projects covered in this guide

R4517	Development of Computer Aids for Fish Stock Assessment and Management Policy
R4823	Guidelines for harvesting species of different lifespans
R5030	Synthesis of simple predictive models for river fish yields in major tropical rivers
R5050CB	Computer Aids in fish stock assessment - Field development
R5484	Analysis of Multispecies Tropical Fisheries
R5953	Fisheries Dynamics of Modified Floodplains in Southern Asia
R5958	Culture fisheries assessment methodology
R6178	Synthesis of simple predictive models for fisheries in tropical lakes
R6436	The performance of Customary Marine Tenure (CMT) in the management of community fishery resources in Melanesia
R6437	Management strategies for new or lightly exploited fisheries in developing countries
R6465	Growth parameter estimation and the effect of fishing on size composition and growth of snappers and groupers: implications for management - Phase I and II
R6494	Evaluation of the biological and socio-economic benefits of enhancement of floodplain fisheries
R7040	Strategic assessment of tropical coastal fisheries management
R7041	Software for estimating potential yield under uncertainty
R7042	Information systems for co-management of artisanal fisheries
R7043	Selection criteria and co-management guidelines for harvest reserves in tropical river fisheries
R7335	Adaptive learning approaches to fisheries management
R7521	Implementing management guidelines arising from project R6465 - an assessment of utility in the BIOT inshore fishery
R7522	The potential for improved management performance with fully age-based stock assessments: Extension of the management strategy simulations to incorporate age-based assessments
R7834	Interdisciplinary multivariate analysis (IMA) for adaptive co-management
R7835	Investigation of the implications of different fish life history strategies on fisheries management
R7947	Integrated fisheries management using Bayesian multi-criterion decision making
R8210	The use of sluice gates for stock enhancement and diversification of livelihoods
R8285	Fisheries data collection and sharing mechanisms for (co-) management.
R8292	Uptake of adaptive learning approaches for enhancement fisheries

Symbols and abbreviations

Note: A **glossary** is not provided with this publication. Readers are instead invited to refer to the glossary given by Cochrane (2002a), which uses much of the same terminology (see http://www.fao.org/DOCREP/005/Y3427E/y3427e0c.htm#bm12). The detailed FAO Fisheries Department glossary is also available at http://www.fao.org/fi/glossary/default.asp.

Symbols

a	Coefficient in the length-weight relationship
a	In Chapter 11, used as a constant "multiplier", conditional on one or more other parameters, e.g. $a(L_c)$; $a(L_c, h)$
b	Power in the length-weight relationship
B	Biomass
B_0	Biomass at start of exploitation (sometimes assumed equal to K)
B_{inf}	Carrying capacity or unexploited biomass (i.e. K), as used in ParFish
B_{now}	Current biomass (as used in chapters 1-5) or current biomass as a propertie of the unexploited biomass, K (as used in the ParFish chapter 9)
C	Catch, in number
C	Oscillation amplitude in seasonal VBGF, as used in LFDA
f	Fishing effort
F	Instantaneous coefficient of fishing mortality
F_{eq}	Fishing mortality rate, estimated by methods assuming equilibrium conditions over age and time
F_{now}	Current fishing mortality rate
F_{ny}	Next year's fishing mortality rate
h	Density dependence or steepness in the Beverton and Holt SRR, as used in "Yield" and Beverton-Holt "invariant" methods
K	Growth rate of individual fish, as in the von Bertalanffy growth model
K	Carrying capacity or unexploited biomass, as in biomass dynamic models
l	Total length of an individual
l_c	Smallest length fully represented in sample (in Beverton-Holt Z estimator, used in LFDA, etc.); mean length at first capture in "Yield"
L_c	Knife-edged length at first capture, as a proportion of L_∞, as used in "Beverton-Holt invariants" methods (in Section 4.2, Chapter 11)
L_{c50}	Length at which 50 percent of fish are captured (selected) by the fishery (in Chapters 10 and 11)
l_m	Mean length at maturity, as used in "Yield"
L_m	Knife-edged length at first maturity, as a proportion of L_∞, as used in "Beverton-Holt invariants" methods (in Section 4.2, Chapter 11).
L_{m50}	Length at which 50 percent of fish reach first maturity
L_∞	Asymptotic length towards which fish grow, according to the VBGF
M	Instantaneous coefficient of natural mortality
N	Number of individuals remaining in a cohort in depletion models, as in CEDA, etc.
q	Catchability coefficient (proportion of the stock taken by one unit of fishing effort; also the constant of proportionality between f and F)
r	Intrinsic population growth rate in biomass dynamic models (in CEDA, etc.)

R^2	Statistical coefficient of determination (or R-squared)
R	Recruitment to the exploitable phase
RY	Replacement yield, i.e. that would maintain stock size at its current level, as estimated by CEDA
S	Stock size (numbers or biomass)
t	Age (usually measured in years, but may be days or weeks for fast growing species)
t_c	Mean age at first capture, in "Yield"
T_{c50}	Age at which 50 percent of fish are captured (selected) by the fishery (in Chapter 10)
t_m	Mean age at maturity, in "Yield"
T	Ambient temperature in the Pauly (1980) natural mortality equation
t_0	Theoretical age (t) at zero length according to the VBGF
t_s	Winter point in seasonal VBGF
W	Individual weight
X	Proportional escapement (in Section 4.5.3)
Y	Yield or catch in weight
Z	Instantaneous coefficient of total mortality
z	Shape parameter in Pella-Tomlinson DRP model used in CEDA

Technical reference points

B_{LOSS}	Biomass at the lowest historically observed spawning stock size
B_{MSY}	Biomass that would produce the MSY
$F_{0.1}$	F at which the slope of the YPR curve is 10 percent of its slope at the origin (also $F_{0.2}$, $F_{0.x}$ etc)
$F_{\%SPR}$	F that reduces SPR to the specified percentage of its level in an unfished stock
$F_{\%SSB}$	F that reduces SSB to the specified percentage of its level in an unfished stock, as estimated in "Yield"
$F_{\%FB}$	F that reduces the fishable biomass (FB) to the specified percentage of its level in an unfished stock, as estimated in "Yield"
F_{crash}	The point on an equilibrium yield curve at which both the biomass and the catches are reduced to zero
F_{LOSS}	F associated with the lowest historically observed spawning stock size
F_{low}	Like F_{med}, the F corresponding to the 10^{th} percentile of the observed points
F_{high}	Like F_{med}, the F corresponding to the 90^{th} percentile of the observed points
F_{max}	F giving the maximum YPR in a dynamic pool model (also F_{maxYPR}) ; in Chapter 11, F_{max} as used in the variable recruitment model is equivalent to F_{MSY}
F_{med}	F corresponding to a SSB/R equal to the inverse of the 50^{th} percentile of the observed R/SSB (in Section 3.5.3)
F_{MSY}	F that would produce the MSY
F_τ (F-tau)	F corresponding to the slope of the SRR at the origin (equivalent to F_{crash})
$F_{transient}$	F giving a specified probability that the %SSB will fall below a specified level during a forward projection of x years, as predicted by the "Yield" software
MBAL	Minimum biologically acceptable level, of spawning stock size, required to avoid recruitment overfishing, as observed in plots of SR data
MEY	Maximum economic yield
MSY	Maximum sustainable yield
$B_{50\%R}$	Biomass at which recruitment is 50 percent of the maximum predicted in a SRR

Conceptual reference points (used in defining control rule frameworks)

B_{lim}	Biomass associated with the LRP
B_{pa}	Precautionary biomass reference point, usually set above B_{lim} according to measured uncertainty and agreed risk tolerance (equivalent to NAFO's B_{buf} and ICCAT's B_{thresh})
F_{lim}	Fishing mortality rate associated with the LRP
F_{pa}	Precautionary fishing mortality reference point, usually set below F_{lim} according to measured uncertainty and agreed risk tolerance
LRP	Limit reference point
PRP	Precautionary reference point
TRP	Target reference point

Other abbreviations

BPR	Biomass per recruit
CBD	Convention on Biological Diversity
CCAMLR	Commission for the Conservation of Antarctic Marine Living Resources
CEDA	FMSP Catch and Effort Data Analysis software
CI	Confidence interval
DFID	Department for International Development of the UK government
DRP	Deterministic recruitment/production models, e.g. Schaefer, Fox models etc., as fitted in CEDA software
ELEFAN	Pauly's (1987) length-based growth rate estimator, as used in LFDA, FiSAT, etc.
FiSAT II	FAO-ICLARM stock assessment tools software
FMSP	Fisheries Management Science Programme of DFID
ICCAT	International Commission for the Conservation of the Atlantic Tunas
ICES	International Council for the Exploitation of the Sea
ICLARM	International Center for Living Aquatic Resources Management
IPOA	International Plans of Action
ITQ	Individual transferable quota (the right to a share of an annual catch quota)
IUU	Illegal, Unreported and Unregulated Fishing
LFDA	FMSP Length Frequency Distribution Analysis software
MEY	Maximum Economic Yield
MPA	Marine Protected Area
MSY	Maximum Sustainable Yield
NAFO	Northwest Atantic Fisheries Organization
ParFish	FMSP Participatory Fisheries stock assessment software
PROJMAT	Projection matrix method of fitting VBGF, as used in LFDA
SLCA	Shepherd's length composition analysis, as used in LFDA
SRR	Stock-recruitment relationship
SSB	Spawning stock biomass
SSBPR	Spawning stock biomass per recruit (or SSB/R)
SPR	Spawning products per recruit
%SPR	SPR as a percentage of the level that would occur in an unfished stock
TAC	Total allowable catch
TURF	Territorial use rights in fisheries
UNCED	United Nations Conference on Environment and Development
UNCLOS	United Nations Convention on the Law of the Sea
VBGF	von Bertalanffy growth function
VPA	Virtual population analysis
WSSD	World Summit on Sustainable Development
YPR	Yield per recruit

Part 1
Framework for using the FMSP stock assessment tools

1. Introduction

1.1 The new international legal regime

Most fisheries books seem to begin with an account of the poor state of the world's fish resources. There are certainly plenty of fisheries that are overexploited, many that are achieving less than their maximum potential and some that have collapsed outright. There are also, however, fisheries that remain healthy and productive, some perhaps by luck, but others by design. While fisheries management *can* be successful, this will surely only be maintained over the long term where clear management policies are implemented by a proactive management process. Where fishery managers are unaware of the status and potential of the resources under their responsibility, they are unlikely to act at the right time or to make the right choices. A suite of international instruments is now in place that promotes effective management action in *all* fisheries, regardless of their size and situation. Different strategies and approaches will work in different places but the requirement of good governance for all is now firmly established.

The legal basis for the management of fisheries was created in 1982 with the agreement of the UN Convention on the Law of the Sea (UNCLOS). Recognizing the need for international coordination for the management of straddling and highly migratory fish stocks, the UN "Fish Stocks Agreement" was signed in 1995. This requires states to cooperate in managing fishery resources both within and beyond their exclusive economic zones. The 1994 FAO "Compliance Agreement" addressed the problems associated with reflagging of fishing vessels as a means of avoiding conservation and management rules on the high seas (Cochrane, 2002b). Both UNCLOS and these two legal extensions to it are now in force and binding on those countries that have signed and/or ratified them.

In addition to these legal instruments, several non-binding guides have been developed to assist states in building good management practices. Chief among these is the FAO Code of Conduct for Responsible Fisheries, also finalized in 1995 (FAO, 1995a). This moves from the single-state, single species, MSY-based focus of UNCLOS into ecosystem management and the precautionary approach (de Fontaubert and Lutchman, 2003). The intentions of the Code are elaborated by the FAO Technical Guidelines for Responsible Fisheries. In particular, Guideline No. 2 deals with the precautionary approach to capture fisheries and species introductions (FAO, 1996, also 1995b; see Section 2.1.2); No. 4 (published in two volumes) addresses the general process of fisheries management (FAO, 1997). Caddy (1996) provides a checklist of fishery management issues seen from the perspective of the Code of Conduct.

Within the framework of the Code of Conduct are the four current FAO International Plans of Action (IPOAs) have been developed. These cover the reduction of incidental catches of seabirds in longline fisheries; the conservation and management of sharks; the management of fishing capacity; and the prevention of illegal, unreported and unregulated (IUU) fishing. National legislation for the formal implementation of these plans is now being developed in many countries.

Beyond the national level, most parts of the world's oceans are now covered by one or more regional treaties, commissions or fisheries management organizations. Only some of these have powers to set management measures that are binding on the fishing fleets of their member countries; many have only advisory functions (de Fontaubert and Lutchman, 2003). None has fully-effective enforcement capabilities, beyond the control exercised by flag states.

At a broader level, the legally binding 1992 Convention on Biological Diversity (CBD) provides guidance on the conservation, sustainable use, and equitable sharing of the benefits of biodiversity. Chapter 17 of the United Nations Conference on Environment and Development's (UNCED) Agenda 21 and the work programme of the CBD's 1995 Jakarta Mandate provide for the protection of the oceans, seas, and coastal areas. At the ten-year review of UNCED in 2002, the Johannesburg World Summit on Sustainable Development (WSSD) agreed a plan to "maintain or restore [fish] stocks to levels that can produce the maximum sustainable yield… where possible not later than 2015"; to "establish effective monitoring, reporting and enforcement, and control of fishing vessels"; to "eliminate subsidies that contribute to IUU fishing"; and to establish "representative networks" of marine protected areas by 2012.

With this legal and advisory regime in place, there is surely no lack of targets for states to work towards nor any lack of guidelines on how they may be achieved. More than ever before, coastal states are being called upon to focus intensively on fisheries management to secure the future of their fish resources and fishing industries. Some argue that the profusion of legal instruments may overwhelm small states with limited funding and capacity. The need to simultaneously achieve both fisheries development and ecosystem management goals presents challenges in turning all of the different concepts and guidelines into achievable operational objectives (Garcia *et al.*, 2003). Solutions can be found, however, by keeping a clear focus on the resource base of sustainable development (see Section 2.5.1). According to the FAO Web site,[1] as of June 2004, 52 countries reported having fisheries management plans in place that incorporate elements of the Code of Conduct, including measures to promote use of selective fishing gear, to prohibit destructive practices, and to ensure that permitted catch levels reflect the state of stocks and allow depleted populations to recover. The pace of uptake varies greatly between countries, but many states still need to put effective frameworks in place.

Much remains to be done then, particularly for small scale, artisanal fisheries. These are reported by FAO as producing about 50 percent of the world capture fisheries harvest that is used for human consumption, and as employing about 20 million fishers with many more in downstream, fishery-related jobs. These fisheries require more transparent involvement of stakeholders in the development of fishery management plans; the decentralization of decision making; and the coordination of inter-sectoral linkages between fisheries and the wider social and ecological systems. All fisheries require responsible management now to sustain their potential benefits to society.

1.2 Purpose and content of the guidelines

Fishery managers in both developing and developed countries are usually required to achieve policy goals aimed at sustainable production of fish yields for the benefit of fisher livelihoods, national food security and economic gain. Many different stock assessment models and software packages are available to assist managers in reaching these goals. These tools range from simple techniques for estimating parameters such as growth and mortality rates, to full simulation models of fishery systems allowing interactions between different species, fleets and gear types, and predicting the effects of different management strategies. The requirements of such tools, particularly the data inputs, vary greatly. Different tools are also applicable to different fisheries, depending on their operational structure, ecology and the intended management strategy. Fishery managers need to select and use appropriate decision-making support tools from the wide range of possible choices, bearing in mind their capacity to collect the necessary data and their ability to use the models and implement the management guidance produced. Finding the best tool, however, can be hampered by the diversity of choices available and the difficulty of comparing the costs (input requirements) and

[1] http://www.fao.org/newsroom/en/news/2004/45169/index.html

benefits (type and precision of management advice) of each tool. As a result, many fisheries in developing countries are either not managed, or are managed with only nominal regulations and without any real assessment of the status of fish stocks. Such countries risk losing the many benefits available from their resources.

This guide attempts to help fishery managers and their stock assessment advisors to choose decision-making support tools that will be appropriate to their circumstances and that will produce outputs that support responsible use of fishery resources, recognizing the need for a precautionary approach in the face of uncertainty. The guide focuses particularly on four software tools – LFDA, CEDA, Yield and ParFish – developed by the FMSP, but also makes reference to other guidance and tools developed both by the FMSP and elsewhere. Such tools are placed in a framework for fishery management and a related process for stock assessment. These are described in Chapters 2 and 3 respectively, and summarized in the following Section 1.3. Chapter 4 provides summary details on the main FMSP tools, concentrating on their main objectives, their data inputs and outputs and their relevance to particular circumstances. Part 2 presents further details about the software tools and Part 3 describes other FMSP analyses and guidelines.

Previous FAO stock assessment manuals for tropical fish stock assessment (Sparre, Ursin and Venema, 1989, and Sparre and Venema, 1998) have focused mainly on length based approaches. Both these manuals and that of Cadima (2003) have paid limited attention to the uncertainty inherent in fish stock assessment and the now widely-recognized need for precaution in decision making (see below). This stock assessment manual takes a different approach, giving less detailed coverage of the mathematical background of the different tools (already well covered in the manuals above-cited, and in textbooks such as Hilborn and Walters, 1992, Quinn and Deriso, 1999, and Haddon, 2001), and paying more attention instead to the estimation of uncertainty in parameters and its subsequent use in the decision making process.

Other software packages for stock assessment have of course been produced outside the FMSP, including the commonly used FAO/ICLARM FiSAT II software. Most fishery analysts will also have their own simple spreadsheets for modelling yield-per-recruit or other fishery indicators. The FMSP tools described here are believed to provide significant benefits over most such alternatives. Advantages include the use of non-equilibrium fitting methods and the inclusion of stock-recruit relationships and parameter uncertainty in the model inputs. All of the FMSP software packages are also now very well documented with their own help files and tutorials, illustrating step by step analyses of different example datasets. The introductions in Part 2 of this guide are essentially shortened versions of the software help files. During the more than 10 years since their first development, LFDA and CEDA have been well tested by many users in a wide variety of fisheries around the world. The current versions of these packages have been developed after extensive feedback from users in the field. Use of the FMSP software should therefore increase the likelihood of fishery analysts providing good and timely advice to their managers especially when they do not have the necessary background and resources to develop complex programming tools themselves.

1.3 A framework for fisheries management

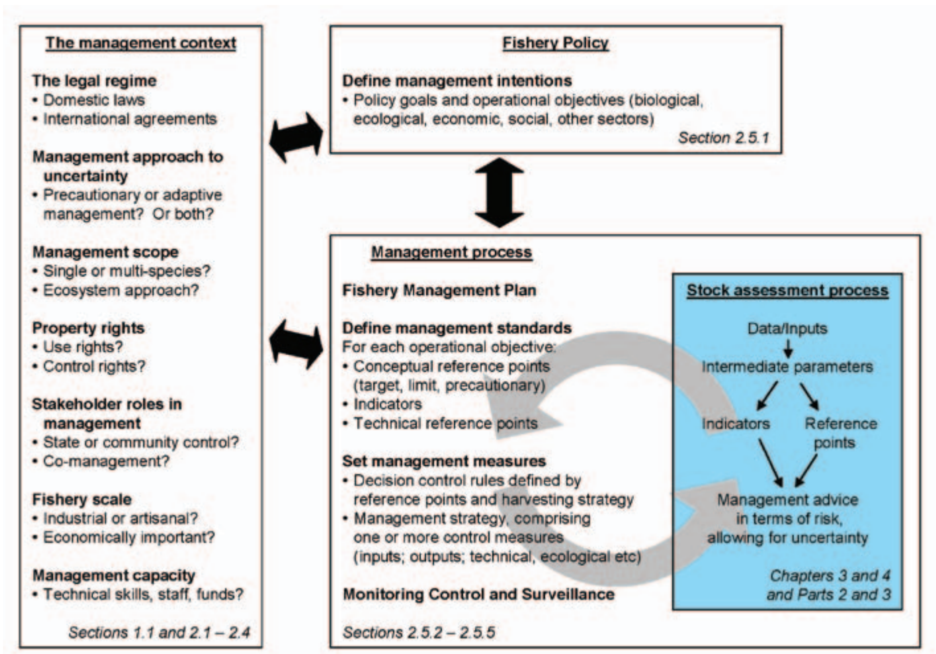
This section outlines a comprehensive framework for fisheries management – including stock assessment – which sets the stage for the application of the FMSP and other stock assessment tools. A complete fishery management system must recognize a wide range of influences that affect the interaction between the fishery, its stakeholders, and the aquatic environment. The system adopted for each fishery must be well adapted to the specific conditions found at that location.

The main components of a modern fishery management framework are illustrated in Figure 1.1. Governing the process, and hence at the head of the framework is the fisheries policy, including the goals and objectives that the management system is intended to address. Interacting with the fisheries policy are two boxes: the management "context" and the management "process". The context box on the left includes a range of factors that are fundamentally important to the way in which the fishery is managed. For example, the last decade has seen the start of a slow but steady move forward from the single stock- and single species-based focus often taken in the past, towards management systems that consider broader conservation goals and more integrated ecosystem-based objectives. Governance regimes are also changing from top-down "command and control" approaches towards more participatory, co-management arrangements, particularly for small-scale fisheries, and to market based measures and property rights for industrial-scale fisheries (Berkes *et al.*, 2001). Decisions taken on these fundamental issues and others listed in the context box will clearly influence the elements needed in both the policy and process boxes.

The management process box in the centre of Figure 1.1 includes the decision-making processes and the specific measures that are used to control the fishery. The stock assessment and research that provide the scientific and technical basis for the management framework are placed in their own box as a key element of this management process. The stock assessment box is central to the effective functioning of the framework, providing a quantitative basis for decision-making at every level. This is the part of the framework to which the four FMSP tools described in this guide contribute.

The arrows connecting the three main components of the framework are bi-directional, in recognition of the intimate and mutually reliant relationships between them. The circular arrow within the process box emphasizes that stock assessment should guide the management process by a regular and routine feedback process. Management measures could for example be adjusted each year, driven by the observed state of the system as measured by the "indicators" and "reference points". The overall system should also be assessed about every 3-5 years with more strategic and holistic analyses, but at a lower frequency than the main stock assessment – management cycle.

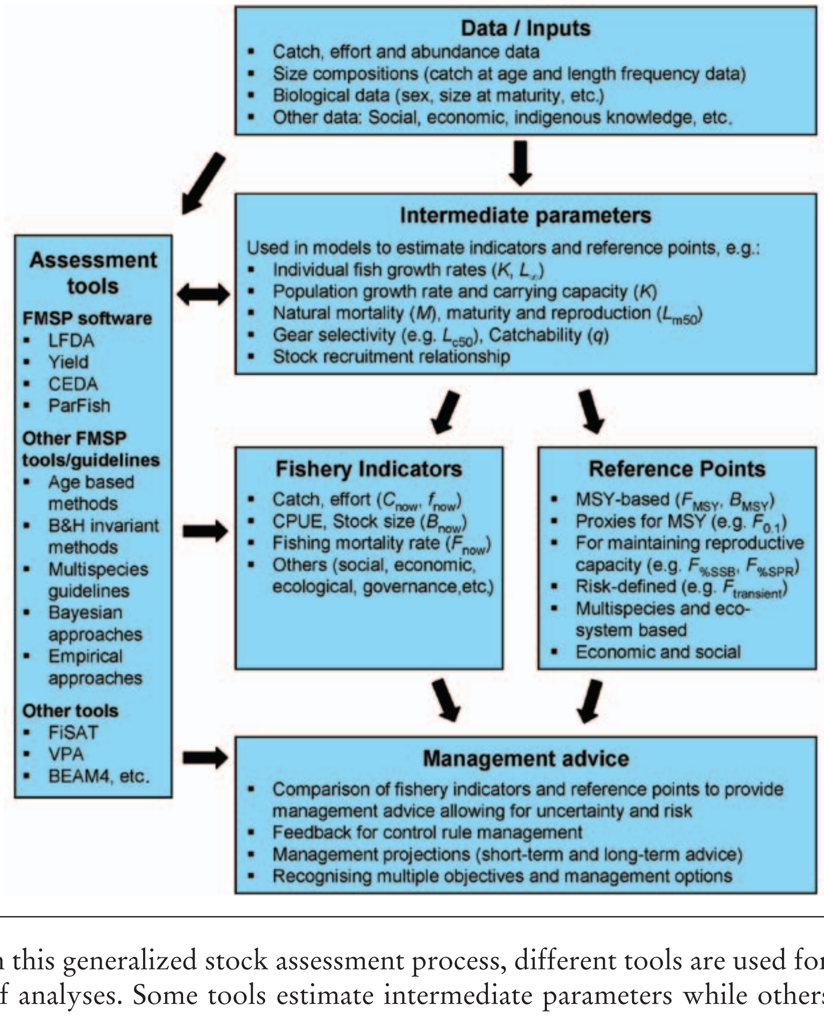
FIGURE 1.1
A framework for fishery management, showing the different elements to be addressed in establishing a fishery management system



Chapters 2 and 3 of this document describe in detail the component parts of the management framework and the stock assessment process. Readers unfamiliar with the concepts and methodologies in Figure 1.1 should refer to the sections indicated to provide the necessary level of understanding for informed use of the FMSP stock assessment tools. The FMSP tools themselves are introduced in Chapter 4, with additional details provided in Parts 2 and 3.

Figure 1.2 expands on the stock assessment and research box in Figure 1.1 giving examples of the different elements in the stock assessment process. As shown in the figure, the FMSP and other standard stock assessment tools use fisheries data to assist in the estimation of intermediate parameters, fishery indicators and/or reference points. Management advice is then usually based on the relative values of the fishery indicators and the reference points, as described in detail in Section 2.5.

FIGURE 1.2
Examples of the different elements in the stock assessment process outlined in Chapter 3, showing the general flow of information towards the provision of management advice



With this generalized stock assessment process, different tools are used for different types of analyses. Some tools estimate intermediate parameters while others estimate indicators and/or reference points. Some tools may need to be used in combination with others to provide a full fishery assessment (e.g. LFDA and Yield, see Figure 4.1), while others may be used on their own (e.g. CEDA and ParFish, see Figures 4.5 and 4.10). Table 1.1 provides a ready reference showing the potential contributions of the four FMSP software tools to the different elements of the stock assessment process. Other FMSP tools and guidelines listed in Figure 1.2 and described in Part 3 provide further alternatives or guidance for specific situations.

TABLE 1.1
Summary of the alternative outputs provided by the four FMSP software tools (see Chapters 3 and 4 for details of methods and notation, etc.)

FMSP Tool	Method(s)	Outputs: Intermediate Parameters	Outputs: Indicators	Outputs: Reference Points
LFDA	Length Frequency Distribution Analysis	Von-Bertalanffy growth parameters (seasonal and non-seasonal); Total mortality, Z	F_{eq}	
CEDA (Catch Effort Data Analysis)	Biomass Dynamic models; Depletion models; Stock projections	r, K, q	B_t , N_t	MSY, B_{MSY} , F_{MSY}
Yield	Analytical models; Stochastic stock projections		B_t , N_t [1]	F_{max} , $F_{0.1}$, $F_{0.x}$, $F_{\%SPR}$, F_{MSY} , F_{crash} , $F_{transient}$
ParFish	Biomass dynamic model with additional Bayesian priors	r, K, q		f_{lim} , C_{lim} , f_{opt} , C_{opt}

[1] The Yield software will project future trajectories of biomass and numbers resulting from a given catch strategy, based on current estimates of these values, but will not provide those current estimates.

2. Fishery management systems

A fishery management system comprises a wide array of activities designed to ensure the rational and responsible use of living marine resources. These activities may include governance arrangements (policy, legal instruments, use rights, control systems etc.), management procedures (setting objectives, control rules, performance measures, reference points etc.), scientific advice (stock assessment methods, management scenario modelling etc.) compliance (surveillance and enforcement, voluntary codes, incentive structures etc) and monitoring. This chapter provides the background and context for fisheries stock assessment, by first considering these overall aspects of the management system. Section 2.1 describes the concepts of precautionary and adaptive management, both of which are recommended as fundamental foundations for successful fishery management under conditions of uncertainty. Section 2.2 describes the potential range in the scope of fishery management, from relatively straightforward assessments of single gear, single species fisheries, through consideration of basic technical and biological interactions between gears and species, to the notion of a fully fledged ecosystem approach to fisheries. Sections 2.3 and 2.4 outline the range and importance of alternative use rights in fisheries, and the options for participatory decision making or co-management. Considering these various elements of the management system, Section 2.5 outlines the steps involved in a precautionary management process.

2.1 MANAGEMENT APPROACHES

The question of how fisheries can best be managed to generate benefits for both current and future generations has been the subject of debate for many years. The question is hard to answer because fishery managers face many uncertainties in the state and the dynamics of both the living resources and fisheries under their responsibility. Uncertainty in fisheries has many sources. Firstly, fish stock sizes and distributions can fluctuate widely even in their natural, unexploited state, due to variations in environmental and climatic factors, and the effects of other species with which they interact (see examples in Hilborn and Walters, 1992). In such a variable environment, the long term unexploited average stock size will always be hard to estimate, especially when changes go beyond random fluctuations in recruitment to significant episodic "regime shifts" in the structure of the ecosystem. Secondly, additional uncertainty arises because stock status can be estimated with only limited precision. In the case of the northern cod, retrospective analysis has indicated that stock abundance estimates may have been off by up to 100 percent (Hilborn, Pikitch and Francis, 1993). Finally, fisheries systems are often extremely complex, involving dynamic interactions within and between the living resources and the people who utilize and manage them. These interactions are only partly understood, if at all, making predictions and management decisions difficult.

Facing these many uncertainties, managers of natural resources (including fisheries) may take three broad approaches towards decision-making: comprehensive rational planning, precautionary management, or adaptive management. Each approach may have its place, depending on the choice of the manager, and on the level of uncertainty associated with the resource system. The origins and basis of these systems are described briefly below.

2.1.1 Comprehensive rational planning

Comprehensive rational planning is a traditional approach to fishery management, which proceeds under the belief that, through research, an understanding of the resource system can be achieved that can lead to effective management and control (Mitchell, 1997). Research is believed to provide best estimates of stock parameters or best practice guidelines that can then be used by resource managers for managing the resource. In the case of the simple reference point MSY, researchers can use the data from the fishery on yields and fishing effort to estimate MSY and the corresponding level of fishing effort required to achieve it, and this can then be used as the management target.

Comprehensive rational planning does not generally begin with an assessment of existing uncertainty or an acceptance that it may not be possible to achieve sufficient understanding of the fishery system and the species affected by it. This type of approach is therefore best suited to conditions of low or no uncertainty. Where considerable uncertainty exists, as in fisheries, believing that decisions can be made with complete confidence is likely to result in disappointment.

2.1.2 The precautionary approach

Due to its failure to account for uncertainty, "comprehensive rational planning" has led to some nasty surprises for fishery managers, with stock collapses and social disruption. Scientists and managers are now aware that the precision of fishery assessments is lower than once thought, that fish populations are less resilient than once imagined, and that the recovery of populations once depleted can be much slower than expected (Hilborn, Pikitch and Francis, 1993; Staples, 1996; and Pikitch, 2002). While pelagic stocks tend to recover quite well when fishing is reduced, longer lived and slower growing demersal stocks may not recover within 10-20 years. The northern cod stocks off Newfoundland, for example are still showing little sign of recovery, despite a nearly complete closure of the fishery since 1992. Valuable fisheries clearly may crash under heavy exploitation, and scientists have only a limited understanding of the processes that govern recovery (Royal Society, 2003).

This change in perception concerning the resilience of natural resource systems has also altered the view of how they should be managed. Building on the 1992 UNCED meeting in Rio de Janeiro, the FAO has vigorously promoted the concept of the precautionary approach to fisheries management, in an attempt to avoid undesirable outcomes. Precautionary management is at the core of both the UN "Fish Stocks Agreement" (in force and binding on signatories since 2001), and the FAO Code of Conduct for Responsible Fisheries (1995a). The Code of Conduct advises that:

> ***7.5.1*** *States should apply the precautionary approach widely to conservation, management and exploitation of living aquatic resources in order to protect them and preserve the aquatic environment. The absence of adequate scientific information should not be used as a reason for postponing or failing to take conservation and management measures.*
>
> ***7.5.2*** *In implementing the precautionary approach, States should take into account, inter alia, uncertainties relating to the size and productivity of the stocks, reference points, stock condition in relation to such reference points, levels and distribution of fishing mortality and the impact of fishing activities, including discards, on non-target and associated or dependent species, as well as environmental and socio-economic conditions.*

An explanation of FAO's interpretation of the precautionary approach was given in Annex II of the Fish Stocks Agreement (see Section 3.5). Further elaboration was provided by the FAO Technical Consultation on the Precautionary Approach to Capture Fisheries held in Lysekil, Sweden in 1995 (FAO, 1995b, republished in 1996 as Paper 2 in the Technical Guidelines for Responsible Fisheries series).

Recognizing that uncertainty pervades fisheries management and complicates informed decision-making, the precautionary approach says "the greater the uncertainty, the more conservative should be the approach" (Cochrane, 2002b). Where a "comprehensive rational planner" might aim exactly at setting fishing effort or quotas to achieve the model-predicted MSY, a precautionary manager would reduce the effort or quotas according to the level of uncertainty with which the MSY is estimated. In a well-managed fishery with an expensive monitoring and analysis system, this "precautionary MSY" might be quite close to the model-predicted MSY. In a data-poor fishery, it should be much lower, if the fishery is to keep on the safe side.

The precautionary approach also proposes a shift in the burden of proof from the regulators to the exploiters of the resource. Would-be exploiters need thus show that their activities will not result in undesirable outcomes for the ecosystem and environment, rather than such outcomes having to become evident before management action is taken to control them. With this shift in the burden of proof, the incentive for the fishing industry to reduce uncertainty should be strong. High uncertainty calls for a high degree of caution, which in fisheries terms means lower catch levels. Better data strengthen the scientific basis for management, and thereby reduce uncertainty and the magnitude of any "precautionary buffers" (Dayton, Thrush and Coleman, 2003). Providing good data and working with managers should in theory mean that the industry will be allowed to catch more fish.

The precautionary approach goes well beyond just setting catch limits. The FAO Guidelines (1996) delineate a comprehensive precautionary approach to fisheries as a whole, addressing the sources of uncertainty (and risk) in all aspects of the production and management process, in research (and the elaboration of advice), management (and decision-making), monitoring (and performance assessment), control and surveillance (tracking and correcting deficiencies in the system) and in operations (reducing the risks of accidental impact to species and habitats). Mace and Gabriel (1999) have argued that the concept of precaution has become over used and that what is really needed is *relevant* and *informative* research, and *effective* monitoring and enforcement. According to them, it is really *management* that should be precautionary, e.g. in reducing the quota to 75 percent or 80 percent of the estimated MSY according to the uncertainty in the assessment. FAO contends (Garcia, pers. com.) that the capacity of management to prevent, reduce or mitigate unwanted outcomes depends on the precautionary performance of each of the sub-processes mentioned above. Uncertain fishery or biological data, poor risk assessment (e.g. using simplistic assessment methods), incomplete advice, inadequate risk communication, non-transparent decision-making and weak enforcement all have the capacity to reduce the precautionary performance of management no matter how precautionary are the management objectives and related reference points (see Section 2.5.2). Hence the need for a more comprehensive approach, as recommended by the experts who developed the FAO (1996) guidelines. In such an approach, research will be *relevant* and *informative* and enforcement will be *effective* (as qualified by Mace and Gabriel) if the risks created by uncertainty, errors or corruption are systematically tracked and quantified, and conveyed to the decision-makers.

Fishery managers must thus learn to live with uncertainty and may use precaution as one possible solution. Progress with implementing the approach since 1995 has been described by Garcia (2000), ICES (2000), Gabriel and Mace (1999) and others. Several regional fishery management bodies, particularly ICES, NAFO, ICCAT and CCAMLR have adopted the approach, as have some states, notably the United States of America, Canada, Australia and South Africa (Garcia, 2000). Different bodies, however, have interpreted the meaning of precaution and the exact definition of reference points in different ways (see e.g. Section 3.5). Hilborn (2002) emphasizes that "the vast majority of the world's fisheries are not precautionary – not because the reference exploitation rates are too high but rather because catch cannot be measured or catch limits enforced, or because abundance cannot be estimated, or because rules do not state how catches will change in relation to stock size."

2.1.3 Adaptive management

Although precautionary management is now being promoted by FAO as the new fisheries paradigm that will substantially reduce the chances of overexploitation of fish stocks, it tends to provide little information about the system being managed. Since the "MSY" of a fishery cannot be predicted well until it has been exceeded, too much precaution may result in a fishery falling short of its true potential with managers never really knowing what might have been. Overly precautionary management policies may thus limit opportunities to increase knowledge about the system that could improve the management policy in the long-term.

To overcome this potential drawback, "adaptive management" may be used alongside the precautionary approach. Adaptive management attempts to reduce uncertainties over time in a structured process of "learning by doing" (Walters and Hilborn, 1978). Management actions are used or interpreted as experiments to learn more about the resource system *at the same time* as it is being managed. New knowledge is generated by the deliberate use of learning processes instead of sticking to rigid technical solutions that may be sub-optimal.

There are two main types of adaptive management, passive and active, both of which are based on increasing understanding and using the results to adjust management policy.

- Passive adaptive management adopts the best fitting model in each year as "true" for that year, and only updates management policy in future according to new data that arise naturally. Passive adaptive management can make use of existing variation in the resource system in order to provide an experiment. Learning may also be gained through temporal and spatial variation arising from both changing resource assessments, and natural variation in the resource system (Walters and Hilborn, 1978). This type of adaptive management has the greatest potential in resource systems that have a high degree of natural variation. In less variable systems it is possible to become stuck in a narrow range of parameter space.
- Active adaptive management attempts to produce better information for the long term management of the resource. It uses management actions to deliberately disturb the system in "probing" experiments that are designed to enable scientists and other stakeholders to learn more quickly about the system and its dynamics. The advantage of active adaptive management is that managers can use management actions to test conflicting hypotheses relating to the resource system (McLain and Lee, 1996). Management decisions may also take into consideration the need to minimize short-term losses and prevent long-term overfishing – key concerns of industry and managers.

In those cases where an adaptive management approach has been successfully implemented, estimates of model parameters have been improved (Sainsbury, 1988; Collie and Walters, 1991; McAllister, Peterman and Gillis, 1992; Middendorp, Hasan and Apu, 1996; and Garaway and Arthur, 2002). However, in order for an adaptive management experiment, active or passive, to be informative, it is necessary that the experimental strategy creates sufficient variation in "treatments" for the parameters to be determined by the assessment process. Tradeoffs will exist between the severity of the adjustments made and the likely time it would take to gain new knowledge. Making only small changes to management strategies (i.e. creating only small levels of variation) may mean that the effect of the change is lost within the ecological, environmental and economic changes that are occurring at the same time within the system.

While it may seem that adaptive and precautionary approaches are incompatible, except in cases of high risk or where the cost to reduce uncertainty is prohibitive, an adaptive approach could be taken within a precautionary framework. While significant adjustments to management actions may need to be made, e.g. in fishing effort or quotas, these do not necessarily need to be made across the whole of the stock. Where fishers can be persuaded or induced to fish in deliberate experimental patterns, the best information returns may be achieved from rotational "crossover" designs that include different levels of fishing in different areas (i.e. with replication) and with some control units to show the natural changes in the systems in the absence of fishing (Hilborn and Walters, 1992; McAllister and Peterman, 1992). While some of the areas might be deliberately pushed to find the limits to exploitation, the less fished and control areas (refuges) can provide a valuable buffer against possible overexploitation elsewhere (see e.g. Leaman and Stanley, 1993). The answers required of management could potentially be found much more quickly with such experiments than with the more usual "one way trip" fishery development where all areas are equally exploited (see Section 4.5.3).

Adaptive management may work best in spatially structured inshore or inland stocks than in the larger offshore unit stocks. Inland fisheries in reservoirs, small water bodies or discrete floodplain river units (Lorenzen *et al.*, 1998; Hoggarth *et al.*, 1999; Garaway, Lorenzen and Chamsingh, 2001), or relatively sedentary coastal resources such as lobster or abalone living in reefs and bays may be effectively split up into small unit stocks, either completely or partially isolated from other resource units. Such units provide excellent opportunities for good experimental designs using replication and randomization. Even simple spatial comparisons may help to accelerate the adaptive learning process, particularly where significant spatial variation in fishing effort or other inputs exists (see Section 14.2.2).

Frameworks to guide the implementation of adaptive co-management approaches were developed by FMSP project R7335 (Garaway and Arthur, 2002) using the example of spatially dispersed small waterbody fisheries in Lao PDR. Earlier FMSP projects (summarized in Hoggarth *et al.*, 1999) described institutional frameworks suitable for adaptive co-management in floodplain river fisheries. Project R7834 also developed multivariate analysis tools that provide statistical advice on how to build models of

TABLE 2.1
Summary comments on the advantages and disadvantages and potential application of the comprehensive rational planning, precautionary and adaptive management approaches

Management options	Advantages / application	Disadvantages / comments
Comprehensive rational planning	• Assumes that management outcomes can be predicted with certainty and that available knowledge provides an adequate basis for sound management • Suitable for conditions of low or no uncertainty about resource status etc	• High risk of failing to achieve management goals in most fisheries, due to many uncertainties about resource dynamics and the interaction with human aspects of the system, including the effects of alternative management options
Precautionary	• Reduces risks according to level of uncertainty and potential danger • Encourages involvement of industry in providing good data by shifting the burden of proof	• May limit exploitation below maximum potential where uncertainty remains high • May limit opportunities to increase knowledge about the system if applied too rigidly
Adaptive	• Reduces uncertainty by experimentation and/or analysis of existing variation • Most useful in spatially structured waters (inland, coastal), and for less mobile stocks • Use "passive" approach where natural variation gives contrast • Use "active" approach for fastest learning • Can be applied within a precautionary framework by making experiments in limited areas and keeping other areas as "buffers"	• Active approach requires industry commitment to principle of experimentation which may increase variability in catches • Harder to apply in large offshore fisheries with an indivisible unit stock • Need to make large adjustments to "treatments" to generate observable effects

co-management performance (equity, sustainability, compliance, yield etc) based upon multidisciplinary (ecological, socio-economic, institutional, etc.) variables. Such tools may accelerate the learning process for adaptive management, where capacity for their use exists (see Section 4.7.2).

For the large, offshore, less-differentiated and more mobile unit stocks, spatial "block design" strategies may be less applicable. Although temporal replication with "interspersion" of treatments (e.g. alternating periods with small and large quotas, see McAllister and Peterman, 1992) may give some benefits, managers of such stocks may need to accept more long-term uncertainty and balance the risks of overfishing with the possibility of missing the highest yields. Large unit stocks are less amenable to adaptive management than smaller, spatially sub-divisible ones as the risks associated with probing are greater, and there will always be considerable uncertainty in the advice provided (and hence the need for precaution).

2.2 MANAGEMENT SCOPE

2.2.1 Single species management

The traditional paradigm of fishery management is that the productivity of a stock[2] is fundamentally a property of its size and reproductive potential and that managers only need to control fishing activities in ways that maintain the size of the stock and protect breeding fish to achieve a good yield. Unfortunately, most fish stocks share their waters with many other fish species, of different sizes and life histories, and are caught by a range of different fishing vessels and gears. Applying the optimum single species management controls for all species and gears at the same time is usually impossible, and some compromises need to be made. Neverthless the assessment and management of unit stocks of single fish species can provide a good start for considering management actions even for complex ecosystems. When applied properly, these methods have proven invaluable in successfully managing a number of fisheries. They are likely to remain the best tools for assessing many fisheries based on one or a few main target species for many years. Most of the remainder of this guide is therefore devoted to single species assessment techniques. Where stocks interact with other species and fleets, or with the wider environment in various ways (see below), some compromises or adjustments will also need to be made as described below.

2.2.2 Multispecies and multigear management (technical and biological interactions)

Nearly all fishing grounds are occupied by several different fish species that are fished by several different types of fishing gear and fishing vessels. These fish and fisheries may interact with each other in various ways. "Technical interactions" between fishing gears exist wherever two or more gears and/or vessels operate within the same space, or catch fish from the same stocks of one or more species of fish. "Biological interactions" between fish species are essentially independent of the fishery (although they may be affected by the results of increased mortality) and include predator/prey relationships and competition for food, habitats or space.

Technical interactions between fishing gears may either be "direct" or "sequential" (Hoggarth and Kirkwood, 1996). In the first case, the gears compete for the same fish at the same time; in the second case, one gear catches fish before they become available to the other, either due to the different selectivities of the gears or to the locations or times that they are fished. Technical interactions are often the cause of problems with

[2] Fishery managers usually aim to work within the boundaries of a unit stock, defined as "a group of organisms of one species, having the same stock parameters, and inhabiting a particular geographical area" (Sparre, Ursin and Venema, 1989, see also Gulland, 1983). The unit stock may only include part of the global distribution of the species, but should form a single unit in terms of ecological factors (e.g. breeding and recruitment) and operational factors (i.e. exploitation).

"bycatches" and "discards". Where such discards reduce the catches available in other fisheries (as with prawn trawl fisheries, where the discards include the juveniles of large fish species caught elsewhere), technical interactions can be very important. Other examples are given by Caddy and Mahon (1995).

Although technical interactions add to the complexity of a stock assessment, they can still be handled relatively easily (see Section 4.4). Extensions to yield per recruit (YPR) models for example can estimate the likely impacts of management measures such as gear bans, effort changes or closed seasons, on the potential yields of each fish species in each fishing gear.

Biological interactions on the other hand are far more challenging. While it may be intuitively obvious that a healthy stock of some prey species should contribute to maintaining the sustainability of one of its predator species, the actual prey stock sizes required are hard to predict or manage. Although a range of theoretical studies can be made (e.g. see summary in Hilborn and Walters, 1992), the data requirements of food web and trophic level models such as Ecopath with Ecosim (Christensen, Walters and Pauly, 2004) are invariably high. The high levels of uncertainty inherent in the outputs from such models must also be carefully taken into account by decision makers. Taking common-sense precautionary measures, e.g. that make nominal allowances for biological interactions while still derived from separate single species assessments for each species, or lumping species together for an aggregated modelling approach may still be the best general strategies for these situations.

In setting goals for multispecies fisheries, managers should also be aware that prolonged fishing at unsustainable levels can result in catch compositions shifting from large, slower turnover, more valuable species to smaller, faster turnover, less valuable species. This effect, known as "fishing down the food chain" (Pauly *et al.*, 1998), occurs due to both economic and biological factors. Cochrane (2002b) notes that in multispecies fisheries, it will be impossible to maximize or optimise the yield from all fish species simultaneously. Realistic goals and objectives must therefore be established (see Section 2.5.1 below).

2.2.3 Ecosystem management

Moving beyond the multispecies scale, fisheries also interact with a number of non-harvested species and with mankind's other uses of the natural environment at an ecosystem scale. Although some fisheries operate far offshore and away from other human activities, most of the world's fisheries are in coastal waters where interactions with other users are an important consideration and frequently a constraint. Other uses of the aquatic environment can include transport, tourism, conservation, oil and gas extraction, offshore mining and shipping, and aquaculture (Cochrane, 2002b). Fisheries management should take account of the effects that these other sectors can have on fishing and also of the converse effects that fishing may have upon them.

The "Ecosystem Approach" aims to consider all significant interactions between species, sectors and the wider environment. Garcia *et al.* (2003) argue that the now rich set of international agreements relating to ecosystem management (including UNCED's Agenda 21, the Convention on Biological Diversity, the Jakarta mandate, the FAO Code of Conduct for Responsible Fishing, etc. – see Section 1.1) provide both a fundamental guidance and a significant challenge for the implementation of the ecosystem approach. The challenge is in turning all these principles and guidelines into operational objectives and ecosystem management plans that incorporate fisheries.

Broadly speaking, the ecosystem approach implies a more holistic approach to management aiming to ensure that flora and fauna are maintained at viable levels in their native habitats and that the integrity of ecosystems is maintained as far as possible while supporting sustainable levels of human use (Grumbine, 1994).

A recent FAO Technical Consultation (FAO, 2003) has adopted the term "Ecosystem Approach to Fisheries" and defined its purpose as "to plan, develop and manage fisheries in a manner that addresses the multiplicity of societal needs and desires, without jeopardizing the options for future generations to benefit from a full range of goods and services provided by marine ecosystems". Garcia *et al.* (2003) explains the multiple elements of the approach and emphasizes its compatibility with the FAO Code of Conduct. It promotes maintaining the reproductive capacity of target resources; maintaining biological diversity (limiting introduction of alien species and protecting endangered species); using networks of MPAs; protecting and enhancing habitats (reducing both fisheries impacts and pollution); reducing bycatch, discarding and ghost fishing; improving institutional arrangements and developing better systems for indicator-based monitoring.

While there are still hurdles to be overcome in merging the two fundamental concepts of ecosystem management and fisheries management, the 2002 Johannesburg WSSD (Section 1.1) called for the application of the ecosystem approach by 2010 as a necessary condition for the survival of the fishing industry (Garcia *et al.*, 2003). The WSSD 2002 Plan of Implementation requires states to promote the conservation and management of the oceans by developing and using "diverse approaches and tools, including the ecosystem approach, the elimination of destructive fishing practices, the establishment of marine protected areas consistent with international law and based on scientific information, including representative networks by 2012 and time/area closures for the protection of nursery grounds and periods, proper coastal land use; and watershed planning and the integration of marine and coastal areas management into key sectors". Article 10 of the FAO Code of Conduct also calls for policy measures and institutional frameworks to be established for the integration of fisheries into broader coastal area management regimes.

These proposals call for a common sense application of the ecosystem approach, recognizing the difficulties of managing biological interactions and focusing instead on the more "tractable" problems. As with biological interactions, theoretical ecosystem models exist but lack empirical underpinning and are not very useful to management in their current state (Royal Society, 2003).

Goodman *et al.* (2002) describe the more tractable ecosystem problems as those where the relationship between cause and effect is relatively clear. These include the direct effects of fishing activity on target and non-target species, such as those due to bycatch, incidental mortality, and the destruction of habitats. These direct effects are relatively easy to detect and can often be mitigated through some modification in the way fishing vessels operate or the configuration of the fishing gear (see Bjordal, 2002). The common thread that identifies the less tractable problems is that they involve indirect effects of fishing, where potential causes and effects may be several steps removed from each other. This tends to introduce complications into the picture, because the fishery may not be the only, and perhaps not even the major cause of the problem. There is, therefore, a much higher level of uncertainty regarding the role played by the fishery in affecting the ecosystem properties in question. Less tractable problems include regime shifts in ecosystems, and the relative influence of fishing and other factors in declines of non-target species (see examples in Goodman *et al.*, 2002). While direct mitigation actions can be taken for tractable problems, the precautionary approach is more relevant for the intractable ones.

Elaborating on the Code of Conduct for Responsible Fisheries, FAO (1999) outline the process to be followed, at national or regional level, to establish a Sustainable Development Reference System (SDRS) which should consider the broad dimensions of ecosystem management (see Section 2.5.2). This includes all aspects of sustainability (ecological, economic, social, and institutional) as well as the key aspects of the socio-economic environment in which fisheries operate. The guidelines are complementary to the FAO Guidelines on Fisheries Management (FAO, 1997), but provide the broader perspective needed for a sectoral and holistic approach to sustainability in fisheries.

The role of MPAs

Marine protected areas (MPAs) or other forms of reserves are actively promoted by conservation NGOs as central elements of biodiversity and ecosystem management. The relative benefits of reserves as fisheries management tools, however, is still a subject of much current debate (see e.g. Hilborn *et al.*, 2004). The effectiveness of a reserve for conservation purposes will depend on the relationship between the reserve size and design, the natural spatial structure and connectivity, and dispersal rates of the populations. Studies have generally shown that MPAs will increase the fish abundances and sizes inside the reserve. In terms of their benefits to fishing, simulation studies have shown they may have little overall impact on the average yield from a fishery, but that reserves should help increase the likelihood of sustainability of the stock, and thus of the fishery. The impacts on fishers will also depend on the locations of reserves relative to fishing ports and open fishing grounds.

On their own, MPAs will not help fisheries if excess fishing capacity is simply displaced to fishing grounds outside the reserve. MPAs should thus be embedded within wider marine management strategies. MPAs may be most successful at protecting and rebuilding the biomass of the more sedentary species, that can then sustain the fishery outside the reserve by exporting juveniles or adults. Although migratory species may not benefit much from the local reduction in fishing mortality caused by an MPA, carefully placed MPAs could still help some of these species by rebuilding the complexity of habitats that have been destroyed by damaging gears such as trawling, or by decreasing the mortality of their juveniles (Pauly *et al.*, 2002).

A balanced perspective on MPAs is offered by the monthly electronic bulletin "MPA News".[3] Issue number 48 (Vol 5, no 6), for example, leads with an article about balancing conservation and fisheries goals, aiming for the "win-win" solution. This describes the potential use of decision-support tools such as MARXAN,[4] that can

TABLE 2.2
Summary comments on the alternative possible scope or scale of fisheries management and assessments (see also Section 4.4)

Management scope	Advantages / application	Disadvantages / comments
Single species	• Simplifies models to main fishery control parameters (e.g. effort, catch, technical measures)	• Ignores interactions with other species and the wider environment • May lead to overly optimistic management advice
Multispecies	• Extends focus to all main species in fishery • At simple level, aims to limit bycatch, discarding etc • Use aggregated biomass dynamic models, or analytical models with technical interactions	• Analytical models with full biological interactions hard to apply • Hard to optimize controls for all species simultaneously - need to accept some tradeoffs
Ecosystem	• Seeks to maintain biological diversity, habitats and ecosystem functions • Management options include use of networks of MPAs, prevention of bycatches, discards and gear damage etc • Common sense measures can be applied to "tractable" ecosystem problems	• Food web and trophic level models not yet useful in providing implementable management advice • Hard to distinguish relative effects of fishing and environmental factors on fish stocks, and hence appropriate management responses.

[3] http://depts.washington.edu/mpanews/

[4] http://www.ecology.uq.edu.au/marxan.htm

optimize across multiple competing objectives, allowing for their costs and measures of uncertainty (see also Section 3.6.3). Where reserve planners do not have the resources to use such sophisticated decision-support tools, "double-payoff" reserve designs can still be achieved by careful problem formulation and an acceptance of both sets of objectives, established in conjunction with a broad range of stakeholders. Comprehensive guidelines on designing MPAs are given by Salm, Clarke and Siirila (2000), Hall (2002), and others.

2.3 USE RIGHTS

The FAO Code of Conduct notes that "States should prevent overfishing and excess fishing capacity". Such problems are usually caused by the absence of property rights. The FAO has further stated that "limited access is widely considered to be essential for efficient and responsible fisheries" (FAO, 1997).

Property rights govern who can do what with respect to the resource system and have been defined by Bromley (1991) as "the capacity to call upon the collective to stand behind one's claim to a benefit stream". Property rights are important in natural resources management as they provide incentives for management, provide authority and control over the resource system, and can reinforce collective action (Meinzen-Dick and Knox, 1991). Thinking forwards 50 years, Rosenberg (1998) predicts that open access will eventually become "a thing of the past", and that property right-based systems will be put in place for all fisheries, though there will be great variety in the types of systems used. Property rights in fisheries management are dealt with in detail in Shotton (2000).

Property rights have been divided into two groups by Schlager and Ostrom (1992). The first group is <u>use rights</u> governing the use of the resource. These may be further divided into <u>access rights</u> and <u>withdrawal or harvesting rights</u>. Access rights authorize entry into the fishery or into a specific fishing ground. These include traditional systems for access control such as TURFs, and limited access controls. Withdrawal (harvest) rights typically involve the right to a specific amount of fishing effort (e.g., to fish for a certain amount of time or with a certain amount of gear) or the right to take a specific catch (quota or trip limit systems). Use rights in fisheries are discussed in detail by Charles (2002). The second group is <u>control rights</u>, including management rights that authorise the making of rules and imposition of restrictions, exclusion rights, which allow the holder to determine who may use the resource, and alienation rights that enable the holder to transfer rights to others, for example by inheritance or through sale or lease. Control rights provide the underlying basis for fisheries co-management, as dealt with in the following section.

These various rights can come from a number of sources including international treaties, statutory legislation, religious practice, local custom, project regulations and user group rules. Several rights may coexist in relation to a single system (Meinzen-Dick and Knox, 1991; Benda-Beckmann *et al*., 1996). There are also different possible combinations of rights that stakeholders may hold and these can vary between and within stakeholder groups.

When fisheries are managed by restricting who can have access to the fishery (access rights) and/or how much fishing effort each individual is allowed or how much catch each can take (withdrawal rights) then those individuals or groups holding such entitlements are said to have use rights. In cases where the state has the capacity to enforce property rights and fisheries regulations, managing the fishery through use rights is an option. These rights can be allocated by the state to individuals or groups either as a permanent transfer or for a predetermined period. Additionally the rights may be transferable, meaning that they can be reallocated or traded. Although such right holders have the right to use the fishery, they still do not usually *own* the fishery, and the fish stocks remain a public good. This is an important point regarding these rights and misunderstanding over this has been the source of many disagreements over use rights management policies. As Charles (2002) notes, decisions regarding allocation of use rights need to be made with care.

2.3.1 Access rights

The need to regulate access to a fishery is a fundamental element of fisheries management (Charles, 2002). Unrestricted or "open access" arrangements, although often used with some technical measures (see below), have led to significant overcapacity in the world's fisheries and much inefficient "racing behaviour" in fishing. Section 7.1.8 of the FAO Code of Conduct thus recommends that "*States should take measures to prevent or eliminate excess fishing capacity and should ensure that levels of fishing effort are commensurate with the sustainable use of fishery resources as a means of ensuring the effectiveness of conservation and management measures*". While measures need to be taken to limit effort in a fishery, particular care will be needed if the measures are intended to be equitable and to reflect historical dependencies and rights (see FAO, 1997; Greboval, 1999).

Access may be restricted (and access rights thereby applied) using two methods. The first of these is the use of territorial use rights (TURFs), where certain areas are recognized as under the traditional or allocated control of certain individuals, tribes and/or groups. The second is by limiting entry to the fishery to certain individuals or vessels, e.g. through restricted licensing. Access regulations used as a sole management measure have been criticized because, while they are effective in controlling the number of fishers or vessels in the fleet, incentives still exist for the fishers to race for the fish and to increase their individual catching power. In such cases additional individual effort and catch rights may also be needed, or incentives for collective responsibility.

2.3.2 Withdrawal (harvest) rights

Withdrawal or harvest rights include the right to apply a certain amount of fishing effort or the right to extract a certain output (i.e. catch) from the fishery. Effort rights exist where measures are taken to control the fishing effort expended e.g. through restrictions placed on the number and/or types of gear(s) used and/or on the amount of time that can be spent fishing. Where effort rights are employed, managers should be aware of "technology creep" whereby the effectiveness of a set of inputs (e.g. a single fish trap haul) will increase over time. Output rights include catch quotas (often a proportion of the Total Allocated Catch) that may be held by groups or individuals, allowing them to harvest that part of the fish resource. Individual quotas (IQs) may be either non-transferable or tradable, as in the case of Individual Transferable Quotas (ITQs). Critical issues with IQs, including their duration, allocation and transferability, are discussed by FAO (1997), Shotton (2000) and Charles (2002).

Output rights are less prone to problems with technology creep than effort rights and avoid the race to fish. However they can also lead to other problems such as social concerns and conservation problems including incentives to under-report catches or to discard low-value sizes of fish to "high-grade" the catches. Data collection and monitoring costs are also higher. Some argue that the full benefits of private ownership will only be realized when the actual quotas are also set by the ITQ holders.

If carefully formulated, use rights should make conservation measures more compatible with the fishers' own long-term interests, and encourage more responsible fishing practices, and greater compliance with regulations. However, although benefits have been demonstrated, use rights remain controversial, perhaps not least because they inevitably result in the exclusion of some parties from what is widely regarded as a public resource. With such a wide range of possible rights systems (Shotton, 2000), it is often hard to find the best option. It must also be remembered that the costs associated with different use rights approaches will vary. A system of ITQs may be costly to apply, though the costs may be recoverable by fees applied to the rights holders. Charles (2002) suggests that community-based rights may be more appropriate for small-scale/artisanal fisheries where multiple fishery and non-fishery goals are pursued; and that market-based rights may be better in industrial fisheries that do not support coastal communities and where economic profitability is the main goal.

All management regimes using harvest rights will require stock assessments to estimate the effort or catch to be allowed each year. Access rights in contrast may only state who (e.g. which community or fisher cooperative) is allowed to fish in a stated area. In community based management systems, traditional rules almost always relate to fisher behaviour and technical measures (Section 2.5.5) rather than quantitative quotas or effort controls. However, while the state can identify targets and limits and set quotas, it often lacks the capacity to enforce withdrawal rights and fisheries regulations or to monitor resource use at the local level. In such cases attention has been turning to the possibility of the state devolving control rights and co-managing the resources with resource users and other stakeholders, as described in the following section.

TABLE 2.3
Summary comments on alternative use rights in fisheries

Use rights options	Advantages / application	Disadvantages / comments
Open access	• Absence of any property rights • May be seen as most equitable arrangement by some societies	• Cause of the "tragedy of the commons" • To be avoided where possible, or supported by strong technical measures ensuring sustainability even with high *F*
Access rights	• Limitations on who may operate in a specific fishing ground (TURFs) or fishery (limited licensing) • TURFs most applicable to small-scale inshore fisheries and co-management • Limited licensing applicable to larger, offshore industrial scale fisheries	• Need fair and transparent allocation systems to ensure legitimacy and equity • Access right holders may still race to catch fish giving incentives to increase effort or capacity
Harvest / withdrawal rights	• Include "input rights" to apply a certain type or amount of fishing effort (e.g. number of fish pots or days at sea)... • ... and "output rights" to take a certain catch, e.g. a specified proportion of the annual TAC (IQs or ITQs) • May be allocated permanently or temporarily • May be transferable (tradable) or not • Output rights may reduce race to fish and overcapacity	• May increase discards for "high-grading" • ITQs may cause social disruption if efficient companies buy out smaller operators • With input rights, need to monitor increase in effective *F* due to increasing catchability (i.e. "technology creep") • Output rights may be harder and more expensive to apply than input rights

2.4 CONTROL RIGHTS AND FISHERIES CO-MANAGEMENT

Following the failure of many existing, centralized management arrangements to ensure the sustainable management of fisheries resources and/or because of economically driven reforms, a popular response has been to devolve some fishery management responsibilities to resource users and other stakeholders (e.g. Hara, 2004; Jentoft, 2003; Hanna, 2003). With the further argument that co-management can provide opportunities for management that are precautionary, adaptive and flexible (e.g. De Young *et al*., 1999; Garaway and Arthur, 2004), the sharing of management roles has become the subject of considerable interest in recent years.

Co-management has been defined by Berkes *et al*. (2001) as a partnership arrangement in which government, local resource users (fishers), external agents (NGOs, academic and research organizations), and other fisheries and coastal resource stakeholders (boat owners, fish traders, money lenders, tourism establishments etc) share the responsibility and authority for decision making in the management of a fishery.

While this definition emphasizes the sharing of decision-making, it has been more common for government to devolve management responsibilities, typically for monitoring and enforcement, without devolving the management rights (Meinzen-Dick and Knox, 1991; Hara, 2004). While this may be as a result of uncertainty about how best to move towards co-management, it is also not uncommon to hear government agency staff talking of the need to create incentives for user groups to take on management responsibility while still displaying reluctance to share real power in making management decisions (and few if any government officials, including scientists working in the research provision "industry" for fisheries, have explicit incentives to foster power sharing or devolution). The outcomes in cases of this type of "instrumental co-management" have not been found to be much better than for centralized management, often because stakeholders still lack the incentive to manage in a sustainable manner (Meinzen-Dick and Knox, 1991; Viswanathan *et al*., 2003; Hara and Raakjaer Nielsen, 2003; Hara, 2004; Raakjaer Nielsen *et al*., 2004).

Where co-management has occurred with devolution of both rights and responsibilities, it has been assumed that stakeholders associated with the fishery will assume the roles previously held by government agencies (Meinzen-Dick and Knox, 1991). To be successful, this requires collective action in order to coordinate and regulate individuals' behaviour.

Collective action and property rights are considered to be interdependent, particularly in common property resources such as fisheries where holding rights in common can reinforce collective action by the group and where collective action is required for resource management (Meinzen-Dick and Di Gregorio, 2004). Together they define incentives for adopting co-management strategies that are both productive and sustainable. The degree to which collective action is possible depends, in the first place, upon existing institutional arrangements providing an enabling environment. This includes the state providing for the possibility of such action through the devolution of control rights without requiring lengthy or costly procedures. In addition, secure property rights are an important element and need to be of sufficient duration to enable a return on investment and be backed by an effective enforcement institution, often, though not exclusively the government, enabling users to take a longer-term view of resource use. While successful collective action is central to co-management arrangements, even when rights are established, much will depend on the attributes of the participants (see for example Dietz *et al*., 2002; Ostrom, 1990; Pomeroy, Katon and Harkes, 2001 and Baland and Platteau, 1998). Capacity building is therefore an important element in many co-management initiatives (Hara and Raakjaer Nielsen, 2003; Cornwall and Jewkes, 1995).

The FAO Technical Guidelines for Responsible Fisheries (1997) promote management partnerships involving the different stakeholders in the fishery. Such arrangements need to be carefully negotiated and detailed in a management plan. The stakeholders involved and their roles and responsibilities will be very context dependent and may need to change over time. As Sen and Nielsen (1996), Dietz *et al*. (2002), Pomeroy (2003) and others have pointed out, there is no single optimum arrangement and the best strategy for managing the resource system will depend upon the characteristics of both the resource and the users. Indeed, it is recognized that co-management arrangements exist in a variety of forms and with differing roles and responsibilities for the stakeholders involved. In some cases the scale and nature of the resource system may be such that networks of small co-management units may offer good opportunities for learning and adaptive management (see Section 2.1.3). For the larger, offshore fisheries, national governments and even international organizations will usually remain the most important players in any management partnership.

In most co-management arrangements, given the devolution of control rights, it can be expected that those dependent upon the fishery, or their representatives, will have, or will develop, the ability to establish rules and sanctions as well as make decisions about organizing collective action and the management of the resource system, including the methods used to guide the fishery (reference points, stock assessment models etc). As noted by Pinkerton (2002) "when communities or organizations of fishers are included as partners in the planning, design, and implementation of the regulations, when they participate in protecting habitat, and even more, when they are part of the crafting of the very policies which underlie management decisions, they grant full legitimacy to the regulations, and are the strongest advocates, monitors, enforcers, and implementers of management decisions".

Although there are clear benefits, experiences with co-management, including within a number of FMSP projects, have shown that it is neither simple nor quick to establish. Co-management will be easier to apply in some places than others: lists of conditions that will encourage effective co-management are given by Pomeroy and Williams (1994), Berkes *et al.* (2001), Pinkerton (2002) and Olsson, Folke and Berkes (2004). Berkes *et al.* (2001) and Hara and Raakjaer Nielsen (2003) emphasize the need to balance the needs of resource management and community development, and to focus on capacity building of individuals and stakeholder groups, and the institutional arrangements that are used (for informed decision making, conflict management, learning processes, legal support, networking etc). Working with local stakeholders is not necessarily easy and requires special training and skills. Amongst other things, they may be sceptical about investing time and effort, particularly if they perceive only limited personal benefits from their involvement in the process (Cornwall and Jewkes, 1995, Eyben and Ladbury, 1995). Co-management requires compromise, respect and trust among stakeholders and a commitment to transparency, empowerment and communication, all of which may take time to develop, especially against a background of top-down regulation and control. Methods that enable this are therefore crucial.

Co-management thus requires that government agencies and researchers adopt a new way of thinking, develop new skills, and find new ways of interacting with other stakeholders (Garaway and Arthur, 2002; Hara and Raakjaer Nielsen, 2003). There is often a legacy of some mistrust on both sides that needs to be overcome. Though this can mean having to accept slow progress in the initial stages, building trust is fundamental in developing co-management (e.g. Jentoft, 2003). Important roles include mediation and conflict resolution as well as providing technical support, credit, marketing assistance and, critically, enabling legislation (Pomeroy and Berkes, 1997; Pinkerton, 2003). While those dependent on the fishery may have knowledge of local resources and needs, they often do not have access to a larger scale perspective and the technical and scientific knowledge that can assist in realizing beneficial resource management decisions. Co-management partnerships must therefore improve the knowledge base for management, and communication between stakeholders about management options and the trade-offs and risks associated with them (Hara and Raakjaer Nielsen, 2003; Borrini-Feyerabend *et al*., 2000). Government agencies and researchers may play an important role in this respect (see Garaway and Arthur, 2004, for guidelines).

In order to assist practitioners, guidelines for co-management have been developed through FMSP projects both for tropical coastal fisheries (Anderson, Mees and Cowan, 1999), and for floodplain river fisheries (see Hoggarth *et al.,* 1999; Hoggarth, 1999). Specific guidelines for using "adaptive co-management", i.e. adaptive management in a co-management setting, where the emphasis is on developing and supporting learning processes, were developed by FMSP projects R7335 and R8292 (Garaway and Arthur, 2002, Garaway and Arthur 2004).

In addition to co-management guidelines and stock assessment tools, the FMSP has also developed a number of other tools that may be used to support co-management.

Project R7834 proposed two complementary multivariate approaches that can help identify important factors affecting management performance in support of passive adaptive management approaches (see Section 4.7.2 and Section 14.3). Project R7335 also described some tools that can be used to enhance communication between stakeholder groups (Garaway and Arthur, 2002). Useful tools for developing partnership arrangements have also been developed by IIED (2001) and others.

TABLE 2.4
Summary comments on co-management arrangements in fisheries management

Management options	Advantages / application	Disadvantages / comments
Government command and control	• Strict, "top-down" control applicable in some large-scale fisheries, where co-management not feasible or where government control required to resolve otherwise insoluble conflicts	• May not be well adapted to the special needs of local stakeholders • Usually hard to enforce and expensive to administer
Co-management / partnerships	• Shares roles and responsibilities for management and enforcement (particularly valuable where government capacity is limited) • Develops more effective local rules by combining local knowledge with the scientific and technical know-how of government agencies • Where users agree with the system adopted, illegal fishing and enforcement costs may be reduced • Traditional community-based management systems may be supported by government, where they are compatible with state goals, e.g. for sustainability and equity • Most common in small scale fisheries, e.g. in coastal or inshore areas, subdivided and managed as "TURF's", but increasingly recognized as valuable in large scale fisheries also	• As well as sharing management tasks, need to share decision making power and allocate use rights (e.g. in TURFs), to strengthen incentives for user participation • Potentially high costs of developing workable arrangements • Developing trust and respect among stakeholders with different perspectives, skills and knowledge requires good social development and facilitation skills • Not applicable in all situations (but conditions increasing chances of success well known) • Can create transaction and other costs for those involved (as can command and control structures)

2.5 A PRECAUTIONARY MANAGEMENT PROCESS

A working definition of fishery management has been offered by FAO (1997) as "The integrated process of information gathering, analysis, planning, consultation, decision-making, allocation of resources and formulation and implementation, with enforcement as necessary, of regulations or rules which govern fisheries activities in order to ensure the continued productivity of the resources and the accomplishment of other fisheries objectives."

This definition implies that objectives for management will be set, and that concrete plans will be made and implemented towards their achievement. Although some broad, notional goals are usually understood, management of many fisheries is still passive, reactive and crisis-oriented, rather than proactive and goal-based. Adjustment of this situation requires firm adoption of a clear management *process*. The process and terminology described below is largely as developed by Cochrane (2002b, 2002c) with some expansions on the interpretation and use of precautionary reference points under uncertainty. It may operate equally well within single-species, multispecies or ecosystem-based fishery systems, but is oriented more towards a precautionary management approach than an adaptive one.

As was introduced in Section 1.3 and illustrated in Figure 1.1, the management process will be influenced by a range of different contextual variables, some of which have been described in previous sections of this chapter. The management process builds on the *intentions* of management (the fisheries policy, goals and objectives) and provides the operational framework by which they will be achieved. It thus translates the operational objectives into clear *standards* and ways of measuring them (the reference points and indicators), and sets the *actions* by which they will be achieved (the overall management strategy and the individual management measures). As shown by the circular arrow in Figure 1.1, a regular cycle of assessment and feedback are used to monitor progress towards fishery goals and to guide the adjustment of the management measures as and when needed. The stock assessment process, along with a system for monitoring control and surveillance (MCS) of the fishery provide the necessary scientific basis for the feedback cycle.

The full management process for the fishery should be clearly outlined for stakeholders in a management plan (see e.g. FAO, 1997; Die, 2002 and Berkes *et al.*, 2001). This should identify each of the elements listed above in addition to specifying clearly the roles, rights and responsibilities of the fishery management authority and any other interested parties.

2.5.1 Goals and operational objectives

An important first step for management is to specify the policies and goals that will drive the management process. A fisheries policy is usually developed at a national level. It applies to all of a country's fisheries, and broadly describes the purpose for which they will be managed. The policy should be supported by national legislation (e.g. a Fisheries Act), which may for example state what type of information should be included in a Fisheries Management Plan. The national fishery policy should clearly be compatible with the terms of any binding international legal frameworks which the country has ratified, such as UNCLOS, the UN Fish Stocks Agreement and any regional fisheries organizations to which the country belongs, as well as any related national legislation, e.g. concerning biodiversity conservation, protected species, etc (Die, 2002).

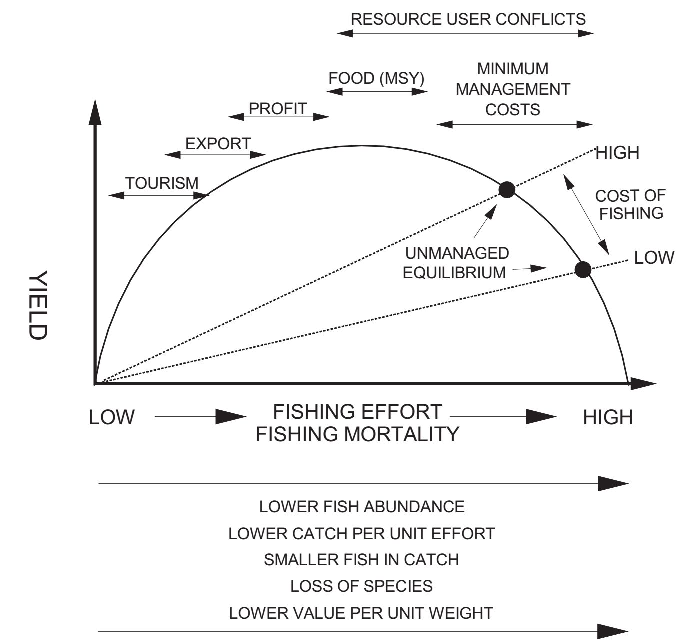
Guided by policy, broad goals should be set, stating the specific priorities for each fishery. These should focus on achieving long-term sustainable use of the fisheries resources (Code of Conduct, Paragraph 7.2.1), along with any further aims related to the social and economic status of each fishery. To enable managers to monitor their progress, the goals for each fishery (the broad qualitative desires) should be further developed into explicit "operational objectives". Like the objectively verifiable indicators (OVIs) in a logical framework[5], these should be precise, measurable, realistic and achievable. They should be negotiated with and accepted by the interested parties in the fishery, and linked to a clear time-frame. Goals and objectives are usually modified infrequently (reviewed say every 3-5 years), but should be further linked to the indicators and reference points (see below) that will form the basis of management and monitoring on an annual basis or other regular time frame.

In setting goals and objectives it is important to be aware that many otherwise reasonable objectives may be mutually incompatible and potentially conflicting. As illustrated in Figure 2.1, different goals can be achieved at quite different levels of fishing effort. Maintaining diverse stocks of large fish for sport fishing or snorkelling tourists will require less fishing pressure than that giving the "MSY" for example. There will also be tradeoffs between the average total size of the catch and the variability in catch between years, and the catch rates of individual fishermen. Different resource users will have different priorities, so it is important to use transparent and participatory decision making processes to achieve a compromise that is, as far as possible, acceptable to all, recognizing their different aims and needs. Hilborn and Walters (1992) observe that politicians are sometimes reluctant to provide explicit instructions about management objectives, preferring less binding statements that can be changed with new political circumstances. Where managers (guided by the politicians and other stakeholders)

[5] See e.g. http://europa.eu.int/comm/europeaid/qsm/project_en.htm

FIGURE 2.1

Possible management objectives for a multispecies fishery resource, their likely relative positions along a scale of fishing effort and other fishery indicators (source: Caddy and Mahon, 1995)



select multiple objectives, some type of score card or objective function may be used to weigh up the tradeoffs between different options (see Hilborn and Walters, 1992).

Both the goals and the operational objectives may usefully be divided into four subsets: biological; ecological; economic and social, where social includes political and cultural elements.[6] Accepting the underlying requirement for *sustainable* development, the biological and ecological goals could be thought of as constraints in achieving the desired economic and social benefits, and should be given priority when deciding management options. The biological imperatives must thus be met first (e.g. maintaining a viable spawning stock), before any allocative decisions are made (e.g. in sharing the catches between industrial and sports fisheries). Examples of goals and equivalent operational objectives under each of the four categories are given in Table 2.5, emphasizing the tradeoffs and giving first priority to the biological needs of the stocks. Formulated in this way, with any conflicts and contradictions resolved as far as possible, the goals may still be simultaneously achievable (Cochrane 2002c).

TABLE 2.5

Examples of fishery goals and operational objectives (from Cochrane 2002b, c)

	Goals	Operational Objectives
Biological	To maintain the target species at or above the levels necessary to ensure their continued productivity	To maintain the stock at all times above 50% of its mean unexploited level
Ecological	To minimize the impacts of fishing on the physical environment and on non-target (bycatch), associated and dependent species	To maintain all non-target, associated and dependent species above 50% of their mean biomass levels in the absence of fishing activities
Economic	To maximize the net incomes of the participating fishers	To stabilize net income per fisher at a level above the national minimum desired income
Social	To maximize employment opportunities for those dependent on the fishery for their livelihoods	To include as many of the existing participants in the fishery as is possible given the biological, ecological and economic objectives listed above

[6] Hilborn and Walters (1992) also add a category for recreational goals, e.g. the numbers of trophy-sized fish.

2.5.2 Indicators and reference points - measuring management performance

To monitor the progress of the fishery and to measure the performance of management in achieving the objectives, managers need "indicators" and "reference points". These should be used in combination with eachother to express the operational objectives in ways that can be estimated in *quantitative* fisheries assessments. Each indicator should thus be linked to one or more reference points and used to track the state of the fishery relative to those reference points.

Building on the example of Table 2.5, with the first operational objective of maintaining the stock at all times above 50 percent of its mean unexploited level, an appropriate reference point would be 50 percent of the carrying capacity, K, as estimated by the Schaefer production model[7] using "X" data and "Y" fitting method. The related performance indicator in this case is the stock size as a fraction of the unexploited level (i.e. B_{now} / K). The first objective of management would be to maintain the stock above the level of the reference point (i.e. to maintain $B_{now} > 0.5\ K$). To do this, a management procedure would be used, with decision rules guiding the actions to be taken depending on the condition of the fishery as shown by observed values of the performance indicator. Examples of such procedures are given below.

Reflecting the multi-dimensional nature of fisheries systems, FAO (1999) show how a wide range of different indicators can be used to monitor and guide the sustainable development of a fishery. Beyond the four dimensions used for the goals and objectives in the previous section, indicators can be measures of "state" (e.g. fish biomass), "pressure" (e.g. fishing mortality) or "response" (e.g. management measures taken, quotas allowed each year, etc.). Indicators may also measure "change", e.g as qualitative indications of increase, decrease, or general direction. Management "performance", however, is measured as the relation between the indicator and the reference point, comparing the present position with the desired one. In this document, a "performance indicator" is thus used to mean an indicator that is expressed as a ratio (or percentage) of its associated reference point.

The concept of reference points was introduced at UNCED in 1992. Since then, it has been adopted and developed by the UN Fish Stocks Agreement, the FAO Code of Conduct for Responsible Fisheries (FAO 1995a), and the FAO Guidelines on the Precautionary Approach (1995b, 1996). In the guidelines included in the UN "Fish Stocks Agreement" (Box 2.1), two categories of reference points were defined: target reference points (TRPs) corresponding to situations considered as desirable and to be achieved on average; and limit reference points (LRPs) indicating situations that are undesirable and to be avoided at all costs. As stated by Cochrane (2002c), the reference points provide signposts for the manager: "here you are doing well" (target) and "go any further down this route and we are in trouble" (limit). In the example above, the reference point of maintaining biomass *above* 50 percent of the unexploited level provides a *limit* signpost, above which the stock should be maintained.

Caddy and Mahon (1995) recognized TRPs and LRPs as "conceptual reference points" designed to guide managers when to take specific actions within an agreed control rule framework (see Section 2.5.3 below). Managers may for example agree to reduce fishing by a certain amount if a performance indicator falls below the TRP, and to stop fishing altogether if their LRP is ever breached. Noting that point 2 in the guidelines of the Fish Stocks Agreement (Box 2.1) implied that LRPs are relevant for "conservation" purposes, LRPs are often used to quantify the constraints imposed by ecological conditions and the productivity of the stock (e.g. the minimum size of the spawning stock biomass needed to maintain recruitment). TRPs were given in the Annex II list as relating more to the "management objectives", and have often been used to define targets for fishing levels and yields (e.g. MSY, $F_{0.1}$, see below). The

[7] See Sections 3.3.2 and 4.5 for further details on production models.

BOX 2.1

Guidelines for the application of precautionary reference points, as given in Annex II of the UN 1995 "Fish Stocks Agreement". As described in the text of this section, "precautionary" reference points are now generally interpreted to mean those that take account of uncertainties and risk; while target and limit reference points are more flexibly applied as "conceptual" elements of management decision rules. Under the ecosystem approach to fisheries (EAF), reference points should now be "ecosystem-specific", not just "stock-specific)

1. A <u>precautionary reference point</u> is an estimated value derived through an agreed scientific procedure, which corresponds to the state of the resource and of the fishery, and which can be used as a guide for fisheries management.
2. Two types of precautionary reference points should be used: <u>conservation, or limit, reference points</u> and <u>management, or target, reference points</u>. Limit reference points set boundaries which are intended to constrain harvesting within safe biological limits within which the stocks can produce maximum sustainable yield. Target reference points are intended to meet management objectives.
3. Precautionary reference points should be <u>stock-specific</u> to account, inter alia, for the reproductive capacity, the resilience of each stock and the characteristics of fisheries exploiting the stock, as well as other sources of mortality and major sources of uncertainty.
4. Management strategies shall <u>seek to maintain or restore</u> populations of harvested stocks, and where necessary associated or dependent species, at levels consistent with previously agreed precautionary reference points. Such reference points shall be used to <u>trigger pre-agreed conservation and management action</u>. Management strategies shall include measures which can be implemented when precautionary reference points are approached.
5. Fishery management <u>strategies shall ensure that the risk of exceeding limit reference points is very low</u>. If a stock falls below a limit reference point or is at risk of falling below such a reference point, conservation and management action should be initiated to facilitate stock recovery. Fishery management <u>strategies shall ensure that target reference points are not exceeded on average</u>.
6. When information for determining reference points for a fishery is poor or absent, <u>provisional reference points</u> shall be set. Provisional reference points may be established by analogy to similar and better-known stocks. In such situations, the fishery shall be subject to enhanced monitoring so as to enable revision of provisional reference points as improved information becomes available.
7. The <u>fishing mortality rate which generates maximum sustainable yield</u> should be regarded as a <u>minimum standard for limit reference points</u>. For stocks which are not overfished, fishery management strategies shall ensure that fishing mortality does not exceed that which corresponds to maximum sustainable yield, and that the biomass does not fall below a pre-defined threshold. For overfished stocks, the biomass which would produce maximum sustainable yield can serve as a rebuilding target.

more recent FAO (1999) guidelines on indicators, however, emphasize that TRPs and LRPs can apply to whichever operational objectives are prioritized by stakeholders, so long as they are compatible with sustainable development. There can for example be conservation targets as well as management ones, just as social or economic limits may be identified by stakeholders as well as constraints relating to the fish stock.

Both reference points and indicators are commonly based on agreed scientific procedures and/or models. Each conceptual reference point may thus be mathematically defined as a particular "technical reference point",[8] showing how it will be calculated. Familiar examples of technical reference points include:

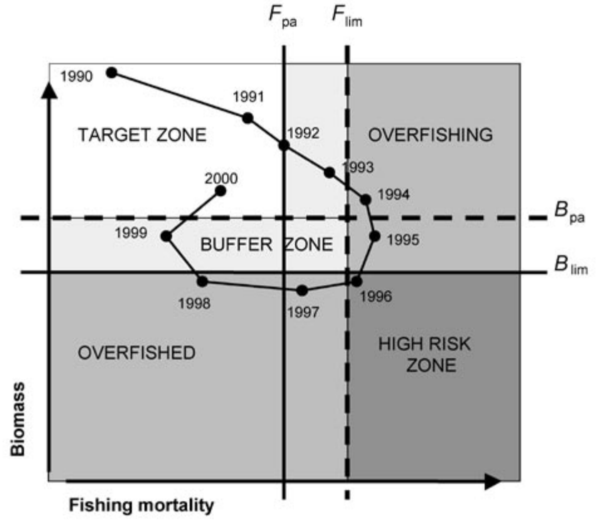
F_{MSY} Fishing mortality (F) giving the maximum total yield in a production model;
$F_{0.1}$ F at which the slope of the YPR curve is 10 percent of its slope at the origin; and
$F_{20\%SPR}$ F giving a spawning stock biomass per recruit of 20 percent of the un-fished level.

Such technical reference points are based on defined population dynamics models (see Section 3.5 for more examples). Conceptual reference points may also be set at arbitrary values which are not explicitly based on models but which are nevertheless agreed with the stakeholders. If, for example, the coverage by MPAs is used as an indicator of management response, and the value of 20 percent coverage has been agreed, through whatever process, then this is the reference value for that indicator.

As shown in Box 2.1, Annex II of the UN Fish Stocks Agreement introduced both LRPs and TRPs as "precautionary" reference points. Since then, ICES (2000) and others have interpreted precautionary reference points more explicitly as a third type of conceptual reference point – a threshold point used to trigger action, if and when a LRP is approached. Such points were adopted in response to point 5 of the Annex II list, recognising the high uncertainty associated with stock assessments, and to help make sure that the LRPs are not violated. Managers can thus take action at the precautionary threshold level, well before the LRP is reached, and thereby avoid disaster. As described in Section 2.5.4 below, the distance by which the precautionary point is removed from the LRP is usually set according to the uncertainty in the data and the risk tolerance of the manager.

The "precautionary plot" of ICES (Figure 2.2) illustrates how fisheries may fluctuate around the reference points for the level of fishing and the state of the stock. Stocks may be said to be within safe biological limits (1) when the spawning stock is above a threshold level at which recruitment is impaired and (2) when the fishing mortality is below that which could drive the spawning stock to such a biomass threshold.

FIGURE 2.2
The "precautionary plot" used by ICES to monitor the progress of fish stocks against stock-related and fishing-related reference points (source: redrawn from Garcia, 2000)



[8] These are referred to as "biological reference points" by some authors. The term "technical" is used here instead to emphasize that operational definitions are also needed for non-biological reference points.

The ICES precautionary plot thus charts the spawning stock biomass on the y-axis (an indicator of the stock "state"), against the fishing mortality rate, *F*, on the x-axis (an indicator of "pressure", Garcia and De Leiva, 2000). Reference points for both the fishing pressure and the stock status are used because fisheries do not operate in equilibrium conditions. Management adjustments to fishing rates will take time to feed through into changes in the stock biomass. Stock sizes may also fall below their defined reference points even if *F* is kept below the precautionary fishing mortality reference point "F_{pa}" simply due to a series of below average recruitments. When either biomass or *F* are beyond their respective LRPs, the situation is considered unsatisfactory (medium grey zones in Figure 2.2). When *F* is too high, it may be said that "overfishing" is occurring. When biomass is too low, the stock may be said to be "overfished" or depleted.[9] When the stock is both overfished and overfishing is still occurring (dark grey area in Figure 2.2), the fishery is clearly in a high risk zone. The light grey "buffer zone" beyond the precautionary reference points reflects an intermediate situation requiring active corrective management. The density of the shades of grey thus reflects the degree of risk (of recruitment collapse) in the fishery.

Most of the currently used technical reference points assume the availability of age-structured stock assessments and several years of stock and recruitment data. Reference points need not be restricted to such biological analyses, however. As noted above, reference points are required for each of the biological, ecological, social and economic goals and operational objectives of the fishery. FAO (1999) provide guidance on the wide range of possible indicators that may assist in tracking progress towards sustainable development, using a comprehensive "sustainable development reference system" (SDRS). When multiple indicators are organized around a "pressure, state, response" framework (or others described by FAO, 1999), any analysis of the fishery system will clearly need to move beyond the simple two dimensional plot above. Caddy and Mahon (1995) give a hypothetical example of a suite of TRPs and LRPs covering biological, ecological and socio-economic factors. Caddy (1998) also shows how a "basket" of multiple reference points could be used in a "traffic lights system", where the severity of the management correction increases as the number of reference points turn from green to red.

While the SDRS framework thus proposes integrated indicator systems of increasing complexity and completeness, both Caddy (1998) and Hilborn (2002) have suggested that simpler approaches may prove necessary to facilitate transparency and management action. Hilborn (2002) argues that management using some of the more technical reference points is *not* transparent because so many arbitrary decisions are made in the stock assessment process. Modern fisheries stock assessments can rely on dozens, sometimes hundreds, of individual judgments about which data to use, how much weight to give them, which years to include, and what to assume about initial conditions in the models. With most stock assessment models and tools, transparency is further reduced because none of the key parameters (reference points and indicators) are directly measured. Thinking beyond the current system, Hilborn (2002) suggests the use of simpler reference points based more directly on outputs from the fishery, such as the CPUE measured in a specific time and place using an agreed procedure. Although the decision control rule framework may still need to be developed with detailed stock assessment simulations, the actual rules and the annual assessments may then be easier to communicate and enforce.

[9] A stock may be in a *depleted* state, without necessarily being *overfished*. This is because factors other than fishing (e.g. disease, predation or adverse environmental conditions) may be responsible for the decline in biomass. However, irrespective of the cause, the depleted state is similar to the overfished state in that it threatens the capability of the fishery to be maintained at MSY, due to reduction in biomass and increased probability of poor recruitment. The difference is subtle and hard to detect, because it may often be difficult or impossible to assign responsibility for declines to fishing or other factors.

TABLE 2.6
Examples of different types of indicators and reference points used to guide fishery management actions. For further details, see Section 2.5.4 – precautionary reference points; Section 3.4 – indicators; and Section 3.5 – technical reference points

	Purpose	Categories and examples
Indicators	Measure the current position of the fishery for a range of different dimensions or criteria	• State, e.g. stock biomass, B_{now}; total catch • Pressure, e.g. fishing effort; fishing mortality, F_{now} • Response, e.g. quota allowed; size limit set; % of total area set aside as MPAs
Performance indicators	Measure the current state of the fishery, relative to the associated reference points	• B_{now} / B_{MSY} • F_{now} / F_{MSY}
Conceptual reference points	Used to define decision control rule frameworks that guide management actions	• Limit reference points (LRPs) identify situations to be avoided, e.g. B_{lim}, F_{lim} • Target reference points (TRPs) identify values to aim at, e.g. MSY [2] • Precautionary reference points (PRPs), trigger management actions before a LRP is reached, and should be set according to the uncertainty in the analysis and the risk tolerance of the fishery stakeholders, e.g. B_{pa}, F_{pa}
Technical reference points	Provide explicit mathematical definitions and/or procedures for quantifying the conceptual reference points	• MSY-based, e.g. B_{MSY}, F_{MSY}, as proposed by UNCLOS etc • Proxies[1] for MSY, e.g. $F_{0.1}$, F_{max} • Protection of reproductive capacity, e.g. $F_{\%SPR}$, MBAL etc, often used as LRPs • Risk-defined, e.g. $F_{transient}$ in "Yield" software • Multispecies, e.g. permitted bycatch levels • Economic and social, e.g. F_{MEY}

[1] Proxy reference points are used when the preferred reference points can not be calculated e.g. due to unavailable data.
[2] MSY is also used as a limit reference point in some fisheries (e.g. in USA)

2.5.3 Harvesting strategies and decision control rules

Annex II of the Fish Stocks Agreement requires that reference points should be agreed with stakeholders in advance and used to trigger specific conservation and management actions, also agreed in advance (see point 4 in Box 2.1). Such agreements may be formalized as "harvesting strategies" and "decision control rules". These jointly define how the conceptual and technical reference points will trigger particular actions at different states of the fish stocks or other economic or environmental indicators. Both the harvesting strategies and the control rules should be clearly specified in mathematical or logical terms, and should show what management action (e.g. an adjustment to next years level of F or TAC) will be taken, depending on the positions of the indicators relevant to the reference points. Formalization of decision making based on such an agreed procedure is an essential element of the new "management oriented paradigm" (de la Mare, 1998).

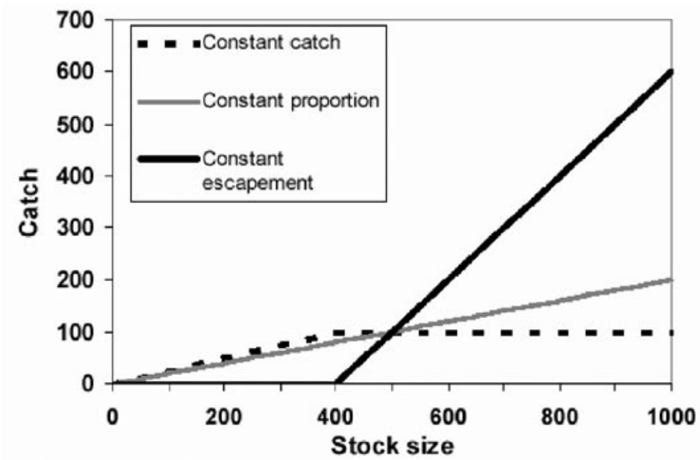
A harvesting strategy defines *how* the allowable catch will be determined or calculated each year. It may simply state, for example, that harvesting will be restricted to only males of the species (e.g. for crabs), or only those fish above a minimum size limit. It may also specify what level of catch will be taken depending on the current size of the fish stock. Such "stock-size-dependent" harvesting strategies fall into three main types:

- constant harvest rate (i.e. fishing mortality, F set as a proportion of the stock);
- constant escapement or stock size; and
- constant catch (usually set as a quota or Total Allowable Catch, TAC).

These alternative strategies are illustrated in Figure 2.3. It may be noted that a constant harvest rate strategy could either be implemented using management measures specifying the allowable level of fishing effort, or the catch quota that may be taken. The harvest strategy thus defines not what management measure will be used (see Section 2.5.5), but how the catch to be taken will be adjusted each year depending on the size of the stock (or any other economic or environmental factors in the fishery). As with all elements of the management system, the harvesting strategies should be discussed and agreed with the fishery stakeholders and clearly stated in the management plan. Scientists should provide advice on the likely outcome of different strategies and the uncertainties involved, but the choice of strategy rests with the managers, politicians, and the fishing industry.

As explained by Cochrane (2002c), there are pros and cons of each harvesting strategy. To implement a constant catch strategy (actually constant *above a limiting threshold* in Figure 2.3), the catch must be set low enough to apply in both bad years (when stock condition is poor) as well as in good years, without damaging the future productivity of the stock. Potentially high catches in good years may thus be missed by this strategy. In a constant proportion strategy, the fishing effort remains constant and therefore there will be changes in catch from year to year as the resource fluctuates over time. This variability will give some uncertainty about the future catches but will usually make good use of the available stock and lead to a higher average annual catch. A constant escapement strategy (or constant stock size strategy) aims to ensure that a constant biomass, sufficient to maintain recruitment, will be left at the end of every fishing season (see depletion model example in Section 4.5.3). Depending on the escapement level that is required, this type of strategy can achieve the highest average annual catch but also with the highest variability, including zero catches in some years (e.g. if stock size is less than 400 units in Figure 2.3). Choosing a harvesting strategy thus depends on the ecology of the fish stock, and the trade-off that is chosen between maximising catch and minimising variability. In an adaptive management context, it might also be mentioned that constant stock size policies are the most uninformative in terms of improving the understanding of the fishery (Hilborn and Walters, 1992).

FIGURE 2.3
Illustration of the three common classes of stock size-dependent harvesting strategies (source: Cochrane 2002c, with permission)



A challenge in working with stock-size-dependent harvesting strategies is in estimating the best harvest rate, catch or target escapement to use. These are usually guided by specific technical reference points, e.g. based on fishing mortality rates or TACs, as described in Section 3.5. As noted above, simpler harvesting strategies can also be used in some cases. Sex-specific harvesting is sometimes used in crustacean fisheries where the females are often much smaller than the males and can be released with little loss in the value of the catch. The catch of berried females may also be regulated. Size limit strategies may be used to protect the spawning stock in fisheries, especially where gears are selective and sub-legal fish can be returned unharmed (e.g. with traps). Setting size limits greater than the size at first maturity ensures that at least some females will be able to reproduce each year. Both of these examples are fairly arbitrary, but can be "very robust and excellent strategies" when the biology and economics are appropriate, and when the more complicated options are not feasible (Hilborn and Walters, 1992).

Harvesting strategies may either be defined as constant rules that ignore the state of the fishery, or as feedback policies where the action to be taken varies with the state of the stock. Setting a minimum mesh size and a target fishing rate (e.g. $F_{0.1}$) from a YPR model for example, could be based on an equilibrium assumption, and implemented with no further monitoring of the stock. A more precautionary strategy would require that the decision rules used to control fishing will respond to feedback on the state of the stock or some other indicators. It is also of course possible to have a fishery managed with a combination strategy, where some measures are constant (e.g. a size limit) and some are based on feedback rules (e.g. fishing effort controls).

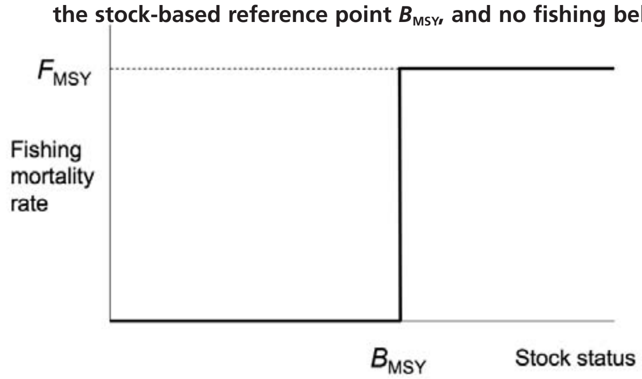
TABLE 2.7
Summary comments on the alternative fisheries harvesting strategies (see also Section 2.5.5)

Harvest strategy	Advantages / application	Disadvantages / comments
Constant fishing rate	• Constant effort provides stability for industry • Gives high annual average catches • Lower monitoring costs if only number of vessels limited, not catches	• Catches will vary with stock abundance • Higher monitoring costs if numbers of days at sea also restricted
Constant catch (e.g. by TAC)	• Provides stability for industry for some reduction in potential average catch	• Fishery potential may be underutilized in years of high stock abundance • High monitoring costs for estimating catches in real time to enable fishery to be closed when quota reached
Constant escapement (biomass)	• Gives highest possible average catches but high variability in catch	• Catches may be zero in years when abundance is lower than target escapement threshold • High monitoring costs
Size or sex-based	• Ensure that some fish can spawn before becoming vulnerable to fishery • Use where non-harvestable sizes or sex can be released unharmed from gears (e.g. pots)	• Sex-based strategies (e.g. males only) may not protect spawning potential if fishing pressure is high, so may need to combine with other measures

A very simple <u>decision control rule</u> is illustrated in Figure 2.4, where the fishing mortality rate is set at F_{MSY} (see 3.5.1) so long as the biomass is above B_{MSY}, and the fishery is closed if the biomass falls below this level. It may be noted that the axes in Figure 2.4 are switched from those in the ICES precautionary plot (Figure 2.2). This is because in the precautionary plot, the state of the fish stock (biomass on the y-axis) is presented as the *result of* the fishing rates exerted (F on the x-axis). In the decision control rule, the fishing rate (on the y-axis) is set *according to* the current state of the stock (on the x-axis).

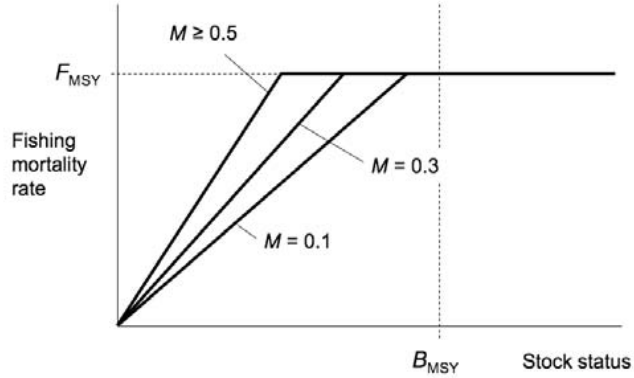
The decision control rule of Figure 2.4 implies a strategy referred to as "pulse fishing" (Caddy and Mahon, 1995). Except when used in a series of fishing sub-areas, in each of which fishing is either "on" or "off", the pulse fishing approach may be expected to give erratic fluctuations in total annual catches. To avoid continual on-off adjustments, "slope-based" approaches to control rules have also been proposed allowing more gradual adjustments depending on the degree of overshoot. The default control rule defined in the US legislation (Restrepo *et al.,* 1998; Gabriel and Mace, 1999) uses such a sloped response, and proposes that the threshold point for reducing

FIGURE 2.4
A simple, "knife-edged" decision control rule, allowing fishing at F_{MSY} for stock sizes above the stock-based reference point B_{MSY}, and no fishing below



F below the F_{MSY} level should be lower for high turnover species (i.e. with a high natural mortality rate, M) than for lower ones (Figure 2.5). Although this control rule allows some fishing (albeit at reduced rates) even if biomass is reduced almost down to zero, where LRPs are used to identify undesirable locations to be avoided, sloped decision rules are more often used to reduce fishing rates in between the precautionary and limit reference points (see following section).

FIGURE 2.5
The default decision control rule adopted by the United States for implementing National Standard 1 of the Magnuson-Stevens Fishery Conservation and Management Act (Restrepo *et al.*, 1998; Gabriel and Mace, 1999)



An important point to mention about the use of decision control rules is that if the reference points or indicators are estimated each year with low levels of accuracy, even with a sloped control rule, the required adjustments to fishing controls may still vary substantially between years. Such fluctuations may be more due to the lack of precision in the stock assessment procedure than the state of the stock or the other indicators. It could thus be impractical to impose the control rule on the fishing industry exactly as it is formulated. Where opposition is high, annual adjustments could be restricted to maximum changes of say not more than a 20 percent increase or decrease each year towards the actual point predicted by the control-rule.

Achieving agreement on the management actions to be taken in response to changing resource conditions will be a high hurdle for fishery managers, but is seen as a necessary step in the long term (Rosenberg, 1998). Pre-agreed harvest control rules may be seen as a good thing for the fishery as they should reduce the influence of short-term political factors in making difficult decisions about future catches. However, since the stakeholders in many fisheries use annual negotiating rounds as opportunities to maintain their benefits from the fishery, fixed strategies may also be difficult to achieve in a political world (Rosenberg, 2002).

2.5.4 Precautionary reference points – allowing for risk and uncertainty

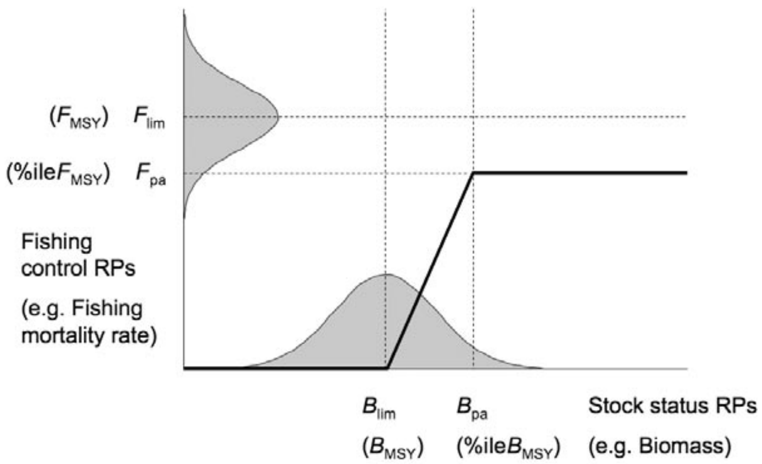
Hilborn (2002) notes that it is very hard to estimate absolute abundance reliably, and even harder to estimate the virgin or unexploited biomass or "carrying capacity". Giving a quote from John Shepherd, Hilborn notes that "counting fish is like counting trees – except they are invisible and they keep moving"! Precautionary reference points provide a means of operating in this arena of high uncertainty.

ICES, NAFO and others (Garcia, 2000), all identify precautionary reference points (PRPs) as "early warnings" used to reduce the probability that LRPs will be exceeded. Without such early warnings, LRPs may be breached inadvertently due to uncertainties in either the LRPs themselves or the estimates of current fishing rate and/or stock status relative to those LRPs, or both (Gabriel and Mace 1999). The important statistic then becomes the *probability* that the fishery has reached or exceeded the LRP. In essence, there needs to be some distance (sometimes called a buffer) between the LRP and the PRP so that a fishery that is believed to be operating in the region of the PRP has an acceptably low probability of actually exceeding the LRP. The higher the uncertainty in the reference points and/or the fishery status, the greater the distance needed between the LRP and the PRP.

The concept of PRPs is shown in Figure 2.6. This example focuses on uncertainty in the LRPs rather than the fishery status, but it is useful for illustrative purposes.[10] Uncertainties in both the fishing control LRP (F_{lim} , here designated the technical point F_{MSY}) and the stock status LRP (B_{lim} , here designated B_{MSY}) are indicated by the shaded normal distributions. The PRP for fishing rate, F_{pa} is *reduced* from F_{lim}, while the PRP for stock status, B_{pa} is *increased* above B_{lim}. The adjustments are made to give the required safety margins for the control rule indicated by the heavy line. Under the control rule, fishing is allowed at F_{pa} while the stock is above B_{pa}. If the stock drops below B_{pa} , the fishing rate is proportionately reduced down to zero as the stock approaches B_{lim}. The exact positions of the PRPs depend on both the uncertainty in the LRPs (the width of the shaded probability distributions) and the degree of risk seen as acceptable by the managers. Both F_{pa} and B_{pa} could thus be set at levels that are more (or less) precautionary where uncertainties are higher (or lower), or where the managers are more risk averse (or more risk prone).

FIGURE 2.6

An example of a decision control rule based on limit and precautionary conceptual reference points and a constant exploitation rate harvesting strategy. Example associated technical reference points are given in brackets



[10] Gabriel and Mace (1999) suggest that estimating the probability that the currently observed fishing mortality rate, F_{now} , exceeds the LRP should really be conditional on the uncertainties in *both* F_{now} and in the LRP. Such probabilities could be estimated explicitly using Bayesian methods. Working with only the uncertainty in the LRP alternatively allows simpler but still precautionary assessments, incorporating definable elements of uncertainty and risk.

As noted earlier, the level of uncertainty in the assessments depends on, among other things, the quality and quantity of the data (see Section 3.6.4). The level of uncertainty is a measure of the quality of the assessment, which may be improved either by better data or better modelling, or a combination of the two, thereby reducing the level of uncertainty.

The stock assessment provides information on the amount of risk associated with different management strategies, but decisions about the level of risk that is acceptable are a matter of choice to be made by the stakeholders. ICES has proposed for example to estimate

$$F_{pa} = F_{lim}\ e^{-1.645s}$$

where *s* is "the log standard deviation in the recruitment series or a coefficient of variation (CV) from the assessment uncertainty" (ICES, 2000). Based on a cumulative normal frequency distribution, the value of 1.645 implies a point where "the probability of exceeding the limit reference point will be no greater than 5 percent in any given year" (Serchuk *et al.*, 1999). Lower or higher risk tolerances could be adopted, as preferred by decision makers and other stakeholders. Caddy (1998) indicates that "*s*" has not always been clearly defined, but is typically taken as 0.2-0.3 in ICES at least. In some of the FMSP tools described in Chapter 4, probability distributions around the technical reference points are estimated using bootstrapping, so that precautionary reference points can easily be identified as the percentile points for the chosen risk levels. This also has an advantage where confidence intervals are non-symmetrical, as frequently occurs. In the FMSP "Yield" software (Section 4.3), the "Transient reference point" is also available to estimate the fishing mortality rate with a specifically defined risk.

Although the idea of reference points has been widely accepted, they have been interpreted differently by different agencies (ICES, 2000). A significant example is the difference in the technical definition of the fishing mortality LRP between ICES and NAFO (see Section 3.5). ICES uses F_{lim} to indicate a fishing mortality rate above which there is an unacceptable risk of the stock size declining below B_{lim} in some medium or long-term period. Hence it is a marker of the longer term risk of incurring recruitment overfishing. In the NAFO framework, based on a more literal interpretation of the guidance of the UN Fish Stocks Agreement, F_{lim} is taken as corresponding to F_{MSY}, hence it is used as a marker of decreasing stock stability and the loss of long-term yield. ICES does not include F_{MSY} in its precautionary framework at all, reportedly considering this reference point as too difficult to estimate reliably. With this key difference between the fishing rate LRPs (and ignoring any differences in the uncertainty of their data or the risk levels adopted), the framework of ICES is potentially much less precautionary than that of NAFO.

Perhaps less importantly, but adding to the potential confusion, reference points that are essentially the same have been given different names. For example, ICES names their PFPs F_{pa} and B_{pa}, NAFO names them F_{buf} and B_{buf}, while ICCAT has proposed to name them F_{thresh} and B_{thresh}, the subscripts standing for "precautionary", "buffer" and "threshold" respectively (Gabriel and Mace, 1999).

2.5.5 Management strategies and measures

Once operational objectives and reference points, and a harvesting strategy and decision control rules have been technically defined and agreed, a management strategy can be developed for implementing the advice. As defined by Cochrane (2002b), the <u>management strategy</u> is the sum of all the <u>management measures</u> (called tactics by some) that are selected to achieve the biological, ecological, economic and social objectives of the fishery. Management measures involve the use of "control variables". These are the aspects of the fishery over which management has some direct control, and which are governed by pre-determined responses under the decision control rule framework.

In a fishery with a single target species, a management strategy could consist of a single management measure, such as a specified total allowable catch (TAC). In practice, the management strategies for most fisheries usually consist of a combination of different management measures. An effective management strategy, however, should not contain so many management measures that compliance and enforcement become so difficult as to be practically impossible (Cochrane, 2002b).

Cochrane (2002a, Chapters 2, 3, 4 and 6) describes management measures in detail, classified as follows:

- technical measures, usually permanent regulations on gear type or gear design, and closed areas and closed seasons;
- input (effort) and output (catch) controls, e.g. a limit on the total number of vessels in a fishery, or an annual total allowable catch (TAC); and
- any access rights designed around the input and output controls (see Section 2.3).

Technical measures thus control how, where and when the catch is taken and are often set as permanent regulations, or changed only infrequently. Input/output measures are used to control the total amount of fishing, either as the effort applied or the catches that are taken. Input/output measures are most commonly used as flexible controls, to supplement any technical measures, and to fine tune the levels of fishing pressure each year in response to the latest stock assessment data. Keeping in mind the ecosystem perspective, some managers may also apply management measures to restrain any negative external impacts on the fishery (e.g. due to pollution). In inland fisheries, the management strategy may also include measures that enhance the fishery such as fish stocking or habitat improvements etc. The pros and cons of these methods are briefly summarized in the following sub-sections (see also Cochrane, 2002a; Cadima, 2003, and others).

Some management measures are clearly associated with specific harvesting strategies. For example, a size limit could be used for protecting the spawning stock, perhaps associated with a seasonal closure of the nursery grounds or spawning grounds. Other measures can be applied in different ways to achieve each of the three main stock-size dependent harvesting strategies (Section 2.5.3). The best choice of measure depends on the nature of the fishery and the levels of uncertainty in stock size, catchability and fishing effort (Hilborn and Walters, 1992). Some examples are given below.

- A fixed catch strategy may be most obviously associated with a total allowable catch (TAC) measure. This should be effective at achieving the intended harvest so long as there is good enforcement and no discarding.
- A fixed escapement strategy may be achieved using a time limit for the annual fishing season, closing the fishery when the target escapement is reached. This may be best combined with effort controls that enable the season length to be approximately predicted, and preferably supported by real-time monitoring of catches and depletion modelling to determine the actual escapement as the season progresses.
- A fixed harvest rate strategy may be achieved by either effort controls or TACs. In the case of effort controls, care must be taken that increases in catchability do not increase the effective harvest rate over time (or downward adjustments in effort may be made annually to balance any upward trends in catchability). When using TACs (e.g. estimated as the stock size times *F*), the intended harvest rate will only be achieved if the stock size is well estimated and if there is good enforcement and no discarding as above.

There are also clear linkages between management measures and use rights (Section 2.3). While management measures can be applied without associated use rights (e.g. by setting a TAC without limiting access to the fishery, or by setting a maximum vessel size without limiting the numbers of vessels to be licensed), there are usually advantages in developing joint systems. The elements of the management strategy should also be chosen at the same time as the set of reference points and the decision control rules and the harvesting strategy are selected. There are usually several ways of regulating a fishery towards a desired reference point, some of which are described in the sub-sections below. Due to the linkages implied by the general equation, $C = FB$, either F-based or biomass-based reference points can usually be achieved by setting either input or output measures.

Table 2.8 summarizes which of the FMSP stock assessment tools may be useful in estimating appropriate levels for each of the management measures. While the advice from "Yield" is mainly F-based, this can be used either to set fishing effort (input controls) if the catchability, q is known, or to set TACs (output controls) if biomass is known. The outputs from CEDA are mostly aimed at setting TACs based on MSY values and on projections from the current stock size. Fishing effort levels giving MSY may also be estimated when the biomass dynamic model is fitted using effort data covering the whole fishery, or using approximate ratio-based methods (see Section 4.5.3).

TABLE 2.8
Summary of the potential use of the FMSP and related stock assessment tools for providing advice on different management measures

	Common sense + biol. studies	Empirical methods (Section 4.7.1)	CEDA / ParFish	LFDA + B&H invariants	LFDA + Yield	Multispp., multigear (Section 4.4)
Input controls (effort manage't)		✓ [1]	✓	✓	✓	✓
Output controls (e.g. TACs)		✓ [1]	✓	✓ [2]	✓ [2]	✓ [2]
Technical measures						
Size limits	✓	✓			✓	✓ [3]
Closed seasons	✓	✓			✓	✓ [3]
Closed areas	✓	✓	✓ [4]			
Gear restrictions	✓	✓				✓ [3]

Notes: [1] Per unit area. [2] If biomass also known. [3] e.g. BEAM4 approach. [4] ParFish only.

Input controls (fishing effort restrictions)

Fishery management is generally most strightforward where the catching capacity of the fishing fleet is approximately in balance with the potential of the fish stocks. This rarely occurs without some form of intervention. Ludwig, Hilborn and Walters (1993) describe the "ratchet effect" by which fishing effort and capacity usually goes up in years of good stocks, then can be very hard to get back down when stocks return to "normal" levels. At a global level, with about 1.2 million decked vessels in 1995, the world's fishing capacity has been roughly estimated as 30 percent over the level that would take the global MSY (and therefore an even higher percentage above any precautionary reference point based on global MSY; Greboval, 1999). Some areas and fish stocks are more overcapitalized than this average figure suggests, while others may still have some room for expansion (see Grainger and Garcia, 1996 and Section 14.1). The FAO Code of Conduct calls clearly for the effective control of fishing effort and capacity.

Fishing effort restrictions aim to limit fishing mortality (F) by controlling one or more of the following factors:

- the total number of vessels in the fishery, e.g. by allocating limited access rights and restricting the number of licences issued;
- the effort allowed by each individual vessel, e.g. the number of gear units allowed, the number of trips that may be made each year, or the number of days at sea; and
- the power of individual vessels, e.g. the size or engine power of the vessels, or the types of gear that may be used.

Recommendations on adjustments to fishing effort (e.g. to bring F_{now} closer to F_{MSY} or F_{pa}) can be produced by analytical models (e.g. using FiSAT, Yield, Beverton-Holt "invariants" methods), or using biomass dynamic or depletion models (CEDA). Multispecies approaches can also be used (see Section 4.4).

An important consideration with effort restrictions is that they will not be entirely effective whenever fishers can increase the catchability of their fishing in some way, e.g. by fishing harder or longer, or by using more gears or more engine power. The importance of such issues for both effort and catch management (inputs and outputs) is analysed by Pope (2002). Where catchability is increasing over time (as is usual), the numbers of vessels or some other input control may need to be adjusted each year to compensate for the extra fishing power, in order to maintain the intended harvest rate.

Fishing effort is difficult to manage in any fishery exploited by several fleets with different effort characteristics, especially if fair allocations of catches must be made between them. In these situations, output controls (catch quotas) are more commonly used (see below).

Fishing effort may also be hard to control in small scale fisheries partly because enforcement is difficult but also because artisanal fishers are often among the poorest of the poor, with no alternative source of income, and politicians may be reluctant to enforce measures that may have painful short term impacts, even if long-term benefits are possible.

Output controls (catch limits)

Output controls such as the total allowable catch (TAC) indirectly control the fishing mortality. As noted above, they may be more or less effective in this aim depending on whether the stock size is well estimated and on whether there is good enforcement and little discarding.

TACs may be estimated directly using biomass dynamic models, or may be set by combining an *F*-based reference point from an analytical model with an estimate of biomass e.g. from CEDA, VPAs, or a trawl survey. Where current biomass is known (and preferably the incoming recruitment), next year's allowable catch can be estimated using short term projections (see Section 3.6.2). Levels of *F* used in estimating the TAC should be derived from the selected reference points or those levels shown in projections to have the desired medium or long-term properties.

Approximate catch limits (e.g. for estimating the development potential of a fishery) may also be estimated using the Beverton and Holt "invariants" methods (see Section 4.2), or using empirical methods based on resource area and nominal effort measures (Chapter 14).

Output controls are commonly used in fisheries that are shared between nations (e.g. in the EU). Shares of a TAC can be allocated more equitably to the different nations than can shares of the allowable fishing effort. Due to variations in fishing power due to boat design, technology, fishing locations etc, the fishing mortality caused by different national fleets depends on far more than the simple numbers of vessels. Even with these complications, a recent Royal Society (2003) paper has argued for replacement of TACs with effort (input) controls to make the fishing regulations more enforceable and effective. The problem with TACs is that they tend to stimulate mis-reporting of catches for obvious reasons. They may also cause discarding of bycatches if quotas for different species are reached at different times in multispecies fisheries. TAC management also requires a major investment in monitoring and surveillance, e.g. using both port sampling and observers at sea to enable the fishery to be closed when the TAC is reached.

Quotas are particularly problematic for small scale fisheries due to poor enforcement, inaccurate catch reporting, difficulties in predicting next year's stock size and the potential catch, and the multispecies nature of stocks etc (Berkes *et al.*, 2001).

A further problem with "unallocated" TACs is that they also promote the "race for the fish", leading to overinvestment in fishing power and capacity. This increases the competitiveness of individual fishermen but also increases the overall F caused by the fleet. This will make it harder to constrain the catch at the quota level and will reduce the profitability of the fishery. One solution to these problems is the sub-division of the TAC into Individual Quotas (IQs or ITQs), as discussed in Section 2.3. Such use of harvesting rights ensures fishermen their allocated share of the catch and reduces the need to compete. On the down side, IQs can also lead to problems with "high grading", when small or low-value fish are discarded to maximize the value of the fish landed. Transferable quotas may also cause social disruption if large efficient companies are able to buy out the smaller inefficient operators.

Technical measures (size limits, closed seasons, closed areas etc)

While input and output measures attempt to control the overall level of fishing pressure, technical measures aim to control the exploitation pattern of the fishery. The main technical measures are size limits (either of the sizes of fish or the mesh sizes of the gear), closed seasons, closed areas and gear restrictions or bans. Technical measures are usually designed to protect reproductive potential, prevent growth overfishing, or prevent the use of destructive fishing gears, as outlined below.

Technical measures for protecting reproductive capacity include size limits, closed areas or closed seasons that are designed to protect spawning stocks, and restrictions on the harvest of reproductively active animals (e.g. berried female lobsters). Size limits may either be set nominally in relation to the size at maturity or according to some technical reference point (e.g. to achieve a particular %SPR, depending also on the level of F, see Section 3.5.3). Myers and Mertz (1998) showed that the use of size limits in a "spawn-at-least-once" policy makes a fish stock resilient to collapse even when fishing mortality rates rise above target levels. Since size limits can introduce problems with discarding of small fish (resulting in the underestimation of F), they should always be set as compatible limits for both fish sizes and gear mesh sizes.

The same types of measures can be used for preventing growth overfishing. In this case, closed areas could be set to protect juvenile or nursery grounds, or closed seasons could be designed to avoid fishing at times when fish are mostly small. Closed seasons are especially useful for fast growing species such as shrimps or squid.

Technical measures may also be used to avoid damage to the resource and reduce bycatches of discards of non-target species. Bjordal (2002) considers the potentially negative effects of various types of fishing gears, including their size and species selectiveness (worst for shrimp trawls having very high bycatches), the possibility of ghost fishing due to lost gears (worst for gill nets), and the negative impacts on habitats (worst for various types of trawls). Bans on poison, explosives and electro-fishing are commonly used in inland fisheries and in coral reefs due to their high effectiveness and unselective nature, and the damage they cause both to habitats and other species. Sorting grids and turtle excluder devices (TEDs) can also be rigged in various ways to ensure that small fish or larger non-target fish, or turtles can escape (see Bjordal, 2002).

Technical measures may either be set with a combination of common sense and limited technical data, or using the output of models. Optimal size limits and the timings of closed seasons can be estimated using analytical yield or YPR models (e.g. "Yield"). Analytical models are needed to provide advice on such factors as they involve a change in the selectivity of the fishery. The benefits of closed areas are more difficult to predict due to the high dependence on the movement patterns of the fish, which will usually not be well known (see MPAs below).

All such technical measures require some capacity for enforcement to ensure that rules are complied with. Enforcement may nevertheless be simpler for technical measures than for input/output controls. Technical measures that can be easily communicated, that intuitively relate to the status of the resource and that can be enforced at the community level may be very appropriate for small scale fisheries and co-management arrangements.

Ecological and integrated management

The multispecies and ecosystem scales of management recognize that the fishery is only one part of the aquatic ecosystem that is required to deliver a broad range of goals for society (Section 2.2). Most management measures aimed at these levels will involve the same input/output and technical rules described above, but applied in a multispecies or ecosystem context, e.g. to avoid bycatches or gear damage (see Section 3.5.5). Other measures more explicitly aimed at the ecosystem level include the use of MPAs, and the restoration or maintainance of "essential fish habitat", as legally required in the US now, since the 1996 amendments to the Magnuson-Stevens Act (see NMFS Web site).[11]

Networks of MPAs are also now being promoted by some (e.g. Pauly *et al.*, 2002) and actively developed as one of the key requirements of the Johannesburg WSSD (see Section 2.2.3). Hall (2002) provides guidance on the integration of fishery reserves and MPAs emphasizing their potential value both in achieving fishery objectives and

TABLE 2.9
Summary comments on alternative management measures

Management measures	Advantages / application	Disadvantages / comments
Input controls (fishing effort)	• Used to control overall fishing capacity. May involve limits on numbers of vessels and their individual fishing power and effort • May be used to achieve constant fishing rate or escapement harvest strategies, e.g. combined with a closed season	• Harder to sub-divide total allowable effort between nations, and between different fleets/gears within nations, due to variation in vessel types and designs • Need to monitor increases in technology and catchability that may increase *F* without apparent increases in effort. • May be politically difficult to restrict effort due to short term impacts and lack of alternative options for displaced fishers
Output controls (TACs, etc.)	• Should be effective at achieving intended harvest rate if enforcement good and no discarding or highgrading • May be easily divided, e.g. between nations sharing a total quota as in EU	• May cause overinvestment in technology and capacity, and "racing" to catch fish before quota reached (less problem if allocated as individual or vessel quotas) • High monitoring and enforcement costs (not suitable for small scale fisheries) • Provides incentives for mis-reporting
Technical measures	• Usually set as permanent regulations on permitted gear types or designs, size limits, closed areas, closed seasons etc • Aim to control exploitation pattern, e.g. to protect reproductive potential or avoid capture of juveniles etc • May be easiest to communicate and enforce	• May not be enough to limit exploitation effectively on their own • Usually combined with input/output controls
Ecological measures	• Often based on technical measures applied to ecological goals, e.g. to avoid bycatch or reduce gear damage to habitats • MPAs and reserves may serve both fisheries and ecosystem goals • Integrated management approaches especially important in inland fisheries	• May be complicated to develop and implement • Can be hard to enforce

[11] http://www.nmfs.noaa.gov/habitat/habitatprotection/essentialfishhabitat.htm

as a wider conservation measure. Where used, reserves should be one component of an overall strategy for fisheries and biodiversity conservation. They will have limited benefits on their own if problems escalate in the waters outside. Salm, Clarke and Siirila (2000) and Hall (2002) describe practical steps towards establishing good MPAs and closed areas. Specific guidelines for harvest reserves for tropical artisanal floodplain river fisheries were developed by FMSP Project R7043 (Hoggarth, 1999).

2.6 THE ROLE OF STOCK ASSESSMENT IN MANAGEMENT

The role of stock assessment in the management process outlined above includes the identification of well defined reference points for the fishery, and the regular (e.g. annual) assessment of indicators showing the status of the fishery and the fish stock relative to the reference points. Under this strongly management-oriented process, a stock assessment is potentially more tightly defined than in the past, referring to a specific set of reference points and indicators, calculated using agreed data and methods (de la Mare, 1998). Building on this "stock assessment", Punt and Hilborn (2001) suggest that a second phase of quantitative analysis should determine the consequences of alternative management actions (usually referred to as a "decision analysis"). As described in Section 3.6, such decision analyses should take account of the uncertainties in the system, and may go well beyond the simple control rule framework suggested in Section 2.5.3. Decision analysis may thus guide the selection of reference points and the actual formulation of the control rule system.

The "stock assessment process" described in Section 3 goes as far as the provision of stock assessment advice. It may provide both short term (tactical) and long term (strategic) management guidance. Short term advice might be on the size of the TAC next year; long term advice on whether a change in the overall management strategy could give better returns. Items such as setting policies and goals, and enforcing the agreed measures fall outside this stock assessment process, but are within the managers remit and clearly need to be considered as elements critical to success.

While stock assessments may form the primary basis for choosing management strategies, they should not be expected to do the impossible – predict the future with certainty (MRAG Americas, 2000). A good stock assessment will not provide a single right "answer", but should rather give a range of choices showing the predicted outcomes and any tradeoffs. The choice between such options should be made by fishery managers, not by stock assessment scientists, guided by their attitudes towards risk and the socio-economic priorities for the fishery.

Even with good data and good stock assessments, management failures can still occur. Sometimes the management is just sub-optimal. At other times, such as with the collapses of the northern cod stock in Canada and the Peruvian anchovy, management failures can affect many thousands of fishing households. Failures in the past have variously been due to a lack of consideration of the reaction of fishermen to regulation, the failure of politicians to implement the advice of scientists and the challenges of effectively enforcing the rules (Rosenberg *et al.*, 1993). Improvements in the future will require recognition of the limitations of the science and better communication of uncertainty as an aid to decision making (Hilborn and Walters, 1992).

Even with these improvements, fishery management will remain complicated, not least because there is no possibility of using controls to test experiments on the scales of whole fisheries. It is thus impossible to find the peak of a sustainable yield curve until the fishing effort has gone beyond the "MSY" level. By this time, yields will be declining and fishermen will be in financial difficulty and the hardest thing to do will be to reduce fishing effort to the MSY level. Facing this reality, managers should attempt to find a balance of precautionary and adaptive approaches, i.e. to detect the "top" as early as possible and to build mechanisms into the fishery so that it will be possible to reduce effort when the time is necessary (Hilborn and Walters, 1992).

It is also important to realize that stock assessment is not the *purpose* of management, but one step in a much larger process intended to achieve management objectives under conditions of uncertainty. For small-scale fish stocks in developing countries, Mahon (1997) has argued that management efforts should be more “management objective driven” (MOD) than “stock assessment driven” (SAD). Factors determining what level of stock assessment will be appropriate are briefly explored in Chapter 5, and mainly depend on the size and value of the fishery and the resources and capacity of the fishery service. Mahon (1997) also emphasizes the need for *fishery* assessments that are broader than *stock* assessments (e.g. including information on fishing capacity, the behaviour of the fishing industry, institutional capacity, environmental impacts, etc). The DFID sustainable livelihoods framework[12] provides a useful guide to the many other factors that can be critically important in determining the outcomes of different management strategies. The development of the technical stock assessment tools described in this guide along with others such as FiSAT, BIODYN etc, reflect the needs of some managers of small fisheries to make some attempt at stock assessment even when capacity is limited. In using these tools, managers should clearly keep in mind their relationship to the broader aspects of the management process and framework (Figure 1.1).

[12] See http://www.livelihoods.org/

3. The stock assessment process

3.1 INTRODUCTION

This chapter of the guidelines describes the stock assessment process. It includes some of the more common scientific methods that are used to improve our understanding of fish and fisheries. These are the methods that enable scientists to answer the questions most often asked by fishery managers, and they include the methods implemented in the FMSP stock assessment tools that are described in Section 4.

Stock assessment methods can be described and classified in a number of ways (see for example Hilborn and Walters, 1992, and Quinn and Deriso, 1999). This chapter does not attempt to cover all of the possible methods in detail, but instead provides a summary of the main building blocks in a *stock assessment process*. Initial investigations of a fishery usually focus on the most basic facts – what types of fish are out there? where are they? how many are there? what species are being caught? who is catching them? and how are they doing it? To provide detailed management advice, the stock assessment process becomes more refined to answer the specific questions posed by fishery managers – how fast do the fish grow? how quickly do they reproduce? what is the best size to start catching them? and of course, how much can we catch sustainably? This is where the stock assessment process becomes an indispensable part of the fishery management framework.

The methods described in this chapter include the estimation of basic "intermediate" parameters, such as growth rates, mortality rates, carrying capacity, maturity and reproduction, stock and recruitment, selectivity and catchability. Options are then given for selecting indicators for the current condition of the fishery and the estimation of reference points as a basis for developing management advice.

Before looking at specific methods, guidance is given on some of the basic choices open to scientists in choosing between alternative stock assessment approaches. Sparre and Venema (1998) also describe the many alternatives and note that the choice of an adequate methodology is often more a matter of personal judgment than strict logic. General comments are made first about the alternative levels of mathematical complexity required in different assessments and about the modeling of uncertainty. Other choices of methods then follow: should we use a "biomass dynamic" or an "analytical" approach? (Section 3.1.3), deterministic or stochastic? (Section 3.1.2), or age-based or length-based? (Section 3.1.5). Finally, can we include a stock-recruitment relationship in the assessment, or must advice be provided on a "per-recruit" basis (Section 3.1.6)? These are just some of the more obvious options. Clearly there are many other choices to be made along the way, and even those indicated here have many other underlying questions and details to be addressed. Stock assessments may also be single species or multispecies or include ecosystem interactions as noted in Section 2.2. While there are many different stock assessment approaches, they all involve many of the basic *process* steps outlined below and illustrated in Figure 1.2. This introductory sub-section thus attempts to describe the basic differences between some of the alternative stock assessment routes, as summarized in Table 3.1 below.

TABLE 3.1
Summary comments on the alternative modelling approaches and their data requirements

Stock assessment approaches	Advantages / application	Disadvantages / comments
Length based	• Lower data needs and costs • Use where ageing not possible (e.g. some crustacea or tropical fish)	• Lower accuracy and precision • Some methods only useful for certain types of species (e.g. growth methods better for fast growing species) • Sampling may be highly biased by selectivity of fishing gear or behaviour of fish (also applies to age based methods)
Age based	• Higher accuracy and precision • Use wherever fish can be aged	• Higher data needs and costs (for ageing fish), but may still be more cost effective in the long run
Black-box (biomass dynamic) models	• Simple to apply (even using non-equilibrium fitting methods) • Only catch and abundance data needed • Useful for species that cannot be aged • Can use aggregated model for multispecies fisheries	• Advice may have high uncertainty where data contrast is low (e.g. with "one way trip" data sets) • Requires long time series of data (several years) • Requires good index of abundance with constant q • Only provide guidance on input/output controls (effort, TAC etc), not size limits or other technical measures
Analytical models	• Required for management advice on technical measures such as age/size at first capture or closed seasons • Useful when different fleets exploit different age groups • Management advice can be provided with only one years' data	• Higher data costs and analytical needs
Per recruit	• Easy to use, low data needs • Use to avoid growth overfishing • Use %SPR as proxy reference point for avoiding recruitment overfishing	
Including recruitment	• Use to avoid recruitment overfishing	• Higher data needs (stock-recruitment data series) • Some reference points (e.g. F_{med}) may not be valid if SR data taken when fishery already depleted

3.1.1 Qualitative or quantitative?

Fish stock assessment has become an increasingly mathematical and complicated science. Incorporating uncertainty in the advice given to managers may now involve the use of maximum likelihood and Bayesian methods, bootstrapping, Monte-Carlo modelling and other modern quantitative techniques. Non-linear estimation methods are now preferred over the older linear fits. Maximum likelihood methods are preferred over the more familiar least squares methods as they allow more exact specification of the form of errors in the models and what distributions they may take. Models have changed from those using only single sources of data (e.g. catch and effort) to fully integrated assessments of data of many different types. Back in 1992, Hilborn and Walters suggested that "quite frankly, if you are not comfortable writing computer programmes and playing with numbers, you should not be interested in fisheries management"! Fish stock assessment is rapidly becoming the realm of a "priesthood" of mathematicians (Hilborn, 2003).

While these new techniques can sound difficult and imposing and may look incomprehensible to non-specialists, the methods themselves are not always that complicated, and many of the latest methods can actually be implemented as spreadsheets (see example spreadsheets available from Haddon, 2001[13] and Punt and

[13] http://www.utas.edu.au/tafi/TAFI_Homepage.html

Hilborn, 2001[14]). Such templates can help those who have the time and inclination to learn these quantitative techniques. In many cases specialist software packages have been developed specifically to enable scientists to use methods that they otherwise would not have ready access to. The FMSP stock assessment software tools are a prime example of this. They include menu-driven options that aim to make the advantages of the new methods available without the user needing the programming skills to implement the methods themselves from scratch. The main advantage that the mathematical priesthood will have over the software users is that they will be able to adapt any given stock assessment methodology to the particular circumstances of their fishery. In either case, it is important to understand at least enough maths to know how the software is working and the assumptions that are made in the methods being used.

One other highly quantitative methodology should be mentioned that looks set to play an important role in the future of stock assessment. This is the concept of "meta-analysis", in which large numbers of data sets are used to develop widely applicable estimates of parameters, which may otherwise be missing for the stock being assessed. Early examples of meta-analysis include Ryder *et al*. (1974), Melack (1976) and Pauly (1980). More recent analyses by Myers (e.g. 2001) and others of the relationships between recruitment and stock size and other key parameters provide scope for much increased use of meta analysis in fisheries. Hilborn (2003) suggests that such analyses may become "exceedingly powerful and general" perhaps including both fisheries and environmental inputs in making predictions. While such models may be more realistic they will also emphasize the large uncertainties that will remain in the predictions. Hilborn suggests they may also become less and less used in the actual decision making process due to the difficulties of communicating the results of the analyses. He foresees an end to running models each year to determine a stock size that is then used to determine management action. The problem with the current methods is that the scientists are free each year to adjust the methods by which stock sizes are estimated, reducing the transparency of the assessment process. To avoid this, Hilborn recommends that management plans state clearly up front how stocks will be assessed and how decisions will be taken. There will be advantages in keeping such assessments simpler (for the sake of better communication) rather than more complex (even though this may be more "right"). Management procedures based on simple data-based rules could accommodate both conservation and socio-economic priorities as preferred. Attention is now being given to the use of simple "synoptic presentations of the state of stocks" (Garcia and De Leiva, 2000). Whether stock assessments are highly quantitative or semi-qualitative, the same basic decision-making process described in Section 2.5 should still be followed. If management decisions are to be based on feedback from the fishery or on other environmental or social indicators, it is clear that some level of quantitative analysis will be required even in small scale fisheries.

3.1.2 Deterministic or stochastic – allowing for uncertainty?

In deterministic models, the parameters remain constant over the time scale of the model's application. For given inputs, a deterministic model will always give the same answers. In constrast, in stochastic models, at least one of the model inputs is allowed to vary in a random way, giving different answers with each run of the model. This provides the potential to show the variability in the outputs produced and their dependence on the inclusion of uncertainty in different parameter estimates. This is the basis of "Monte Carlo" simulations (see Haddon, 2001). Risk assessments of future fishery projections (such as those from the FMSP "Yield" and "CEDA" software; Sections 4.3 and 4.5) are all based on the inclusion of uncertainty in stochastic models.

[14] http://www.fao.org/DOCREP/005/Y1958E/y1958e0d.htm#bm13

The shift from simple equilibrium models to more detailed stochastic analyses should in theory produce better advice, particularly about the risks of alternative management actions.

3.1.3 Biomass dynamic or analytical models?

Fishery models relate inputs (fishing) to outputs (catches). "Analytical" models such as the FMSP "Yield" package include a number of intermediate processes (both biological and fishing-related) to represent the process by which catches result from fishing. Analytical models may be either length-based or age-based (see Sparre, Ursin and Venema, 1989, and Section 3.1.5), and can require a large number of parameter inputs, some of which will only be known with low accuracy. Biomass dynamic models, in contrast, are more direct "in-out" approaches, usually using only catch, effort and/or abundance data either from the fishery or from surveys.

Fisheries scientists for many years considered age-structured analytical models superior to the biomass dynamic models (see Section 4.5). Given the problems with the equilibrium fitting methods (see below), the use of the old surplus production forms of the biomass dynamic models went out of fashion in the 1980s. Studies have shown however that the non-equilibrium biomass dynamic models may produce answers that are just as useful and sometimes better for management purposes than those produced by age-structured models, and at a fraction of the cost (Walters, 1985, 1989, in Haddon, 2001). Hilborn and Walters (1992) suggest trying both types of model, where data are available, and comparing their predictions for different management options. Neither approach is more right or wrong than the other – they are just based on different models and assumptions.

Biomass dynamic models such as the CEDA package may also be particularly useful for fishes that are hard to age, or for multispecies resources where single-species age-based models are impractical, e.g. where resources are not available for adequate data collection or for enforcement of species-specific regulations. On the negative side, biomass dynamic models can not give advice on technical management measures such as size limits or gear mesh sizes or types, or fishing seasons, but are usually restricted instead to basic estimates of total allowable catch quotas and effort limits. Either method can be used to assess the impacts of closed areas, if some basic assumptions are made about the movement of fish (see e.g. the ParFish software, Section 4.6.2).

One modelling approach that is in between biomas dynamic and analytical models is the "delay-difference" concept introduced by Deriso (1980). These ad hoc models are recommended only with caution by Hilborn and Walters (1992) as it is always possible to use enough "fudge factors" to get a "good" if meaningless fit. Punt and Hilborn (1996) also report Monte Carlo studies showing that simpler biomass dynamic models can perform better than delay-difference models and recommend that "if a more complex model is to be used, then it should be an age structured dynamic model" (such as used in the FMSP "Yield" software).

3.1.4 Equilibrium or dynamic?

The original methods for fitting biomass dynamic models and several other stock assessment methods involved assuming that the input data came from a stock in an "equilibrium" state. Equilibrium methods for fitting biomass dynamic models are computationally simple and easy to use. Unfortunately, they also usually overestimate the sustainable catches because they fail to take into account the dynamic nature of fisheries in the real world. It is nowadays recommended that non-equilibrium, dynamic models are used wherever possible. The dynamic fitting methods used in CEDA (Section 4.5), BIODYN (Punt and Hilborn, 1996) etc are not much more complicated computationally than the equilibrium methods, and produce much more reliable outputs with good data.

Equilibrium biomass dynamic fitting methods will always provide estimates of MSY and the related fishing effort, f_{MSY}, even if the data are extremely poor, due to the negative correlation between the effort in both the dependent and independent variables. In contrast, the newer dynamic methods will sometimes fail to provide any reasonable fit, usually where few data are available or where the data are incompatible with the assumptions of the models (e.g. if catch rates go up instead of down when higher total catches are taken). Where a fit can be made, confidence intervals will sometimes be so wide as to be almost meaningless. In these situations, it should be realized that one's information is inadequate for the production of useful advice. This may still be preferable to an equilibrium fit which is simply wrong. As Haddon (2001) and Hilborn and Walters (1992) both note, it is far better to recognize the limitations in the data, than to follow results blindly and provide bad advice.

It may also be noted that the move from equilibrium to dynamic assessments has largely been made possible with the development of powerful personal computers. Early fishery models were all based on "continuous" differential equation models that could be solved to give exact answers with analytical solutions. The application of these models was limited to the assumption of equilibrium conditions and those situations that could be solved (Haddon, 2001). With the introduction of modern computers, more realistic dynamic situations can now be simulated and solved numerically using discrete difference equation models. Modern "solver" routines can thus estimate parameters even with complicated non-linear model formulations that have no analytical solution.

3.1.5 Age-based or length-based?

Length data are generally much easier and cheaper to collect than age data. In many cases, age data are simply not available. Consequently, much attention has been paid in recent decades to the development of length-based stock assessment methods, often promoted as suitable for tropical fish stocks and data-limited fisheries (see e.g. Sparre, Ursina and Venema, 1989; Sparre and Venema, 1998). The FAO FiSAT software package (Gayanilo, Sparre and Pauly, 1995) is dominated by length-based methods, having evolved from two previous length-based tools: FAO's LFSA package and ICLARM's Compleat ELEFAN. The FMSP LFDA package (Section 4.1) is also specifically designed to estimate growth parameters directly from length data. The attention given to these packages may lead users to assume that tropical fish species simply cannot be aged and that length-based approaches are therefore the best option for these species. Four FMSP projects have, however, have confirmed the relative benefits of age-based over length-based methods, as summarized below and in Chapter 10.

In 1996, FMSP project R6465 confirmed that age-based methods (otolith readings) can indeed be used to estimate growth rates for many (but not all; see Pilling *et al.*, 2000) slow growing tropical fish (e.g. snappers and emperors). Ageing methods have also been validated for many other tropical species (Fowler, 1995). Although ageing puts up the costs of an assessment, management strategy simulations and cost benefit analyses in project R6465 further confirmed that using ageing to provide more reliable estimates of the growth parameters, which were then fed into the stock assessment process, was also more cost effective in certain circumstances. Follow-on projects (R7521 and R7522) found that fully age-based assessments (assessing both growth and mortality directly from age readings) performed better than length-based or semi age-based approaches. The higher costs of fully age-based assessments, however, were not justified by the benefits observed in the study fishery.

Most recently, project R7835, has compared the relative benefits of age- and length-based stock assessments for both slow growing and fast growing reef species, under conditions of both low and high fishing intensity. This project found that, under the assumptions made within the simulation process, length-based methods were consistently inaccurate, leading either to very precautionary management with high levels of under-exploitation, or high levels of over-exploitation of the stock (see Chapter 10). In contrast, with the exception of very heavily exploited fisheries, age-based methods were more likely to manage the stock around optimal levels, leading to long-term sustainability of the resource. Age-based methods produced more accurate estimates of both the selected reference point ($F_{0.1}$ was used), and the annual levels of fishing mortality (F_{now}), used in the control rule. Within the heavily exploited fishery, the absence of large individuals produced less accurate age-based growth parameter estimates. This led to biased reference points ($F_{0.1}$) since empirical estimates of natural mortality were used. Under these circumstances, management performance could be improved by obtaining independent estimates of natural mortality.

On the basis of the outputs from project R6465, the study fisheries in the Seychelles and British Indian Ocean Territory have adopted age-based assessment methods for selected indicator species from their bank-reef fisheries (see Pilling and Mees, 2001). The follow-on projects described above further support the validity of this move.

The general conclusion from these and similar studies is that age-based methods will usually perform better (and potentially be more cost effective), and should be used where possible. Scope still exists for the use of length-based methods for those species which genuinely can't be aged directly (e.g. lobsters and other crustacea), or where length frequency data already exist, especially if they are the only data available. Moreover, if age-based methods cannot be used on a routine basis to estimate annual levels of fishing mortality (F_{now}), management performance could still be improved by calculating reference points using age-based methods.

Rosenberg and Beddington (1988), Gulland and Rosenberg (1992) and Sparre and Venema (1998) provide comprehensive introductions to length based methods. Users should take care to consider the details of the methods, particularly that most length-based methods assume equilibrium conditions in the stock (e.g. that both mortality rates and recruitment have been constant over the year classes included in a sampled length frequency). Due to this assumption, the standard length-based VPA is fundamentally different to its age-based relative (see Section 3.4.3). Gulland and Rosenberg (1992) described how length frequency data may take the following four general forms and that different length based approaches may be more or less useful for each type.

- <u>Type A - a single mode that always appears at about the same length</u>. This is usually due to highly selective gear such as gill nets, or sometimes when migratory fish are sampled only at one point in their life cycle. Such length samples have no real information on either growth or mortality and better sampling methods must be sought.
- <u>Type B - a single mode moving steadily upwards with time</u>, showing the growth of a short lived, high mortality species such as a tropical shrimp or squid. Such a growth pattern can sometimes be confirmed by the appearance of two modes for a short time of the year, when a few adults remain after spawning at the same time as the new recruits enter the fishery. Such samples can give good fits to seasonal growth curves and YPR analyses for the optimum timing of closed seasons. Mortality rates cannot be estimated from the length data while only the single mode is apparent. Where cohorts can be reliably split, however, the ratio of the two cohorts can be used to estimate Z (see Section 3.4.3), assuming that both are equally well sampled by the gear and that recruitment was equal in both years. Extra sampling may be justified at the time of year when both cohorts are visible. Catch and effort data and depletion models could also be used to estimate numbers at the start of each year for such species, enabling a stock recruitment plot to be examined for recruitment overfishing reference points (see Section 3.5.3).
- <u>Type C – Several modes, well distinguished among the smaller size classes</u>, assumed to represent one or two individual modes, and then merged at older ages.

Where the assumption of the individual modes can be confirmed by following their progress across a year, such distributions are fairly good for both growth and mortality estimation. Attempts could also be made to obtain independent estimates of ages for some of the older fish, e.g. from otolith readings.

- Type D – only one mode, but with an extended right hand limb, assumed to be an extreme form of type C, with no separation between cohorts even at the smaller sizes. Such length frequency distributions can appear in fish with slow growth and low mortality rates, with a very extended spawning season, or where the sampling gear only captures relatively large fish after the age classes have merged. Such samples have no real signal on growth rates, but changes in the slope of the right hand limb may indicate variation in Z (see Section 3.4.3).

From an examination of 441 fisheries, Pilling and Halls (2003) found that length-based methods are most commonly used to assess the growth rates of small, fast growing species. This is where they should in principle work best, as described above. Hilborn and Walters (1992) go as far as to say that "attempts to use length-based analysis to formulate management advice for species that do not exhibit unambiguous modes are misguided and fundamentally hopeless"! Where length frequency data are used, the lower accuracy associated with these methods must be well factored into the stock assessment process. Section 2.5.3 for example mentioned how some form of damping may be used in a control rule framework, in order to avoid excessive annual changes in management measures.

3.1.6 Include stock-recruitment relationships or make assessments "per recruit"?

The number of fish recruiting to a fishery each year was once assumed to be largely independent of the size of the adult stock, at least over the likely range of stock sizes. This assumption was supported by the high levels of scatter in graphs of recruitment plotted against stock size. Unfortunately, many fish stocks have now been fished down to sizes below the "likely" range, and recruitment has then been seen to have dropped below the average historical levels. In many cases, this has sadly been followed by the collapse of the stock and economic disaster in the fishery. Myers *et al.* (1994) and Myers and Barrowman (1994) showed that for those fish stocks for which stock and recruitment data were available, thresholds can be identified at which the average recruitment is lower below than above. These and other studies confirmed the existence of "recruitment overfishing", where the recruitment is impacted below such threshold levels.

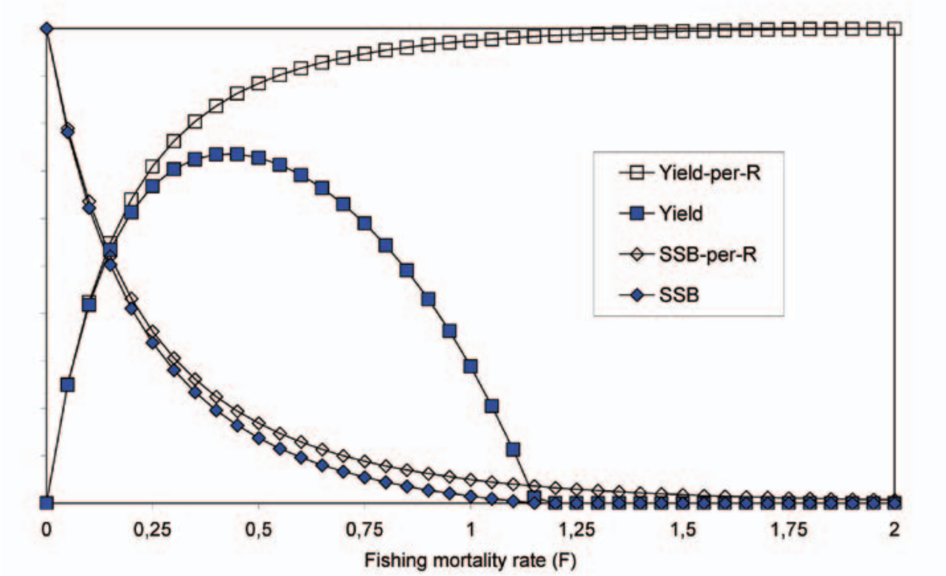
Stock-recruitment relationships (SRRs) can be included in fish stock assessments either as explicit sub-models in analytical approaches, or implicitly in biomass dynamic models.[15] Where SRRs are not included is in the analytical yield per recruit (YPR) type models. Such "per recruit" models predict the average relative catch available from a single recruit to the fishery at different levels of fishing mortality, F. The actual number of recruits is ignored and it is assumed that "average" recruitment will continue regardless of the level of fishing. Basic YPR models are very useful for managing fisheries to avoid "growth overfishing". This is where too many fish are caught before the cohort has reached its maximum biomass. The biomass of the cohort depends on the relative balance between the natural mortality rate, M, at which fish are dying, and the growth rate, K, at which they are increasing in size. As examples, the maximum biomass is reached at about 4 years old when $M/K = 0.5$, and at about 2 years old when $M/K = 2$. If there were no such thing as recruitment overfishing, fishery managers would only need to find the optimal size at first capture using a YPR model and set a

[15] Biomass dynamic models assume that population growth is related in some way to population size, but they are not explicit about whether this is a function of recruitment or fish growth.

size limit or gear regulations to allow capture above this size. Fishers could then fish as hard as they liked and no fishery would ever collapse. Unfortunately, heavy fishing can and does reduce stock sizes to the point where recruitment and subsequent population size (and hence catches) are reduced. Figure 3.1 illustrates the effect of including a SRR in a YPR model. While the hypothetical maximum YPR without the SRR is taken at a high fishing mortality rate of around 2.0, the maximum yield *with* an SRR (plotted on a relative scale for comparison) is taken at only $F = 0.45$. More critically, the catches with the SRR model actually fall to zero at an F slightly above 1.1, similar to the dome-shaped forms of the biomass dynamic models. This happens of course because, both with and without a SRR, the spawning stock biomass (SSB) declines progressively as fishing increases (Figure 3.1). The yield curve with the SRR model takes this reduction in spawning potential into account while the YPR curve (without the SRR) does not.

FIGURE 3.1

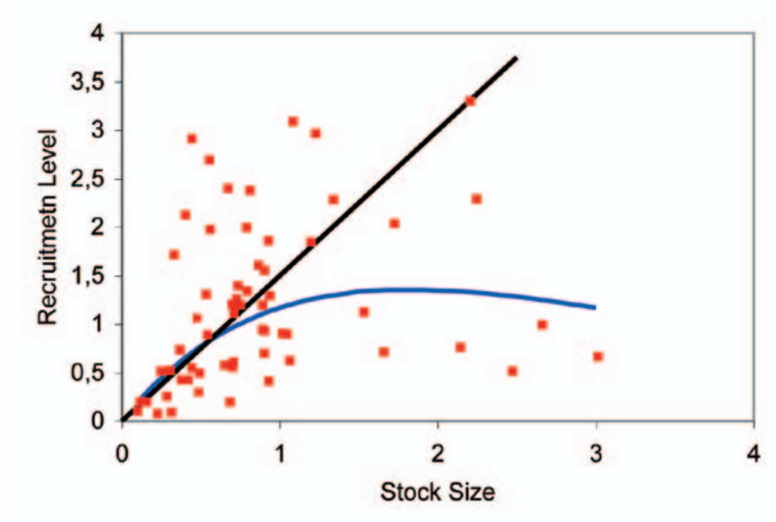
Comparison of the relative values of yield and spawning stock biomass (SSB), at different levels of fishing mortality, as estimated in a "per recruit" analytical fishery model (open symbols) and when including a stock recruitment relationship (filled symbols). Data simulated by the FMSP "Yield" model (see Section 4.3)



Myers (2001) described the understanding of the relationship between spawner abundance and subsequent recruitment as "the most important issue in fisheries biology and management". Recent initiatives by the FAO and others towards precautionary management in fisheries are largely driven by the desire to avoid recruitment overfishing and stock collapses. Sparre, Ursin and Venema's (1989) manual on tropical fish stock assessment and the updated 1998 edition (Sparre and Venema, 1998) both, however, relegate the "unsolved stock/recruitment relationship" to an essay in a back chapter and suggest that "no really convincing models to handle the problem have yet been developed". Part of the problem has been the difficulty of collecting time series of stock and recruitment data that are good enough and long enough to detect the level of biomass at which recruitment starts to decline. Measuring the abundance of fish, either as spawning adults or as recruits, requires high levels of sampling effort and careful analysis. Only one new data point is added each year. Even with good data collection programmes, normal levels of sampling error in the data can make it quite hard to detect the actual form of the SRR, as illustrated in Figure 3.2. The uncertainties in data for estimating SRRs can easily be great enough to make it largely impossible to distinguish between either the asymptotic Beverton and Holt form and the dome-shaped Ricker form, especially where little contrast exists in the data.

FIGURE 3.2

Simulated example of a linear stock recruitment relationship (SRR), indicated by the straight line, with scatter in the data generated only by log-normal measurement errors in the stock size and the recruitment data. The curved line shows the Ricker SRR fitted to the error-ridden data. (Figure produced using Haddon's (2001) example box 9.5, see also Hilborn and Walters, 1992, p288)



Hilborn and Walters (1992) also mention the possibility of problems with "non-stationarity" in SRRs, where the relationship between stock and recruitment changes over time. This may happen due to changes in stock structure (fishing out of adult size fish) or changes in external factors (prey availability, destruction of spawning habitats etc). Non-stationarity may be detected by checking the residuals in fitted SRRs to find time periods where recruitment has been consistently above or below average.

While it may be hard either to distinguish or to fit the exact form of the SRR, this may not matter too much. More important is recognising the fact that recruitment *will* drop off at some point if stock sizes get too low. The threshold may be at smaller relative stock sizes for some fish species than for others, giving different levels of "steepness" in the SRRs, but it must exist somewhere for all fish species. The implication is that where only per-recruit models are possible, priority should be given to setting *limit* reference points (LRPs) based on *biomass* per recruit. Target reference points may also be estimated based on *yield* per recruit, but these should take a lower precedence than the biomass-based LRPs as discussed in Section 2.5.2. Biomass-based reference points designed to protect the reproductive capacity of the stock and thereby avoid recruitment overfishing are described in Section 3.5.3. Both yield and biomass-based reference points, with and without SRRs, may be estimated using the FMSP "Yield" software.

3.2 COLLECTING FISHERY DATA

Quantitative data are required under the precautionary approach, to evaluate the performance of the fishery in meeting its selected goals and objectives, and to enable managers to make rational decisions "based on the best scientific evidence available". Data needs will vary according to the objectives and management strategies adopted for the fishery. The best ways of collecting data will also vary between fisheries, depending on the budgets available, the landing and marketing routes of the catches, the extent of cooperation with industry, and various other factors. Useful guidelines for the routine collection of data for fishery assessments have been given by Shepherd (1988), Pope (1988), Sparre, Ursin and Venema (1989, chapter 7) and others. More recently, FAO (1998) have provided detailed guidance on possible data types, and the development of broad, objective-oriented data collection strategies. Bergh and Davies (2002) discuss data collection in a wider framework of monitoring, control and surveillance (MCS) for a fishery. Berkes *et al.* (2001) propose data collection methods for small scale and co-managed fisheries, suggesting the greater use of traditional ecological knowledge and participatory appraisals. An FAO Fisheries Technical Paper is currently in preparation providing guidelines for designing data collection systems to support co-management building upon the output of FMSP Project R7042 (Halls, Lewins and Jones, 2001). The FAO Code of Conduct (Paragraph 6.4) emphasizes the need to take into account traditional knowledge of fish resources and habitats.

The following sub-sections focus on the data most likely to be useful for stock assessment purposes – catch, effort, and abundance; age and length frequencies; and other biological information. The FAO Code of Conduct advises that fishery assessments should also include data on other relevant environmental, economic and social factors. For developing full fishery management plans and guiding managers and policy makers with scientific advice, Cochrane (2002c) describes potential data requirements in four categories: biological, ecological, economic and social. In addition to the main stock assessment data, biological monitoring may also focus on the discards of each major species made by each fishing fleet. Ecological data may be required about the impacts of fishing gear and activities on physical habitats, and the changes in critical habitats brought about by non-fishing activities. Important economic data may include the average incomes, costs and profitabilities of fishing units in each of the main fleets. Social data requirements may include the total number of fishers employed within each fleet; and the numbers employed in shore-based activities related to each fleet, by gender and age group where appropriate. FAO (1997) describe the potential use of such data in formulating policy, fishery management plans, and in monitoring performance. FAO (1999) also describe the need to collect indicators on governance (e.g. the compliance regime, property rights, transparency and participation, capacity to manage) to better understand the outcomes in the system.

For the actual fish stock assessments, Shepherd (1988) discussed the relative values of different data types for estimating key information requirements. For the analytical methods, information is required on the imminent recruitment, the natural mortality rate, the exploitation (selectivity) pattern, the long-term stock recruitment relationship (SRR) and various biological data (growth, size at maturity, fecundity, weight at age etc). Such information may be derived from raw data in the three main categories: catch/effort/ abundance; age/size compositions; and other biological characteristics. However, with the multitude of different stock assessment methods, the relationships between the data types and their information content are far from clear cut. At a basic level, Shepherd notes that short-term assessments (e.g. to predict the TAC next year) will be heavily dependent on the current stock size and the imminent recruitment. Long-term assessments, e.g. of the maximum sustainable yield (MSY) and any *F*-based reference points, will be more dependent on the exploitation pattern (the size that fish are caught relative to their size at maturity) and the long-term SRR. Long-term assessments must therefore either include data that provide such information (e.g. catches at age for use in VPAs, or biomass dynamic models), or in their absence apply appropriate levels of precaution (e.g. using an $F_{30\%SPR}$ reference point with a YPR model, see Section 3.5.3). A few comments are made on the main data types below, and the detailed data requirements of the FMSP tools are provided in Chapter 4 below.

In designing data collection systems, fishery managers should keep in mind the anticipated stock assessment approaches (see Chapters 4 and 5), and the likely levels of variability associated with different levels of sampling. While good basic standards are necessary, collecting data is expensive and no more routine data should be collected than will be used directly in the management feedback process. Hilborn and Walters (1992) argue that the need is for "better" data, not for just more data or greater precision.

Feedback from deliberate experimental designs (see 2.1.3) may thus be more useful than good monitoring of uninformative "one-way trips". Managers also need to pay particular attention to understanding the life history and migratory behaviours of their fish stocks. Where fish migrate and the fishery does not cover the whole distribution of the species, samples of catches or length frequencies may only give a partial picture of the stock. Analyses of such data can be highly misleading and data collection should always include a spatial element (see e.g. Sparre, Ursin and Venema, 1989, Chapter 11).

3.2.1 Catch, effort and abundance data

Catch and effort data are among the most important information to obtain from a fishery, and the establishment of a good monitoring system for these data should be the first priority for a new fishery. In combination, catch *per unit* effort (CPUE) may be used as an index of the abundance of the fish stock, which is one of the most important indicators for the fishery. These data thus form the back bone of most good stock assessments, whether based on analytical or biomass dynamic approaches (e.g. using CEDA).

Catch and effort data are usually obtained by interviewing fishers as they land their catches at port, or by the completion of log books. Port landings are usually sub-sampled and raised to total catches within different "strata" based on a "frame survey" of the numbers of active vessels. Log book schemes may aim for a complete census of the catches of all vessels or only a sample of cooperative fishers. Observers may also be used on board vessels, e.g. when problems exist with bycatch and discards that might otherwise go unrecorded. Specific guidance for the collection of catch/effort data is given by Gulland (1983). Guidelines for resource mapping, frame surveys and data collection in manpower limited situations were given by Caddy and Bazigos (1985). Stamatopoulos (2002) describes the alternative types of fishery surveys, using different combinations of complete enumeration (census) and sub-sampling across space and time. The FAO ARTFISH database software is designed for the storage of catch and effort data collected in these types of surveys.

Abundance indices may either be estimated from the CPUE in the commercial fishery, or using various types of "fishery-independent" surveys. Commercial catch data tend to be concentrated on the main densities of the stock, and may therefore not reflect the overall situation of the whole population. Fishing vessels and technology also change over time and fishers become more knowledgeable about the best fishing strategies (times, places, methods etc). The catching power or "catchability" of the commercial vessels thus tends to increase with time, and CPUEs from the fishery rarely provide a very good index of abundance. Survey-based abundance indices are less biased for spatial effects and effort changes because the survey track and the fishing gear used can be kept constant over the years. "Swept area" surveys may use standardized trawl nets for groundfish; or photographic approaches for less mobile targets such as scallops (Pope, 1988). Plankton sampling gear may be used for egg and larval surveys to estimate spawning stock biomass (combined with fecundity data). Acoustic surveys may also be used, with annual indices calibrated retrospectively, usually based on the results of a VPA. Guidance on planning stratified swept-area surveys and estimating fish abundances is given by Sparre, Ursin and Venema (1989).

While survey-based estimates of abundance can be very useful, data from the commercial fishery are also essential for estimating the total catches and fishing effort, and for raising the samples of catches at length or age for analytical models. Samples from commercial fisheries are usually cheaper and easier to obtain in large quantities than research vessel survey data. Sample sizes are usually larger and variances therefore lower. Where the fishery is exploited by more than one gear type, or where catchability has changed over time, commercial effort measures may be standardized using General Linear Models (GLM).

3.2.2 Size compositions (catch at age and length-frequency data)

Fishing affects fish stocks in two basic ways – reducing the overall abundance of the stock, and changing the stock composition. With higher fishing mortality rates, there will be relatively fewer older fish in the stock. The age structure will be shifted towards younger fish and the length structure will be shifted towards smaller fish. Catch composition data are thus required to estimate the relative abundance of different age classes or cohorts. This information is primarily used to determine the current mortality rate in the stock – an indicator of the level of fishing pressure. When raised to the total catch composition of the fishery, these data can also be used in VPA methods to estimate the numbers of fish in each age class or cohort. This information is used to fit the relationship between the spawning stock and the subsequent recruitment, and thereby estimate the levels of stock biomass and fishing mortalities that would avoid recruitment overfishing (see 3.5.3). Catch composition data also reveal the selectivity of the fishing gears and can be used to estimate the growth rates needed in analytical models.

As noted above (Section 3.1.5), stock assessments based on catches at age (e.g. using age length keys and VPAs) will usually be much more accurate than those based on length frequency data, given similar levels of sampling effort. Where ages can be estimated directly from hard parts such as otoliths or scales, this will usually give more reliable estimates of mortality rates than any of the length based methods. The problem with length based methods is that since mortality rates need to be calculated per unit of time, the lengths need to be converted to ages. Since individual fish grow at highly variable rates, any growth model used to make the conversion will allocate the wrong ages to some fish and this can result in biased estimates of mortality rates.

The potential value of length frequency data for species which can not be aged will depend on the relative growth and mortality rates of the species (Gulland and Rosenberg, 1992, see Section 3.1.5), the selectivity of the gear sampled and the extent of any biases caused by sampling problems (Hilborn and Walters, 1992). Fast growing fish will usually be the easiest to age using length based methods since the progression of modes can be more clearly observed in the length data. Sampling from gears that select the widest possible range of fish sizes will improve the chances of distinguishing age classes. Some length-based methods for estimating mortality rates can however be difficult to use with fast growing fish. Gulland and Rosenberg (1992), advise that a few samples should be taken to identify the species types and indicate the potential of length based methods (see Section 3.1.5).

Although growth rates may be estimated from relatively small samples of length frequency data, good estimates of mortality rates (either from length or age-based methods) require data on the *total* catches at length in the fishery. Guidelines on sampling schemes to estimate such length compositions (stratified across different fleets, fishing grounds, ports and time periods) are provided by Sparre, Ursin and Venema (1989, Chapter 7). Samples should usually be taken in each month, and from all varieties of gear and capture locations. Enough samples should be taken to determine the levels of variance within each stratum. Length frequencies should then be raised to the whole commercial catch using the catch and effort data.

Where fish can be aged (e.g. using otoliths or scales), sub-samples of the length frequency data are usually taken to estimate the proportions in each length class in each age group. This is known as an age length key (ALK). Fish for ageing are usually selected as a stratified sample (e.g. picking the first 5 fish in each length class) so that sampling is evenly allocated across both small and large fish. ALKs are usually re-sampled every year since the numbers of fish in each age class vary with the annual recruitment strengths and since growth and mortality rates can also change over time.

3.2.3 Other biological data

As described above, the priority data for fish stock assessments are fish catches, fishing efforts and catch compositions; from which abundance indices, SRRs, selectivities, growth rates and current mortality rates can be estimated. Other biological data needed for the analytical stock assessments include the sizes (or ages) at maturity, the fecundity (the number of eggs produced at a given size), and the average weight at length (or "condition factor"). All of these biological characteristics may change to some extent between years reflecting, e.g. the overall health of the environment or the availability of food items (e.g. other species). Special sampling programmes are usually used to estimate these characteristics, perhaps every few years. Information on spawning seasons and feeding patterns may also be useful to understand the seasonality of growth and recruitment and to consider the possible value of closed seasons in managing the fishery.

TABLE 3.2
Summary comments on the data required for fishery assessments (see also Chapter 5 and Table 5.1 and Table 5.2)

Data type	Advantages / application	Disadvantages / comments
Catch, effort and abundance	• Use to estimate total catches and stock abundance • Fishery dependent catch and effort data easy to obtain • Survey approach may give less biased estimates of abundance though precision may be lower	• Fishery dependent data may be biased by changes in catchability over time and by spatial factors in fishing patterns (may be possible to standardize) • Survey approach expensive
Catch compositions	• Use to estimate stock structure and exploitation rates in analytical models	• Not required for biomass dynamic approach • May be either length frequencies or age frequencies (see comments above)
Biological data	• Required for analytical models e.g. to identify size at maturity to estimate spawning stock	• Some parameters such as *M* almost impossible to estimate accurately (so test sensitivity to values used)
Other data	• Economic, social and ecological data needed as defined by fishery goals	• Fully comprehensive data collection needs can be overwhelming

3.3 ESTIMATING INTERMEDIATE FISHERY PARAMETERS

Most fish stock assessments involve some initial fitting of intermediate parameters that are then used in some final model (or models) to estimate the indicators and reference points needed by managers. These intermediate parameters are not directly of interest to managers but usually have direct impacts on the real quantities of interest. They can include both biological parameters and parameters related to fishing (catchability and selectivity). Key intermediate information for the analytical fishery models include the growth rates of individual fish, the natural mortality rate, the reproductive biology and the stock-recruitment relationship and exploitation patterns. Key intermediate parameters for the biomass dynamic models are the intrinsic rate of population growth and the carrying capacity of the fish stock. Both models can also require an estimate of the catchability coefficient if fishing mortality rates are to be converted to fishing effort levels for use as a management measure. Common uses and fitting methods for these intermediate parameters are summarized below. Estimation of the fishing mortality rate is covered in Section 3.4 as one of the key indicators of the status of the fishery.

3.3.1 Growth rates of individual fish

Growth rates are used in analytical stock assessments to model the average changes in fish size with age. In length-based approaches, growth rates are required to partition the length composition into ages to estimate mortality rates. In both length- and age-based stock assessments, growth information is central to the yield or YPR models used to estimate reference points. Fish growth is most commonly modelled using the von Bertalanffy growth function (VBGF), in which L_∞ is the asymptotic length, and K is the rate at which fish grow towards this size. Where fish do not grow according to the pattern of the standard VBGF (e.g. if growth rates slow down after maturity is reached), analytical models can also be formulated to use the empirical mean lengths at each age.

The VBGF may be fitted either to age or length composition data. Where fish have been aged, the linear "Gulland and Holt" or "Ford-Walford" plots may be fitted to the mean sizes at each age (see Sparre, Ursin and Venema, 1989). Superior non-linear fitting methods may also now be used, e.g. using a "minimizer" routine in a spreadsheet (see Haddon, 2001).

Where fish cannot be aged, several length-based methods are also possible, though lower precision must be expected. The FMSP LFDA software may be used to fit K and L_∞ using three alternative methods including the ELEFAN routine (see Section 4.1). Both standard and seasonal growth patterns can be fitted. These methods work by scoring the fits of different combinations of parameters to the modes in the length frequency data. Samples should be available spaced over at least a full one year cycle so that the progression of the modes over the year can be clearly interpreted as shifts due to the growth of the fish.

A variety of other length based methods are also available in the FAO FiSAT II programme. These include the Battacharya and NORMSEP methods of separating modes believed to represent age classes. Pairs of modes may then be identified using the "linking of means" procedure (which can be quite subjective). Either these average growth increments or the results for individual fish from tagging studies can be analyzed in FiSAT II using four alternative routines: Gulland and Holt; Munro; Fabens; and Appeldoorn.

According to the VBGF, individual fish grow on average towards their asymptotic length L_∞ at an instantaneous growth rate K, as shown below:

$$l_t = L_\infty\,(1 - e^{-K(t-t_0)})$$

According to the VBGF, fish grow towards their L_∞ at a constant proportion of the distance *remaining* to grow (i.e. $L_\infty - l_t$). Most fish species have a growth rate, K, of between 0.1 and 1.0 per year. With a K of 0.1 per year, fish grow 9.5 percent closer to L_∞ each year. With a K of 1 per year, they grow 63 percent closer to L_∞ each year. The parameter t_0 is the theoretical age (t) at which the fish would have had zero length if growth had followed the VBGF from birth.

Since many indicators and reference points are expressed in terms of weight, not length (e.g. YPR, B, MSY, B_{MSY}), most analytical stock assessment models, including "Yield", convert length to weight using a "power" relationship, in which the weight, $w_t = a\, l_t^{\,b}$. The parameters, a and b are commonly fitted to a sample of fish of different sizes, each measured for both length and weight (see Sparre, Ursin and Venema, 1989 and other standard texts).

3.3.2 Population growth rate and carrying capacity

At a *population* level, according to the logistic (Schaefer) model, a fish stock grows towards the carrying capacity of its environment, also denoted K (or the lower case k by some authors), at a maximum rate r. The discrete form of the logistic model can be written:

$$N_{t+1} = N_t + rN_t\,(1 - N_t/K)$$

Where N_t is the population size at time t. The growth rate of the population, r, is equal to the difference between the birth rate and the death rate. The parameter r was originally defined in terms of the continuous time exponential growth equation $dN/dt = r\,N$.

It has been called the intrinsic rate of increase and it is perhaps more properly thought of as the per capita rate of population growth. On an "instantaneous" basis, a growth rate r of 0.1 implies that a population of 100 will increase by 10 in one time interval. An r of 1 would give a doubling of the population size. Integrated over a year or some other time period (like compound interest rates), these same rates would cause population increases of 10.5 percent and 172 percent respectively, if there were no constraints on growth. Constraints do exist on the maximum growth potential, of course, as included in the logistic model in the form of the carrying capacity, K. The actual (i.e. not per capita) increment in population size over unit time is given by $rN_t(1\text{-}N_t/K)$. The maximum actual increment (or MSY) is achieved at $N_t = K/2$. This is the basis of the familiar symmetrical dome-shaped form of the Schaefer surplus production model, of which r and K are the main intermediate parameters. These parameters are best estimated using non-equilibrium fitting methods such as in the FMSP CEDA and ParFish software packages.

The carrying capacity, K, like the L_∞ in the VBGF, is specific to each fish stock, perhaps ranging from a few hundred fish in a small pond, to many millions of fish for a large stock in the sea. The population growth rate, r, like the individual growth rate K in the VBGF, tends to vary again within a limited range of between about 0.1 and 1. Population growth rates above 1 imply very fast growth rates and r values in the range of 2.5-3.0 produce "chaotic" dynamic behaviour as the population jumps erratically around K (see Haddon, 2001, page 33).

3.3.3 Natural mortality rate

The natural mortality rate M is the instantaneous exponential rate at which fish in the population die from natural causes. In the absence of fishing, the number remaining in a population at time t can be estimated as $N_t = N_0 e^{-Mt}$. An M of 1 per year implies that 63 percent of the population would die each year due to natural causes. M's of 2 and 3 per year imply annual death rates of 86 percent and 95 percent respectively. M can range quite widely depending on the life history strategy of the species, but is usually correlated with the value of K. The ratio M/K is most commonly in the range 0.5 to 4 (Kirkwood, Beddington and Rossouw, 1994, based on the data of Pauly, 1980). M is important in determining reference points using "per recruit" and yield/biomass models. High-M species are in general best fished harder than low-M species in which the maximum cohort biomass takes longer to accumulate.

M (or M/K) would best be calculated from catch compositions sampled from unexploited stocks or lightly exploited fisheries. Unfortunately, the opportunity for this is often missed because it is the fishers rather than the scientists who get there first. M may also be separated from fishing mortality, F, by plotting annual values of the total mortality, Z against fishing effort. However, this method is also hard to use effectively as the value of M is highly correlated with the catchability which will usually vary over the time series (Shepherd, 1988). Tagging is also a possibility, but is hard to use on the scale required in wild capture fisheries.

With these methodological constraints, M is often estimated from Pauly's (1980) regression method, based on the growth parameters K and L_∞ and the ambient water temperature. Gulland and Rosenberg (1992) note that 95 percent confidence intervals for M based on Pauly's method (due to the residuals in the original data set) may be 2.5 times the central estimate, i.e. much lower than the precision with which other parameters such as L_∞ can be estimated. Other methods suggested in Sparre, Ursin and Venema (1989) and available in FiSAT (e.g. the Rikhter and Evanov prediction based on the mean age at maturity) are likely to be equally inaccurate. Estimates of M derived for other fisheries, may also be found in Fishbase, and applied in the absence of a derived estimate for the fishery in question. Users should be aware, however, that many of the estimates in FishBase are themselves based on Pauly's method!

M is thus often the least certain parameter in a stock assessment. It is also usually assumed to be constant over all ages and in all years. With fluctuations in abundances of predators, competitors and other cohorts of the same species, and with variations in the natural environment this is highly unlikely to be true. Stock assessments should thus take into account the uncertainty in the value of M. This can be done in several ways, commonly by using a programme that allows M to vary stochastically, or by using sensitivity tests (e.g. using the FMSP Yield software, Section 4.3).

3.3.4 Maturity and reproduction

The size at maturity and the size-dependent variation in the reproductive potential of fish are needed in analytical models to estimate the spawning potential of the fish stock at different levels of fishing effort (i.e. the "reproductive capacity" reference points – Section 3.5.3). With the numbers of eggs (like the fish weight) increasing approximately as the cube of the fish length after maturity is reached, one large female can produce many more eggs than even a large number of small, newly mature ones. In most cases, the collection and analysis of these data present no particular problems and do not need to be updated on an annual basis. Special consideration may be needed where the size at maturity varies greatly between males and females, and particularly in those "protogynous" species which change sex as they grow (e.g. groupers (serranidae) and some emporers (lethrindae)).

3.3.5 Stock and recruitment

Section 3.1.6 noted that some understanding of (or at least some recognition of the existence of) the relationship between stock and recruitment is critical to avoiding recruitment overfishing and stock collapse. For fish species that breed over several years after maturing, stock-recruitment relationships (SRRs) need to be incorporated into analytical models to enable the total recruitment to be estimated (i.e. combined across all mature age classes) at given levels of fishing mortality and ages at first capture. Multiplying this by the estimated YPR gives the total yield corresponding to those levels of the management control variables. For "semelparous" fish species that breed only once and then die (e.g. Pacific salmon and some squid), MSY stock sizes and harvest rates can be calculated directly from the fitted SRR (see Hilborn and Walters, 1992, p270).

SRRs should be examined visually by plotting the numbers or biomass of recruits (new fish entering the fishery) against the numbers or biomass of the spawning fish stock in the years they were spawned. The data for plotting are usually obtained from age-based VPAs (see Section 3.4.2) although survey-based indices can also be used. The "spawning stock size" should include all fish of ages above the size at maturity and, where possible, allowances should be made for differences in fecundity and reproductive potential at different sizes. In plotting the pairs of points, adjustment is made for the number of years between the year of spawning and the year in which the new cohort arrives in the fishery as recruits (a function of the size selectivity of the fishing gear and the behaviour of the fish stock).

Hilborn and Walters (1992) provide an extensive coverage of stock and recruitment relationships, describing several biological mechanisms leading to different forms of density dependent recruitment processes. "Compensatory" SRRs are where fewer recruits are produced per spawner as stock size increases, so that the curve becomes flat (in the "Beverton-Holt" form) or domed (in the "Ricker" form). All fish stocks may be assumed to have SRRs that are compensatory in some way, due to the limitations imposed by the environment and the resources available for feeding, spawning etc. "Depensatory" SRRs have also been hypothesized, where there is an initial increase in the number of recruits per spawner as stock sizes increase from the origin. Eventually, the compensatory processes take over resulting in an S-shaped curve. Depensation may occur due to higher relative predation rates when stocks are small, or due to the difficulties of finding mates at small population sizes. It may in theory be quite important as it implies that recruitment will decline faster as stock sizes are reduced than with a normal SRR. Myers *et al.* (1995), however, concluded that depensatory dynamics could not be detected in fish populations at least at the levels studied.

SRRs can be formulated mathematically and fitted in various different ways. Hilborn and Walters (1992, p270) suggest fitting the Ricker SRR with log-normal errors and a linear regression model and the Beverton-Holt version with a non-linear regression. Hilborn and Walters also caution against fitting SRR curves by eye. However, where few data points exist and where recruitment appears to have varied randomly about a constant level at the stock sizes observed, taking a precautionary qualitative view that recruitment might decline if stocks are reduced below the lowest levels observed may be better than searching extensively for the "best fitting" curve. Care should also be taken not to mistake any fitted SRR curves for the "true" relationship. Even when a curve seems to be well fitted, future actual recruitment will surely continue to show wide scatter. Precautionary stock assessments should always make full allowance for the uncertainty in the SRR, as for the other types of "intermediate" information.

3.3.6 Exploitation pattern (gear selectivity)

Information on the selectivity of fishing gears is needed for the analytical models to show the length and/or age of fish at first capture. This is one of the possible management "control variables" (Section 2.5.5), that may be adjusted by setting fish size limits and/or mesh size limits. Selectivity can also be a function of the time and place where fish of different sizes and ages occur, hence time and area closures may also be effective in controlling the size and/or age of fish in the catch.

The selectivity of a given fishing gear and mesh size is usually estimated as the proportion of the fish available that are captured by the gear at different fish lengths. In the case of nets, due to variations in the girth or fatness of the fish, some fish of a given length will slip through the net while others will be caught. Selection is thus rarely "knife-edged" (though it is sometimes modeled as such for the sake of simplicity), and S-shaped selection curves or "ogives" are fitted. For some gears such as gill nets, fish may grow too large to be caught and selectivity then declines for larger and older fish. Further details are provided by Sparre, Ursin and Venema (1989), including the main methods for fitting selectivity curves: length-converted catch curves (e.g. in FiSAT), mesh selection experiments, and separable VPAs (see e.g. Lassen and Medley, 2001).

3.3.7 Catchability

The catchability coefficient, q, is used as a "constant of proportionality" both between fishing mortality F and fishing effort f (i.e. $F = qf$), and between CPUE and stock abundance (i.e. CPUE = qB). The latter equation provides the usual definition of catchability, as the proportion of the fish stock taken by one unit of fishing effort. Catchability is thus a measure of the efficiency of a fishing gear. It is usually a very small number. The actual size will depend on the way fishing effort is measured: catchability for a hook-hour effort unit for a long-liner will thus be lower than for a boat-day effort unit for the same vessel.

Catchability is a key component of the biomass dynamic and depletion models, and is usually estimated using these methods (e.g. using the CEDA software, Section 4.5). It is critically important where catch and effort data are used as the index of abundance in the biomass dynamic model. The problem, as noted earlier (Section 3.2.1) is that catchability is not constant over any extended period of time. Even if good fishing effort measures have been used (see suggestions for "good" measures in FAO, 1998), and if the data have been well standardized for changes in vessel characteristics not accounted for by the effort measure (e.g. using GLM methods), effective catchability can still vary with spatial or temporal changes in the distribution of the fish stock and the fishing effort. Gulland (1983) gave particular attention to the possible reasons for changes in catchability. He advised that data sets for different fishing fleets (gear types) and different sub-areas of the stock should be kept separate and time series of abundance indices compared between the different sets. Differences between the patterns shown may then reveal changes in catchability which could perhaps be explained by changes in fishing technology (e.g. the introduction of improved sonar gear in purse seine fisheries). Where no explanations can be found, some data sets may need to be rejected, with caution, as unsuitable for further analysis.

3.4 INDICATORS – MEASURING THE CURRENT STATUS OF THE FISHERY

As outlined in Section 2.5.2, "indicators" are required to monitor the status of the fishery relative to the chosen "reference points" (see following section). The most important indicators are commonly the fish catch, the stock biomass and the fishing mortality rate, F, as related nominally in the short term by the equation $C = FB$. In the useful "precautionary plot" of Figure 2.2, the biomass axis shows whether the stock is currently overfished, while the fishing mortality axis shows whether the current catches are overfishing the stock and thus whether it is likely to decline further in future.

Beyond these key status indicators, some management regimes may also choose to monitor the multispecies or ecological status of the fishery, or the socio-economic conditions. The indicators required depend on the ecological and socio-economic goals and objectives set for the fishery (Section 2.5.1).

Methods for measuring the current status of the fishery are described in the following sub-sections. Indicators should be measured on a regular basis, annually where possible or less frequently for long-lived or low-priority species. The precision with which the indicators can be estimated may not always be high. Confidence intervals should therefore always be estimated and management measures set with appropriate precaution (as described in Section 2.5.4.

3.4.1 Catch, effort and CPUE

Total catch is clearly an important signal for the fishery, as most managers will wish to sustain, maximize or optimize it in one way or another. Declines in catch are usually the triggers for serious management concern. On its own, catch may be used as an approximate indicator of the state of the fishery. Where fishing effort data are available, CPUE may also be estimated as an indicator of the state of the fish *stock*.

Using only time series of total catches, Grainger and Garcia (1996) classified fisheries as either "undeveloped", "developing", "mature" or "senescent" according to a generalized fishery development model. This method was used by FAO to assess the relative phases of development of the 200 top fish stocks in the different FAO statistical areas. It was also used by FMSP project R7040 to assess the relative status of aggregated, multispecies "meta-fisheries" in the world's large marine ecosystems (see Section 14.1). At a more local scale, this approach may be useful as a rough indicator of the level of development of a fishery where no detailed effort data are available but where the general trend in fishing effort is known or can reasonably be assumed.

Where total fishing effort is also available, CPUE can be calculated as an index of stock size or abundance (given the various caveats and hard-to-test assumptions outlined elsewhere, e.g. Sections 3.2.1, 3.3.7). The trends in catch, effort and CPUE can then be used in simple relative ways, to show both the position of the fishery and the status of the fish stock. If for example, both catch and effort are increasing (or both are decreasing) so that CPUE is fairly constant, it may be that the fishery is having little effect on the fish stock (it would be worth looking at the geographic distribution of the effort to check that catches are not being maintainted by a pattern of sequential depletion of different areas). If the fishing effort has been fairly constant but catches have gone up or down, it may be assumed that the stock size has also gone up or down, e.g. due to variations in annual recruitment. If, on the other hand, effort is increasing, but catches have remained fairly constant, it suggests that the fish stock is declining in size. In the worst case, if effort has increased while catches have declined, this may imply that the stock is declining even faster than the catches.

3.4.2 Stock size

The absolute size of the fish stock is the single most important indicator of its status and its potential to provide future catches. Stock size may be estimated by a variety of VPA and statistical catch-at-age methods, using time series of annual catch at age data and various tuning or auxiliary inputs. The age-based versions of these models estimate both the numbers of fish and the fishing mortality rates at each age in each year in the fish stock. VPA thus provides the two main indicators required by fishery managers, making this a very useful method where age-based data can be obtained. The drawback is that VPA requires data on total catches at age, usually derived from large scale length-frequency sampling, supplemented by an age-length key (Section 3.2.2). Ages must be determined by reading otoliths, scales or other hard parts. Biomass dynamic and depletion models may also be used to estimate stock size, but only as the overall numbers or biomass of the stock at a given time, not separately for each age class.

Age-based virtual population analysis (VPA) was originally conceived as a method for sequentially estimating the stock numbers and Fs by age and year, by working backwards through a time series of catches at age. At the simplest level, the method just estimates how many fish must have been present, given an input level of M and a starting level of F (or "F-terminal"), to produce the catches that are observed in the fishery.

As the numbers are disaggregated by age classes (or length classes in the length-based VPAs), the outputs from a VPA can be combined with other data in analytical models to estimate the biomass of the spawning stock (above the age or length at maturity). This can be compared with the relevant "SSB"-based reference points, introduced below. Although all of the VPA methods work in numbers, outputs can be converted to biomasses using data on the mean weights at age or length.

The main problem with VPA methods is that the stock sizes and Fs are least well estimated for the most recent year and the oldest age groups, both of which require an initial estimate of the terminal F to start the calculations. Retrospective analyses have shown that VPAs provide robust estimates of numbers at age and fishing mortalities for cohorts that have already fully passed through the fishery (as most of the catches from the cohorts are by then known). The best results are obtained when F is high compared to M (as most of the recruitment will be caught and thus sampled, and uncertainty in M is less important). Stock sizes, and hence the annual recruitments available are least accurate for the youngest age classes in the current year for which perhaps only one or two catches are so far known. This is unfortunate as these ages usually dominate the stock, and the most recent years are the ones needed to gauge the current "state of the stock" and make projections etc.

To reduce these problems, VPA methods may be "tuned" in various ways using "auxiliary" data, such as absolute estimates or indices of abundance, biomass or effort, either from the fishery or surveys. There are also now several new versions available for "statistical" fitting of VPA-type models (see Lassen and Medley, 2001), sometimes referred to as "statistical catch-at-age" methods, or "synthetic" or "integrated" analyses. The statistical methods provide more formal methods for using auxiliary inputs which should in principle be better than tuned VPAs (Hilborn and Walters, 1992). These methods all involve some form of minimization of the differences between the observed data and the expected values, as predicted by a specified model. Many different forms exist, with some that work backwards through the time/age series like

VPA, and others that work forwards. The statistical methods usually estimate fewer parameters than in the original VPA (F and N for each year and each age), though they still commonly estimate tens of parameters at a time. Although perhaps more difficult to understand, the statistical methods are less stringent in their data requirements, making them potentially more useful in countries without long time series of detailed catch at age data. Spreadsheet templates for fitting simple catch-at-age models are given by Haddon (2001) and Lassen and Medley (2001), but specialist applications will be required for the most complete applications using auxiliary data. Although the outputs can be improved by the auxiliary data, estimates of F and N will always be poorest for the most recent and most important years.

Depletion methods and biomass dynamic models (see Section 4.5) can also be used to estimate stock sizes by year. Since these methods use undifferentiated biomass (or numbers in some models), not subdivided between ages or lengths, they provide estimates of the total size of the fish stock aggregated across all the ages that are caught. Such estimates can still be compared with the B_{MSY} or other reference points to determine whether the stock is currently above or below the level expected to provide the long term MSY.

The above methods give estimates of *absolute* abundance. Qualitative (or more quantitative) examination of catch and effort data can also be used to obtain an *index* of stock size or abundance as described above (Section 3.4.1). The other main option for getting a short term estimate or index of stock size is to use a purpose-designed survey. The "swept area" survey works best for trawl fishing gears where the area covered can be at least roughly estimated by the width of the trawl and the distance towed. Surveys can be better than CPUE data as noted in Section 3.2.1 as they can cover fishing grounds in a systematic way and can avoid problems with the assumption that commercial CPUEs are proportional to abundance (which can be very wrong where fish aggregate in shoals such as tunas, or where the fishery "mines" a small area of the total stock). Useful guidance on survey designs for estimating abundance indices is given by Hilborn and Walters (1992, p169).

Finally, tagging methods are sometimes suggested for estimating abundance. Tagging often has limited value because reliable estimation of abundance requires appropriate levels of mixing between tagged and untagged fish, and because proper account needs to be taken of tag-shedding and non-reporting. The last can cause particular problems unless there is a dedicated observer programme in place. When these assumptions can be satisfied, tagging can produce invaluable estimates of abundance that are largely independent of more commonly used assessment methods, which as shown above, have many problems of their own.

3.4.3 Fishing mortality rate

The fishing mortality rate, F, is the instantaneous exponential rate at which fish are being removed from the fish population by fishing. With both fishing and natural mortality, M, the number remaining in a population at time t may be estimated as $N_t = N_0 e^{-(F+M)t}$. F and M together make up the total mortality rate Z. Methods for estimating F usually involve estimating Z and then getting F by subtracting M (which may not be accurately known – Section 3.3.3).

There are several different methods for estimating F. The first main group of methods assume that the stock is in an equilibrium state, and estimate an average F(equilibrium) or F_{eq} for the year classes included in the data set. The second main group of methods estimate different values of F for each year and/or each age or size class. There are both length-based and age-based methods in each group, but the assumptions and outputs of the alternative methods can be quite different, as outlined below. For monitoring the fishing mortality as an indicator of the current status of the fishery, the methods giving separate F estimates in each year (especially the latest versions of age-based VPAs) are clearly the most useful. The simpler equilibrium methods are more likely to be used for data-limited fisheries that are perhaps only assessed every 2-3 years.

Equilibrium methods

Equilibrium fishing mortality rates, F_{eq}, may be estimated by subtracting M from Z, where the latter is first estimated using the different forms of catch curves and related methods. These methods assume not only that fishing and natural mortality have been constant over the years in the data set, but also that recruitment has been approximately the same in each year. Any differences in the initial recruitment strengths of the different cohorts are ignored, or assumed to cancel each other out over all the ages in the data set. These assumptions enable the methods to be applied with minimal data, but can of course give very misleading results if they are substantially violated.

In age-based catch curves, Z is estimated by fitting a straight line through the log numbers at age over the descending part of the curve (see e.g. Sparre, Ursin and Venema, 1989, p140). The low numbers in the ascending limb of the curve are assumed to indicate cohorts that are only partly recruited or are not yet fully selected by the fishing gears in use. Selectivity is assumed to be constant for the fully recruited ages. If, however, the larger fish are not fully selected (e.g. if they migrate away from the main fishing grounds, or are able to escape the gear), then Z can be overestimated.

Where fish cannot be aged, or where only length frequency data are available, Z may be estimated from length converted catch curves and other related methods. These use the von Bertalanffy growth parameters, K and L_∞ to convert the length data into age-based forms from which annual mortality rates can be found. Six different length-based methods are available in FiSAT for estimating Z, three of which are also available in the FMSP LFDA software (the length converted catch curve, the Beverton-Holt mean length method, and the Powell-Wetherall method, see Section 4.1).[16] Each of the methods require the user to select which points to include in the analysis or to estimate some minimum size above which fish are believed to be fully represented in the sample. Most of the length-based methods can either estimate Z if K is know, or estimate Z/K when K is not known.

In between the above methods for fitting equilibrium Z and the full age-based VPA is the length based cohort analysis or VPA. Two different methods are available in the FiSAT suite, both of which convert lengths to ages using K and L_∞ as above. The "length-structured VPA" method of Jones and van Zalinge (1981, in Gayanilo, Sparre and Pauly, 1995) estimates Fs and Ns for each length group, while the "VPA with pseudocohorts" uses the growth parameters to slice up the length frequency and make estimates for each "pseudocohort" in each month. The "length-structured VPA" procedure is very different to the full age-based form as only a single length frequency is used representing the mean annual total catch at length. The stock is thus assumed to be at equilibrium and the routine estimates the average Z in each length class. Although information can be generated on the difference in Z between lengths (albeit highly dependent on the growth parameters used), Z is assumed as with the other equilibrium methods to be constant over the years in the data set. The "VPA with pseudocohorts" version can use longer time-series of length frequencies and is potentially capable of estimating separate F's for each sliced pseudocohort in each month. Hilborn and Walters (1992), argue however that "length-based VPA is a poor imitation of age-based VPA", that is only likely to be worthwhile where the progression of cohorts is clearly visible to the naked eye (i.e. for species like anchovies with very seasonal growth and a very short life span).

---

[16] The other methods available in FiSAT are the inferior Jones/van Zalinge form of length-converted catch curve; the Ault-Ehrhardt mean length method most applicable to short-lived tropical fish species, and the approximate Hoenig methods based on the longevity t_{max} of the fish.

Non-equilibrium methods

In contrast to the methods above, age-based VPAs estimate the fishing mortality experienced in each year by each actual cohort or year-class of fish. Standard VPAs estimate the F experienced by each cohort in each year, by comparing the numbers estimated in each group ($Z = \ln (N_{t+1} / N_t)$). This produces a two-dimensional matrix of outputs of both N and F. "Separable" VPA models distinguish the contribution to F arising from the exploitation rate (the variation between years) and the selectivity (the variation across ages, depending on the mesh sizes, migration patterns etc). Many of the comments made above about using VPAs for estimating stock sizes apply equally to the estimation of fishing mortality.

Another possibility for estimating non-equilibrium fishing mortality rates (and stock sizes) is the MULTIFAN-CL software of Fournier, Hampton and Sibert (1998). This length-based method provides an integrated approach to estimating age compositions, growth parameters, mortality rates, recruitment, and other parameters, from combined time series of fish catches, fishing effort and length frequency data. It incorporates Bayesian parameter estimation, and gives confidence intervals for its outputs. Although very adaptable, the software is not easy to understand and the uncertainties in the outputs will always likely be higher than for age based methods. Wherever possible, fish should be aged to allow the best analyses.

3.4.4 Other indicators

The two previous sub-sections have focused on the stock size and the fishing mortality rate as the two primary indicators of the state of the fish stock and the level of fishing pressure. Most of the reference points that have so far been developed relate to one or other of these indicators (see following section). Indicators such as these clearly require expensive monitoring programmes and scientific assessments to estimate. They have nevertheless become central elements of the management systems used in Europe, north America and elsewhere (largely based on VPAs and statistical catch at age methods).

Of course, many other indicators could also be used. Simpler indicators such as the percentage of mature fish in the catch (Caddy, 1998) or the CPUE of a standard vessel could be estimated more easily and may be equally acceptable to fishermen as thresholds for management action, especially if they are better understood and seen as more transparent.

As emphasized in Section 2.5.1, a *range* of goals and objectives should also be set for the fishery. Ecological objectives should be adopted as limits to exploitation while social and economic objectives may be set as targets to aim at. Indicators and reference points should be set for each of these objectives (Section 2.5.2). FAO (1998) suggest to monitor indicators of fishing operations, biological characteristics, and the economic and socio-cultural objectives of the fishery. They provide 26 pages of examples of the types of data that may be collected in deriving such indicators. FAO (1999) further suggest that a full "Sustainable Development Reference System" should monitor indicators in each of the ecological, economic, social and institutional / governance dimensions of a fisheries. In their framework, important ecological indicators may include catch rates and catch composition (sizes and species), the state of critical habitats, and the fishing pressures in different areas; economic indicators may include the profitability of different fleets, the value of any fishing rights (e.g. ITQs) and the subsidies used in the fishery; social indicators may include employment, the consumption of protein and the maintenance of traditional cultures; and governance indicators may relate to management capacity, the extent of compliance with fishing rules, and the degree of transparency and participation in the management regime. Readers are referred to the above sources for possible indicators in each of these categories.

TABLE 3.3
Summary comments on the key fishery indicators

Indicators	Advantages / application	Disadvantages / comments
Catch, effort and CPUE	• Use catch history to show phase of fishery development • If effort data also available, use CPUE as an approximate index of state of stock	• Note that the catch history depends on both the fishing effort and the state of the stock
Stock size	• Estimate cohort strengths by age and year using VPA methods (enabling SRRs to be fitted) • Biomass dynamic and depletion models also estimate overall stock size, but not separately for each age class (so less useful for fitting SRR)	• VPA methods have high data needs and are least accurate for most recent years • Most length-based VPA methods assume equilibrium conditions and do not estimate stock size separately for each year (so less useful as indicators)
Fishing mortality rate (*F*)	• Age-based VPA estimates *F* separately for each year (but least accurate for recent years) • Length-based "VPA with pseudocohorts" and "MULTIFAN-CL" methods estimate *F* for each year, but less accurate than age-based VPA and only useful for fast growing species • Equilibrium methods useful for fisheries that are only assessed every few years	• Most length-based methods (and age-based catch curve) assume that the stock is in an equilibrium state (i.e. estimate average *F* over the years included in the sample) • Equilibrium methods may be biased by variations in recruitment strength between years
Others (goal-based)	• Needed to monitor achievement of agreed fishery goals • May be easier to understand than e.g. *F* and allow better communication with industry	• Full "Sustainable Development Reference Systems" (SDRS) may be very complex but very useful in examining possible causes of fishery trends

3.5 ESTIMATING TECHNICAL REFERENCE POINTS

As described in Section 2.5, reference points should be used to give quantitative meanings to the goals and objectives set for the fishery. "Conceptual" reference points define "limits" and "targets" that guide when to take pre-agreed management actions within decision control frameworks. Recognizing the uncertainty in the stock assessment process, the framework may be elaborated with further "precautionary" reference points: these provide thresholds that help to ensure that the limits are unlikely to be broken. Each of these reference points must be defined explicitly as "technical" forms stating exactly how they will be estimated. This section describes some of the technical reference points that have so far been defined. More detailed reviews of the wide range of different reference points were made by Caddy and Mahon (1995) and Caddy (1998).

Technical reference points are usually estimated with fisheries models such as the biomass dynamics and YPR approaches described in Chapter 4. Though the estimation methods may differ substantially, most reference points focus either on the yield that will be produced or the level of protection that will be given to the spawning stock and its recruitment potential. Yield-based reference points are most often used as targets for management. Reference points for the reproductive capacity of the stock are more often used as limits to ensure the conservation of the stock. Although some authors (e.g. Cadima, 2003) define the different technical reference points as either targets (TRPs) or limits (LRPs), there is in fact some variation in the way they are interpreted by different agencies. The allocation of a reference point as either a target or a limit thus depends on how it is included in a decision control rule framework (Section 2.5.3), and not on its technical formulation. Reviews of the use of the alternative reference points by different agencies have been made by Gabriel and Mace (1999), ICES ACFM (2000) and Garcia (2000).

Reference points provide specific values to aim at (targets) or to avoid (limits) for the indicators adopted for the fishery. Several reference points can relate to more than one indicator. Where MSY is adopted as an objective for example, reference points can be specified for three different indicators: the stock size at which MSY is available (i.e. B_{MSY}), the fishing mortality (F_{MSY}) that would generate MSY, or the MSY catch itself.

The specific reference points that are going to be used in the management of a fishery should be agreed with stakeholders and may be renegotiated every few years or whenever management strategies are changed or improved methods are developed. The value of a specific referenct point may be updated whenever new data become available (so, for example, both the indicator B_{now} and the reference point B_{MSY}, may be updated with each new annual assessment). Some reference points (e.g. the 40 percent proportional escapement adopted for the Falkland Island squid fishery – see Section 4.5.3), could be updated less frequently than the indicators.

Technical reference points are described below relating to the status of the fishery in terms of the catches (MSY and other yield-based reference points), the reproductive potential of the stock, the biodiversity and health of the fishery ecosystem, and the economic and social conditions. Comments are made on how the different reference points are *usually* interpreted or used (e.g. as TRPs or LRPs). Section 2.5.4 described how LRPs are best used in control rule frameworks adjusted to precautionary reference points, i.e. allowing for the uncertainties in the analyses and the risk tolerances of the managers. Such precautionary adjustments can in principle be applied to any of the basic reference points. Section 3.5.4 below also describes how specific "risk-based" reference points can also be formulated using Monte Carlo-type stock assessments.

Different reference points require different types and volumes of data for their estimation. Although the UN Fish Stocks Agreement and the FAO Code of Conduct recommend the use of MSY-based reference points, these and others often cannot be estimated in data- or capacity-limited situations. The available data, for example, may not cover a sufficient range of fishery conditions for clear conclusions to be drawn. Alternative "proxies" are therefore identified which may be used as substitutes for the ideal reference points, because they are "easier to calculate, or require fewer data, or are more robust" (Gabriel and Mace, 1999). The FAO guidelines on the precautionary approach (FAO, 1995b, 1996) recognize that proxies for the preferred reference points will often be necessary. Further guidance on proxy reference points is given by Caddy (1998), Gabriel and Mace (1999), and Serchuk *et al.* (1999). Berkes *et al.* (2001) also suggest the use of "Management Reference Directions" as an adequate basis for action in small scale fisheries. In these fisheries, the exact point to aim for may not be well known, but it is often clear which *direction* management should be moving (e.g. to increase mesh sizes in pot fisheries to reduce the numbers of immature fish being caught).

3.5.1 MSY reference points

The maximum sustainable yield, MSY, is "the highest theoretical equilibrium yield that can be continuously taken (on average) from a stock under existing (average) environmental conditions without affecting significantly the reproduction process" (Cochrane, 2002a). The fishing mortality that would produce this yield is referred to as F_{MSY}. B_{MSY} is the stock size that would produce MSY. In the case of the Schaefer production model this is half the unfished stock size. F_{MSY}, B_{MSY} or the MSY catch can be used as reference points to manage a fishery at the point where yield will theoretically be maximized.

MSY reference points have a special priority due to their prominence in the international fisheries legislation. MSY was included specifically in the 1982 UN Convention on the Law of the Sea. The 1995 UN Fish Stocks Agreement further defined LRPs and TRPs entirely in terms of the biological reference points related to maximum sustainable yield: B_{MSY} and F_{MSY} (see Section 2.5.2). As stated in Annex II of the FSA, "the fishing mortality rate which generates MSY should be regarded as a minimum standard for LRPs". Gabriel and Mace (1999) interpret this wording as meaning that F_{MSY} should be viewed as an upper bound for fishing mortality LRPs. TRPs and any precautionary reference points for F should therefore always be *below* the MSY positions. This is a significant departure from historical fisheries management practice where F_{MSY} has most often been treated as a target, rather than as a limit, and often exceeded.

Cochrane (2002c) explains why a fishery will be better managed using B_{MSY} or F_{MSY} as precautionary LRPs (see e.g. Figure 2.6) than as TRPs. Using MSY as a TRP has been found to be dangerous because it cannot be estimated precisely for any stock. Whenever MSY is over-estimated, fish catches will exceed the surplus production of the stock and the stock will decline every year. The stock will soon be fished down to the point of collapse. Such failures in the past have partly been due to the inappropriate use of equilibrium fitting methods (Section 3.1.4). The new and improved biomass dynamic models are less likely to produce such outcomes. Recognising the possibility of overshooting the target, values of 2/3 MSY were proposed as safer targets for many years.

NAFO and the current US fisheries legislation (the "Magnusson-Stevens Act") confirm F_{MSY} (or proxies) as the preferred LRP for fishing mortality. ICES on the other hand have adopted the less restrictive F_{crash}, F_{LOSS} or F_{med} (see definitions below) as their LRPs (Gabriel and Mace, 1999). The adoption of different technical reference points to represent different conceptual or decision control reference points indicates different interpretations and implementations of the precautionary approach between organizations and states. The degree of precaution afforded by each reference point clearly differs quite substantially, and it remains to be seen which approaches will prove to be sustainable.

MSY reference points may either be estimated using biomass dynamic models (e.g. using the CEDA software – Section 4.5) or using age-based production models that include a stock recruit relationship (e.g. using the Yield software – Section 4.3). The simpler biomass dynamic models (see Section 3.1.3) can sometimes produce relatively good estimates of MSY and f_{MSY}, but are less able to give precise values of F_{MSY} and B_{MSY} unless the catchability, q is well known. A frequent problem with these methods occurs when the available data have poor "contrast" and do not cover a sufficiently wide range of fishery conditions for clear conclusions to be drawn (see Section 4.5.3). The age based, analytical production models directly produce estimates of F_{MSY} and B_{MSY} by multiplying the curves for YPR by the recruits per unit biomass at equivalent levels of spawning stock biomass per recruit (SSBPR). Although the data inputs of the analytical methods are higher, the accuracy can also sometimes be higher than the biomass dynamic models (though see Section 3.1.3). MSY stock sizes and harvest rates can also be calculated directly from the fitted SRR for "semelparous" fish species (see Section 3.3.5).

Another important point is that MSY should not be regarded as a constant but as a quantity that will vary with the current size of the stock in response to natural environmental fluctuations. Rosenberg *et al.* (1993) argued that the inclusion of the MSY concept in UNCLOS was never intended to imply extraction of a constant yield every year, but rather to promote the conceptual policy need to avoid an overfishing situation. Although a constant yield can be used as a harvesting strategy (see Section 2.5.3), "fishing for MSY" is more often interpreted as taking the highest catch currently available that should enable the stock to stay at or recover to its average MSY size. This may be calculated approximately by multiplying the current biomass by the F_{MSY} (or an adjusted F_{pa}). Checks on the likely future changes in the stock size may also be made using projection models (see e.g. the CEDA approach in Section 8.3). While there may be a long term average MSY about which catches may fluctuate, fishery managers should also keep alert for significant changes in the potential of the stock which may imply major "regime shifts" in the fishery ecosystem.

3.5.2 Proxies for MSY and other yield-based reference points

Proxy reference points for F_{MSY} may be most easily calculated using YPR models. YPR reference points are derived from those analytical models that ignore the stock recruitment relationship (SRR, see Section 3.1.6). They describe the changes in the biomass of a "standard" year class as the balance between the reduction in numbers due to natural and fishing mortality and the increase in individual weights due to growth. The most commonly used YPR-based reference points for fishing mortality are:

F_{max} F giving the maximum YPR; and
$F_{0.1}$ F at which the slope of the YPR curve is 10 percent of its slope at the origin

YPR reference points can be useful for avoiding growth overfishing, but should not be relied upon where recruitment overfishing is a possibility, due to the absence of any recruitment sub-model (see Section 3.1.6). Simulation studies have demonstrated that F_{max} invariably overestimates F_{MSY} if an asymptotic Beverton-Holt stock-recruitment relationship applies, although F_{MSY} can sometimes exceed F_{max} when recruitment is based on a domed "Ricker" form. F_{max} should in general not be used unless stock sizes can be shown to be above the point where recruitment might be affected by stock size.

To avoid the risk of recruitment overfishing, many managers have adopted $F_{0.1}$ policies rather than aiming for F_{max}. $F_{0.1}$ is particularly useful in cases where F_{max} occurs at infinitely high values of F, as often found for the higher sizes at first capture. It is also widely applied, however, even where a clear F_{max} does exist. The adoption of the 0.1 (10 percent) level in an $F_{0.1}$ strategy is ad hoc. There is no specific justification for this value, except that it is more conservative or risk averse than selecting F_{max}. It does not necessarily ensure that recruitment overfishing will be avoided (Mace and Sissenwine, 1993). Reference points for alternative points on the YPR curve are used in some countries, e.g. $F_{0.2}$ in South Africa. This and any other value of $F_{0.x}$ can be calculated in the FMSP Yield software (Section 4.3). While F_{max} is usually interpreted as an LRP, $F_{0.1}$ is more applicable as a TRP (Caddy, 1998).

YPR models can vary greatly in their complexity from fully empirical Thompson and Bell, multispecies versions, to the simplified Beverton and Holt (1964) model which estimates YPR from only three ratios: M/K – the relative longevity and growth of the species, F/Z – the level of fishing relative to M, and l_c/L_∞ – the size at first capture relative to the asymptotic size. YPR reference points can be estimated in the Yield software along with their confidence intervals arising from the uncertainties in the inputs. Most YPR models require larger numbers of parameters to be estimated than for the biomass dynamic models, though this can be achieved with only length frequency or catch at age samples: full catch and effort data for the fishery are not required. Data inputs are also much lower than for the full age based analytical models that include SRRs.

Proxies for B_{MSY} (i.e. biomass-based reference points indicating the maximum sustainable yield) can be estimated roughly as a percentage of the unexploited biomass, B_0. This may be valuable where an estimate of this biomass has been made by a survey in the early days of a fishery. The fraction of the unexploited biomass that would produce the MSY is usually in the range 30-60 percent according to Gabriel and Mace (1999), with "higher percentages being used for less resilient species, and lower percentages for more resilient species". B_{MSY} for the Schaefer model of course is at 50 percent of the unexploited biomass or carrying capacity K: the percentage is less than 50 percent for the asymmetrical Fox model.

Proxies for the MSY catch may be estimated from the well-known "Gulland formula" MSY = $0.5MB_0$, and its relatives (see Section 4.2). Cadima's related formula allows MSY to be estimated where some catch is already taken as:

$$MSY = 0.5\ (Y + M\bar{B})$$

where Y is the total catch in a year and $\bar{B}$ is the average biomass in that same year. These formulae rely on an estimate of the natural mortality, M which may not be well known. They also of course require an estimate of the unexploited or current biomass to be useful. As found by Beddington and Cooke (1983), the constant in the equation will usually be less than 0.5, with the degree of correction depending on the growth rate K and the age or size at first capture. Mace (1994) found that the value of $F_{0.1}$ falls below M for stocks that are slow growing or have a low age at recruitment and above M if the stock is fast growing or has a high age at recruitment. Caddy (1998) provides a variable constant of proportionality "P" ($F_{MSY} = P.M$) that is lower for shorter lived (high-M) species. With this adjustment, although M may vary between say 0.1 and 1.5 per year, F_{MSY} may not go much above 0.6 per year even for the high-M species.

A final mention should be given to the proposal of "reference points" such as $F_{2/3MSY}$ where the fishing mortality is reduced to two thirds of the MSY level (Caddy and Mahon, 1995). Strictly speaking, $F_{2/3MSY}$ is not a "proxy" for F_{MSY}. It is better envisaged as an attempt at making precautionary management adjustments to the reference points (Section 2.5.4), where data on the uncertainty in the reference point is not available. In a similar way, $F_{0.1}$ is not strictly a proxy for F_{MSY}, but is rather a yield-based reference point that takes account both of the inadequacy of the YPR approach (i.e. that it ignores the SRR), and that should give better economic outcomes than F_{max}.

3.5.3 Reference points for maintaining the reproductive capacity of the stock

To prevent recruitment overfishing, fish stocks should be managed to maintain sufficient spawning biomass to ensure continued high recruitment. Complementing the MSY and other yield-based reference points (that provide *harvesting* goals for the fishery), a variety of reference points have been defined that look explicitly at the recruitment process and can thus be used to set *conservation limits* for the fishery. As outlined below, these can be based on plots of stock and recruitment (SR) data or functional relationships (SRRs) fitted to such data. Where SR data are not available, proxy reference points can be used, either based on the spawning stock biomass per recruit or simply on the size of the fish harvested. As with the yield-based points above, these reference points may either be stated in terms of a stock or spawning stock biomass that is expected to yield the desired number of recruits, or as an associated fishing mortality level.

The best reference points in this section should in principle be those based on a time series of actual SR data for a fishery, ideally spanning a range of stock sizes. Unfortunately SR data are hard to collect and even good data sets sometimes provide little certainty as to which model should then be used to represent the relationship between spawning stock biomass and recruitment (see Section 3.1.6). Allowing for this situation, the first set of reference points below are derived from only a plot of SR data, assuming no fixed functional relationship.

Reference points from a stock-recruitment plot

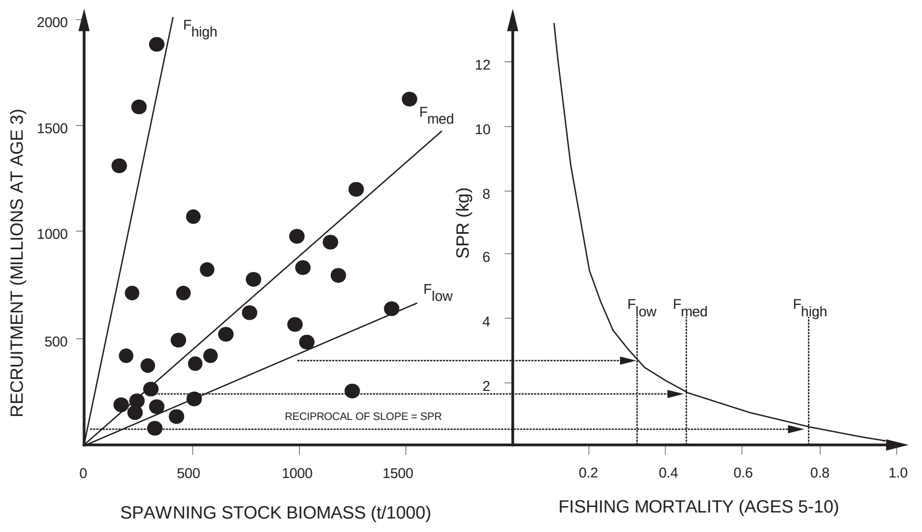
These reference points include MBAL and B_{LOSS}, and F_{med} and its relatives. "MBAL" – the Minimum Biologically Acceptable Limit, as used by ICES for the North Atlantic – is the spawning stock biomass (SSB) below which the recruitment R is noticeably reduced. No formal definition is given to MBAL which is usually fitted "by eye". Such a point is nevertheless very useful in those situations where a threshold SSB can be identified in the SR plot at which R is consistently or usually higher above than it is below.

As with MSY, the true value of MBAL will only become known after it has been exceeded. This is a potential drawback for a limit reference point, at least for a still-developing fishery. In SR plots where there is no reduction in *R* even at the lowest observed levels of SSB, it will be impossible to identify the MBAL. Where this occurs, a precautionary reference point $\underline{B_{\mathrm{LOSS}}}$ has been proposed as the biomass at the "Lowest Observed Spawning Stock". On the evidence of the limited information available, this *may* be a safe limit for SSB. A related point, $\underline{F_{\mathrm{LOSS}}}$ can be calculated as described below.

The standard SR plot shows the number of recruits that are produced in each year per unit weight of spawning stock biomass (Figure 3.3). Any line drawn through the points in the SR plot starting from the origin represents a constant ratio of the number of recruits produced per unit of spawning stock biomass (R/SSB). The reciprocal of this value (assuming the same units are used) is the spawning stock biomass per recruit (SSBPR or SSB/R) that can be calculated using standard "per recruit" models. The fishing mortality corresponding to any given R/SSB ratio can thus be read off a graph of SSB/R versus *F*, as illustrated in Figure 3.3. The level of fishing mortality corresponding to a R/SSB line with half the observed recruitment points above the line and half below has been defined as the $\underline{F_{\mathrm{med}}}$ reference point. This has been proposed as a LRP for avoiding recruitment overfishing, as it is an estimate of the fishing mortality that should, on average, allow for replacement of successive generations over the observed range of stock and recruitment data (MRAG Americas, 2000). Assuming that recruitment continues at the rates seen in the SR plot, any fishing mortality rate lower than F_{med} should allow the stock size to increase while any *F* exceeding F_{med} should result in a decline in the stock size. As illustrated in Figure 3.3, *F* can be estimated for any R/SSB line through the SR data points. A line cutting the SR plot so that 90 percent of the SR data points are above the line (i.e. the "10$^{\mathrm{th}}$ percentile line) has been termed the $\underline{F_{\mathrm{low}}}$ reference point. The 90$^{\mathrm{th}}$ percentile line is known as $\underline{F_{\mathrm{high}}}$. F_{high} has also been proposed as a LRP, but there is a clearly a much higher chance that the stock biomass will decline at this level of fishing. The central F_{med} is used as a LRP by ICES (2000).

A problem with the use of F_{med} is that it will only be a reliable reference point if the SR data originate from a time of "good health" in the fishery, e.g. when the biomass

FIGURE 3.3
Illustration of the methodology for estimating F_{low}, F_{med} and F_{high} by combining stock and recruitment data (left) with a per-recruit model (right). (source: Caddy and Mahon, 1995)



has been fluctuating around B_{MSY} levels. If the stock has already been fished down, the available SR data may only indicate the potential spawning available at small stock sizes. If the stock is already reduced below the "MBAL" threshold, the median or 50th percentile line of the data points will not be the true average "replacement" level of the overall SRR. The use of F_{med} may therefore be dangerously misleading for stocks that have been consistently over-exploited for the period covered by the SR data. Where SR data are available from a wider range of conditions in the fishery, these reference points are potentially less biased and more useful. Simple Excel spreadsheets using the "solver" routine for estimating F_{med} are included in the software package of Lassen and Medley (2001).

Reference points from a fitted stock-recruitment relationship (SRR)

Where SR data plots can be reasonably fitted by stock recruit relationships such as the Beverton-Holt or Ricker forms (see Section 3.3.5), reference points can be calculated from the parameters of the SRR. Where the dome-shaped Ricker SRR provides the best fit, an obvious reference point is the spawning stock biomass at which recruitment is highest. This is not appropriate for the Beverton-Holt SRR, however, as its asymptotic form means that the maximum recruitment will be obtained at an infinite biomass.

As a biomass threshold for defining recruitment overfishing, Myers *et al.* (1994) recommended the use of the biomass at which recruitment is 50 percent of the maximum level R_{max} as predicted by the fitted SRR This reference point, $\underline{B_{50\%R}}$ effectively allows for the steepness of the SRR (see Section 3.1.6), and is usable with both the Beverton-Holt and Ricker forms. Gabriel and Mace (1999) have cautioned that $B_{50\%R}$ (like MBAL) could be a dangerously low level of biomass. More conservative, if ad hoc points on the SRR curve such as $B_{90\%R}$ could therefore also be considered (as with the ad hoc $F_{0.1}$ and $F_{0.x}$).

Mace and Sissenwine (1993) have also proposed the reference point F_τ (<u>*F*-tau</u>) as the F corresponding to the slope of the SRR at the origin. This is equivalent to the $\underline{F_{crash}}$ recognized by ICES (2000, see also Caddy, 1998) as an extreme LRP for fishing mortality. F_{crash} is the point on an equilibrium yield curve at which both the biomass and the catches are reduced to zero and the stock becomes extinct (see e.g. the "Yield" and "SSB" curves in Figure 3.1). This point may be derived either from a biomass dynamic production model or an analytical one. It must clearly be interpreted as an extreme LRP to be avoided by strong precautionary thresholds (see below). Fishing at mortality rates beyond F_τ or F_{crash} should be expected to lead quickly to extinction of the stock.

"SPR" reference points from per recruit models without a SRR

Where no SR data are available, proxy reference points for conserving the spawning stock can also be estimated using per recruit models. In this case, the standard YPR model is extended to include maturity and fecundity at age or size. This enables the spawning stock biomass per recruit (SSBPR) or more generally the spawning (products) per recruit (SPR) to be estimated at different levels of fishing mortality. Spawning "products" may thus be the biomass of mature fish, the egg production, or other related metrics (Gabriel and Mace, 1999). Such an approach works without the need for SR data or a SRR, and instead proposes to set fishing mortality at a level where the SPR will only be reduced to levels commonly found to be sustainable. Such levels are usually estimated as a percentage of the SPR that would occur in an unfished stock (i.e. with natural mortality, M, but no fishing mortality, F). This indicator, known as the <u>%SPR</u>, always decreases monotonically as fishing mortality increases (see Figure 3.1). With no fishing mortality, 100 percent of a stock's spawning potential is achieved. As F increases, SPR is reduced. The fishing mortality $\underline{F_{\%SPR}}$ corresponding to any level of %SPR can thus be read off the curve or calculated analytically (e.g. using the FMSP Yield software).

The advantage of %SPR reference points is that they do not require a time series of spawning stock sizes and related recruitment data, that can be hard to collect. Where SR data are unavailable and the level of F corresponding to MBAL or F_{crash} etc is unknown, safe values of $F_{\%SPR}$ are instead sought that can be used as proxies. The key question in using %SPR is to decide exactly what percentage reduction in SPR should be allowed in setting a "safe" reference point that will prevent recruitment overfishing. Several studies have looked at the optimum percentage over the last decade using meta-analyses, and values of 20-30 percent SPR are now commonly used. Mace and Sissenwine (1993) advocated $F_{20\%SPR}$ as a recruitment overfishing threshold for well-known stocks with at least average resilience and $F_{30\%SPR}$ for less well-known stocks or those believed to have low resilience (Gabriel and Mace, 1999). Gabriel and Mace (1999) further argue that such $F_{\%SPR}$ reference points may be better than using F_{med} or other reference points that are derived from SR data, if such data are in fact biased (as in the situation described above).

Gabriel and Mace (1999) also proposed the use of SPR reference points in the range $F_{30\%SPR}$ to $F_{40\%SPR}$ as proxies for the *yield*-based reference point F_{MSY}. The use of SPR reference points in this way may however cause some confusion as a reference point aimed at protecting the *spawning stock* is being used as a proxy for the goal of maximizing *yield*. Care must clearly be taken over which reference points are selected and for what purpose. The relative proximity of the yield-based and spawning capacity-based reference points is not always clear cut. As should be expected, lower SPR reference points are recommended as proxies for F_{MSY} (i.e. the F that reduces SPR to 30-40 percent of its unexploited level) than for those limit reference points aimed at avoiding recruitment overfishing (20-30 percent SPR). The more extreme spawning capacity reference points such as F_{crash} will also always be above F_{MSY}. The fact that $F_{\%SPR}$ reference points in the range 20-30 percent will usually instead be *below* F_{max} and may also be below $F_{0.1}$, emphasizes the problem with using per recruit models to develop *yield-based* reference points (see also Section 3.1.6).

Size-based reference points

Where no SR data are available, nor any data for SPR analyses, some protection may still be given to the spawning capacity by the use of size limits. Possible precautionary approaches could be to set size limits to ensure that no (or few) immature fish are caught in the fishery (Cochrane, 2002c), or to ensure that the average size of fish caught is equal to, or greater than, the average size at maturity (Caddy and Mahon, 1995). Limit reference points in these cases could either be set as minimum size limits (e.g. based on a selectivity ogive – see Section 3.3.6), or as the mean size of fish in the catch. In the latter case, at least 50 percent of individuals should have an opportunity to reproduce at least once. The mean size of fish in the catch will of course depend both on the size limit used and the fishing rate on the stock. If fishing rates increase, it may be necessary to further increase the minimum legal size limit to maintain the stock of mature fish.

Such simple size-based reference points can be useful where full age-based stock assessments are difficult (e.g. for invertebrates or fish species which can not be aged) or where fisheries are not large enough to justify the data needs of the more intensive stock assessments.

3.5.4 Risk-defined reference points

Both the selection of reference points and the way they are used in a precautionary management framework (see Sections 2.5.2 and 2.5.4) require some decisions to be taken by managers about the risks involved in managing fish stocks against a background of uncertainty. Similar overall levels of risk may be achieved in different ways. The "extreme" F_{crash} could, for example be adopted as the conceptual limit reference point, F_{lim} and applied with a strong precautionary adjustment to the threshold F_{pa}. Alternatively, the more conservative $F_{30\%SPR}$ could be adopted and used with a closer precautionary threshold. The degree of adjustment to F_{pa}, depends on both the uncertainty in the assessment and the degree of risk tolerance adopted (see Section 2.5.4). The former can only be reduced by better assessments, but the latter can be chosen as desired by the manager and/or the fishery stakeholders.

The risk of any particular outcome (e.g. of exceeding F_{lim}) can therefore be managed for each of the other reference points in this section according to the way they are used in a precautionary management framework. As an alternative, explicit <u>risk-based reference points</u> can also be defined and estimated analytically. These have commonly been estimated as the fishing mortality where the probability of reducing the spawning stock below a defined threshold is less than a user-selected percentage. The probability can be estimated for example of reducing SSB below MBAL, or of reducing SPR below 20 percent of the theoretical level in the unexploited stock. In the FMSP "Yield" software, the risk-defined "<u>Transient</u>" reference point is estimated by repeatedly adjusting the value of F until the level is found that gives the required probability threshold (see Sections 4.3 and 7.4).

3.5.5 Multispecies and ecosystem-based reference points

The FAO Code of Conduct advises that fisheries should be managed to ensure that the "catches of non-target species, both fish and non-fish species, and impacts on associated or dependent species are minimized" and also to ensure that the "biodiversity of aquatic habitats and ecosystems is conserved and endangered species are protected" (Paragraph 7.2.2). These and other multispecies and ecosystem impacts (see Section 2.2) must be taken into account when determining management strategies and reference points for the fishery.

As discussed in Section 2.2.3, management at a multispecies or an ecosystem scope may best be achieved by attempting to manage "technical interactions" between gear types and limiting the impacts of the fishery on the environment. Although indices of species diversity could theoretically be used as reference points in multispecies fisheries, the more common approach at present is to develop a suite of single-species indicators covering the priority species and to set management decision rules according to these. Under this approach, not only would reference points be developed and applied for the major target species, but also for key bycatch species, indicator species and species identified as being vulnerable or depleted. Possible reference points could include the percentages of fish discarded in the fishery, or caught as a bycatch (see Caddy and Mahon, 1995). Such reference points could be estimated based on the results of single or multispecies models (see Section 4.4) or simply as ad hoc precautionary values agreed with stakeholders.

A well known example of the application of the ecosystem approach (and the precautionary approach) is offered by the Convention for the Conservation of Antarctic Marine Living Resources (CCAMLR).[17] Article II of the convention requires CCAMLR to take account of ecological relationships, the effects of fishing on non-target species, and particularly the needs of dependent predators. CCAMLR TACs for some target species are tied to catch limits for bycatch species, so that a fishery may be closed when a bycatch limit is reached, even if the TAC for the target species has not yet been taken. Technical regulations (Section 2.5.5) are also used to reduce the risk of catching bycatch species. For example, to reduce bycatch levels, CCAMLR has prohibited the use of bottom trawling for mackerel icefish in Subarea 48.3 (South Georgia), allowing only mid-water trawling, which is considered to produce cleaner

[17] See CCAMLR web site: http://www.ccamlr.org/pu/E/pubs/am/toc.htm

catches. The bycatch limits thus provide an overall cap on the fishing mortality of certain non-target species, while technical regulations assist the fishery to achieve the target species TAC before the bycatch limits are reached. The catch control rule for the target species catch is also designed to allow for the needs of icefish predators. The rule can be expressed as "the fishing mortality which would result in a probability of no more than 0.05 that the spawning stock after fishing over a two year period would be less than 75 percent of the level that would have occurred in the absence of any fishing". Also used for krill, an important forage species in the Southern Ocean, the 75 percent level is an arbitrary target, being a compromise between 50 percent and 100 percent. The former is the biomass level of the target species conventionally assumed to give the greatest net annual increment (i.e. 50 percent of the unexploited level). The latter represents the best possible position for predators in which there is no mortality of their prey due to fishing. The extra 25 percent thus allows something for the predators with no real way of knowing if this is enough, or too much (Parkes, 2000).

As in the above example, multispecies reference points may not need to give detailed restrictions for every species in the fishery, but may instead focus on the main species of interest. Chapter 12 in Part 3 describes a procedure for identifying the most vulnerable species in a multispecies assemblage, and for setting effort levels to protect them. If fishing rates are conservative enough to protect the most vulnerable species, it is likely that other species in the fishery should also be protected.

Whether or not multispecies reference points are explicitly set to guide the management of the fishery, ecosystem-based indicators should also be monitored to determine the possible impact of external factors on the status of the fishery. Such indicators may help to distinguish whether a change in the stock abundance may be due to pollution for example, or the latest El Nino or any other factor, rather than the fishing mortality rate being too high. Due to the uncertainty of causal relationships, it may be hard to set actual reference points relating to these factors, but their potential influence should be considered (FAO, 1999).

3.5.6 Economic and social reference points

As outlined in Section 3.4.4, fishery objectives and indicators may also focus on a wide range of economic and social priorities. Reference points should in principle be set for each indicator adopted in the fishery, according to the goals and operational objectives that are selected (Section 2.5.1). In practice, some limit must be set to the number of points that can be used, reflecting both the monitoring capacity of the management agency and the need to limit the complexity of the decision making process.

Reference points in this category could relate to indices of employment; income or profitability (resource rent), either of the whole fishery or of individual vessels; the distribution of benefits (e.g. the percentage of the catch allocated to industrial and artisanal fisheries); or any other measure of the levels of satisfaction or benefits that are generated (Cochrane, 2002c). Considering such indicators re-emphasizes the tradeoffs that will always exist in fisheries, such as between the catch rate and the total catch, and between the economic efficiency and employment (see Figure 2.1).

The most well-known economic reference point is of course the maximum economic yield (MEY), which is always taken at a lower fishing mortality rate (F_{MEY}) than F_{MSY}, due to the need to subtract the costs of fishing, often assumed proportional to the fishing effort. MEY can be estimated using simple extensions to surplus production models to include economic data on fishing costs (fixed and variable) and the value of the landings. The latter may need to take into account the change in fish value with size, and the reduction in average size associated with higher fishing rates. Where economic goals are prioritized, it may be argued that the MEY gives a higher contribution to society than does MSY. Where social goals are prioritized, higher employment or food security may instead be preferred, which may be available at higher effort levels.

While some points such as MEY will have a clear maximum that can be estimated as a technical reference point, other points such as the minimum tolerable catch per unit effort or the levels of employment in the fishery will decrease or increase steadily with fishing effort (like the spawning stock biomass per recruit curve illustrated in Figure 3.1). Reference points for these types of indicators may therefore need to be set as ad hoc values, negotiated and agreed with industry members and other stakeholders.

TABLE 3.4
Summary comments on the alternative technical reference points (see also Section 2.5.2)

Technical reference points	Advantages / application	Disadvantages / comments
MSY, f_{MSY}, B_{MSY}, F_{MSY}	• Yield-based reference points mentioned in UNCLOS, UN Fish Stocks Agreement etc • Estimate using biomass dynamic or analytical models with SRRs • Estimate directly from SRR for semelparous fish species • Estimate using "Gulland equation" and extensions where biomass and life history parameters available	• Biomass dynamic models only give precise values of F_{MSY} and B_{MSY} if q is well known • Note that MSY is not a constant but will vary with the current size of the stock. A long term average MSY may exist but may be hard to estimate and may vary with "regime shifts"
F_{max}, $F_{0.1}$, $F_{0.x}$	• Estimate using YPR methods as "proxies" for F_{MSY} • Use to avoid growth overfishing • SR data not required	• No consideration of spawning capacity, so use as secondary TRP, with e.g. $F_{\%SPR}$ as primary LRP
MBAL, B_{LOSS}, F_{med}	• Spawning capacity reference points obtained directly from SR data plot • Useful where SRR can not be fitted	• Requires SR data to fit • F_{med} may not be valid if SR data only collected when fishery already depleted
$B_{50\%R}$	• Spawning capacity reference point from fitted SRR • Allows for "steepness" or slope of SRR	• Requires SR data to fit • Could be a dangerously low level of biomass – consider e.g. $B_{90\%R}$ instead or use strong precautionary adjustment
F_{crash} / F_{τ}	• Most extreme reference point indicating fishing level associated with stock collapse • Estimate using biomass dynamic or analytical models with SRRs	• Requires SR data to fit • Need to use with strong precautionary buffer
$F_{\%SPR}$	• Spawning capacity reference point from per-recruit models including reproduction data (e.g. maturity, fecundity) • Does not require SRR data to estimate	• Optimum level of %SPR uncertain - values of 20-30% suggested by meta-analyses depending on species "resilience"
Size-based	• Use to protect spawning potential by ensuring that at least some fish have the chance to spawn before capture • May be useful where fish can not be aged or fisheries are small-scale or less valuable	• Approximate • Optimum size limit may need to be adjusted depending on the fishing rate
Risk based, e.g. Yield's $F_{transient}$	• Set F for explicitly defined risks using Monte Carlo simulations • Note that risks may also be defined using precautionary reference points in a decision control rule framework	• Need information on uncertainty • Need managers to define acceptable risk levels
Multispecies	• Define permitted bycatch or discarding levels etc • Set F to protect most vulnerable species	• May be hard to optimize and need clearly agreed goals and prioritization • May underutilize some species

Note: Target Reference Points (TRPs), and Limit Reference Points (LRPs) are conceptual reference points used to define the decision control framework. Precautionary reference points may also be set as thresholds or buffers, particularly used to ensure that LRPs are not exceeded. Each TRP and LRP should be defined explicitly as a technical reference point such as those above.

3.6 PROVIDING MANAGEMENT ADVICE

Having estimated the levels of fishing mortality, biomass or other indicators to be used as reference points, and the current levels of these indicators in the fishery, the next step is to provide clear advice to the managers. The provision of such information should be seen as a regular (e.g. annual) process, that is driven by the objectives of the fishery and that guides the management actions that will be taken in the near future. Feedback to the advice should be provided by the managers and other interest groups to guide the future supply of information for the fishery (see Figure 10 of Cochrane, 2002c).

In the simplest case, and where a decision control rule system is already in place, the advice to managers may simply provide the current levels of the indicators relative to the reference points, as required for the pre-agreed control rule management approach (see Sections 2.5.3, 3.6.1). Usually this advice will need to be supplemented with other information providing a more detailed assessment of the fishery's prospects. As described in the following sub-sections, information may thus be provided on the implications of alternative management strategies for each of several indicators relating to the fishery objectives. Decisions taken will need to recognize the tradeoffs between the different objectives. Projections may also be made predicting the levels of the indicators in the future and the time that different management actions may take to achieve their objectives. Advice must also be provided on the various uncertainties in the assessments and the risks of bad results being obtained with each alternative management strategy. Although the simple control rule system is listed first below, the actual formulation of the control rules and the selection of the limits, targets and precautionary thresholds should ideally be decided based on a full examination of the tradeoffs and uncertainties from the other analyses.

Although enormous advances have been made in stock assessment methods in recent decades, fuelled especially by easy access to powerful computing capacity, formal approaches to decision-making in fisheries have made less progress (Cochrane, 2002c). The need for participation of stakeholders in decision making is now well recognized but not yet always well facilitated. Since different stakeholders will have different objectives for the fishery, and since managers usually set multiple competing objectives, the selection of management options can be the subject of much debate and argument. Without a clear decision-making process, the outcome can be dominated by the strongest personalities and prone to bias due to "self-interest, short-term objectives prompted by immediate problems, and hidden agendas" (Cochrane, 2002c). Formal statistical methods are available to assist with decision making but are not in common use.

To reduce the chance of bad decisions being made, and to achieve the long-term goals and objectives of the fishery, it is therefore essential that decision makers and other stakeholders are provided with relevant, objective and easily understood information by fisheries scientists. As described below, advice can either be provided in graphical form or using "decision table" approaches. Managers should guide the scientists on which formats are most useful to them. Whatever approach is used, decision makers must understand the importance of considering uncertainty, of weighing up competing objectives and of taking a long-term (as well as a short-term) view.

Finally, as emphasized by the precautionary approach, although management should be based on the "best available science" (e.g. *all* the advice described below), the absence of full scientific analyses should not be used as an excuse to avoid necessary management actions. Where the fishery is "data poor" and the scientific advice is less than complete, decision makers still have an obligation to make management decisions, aimed at achieving the goals and objectives of the fishery, and keeping precaution in mind. The provision of technical advice should be seen as a step in this management process, not as an end in itself (Mahon, 1997). The flow of advice, consultation, decision-making and feedback should be clearly identified (Caddy and Mahon, 1995; Cochrane, 2002c).

3.6.1 Feedback for "control rule" management

Where the "harvesting strategy" and the "decision control rule" for the fishery have already been agreed with stakeholders (Section 2.5.3), annual advice is required on the levels of the chosen indicators relative to the different reference points.

Where biomass-based indicators and reference points can be estimated, managers should be provided each year with estimates of B_{lim} and B_{pa}, along with B_{now}. These would then be used to set the next year's fishing mortality F_{ny} according to the agreed control rule (e.g. at or below F_{pa} in Figure 2.6). If B_{now} is below B_{pa}, then the stock should be regarded as approaching an overfished condition. In that case, whether adjustments are required to F_{ny} would depend on the probability of returning to a healthy stock state (given expected average recruitments), and hence on the current level of F compared to F_{pa}. If F_{now} is less than F_{pa}, the low state of the stock may be due to a chance occurrence of several bad years of recruitment in a row but recovery may still be expected. This should be confirmed by making a medium-term projection as described below. If F_{now} is greater than F_{pa}, regardless of the state of the stock, it should be reduced according to the control rule to reduce the chance of the stock becoming overfished (if it is not already).

If only F-based indicators and reference points are available, as may be the case in some data-limited fisheries, management actions can be based only on these points. If F_{now} is above F_{pa} , then this should be interpreted as overfishing. Adjustments should then be made to F_{ny} as required, according to the degree of overshoot. In this case, fishing mortality is conceptually on both the x-axis (F_{now}) and the y-axis (F_{ny}) of a control rule plot.

Other indicators and reference points can also be used, e.g. relating to ecosystem or socio-economic objectives, as described in Sections 3.4.4, 3.5.5 and 3.5.6.

If stock assessment outputs are to be used in this way, it should be clear that both reference points and related indicators must be available. There is no point in estimating reference points (e.g. $F_{0.1}$ or $F_{\%SPR}$) unless a plan is in mind and data have been collected to also estimate the current indicators (i.e. F_{now}) with some degree of accuracy. In biomass dynamic models, where both the reference point B_{MSY} and the current indicator B_{now} are estimated together, some software tools (e.g. ASPIC - Section 4.5.3, and ParFish – Section 4.6.2) present the results in ratio form e.g. as B_{now}/B_{MSY}.

3.6.2 Making projections: short-term and medium-term advice

Simple feedback for "control-rule" style management provides no guidance on how long the fishery might take to respond to the adjustments made in the management measures. This will depend on the age structure of the fishery (how many years it will take for all of the age classes to reach equilibrium at a new F level), and of course also on the future recruitment and the current size of the stock.

Where a fishery is in the "danger zone" (exceeding one or more PRPs) and F adjustments are needed, projections may be made to estimate the tradeoffs between the severity of the adjustment to F and the time that the stock will take to recover. This is the basis of "rebuilding plans" for overexploited fisheries. Given the uncertain influence of the actual levels of future recruitment, the time cannot be predicted exactly. As with other models, though, indications can be presented to decision makers of the relative tradeoffs and risks of alternative strategies, at expected levels of recruitment.

Projections can be made using a range of models, including age-based and length-based analytical models and biomass dynamic forms. A useful breakdown of the analytical model options is given by Sparre and Venema (1998). Stock projections extend the normal equilibrium approach of these models to predict the status of the stock for a number of years into the future. Projections are clearly of the most value where the current state of the stock is known reasonably well and is used as the basis for the prediction of the future states. In the FMSP CEDA software (Section 8.3), current biomass is estimated with a biomass dynamic model and the likely future trajectory of the stock may be estimated at different "scenarios" of fishing effort or catches (Figure 8.2). In the "Yield" software (Section 7.4.1), the current biomass may not be known, but projections can be made of the future stock size starting at the current *F* level (with its associated equilibrium biomass or SSBPR), at different future levels of *F* (see e.g. Figure 7.1 and Figure 7.2).

Lassen and Medley (2001) distinguish between short, medium and long-term projections according to the degree of dependence on the current cohorts comprising the stock. A short term projection might look 2-3 years into the future and a medium one 5-10 years for a fish species of average longevity. A long-term projection should demonstrate the equilibrium state but including the stochastic variation in recruitment and model parameters (e.g. the "Yield" "Transient" reference points – Section 7.4.2). Short term projections are mainly used for calculating the TAC in the next year. Medium-term projections are used to show the most likely consequences of setting TACs over the next few years (will a given TAC allow the stock to re-build, and in how many years?; or will it lead to a decline?). Long-term projections show the eventual position of the policy relative to the reference points.

For short-term projections of next year's TAC, the accuracy of the prediction will depend on whether the size of the incoming year class is estimated as an average long-term figure from a stock-recruit relationship (SRR) or as an actual estimate of this year's recruitment, e.g. derived from a pre-recruit survey. The importance of the contribution of the recruitment to the following year's catch depends on the number of age classes in the fishery, but is usually quite high.

Short term projections may be misleading if *F* is such that the stock is likely to be overexploited in the long-term, but where the most recent year classes are, by chance, strong. Medium-term projections investigate the expected situation of the stock in the future assuming that more "normal" recruitments will prevail. In both medium and long term projections, the incorporation of the long-term expectations of recruitment become more important. These stock assessments are therefore strongly dependent on SR data, e.g. from age-based VPAs or subsumed in the population growth rate of biomass dynamics models.

Projections of potential yields and stock sizes in future years depend not only on uncertainties in the current stock size and the future recruitment, but also on assumed population parameters (individual growth rates, *M* etc) and the fishing mortality that results in the years of the projection. Lassen and Medley (2001) note that the standard practice with projections is to assess the errors in the stock size and the SRR, with other possible sources of error often being ignored. The Yield model also allows the uncertainty in all of the basic input parameters to be included. Detailed consideration of uncertainty is given in Section 3.6.4 below.

3.6.3 Recognizing multiple objectives and management options

With multiple objectives and indicators, fishery decision-makers have the difficult job of choosing optimal management strategies that will involve tradeoffs between their various goals and objectives. No solution will ever simultaneously maximize all the potential benefits and minimize all the potential risks (Cochrane, 2002c). Advice should therefore be provided on the expected implications of alternative management strategies for each management objective (e.g. the expected values of the indicators, relative to the reference points). A third dimension also needs to be considered: the uncertainty in the predictions arising from alternative possible states of nature (FAO, 1996), as discussed in the following sub-section.

In the simplest case, advice may be provided on the level of a single indicator (e.g. %SPR) for different levels of a single management strategy (e.g. adjustments to fishing effort, estimated as the fishing mortality rate, *F*). In this case, either a simple graph or a table can be used to present the results. The tradeoffs between different indicators can be shown by plotting separate graphs for each indicator (e.g. for both the YPR and the SSBPR, as in Figure 3.1 or Figure 4.2). Such graphs should assist in the selection of a precautionary management strategy e.g. by identifying the relative positions of alternative reference points (e.g. a %SPR LRP at say 20-30 percent of the unexploited level, and a yield-based TRP at $F_{0.1}$ or elsewhere). If one had reason to believe that CPUE is broadly proportional to biomass, the SSBPR curve may also be examined as an index of the likely catch rates and the fishermen's incomes. Current levels of the indicators and the reference points can be marked on such graphs.

Graphical methods are clearly useful for presenting results from stock assessments especially where the number of possible management actions is only one or two. If alternative levels of two management actions are being considered, a three dimensional graph can be used such as the classic YPR "isopleth" diagram, in which contours of yield are plotted against fishing rates and mesh sizes. Where there are two or more indicators (e.g. both yield and SSBPR), several such graphs can be viewed to determine regions of parameter space that are acceptable for all of the indicators. The constraint in such a graphical approach is the number of axes. With a maximum of two independent variables for a contour plot approach, policies can only be analysed on a "two at a time" basis. Adding a third or more policy variables requires multiple plots to be produced and compromises the advantage of simple, graphical presentations. Either a decision table approach may then be used as described below, or more quantitative methods of optimization may be considered (see Hilborn and Walters, 1992, chapter 16).

Decision tables enable information to be presented to decision-makers in a form that facilitates comparison and decision-making. A well-structured and complete decision-table will not only summarize and present key results from the analyses, but can also serve to remind the decision-makers of their operational objectives, and how different management strategies might perform against each of them (Cochrane, 2002c). Table 3.5 provides a simple format for a decision table which could be extended to compare a larger number of management strategies across a range of alternative indicators. As fewer management strategies (values of *F* here) might be included in the decision table than on the graphs, it might be useful to present the overall picture in the graphs and give the numerical results for feasible levels of the management strategies as decision tables. Confidence intervals for the predictions should be included in both graphs (e.g. Figure 4.2 from "Yield") and in decision tables. Cochrane's (2002c) example of such a decision table (his Table 5) describes the tradeoffs that often appear in these tables, and that may present managers with some difficult decisions.

TABLE 3.5
Illustration of a simple decision table format comparing the results of three management strategies for several indicators

	Management Strategy 1 (No change to *F*)	**Management Strategy 2** e.g. *F* up 20%	**Management Strategy 3** e.g. *F* down 20%
Biological Indicators			
e.g. B/B_{MSY} %SPR			
Ecosystem Indicators			
e.g. *B* of bycatch species			
Economic Indicators		Means and confidence intervals	
e.g. Annual catch (% of MSY) Annual income per fisher Variability in incomes			
Social Indicators			
e.g. Change in number of fishers			

3.6.4 Providing advice on uncertainty and risk

In making projections and preparing graphs and decision tables, there will always be some degree of uncertainty in the advice that is provided. While uncertainties have often been ignored in the past, the precautionary approach now requires that fishery managers estimate the risks associated with the various uncertainties, and attempt to manage these risks by choosing appropriate management measures and strategies (Cochrane, 2002c).

FAO (1996) suggest that precautionary assessments should at the very least, calculate the theoretical response of the system to a range of alternative management actions, while considering (a) uncertainties in the data and (b) specific alternative hypotheses about underlying biological, economic and social processes. Uncertainties and alternative hypotheses are described further below. While the depth of the analysis may vary, this basic requirement applies equally for both data-rich and data-poor analyses (FAO, 1996).

Uncertainty was defined in an FAO consultation (Caddy and Mahon, 1995) as "the incompleteness of knowledge about the state or process of nature". This is quite different to the meaning of *statistical* uncertainty given as "stochasticity or error from various sources as described using statistical methodology." Cochrane (2002c) and Caddy and Mahon (1995) summarize the main types of uncertainty inherent in fishery management and stock assessment as including the following.

- *Process uncertainty*, or random variability, is the underlying stochasticity in the population dynamics such as the variability in recruitment.
- *Observation or measurement uncertainty* arises with the collection of basic fishery data and the estimation of quantities such as the total catch, biomass (e.g. from urvey), or the effective fishing effort;
- *Model uncertainty* is the misspecification of model structure (e.g. using a Schaefer model with normal errors, when a Fox model with log-normal errors is the "true" relationship);
- *Estimation uncertainty* in the estimates of intermediate parameters (e.g. $K = 0.5$ or 0.9?), of the indicators (e.g. the estimated stock size), or the reference points (e.g. B_{MSY}) is the combined effect of process, observation and model uncertainties as described above.
- *Implementation uncertainty* occurs with the implementation of management measures, including how effective they will be and how well the fishers will comply with them.
- *Institutional uncertainty* refers to how well participants in the process can communicate with each other, to what extent people are willing to compromise and how well the scientific information is understood; all of these factors influencing how decisions are made and therefore how good those decisions will be.

Uncertainties in the data and the parameter estimates arise largely from the inherent process uncertainty, but also depend on the quality and quantity of data collected and the fitting methods used. Process uncertainty includes the high variability in annual recruitment generally attributed to various environmental factors and visible in standard SR scatter plots. Measurement errors may also be a strong feature of the variation in these plots, however (see Section 3.1.6). Measurement errors in catch or abundance estimates will exist in both standard catch/effort data collection and in randomized fishery-independent biomass surveys (Section 3.2.1).

Uncertainties in processes and models provide the "alternative hypotheses or states of nature" (FAO, 1996) that need to be assessed in precautionary analyses. These may include the need to test alternative production models or SRR forms; the possibility of depensatory recruitment or other factors giving an increased likelihood of rapid collapse; systematic under-reporting of catches or discards; non-constancy in the catchability coefficients, and so on. Such uncertainties may thus include both ecological process and those relating to the operation or management of the fishery. While uncertainties in parameter estimates may be envisaged as having a probability *distribution* (e.g. a mean with a defined error distribution and confidence interval), uncertainties in hypotheses or states of nature are more often *discrete* possibilities (e.g. the Schaefer and the Fox production models are two alternative model hypotheses). Flexible model forms such as the Pella-Tomlinson production function can, however, also be used that can include both the discrete alternatives and a range of others.

Estimating uncertainty

Depending on the data available and the fitting method used, uncertainties can usually be estimated for some intermediate parameters and for some indicators and reference points. Bootstrapping techniques have proven particularly useful for estimating uncertainties where parameters are fitted with non-standard fitting methods (e.g. as in CEDA). Monte Carlo techniques are more often used where reference points are estimated by simulations and projections (e.g. as in Yield). Haddon (2001) provides an introduction to these and other alternative methods.

Both Monte Carlo simulations and bootstrapping methods involve forms of random resampling of data. With each new sample of data, the model is run to produce a new estimate of the outputs. Repeating this process many times allows the distribution and confidence intervals of the outputs to be calculated. In Monte Carlo simulations, the mean and variance of the input parameters may be specified, and the samples taken from the resulting probability density functions (PDFs) of each parameter. In bootstrapping methods, the samples are instead taken from the actual raw data used in fitting the models. Hilborn (2003) notes that bootstrapping is now being replaced by Bayesian methods as the preferred choice for analyses of uncertainty in stock assessments. Distributions from bootstrapping methods have the advantage that they are conceptually simple to understand, but the disadvantage that they should not be used as probabilities, though they are often treated as such (Hilborn, 2003). Bayesian methods do produce statistically rigorous probabilities and have the further advantage that they can use "auxiliary" data to reduce the uncertainties in the assessment. They can also integrate across uncertainties and alternative hypotheses to simplify the presentation of results (see Section 4.6 and Chapter 13). The disadvantage of Bayesian methods is that they are computationally complex (see Section 3.1.1).

Once calculated, uncertainties can be expressed either as variances or confidence intervals (e.g. as in Yield's indicator plots, Figure 4.2), or as distributions (e.g. parameter estimates from CEDA, Figure 4.7). Either confidence intervals or distributions may be easier to present than variances or coefficients of variation where confidence intervals are non-symmetrical.

Testing the robustness of management advice to the uncertainties

Information on uncertainties may be used in two main ways: (1) to test the "robustness" of the management advice; and (2) to make quantitative assessments of the risks of different outcomes for the management strategies under consideration. In the first case, the general approach of "sensitivity analysis" is used to test the impact of alternative data inputs, parameter values and assumptions on the results of the analysis. Stock assessment tools like "Yield" make it easy to test the influence of different values of M, K or any other inputs which are not well known. The sensitivity to particular data points or observations can also be tested, e.g. the survey estimate of abundance from a particular year if it was felt to have been measured in error for some reason. The tutorial help files for both Yield and CEDA pay particular attention to the use of sensitivity analyses (see also Section 8.2).

Where stock assessments are made on two or more different sources of data (e.g. CPUE from a research survey and from fishing vessels) that produce contradictory interpretations of the state of the fish stocks, consideration should be given as to why this might have occurred instead of just averaging the different answers. Although Bayesian or other methods may be used to combine data from different sources, this should only be done where the additional data contribute information that is otherwise poorly known (e.g. a value of r from meta-analysis) and improve the overall fit of a model. Where there are different sources of the same basic data (perhaps with different assumptions), it is better to present the alternatives to the decision makers along with their assumptions to allow them to weigh up the risks. Decision tables can again be used instead of presenting any "single best assessment". In this case, the rows in the decision table are due to the alternative states of nature or uncertainties. If tradeoffs are still being considered for two or more indicators, multiple versions of Table 3.5 may need to be produced for each state of nature or major uncertainty. Where the relative probabilities of the different hypotheses are largely unknown, precautionary decisions can still be made in simple ways using "maximin" or "minimax" criteria (FAO, 1995b, 1996, paragraphs 74-79).

The process of sensitivity testing enables managers to make decisions which are "robust to the uncertainties in the data". As described by Cochrane (2002c), robustness testing provides a means of identifying possible undesirable outcomes of a management strategy before they occur, thereby allowing modifications to be made to the strategy before it is implemented to try to avoid such outcomes.

Quantitative risk assessments

Risk assessment is one of the foundations of the precautionary approach, as required by the UN Fish Stocks Agreement and the FAO Code of Conduct. Risk may be generally defined as the probability of something bad or undesirable happening. To assess and manage risks it is necessary to define exactly what is considered "undesirable" and to quantify the chances of this occurring. Outcomes of concern will relate to the operational objectives of the fishery, and could include the spawning stock falling below a minimum threshold level (see Section 3.5.4) or the income to the fishery or the numbers of employee days or jobs falling below their specified thresholds. There are as many possible questions regarding risk as there are management objectives, or combinations of management objectives.

Risk assessment uses information on uncertainty in a formal quantitative way. To fully quantify the meaning of the risk, three factors may be specified: the critical threshold (e.g. B_{lim}), the probability or risk that it will be broken (e.g. 10 percent), and the time-horizon over which such an event may occur. Any event has a higher probability of occurrence over a 20 year period than over a 5 year one, so the time frame is clearly important. Periods of between 10 and 20 years are frequently used in estimating risks in fisheries (Cochrane, 2002c). Each of the three factors that define the risk assessment should be set by the fishery managers, preferably in discussion with industry stakeholders and other interested parties. Fishery scientists should undertake the quantitative risk assessments, but should not be expected to advise on the acceptability of alternative risk levels (Caddy and Mahon, 1995).

The "Transient analyses" in the Yield software estimate the actual value of F associated with a particular risk that the %SPR will fall below the threshold (e.g. 20 percent of the unexploited level) over a defined projection period. Using the "Transient" routine, the value of F could be estimated with a range of different risks (e.g. a 10 percent, 20 percent or 30 percent chance that %SPR might fall below 20 percent; or a 10 percent chance that %SPR will fall below either 20 percent or 30 percent). Which of these levels of risk is acceptable should be decided by the managers as emphasized above.

Simpler forms of risk assessment may also be made wherever the uncertainties of output parameters are estimated by bootstrapping or other methods. In Yield's equilibrium YPR plots, for example (Figure 4.2), setting a probability interval of

80 percent would enable the %SPR to be estimated for each level of *F* that would have a 10 percent risk of being broken. This point could be read off the lower confidence interval line in the top right graph in Figure 4.2 (after toggling the display option to the fraction of unexploited biomass). Alternatively the actual numbers could be retrieved by clicking on the button for the "medians and intervals" data table. In a CEDA projection (Figure 8.3), with a 50 percent confidence interval, it may be said that there would be a 25 percent risk that the estimated stock biomass in projection year X might be below the estimate given as the lower confidence interval. The biomasses with these risk levels could be estimated for a range of alternative management strategies (e.g. each of the TACs illustrated in Figure 8.2). Using the confidence intervals in this way does not fully specify the risk as there is no time scale included in the assessment. The confidence intervals are instead derived from the Monte Carlo simulations made in Yield, or the bootstraps in CEDA and thus give the value of the threshold for each level of "risk" as indicated by the confidence interval.

Since the "Transient" risk assessments also include stochastic variability in recruitment, which is not included in the equilibrium YPR or Yield plots discussed above, the *F*s and the risk levels estimated by each approach could be compared (at least where recruitment variability data are available).

Presentations of risk analyses, like any stock assessment, need to be tailored to the experience of the audience. The outputs from risk assessments could be incorporated into the decision table format of Table 3.5, or simply presented in graphical form (see e.g. Figure 13 in Caddy and Mahon, 1995). If structural uncertainties are also being considered, risks may be estimated for each alternative hypothesis. A sophisticated example of a risk assessment in a Bayesian setting is given in Table 5 in Chapter 13.

Noting that a range of different risk assessment methods may be used, Hilborn and Walters (1992) argue that it is "far more important to explicitly consider uncertainty than to apply sophisticated analytical techniques". FAO (1996) advise that every policy evaluation should present the consequences of different management options for a range of plausible hypotheses about the state of the stock and the values of the key input parameters. When scientific analyses include no information about the uncertainty of the advice, managers should be aware that this does not mean that the estimates presented are exact. Until better assessments are made, managers should adopt some other approach for allowing for uncertainty – e.g. using the ad hoc 2/3 MSY instead of MSY. Caddy and Mahon (1995) note that "the mathematical complexity of models incorporating risk, and the research costs associated with quantifying uncertainty will probably preclude this approach for most of the world's smaller fish stocks in the near future". For the managers of those stocks, they suggest that the focus must instead be on developing the decision-making process, deciding what risks are acceptable, agreeing upon informed, even if occasionally arbitrary, target and limit reference points, and taking management action in a timely and adequate fashion. As an example, limiting access to the spawning aggregations of fish such as snappers and groupers could be used as a common sense way of managing the risk that such fishing may lead to the extinction of these spawning stocks (Caddy and Mahon, 1995). No detailed stock assessment is needed for this precautionary management decision.

3.6.5 Management procedure evaluation

A management "procedure" represents the full regime used for monitoring (data collection), fishery assessment and management (e.g. harvest control rule), as defined by a set of simplified but quantitative decision rules. In the framework given in Figure 1.1, the management procedure would include each of the elements in both the management and stock assessment process boxes. Although the benefits of management procedures for conservation are widely acknowledged, the inclusion of precautionary elements does not necessarily mean that the management procedure will be precautionary in practice (Kirkwood and Smith, 1996). Procedures therefore need to be evaluated to determine whether they are likely to achieve the goals for fisheries management, given various types of uncertainty. Their success depends upon the dynamics of and interactions between the monitoring regime, the stock assessment procedures, the choice of biological reference points, and the management options, rather than each in isolation.

In general, evaluation of management procedures involves simulation modelling (McAllister *et al.*, 1999). Such an approach is computer-intensive and not straightforward, so this section aims to provide the reader with the general concept, options and benefits of the approach. For more information, the reader is referred to the references listed. There are a number of examples of management procedure evaluation, applied in Australia and New Zealand (e.g. Punt and Smith, 1999), South Africa (e.g. De Oliveira and Butterworth, 2004), the U.S.A., Europe (e.g. Kell *et al.*, 2005), and in the International Whaling Commission (e.g. Kirkwood, 1997). The same style of approach was also used in FMSP projects R6465, R7522 and R7835 (Chapter 10), where management *strategies* were assessed (specifically options for assessment) rather than the more complete management *procedures*.

In brief, the "true" stock and fishery dynamics are represented as the *operating model*, in effect representing the dynamics of a fish stock in the sea. Usually, several operating models are developed, so that the extent to which the set of candidate management procedures are robust to uncertainties can be tested (e.g. uncertainties in the value of natural mortality or growth). A "base case" set of simulation trials is usually developed, representing an agreed-upon "most plausible" set of parameters for the operating model. The sensitivity of results to alternative specifications for the operating model (e.g. reductions in survival or recruitment) can then be examined to determine the robustness of the management procedure to unlikely, but highly consequential, factors. The operating model must be able to generate the types of data available for uptake in the management procedures in a realistic manner. In a typical simulation, simulated data are sampled from the operating model (mimicking catches from the fishery and subsequent sampling of data at port). These data are then used within an *assessment model* (modelling the assessment approach selected within the management procedure) to assess the status of the stock. Then, depending on the perception of the stock, management controls are applied to the fishery within a *management model* before being fed back into the operating model (e.g. a reduced fishing pressure should mean that the stock in the sea will start to recover). Performance is compared through performance measures (see Chapter 10 for examples). These sampling, assessment and management procedures represent the "perceived" state of the stock (i.e. the best combined perception of both assessment scientists and managers, but not necessarily the "true" status represented by the operating model owing to sampling uncertainty, model uncertainty, etc.).

Management procedure evaluation addresses uncertainty in all aspects of the management and assessment process, and consequently can identify the data and analyses needed for the procedure to be robust to uncertainty (e.g. Kell, Pilling and O'Brien, in press). It forces decision-makers to define management goals clearly and quantitatively, and the evaluation of alternative management procedures then clearly indicates the trade-offs inherent in managing natural populations (e.g. the trade-off between expected catch and risk). In turn, a longer term view of management is taken. Such use of simulation-tested feedback-control management systems represents the culmination of the process of deriving reference points and harvest control rules, and the provision of scientific advice to managers.

4. The FMSP stock assessment tools and guidelines

This section of the document introduces the FMSP stock assessment tools and shows where they fit into the overall stock assessment process outlined in Chapter 3. A "tool" in this context may be a software package, or an assessment method or procedure, or even a handbook or set of guidelines. Summary details are given below about the four FMSP software packages – LFDA, CEDA, Yield and ParFish. Other sections focus on the estimation of reference points from minimal population parameters (Section 4.2) and for multispecies fisheries (4.4); the use of Bayesian (4.6) and empirical approaches (4.7); and the special needs of inland fisheries (4.8). Each sub-section gives a short summary of the purpose of the tool and the methods offered, the data inputs required and the outputs produced, and their relevance to particular circumstances. Comparisons are made with alternative software packages relevant to each purpose. Further details on the software tools are given in Part 2 of the document and about the other FMSP analyses and guidelines in Part 3.

4.1 GROWTH AND MORTALITY RATES FROM LENGTH FREQUENCY DATA (THE LFDA SOFTWARE)

4.1.1 Purpose and methodology

The Length Frequency Distribution Analysis (LFDA) package provides a variety of methods for estimating growth parameters and mortality rates from fish length frequency distributions. As described in Sections 3.3 and 3.4, growth parameters are used as intermediate parameters in analytical fishery models (such as the "Yield" software, described below), while mortality rates (particularly F, estimated as Z minus M) are used as indicators of the current levels of fishing pressure in the fishery.

The current Windows-based Version 5.0 of LFDA includes methods for estimating the parameters of the non-seasonal version of the von Bertalanffy growth curve and of two versions of a seasonal von Bertalanffy growth curve. The parameters of these growth models may be estimated using three alternative fitting methods: Shepherd's Length Composition Analysis (SLCA), the projection matrix (PROJMAT), and a version of the ELEFAN method (see software help files for details and references). A facility is provided that allows conversion of length frequencies to age frequencies using the estimated growth curves.

The package also includes two methods for estimating the total mortality rate Z, using the estimates of the von Bertalanffy parameters as inputs: the Beverton-Holt method, and a length converted catch curve method. Alternatively, the Powell-Wetherall method may be used to directly estimate the ratio Z/K and the asymptotic length L_∞. Details of these methods are given in Chapter 6 and in the LFDA software help files.

A number of comparative studies of these and similar length-based methods have been carried out (see for example, Isaac, 1990). The results of these studies are probably best summarized by saying that no one method in this package is uniformly superior to any other. Rather, the relative performance of each method varies with the type of data on which they are used (see Section 3.1.5). Users are thus advised to try each of the methods on their data, and then judge which set of parameter estimates appears to provide the best fit (see Section 6.1). Having estimated the growth rates, the different mortality estimators should usually be attempted for each feasible combination of growth parameters.

4.1.2 Inputs and outputs

The LFDA software assumes that a time series of length frequency samples is available, perhaps collected every other month, over at least a full year. For species with moderate or fast growth and with reasonably non-selective sampling (see Section 3.1.5), such length frequencies should show a seasonal progression of modes as fish grow through the length classes. Some other length-based methods (e.g. as available in FiSAT) can provide parameter estimates from only a single sample, but little confidence can usually be placed in these estimates as there is no chance of following the modes through time to confirm their assumed identity as annual cohorts.

The inputs required in LFDA and the outputs produced by each method are compared in Table 4.1. As explained in Chapter 6, the precision of the estimated growth parameters K and L_∞ may be determined only qualitatively from the relative values of the score functions, as shown in the response surface plots. Growth parameters estimated from length frequency data usually show high negative correlation between K and L_∞ with a fairly wide range of pairs of values giving almost equally good fits. LFDA provides maximization routines to find the best fitting parameters, but the response surfaces should also always be examined. Standard errors of the mean Z estimates are calculated from the Zs for each individual sample, but these assume that the growth parameters are estimated without error, and will thus underestimate the real uncertainty.

TABLE 4.1
Inputs and outputs for the different routines available in the LFDA software

	Notation	VBGF Estimators			Total mortality rate Z		
		SLCA Non Seasonal (NS)	Projmat NS or Seasonal	Elefan NS or Seasonal	Catch curve	Bever-ton and Holt	Powell and Wetherall
Inputs							
Length frequency data time series		Yes	Yes	Yes	Yes	Yes	Yes
Smallest fully represented length in sample	L_c					Yes	
Graphical (by eye) selection of points					Yes		Yes
VB Asymptotic length	L_∞				Yes	Yes	
VB Growth rate / curvature parameter	K				Yes	Yes	
Outputs - Parameters							
VB Asymptotic length	L_∞	Yes	Yes	Yes			Yes
VB Growth rate / curvature parameter	K	Yes	Yes	Yes			
VB Age "at zero length"	t_0	Yes	Yes	Yes			
VB Seasonality winter point (a.k.a. WP)	t_s		Yes	Yes			
VB Seasonality oscillation amplitude	C		Yes	Yes			
Total Mortality	Z				Yes	Yes	
Z / K ratio	Z / K						Yes
Outputs - Uncertainty							
Response surface (e.g. K by L_∞)		Yes	Yes	Yes			
Standard errors of parameters					Yes	Yes	Yes

4.1.3 Applicability and related approaches

LFDA and other length-based methods enable growth and mortality rates to be entered for some fish species that cannot be aged, but with lower accuracy and lower precision than most age-based methods (see Section 3.1.5 and Chapter 10 in Part 3). Where fish can be aged, age-based methods are likely to give better stock assessments. Haddon (2001) provides simple age-based spreadsheets for fitting standard or seasonal versions of the VBGF using non-linear least squares. Age-based catch curves for estimating Z may also be easily fitted using spreadsheets.

The methods available in the LFDA software may also be implemented in the FAO FiSAT II package, as may a wider range of other routines using both length frequency and age based data (e.g. modal progression analysis, fitting VBGFs using growth increment data, and estimating natural mortality rates, recruitment rates and selectivities). The FiSAT suite is thus considerably more comprehensive than LFDA. For the methods available in both packages, similar results should be obtained from each, at least for good data sets (slightly different results may be achieved using the same basic routines due to the use of different maximization algorithms). LFDA is believed to have a better data smoothing routine than FiSAT, allowing automatic parsing of data into different bin sizes. LFDA also routinely estimates Z separately for each monthly sample, and then averages the results; while the FiSAT approach is to aggregate the data before estimation. No comment is made here on which of these approaches is likely to be more accurate or precise.

TABLE 4.2
Summary comments on the alternative growth and mortality rate estimation approaches

Assessment Tools	Advantages / application	Disadvantages / comments
Age-based methods	• Likely to give best results wherever fish can be aged	• Cost of age determination • Need to validate ageing methods
LFDA	• Use where fish cannot be aged	
FiSAT	• Wider variety of fitting methods available	

4.2 REFERENCE POINTS FROM MINIMAL POPULATION PARAMETERS (THE BEVERTON AND HOLT "INVARIANTS" METHODS)

As described in Section 3.5.2, rough approximations of the MSY catch may be estimated using the well-known "Gulland formula" MSY = $0.5MB_0$, and its relatives. Analytical examinations of this simple formula (e.g. Beddington and Cooke, 1983, and Caddy, 1998) have shown that it tends to be over optimistic in its estimation of the available yield for most combinations of parameters. In 1992, one of the first FMSP projects (R4823) extended the Gulland approximation to give more exact constants of proportionality for different values of M/K and length at first capture (Kirkwood, Beddington and Rossouw, 1994). While providing more realistic estimators, these models still relied on natural mortality (M) and stock biomass (B) as inputs, both of which can be difficult to estimate.

In 2000, project R7040 developed even simpler formulations of these models based on the Beverton and Holt "invariants". These are the fundamental theoretical relationships among M, K and the age or size at maturity. For von Bertalanffy growth, it has been found that an average life history pattern follows the relationships $M/K = 1.5$, $M.t_m = 1.65$, and $L_m = 0.66$ (where tm is the age at maturity and L_m is the length at maturity as a proportion of L_∞, see Chapter 11). When these relationships are fixed at these levels, relative yield (as a fraction of the biomass, B) can be estimated from only K and L_c (the length at first capture as a proportion of L_∞). The inputs and outputs of these methods are given in Table 4.3, while the derivations of the formulae are given in Chapter 11. Two versions were derived, with and without a stock-recruit relationship (SRR). Where this is included (see Section 3.1.6), the length at maturity and/or the density-dependence (steepness parameter) in the SRR are also required as inputs. The growth rate K can be relatively easily estimated (e.g. by LFDA, Section 4.1) as can the lengths at first capture and at maturity. The SRR steepness may of course be harder to obtain, though reasonable assumptions or meta-analyses (Section 3.1.1) may be used to give approximate values. The sensitivity to this parameter could also be tested (see Section 3.6.4).

These equations thus enable Y/B_0 and F_{max} (equivalent to F_{MSY} for the SRR version) to be estimated from very limited inputs (see Table 4.3) and without needing the natural mortality rate M.

Where the current fishing mortality F_{now} can also be estimated (still requiring either B or M), these simple methods can be used to guide managers by showing whether the current fishing rate is likely to be over or under the optimal level F_{max}.

TABLE 4.3
Inputs and outputs for the Beverton and Holt "invariant" methods and the Yield software (see Section 4.3 below)

	Notation	B&H "invariant" methods		Yield		
		Constant recruitment	With SRR	Equil. YPR	Equil. Yield	Trans. Yield
Inputs - Ecological						
VB Assymptotic length	L_∞	(Yes)	(Yes)	Yes	Yes	Yes
VB Growth rate / curvature parameter	K	Yes	Yes	Yes	Yes	Yes
VB Age "at zero length"	t_0			Yes	Yes	Yes
Length / Weight parameters	a, b			Yes	Yes	Yes
Natural Mortality	M			Yes	Yes	Yes
Ambient temperature (for Pauly M equation)	T			(Yes)	(Yes)	(Yes)
Mean length (or age) at maturity	l_m (t_m)			Yes	Yes	Yes
Length at maturity as a proportion of L_∞	L_m		Yes			
Spawning seasons				Yes	Yes	Yes
Stock-Recruit Relationship (form and parmeters)					Yes	Yes
Density Dependence in SRR (B&H steepness)	h		Yes			
Inter-annual variability in recruitment						Yes
Inputs - Management controls						
Fishing mortality (simulate a range)				Yes	Yes	Yes
Mean length (or age) at first capture	l_c (t_c)			Yes	Yes	Yes
Length at first capture as a proportion of L_∞	L_c	Yes	Yes			
Fishing seasons				Yes	Yes	Yes
Outputs - Indicators						
Equil. YPR as fraction of Exploitable BPR_0	YPR / BPR_0	Yes				
Equil. YPR	YPR			Yes		
Equil. BPR (Total, Fishable or Spawning Stock)	BPR			Yes		
Equil. Yield as fraction of Exploitable B_0	Y / B_0		Yes			
Equil. Yield (including SRR)	Y				Yes	
Equil. Recruitment	R				Yes	
Equil. Biomass (Total, Fishable or Sp. Stock)	B				Yes	
Outputs - Reference points						
F giving maximum yield (= F_{MSY} for SRR version)	F_{max}	Yes	Yes			
F giving MSY	F_{MSY}				Yes	
F giving maximum YPR	F_{maxYPR}			Yes		
F giving 10% marginal YPR	$F_{0.1}$			Yes		
F giving SSBPR as target % of $SSBPR_0$	$F_{\%SPR}$			Yes		
F giving spawning biomass as target % of SSB_0	$F_{\%SSB}$				Yes	
F giving fishable biomass as target % of FB_0	$F_{\%FB}$				Yes	
F giving % risk of breaking LRP (e.g. $20\%SSB_0$)	$F_{\%}$					Yes

4.3 REFERENCE POINTS FROM YIELD AND BIOMASS MODELS (THE YIELD SOFTWARE)

4.3.1 Purpose and methodology

The Yield software developed by project R7041 was designed to estimate target and limit reference points under uncertainty. The age-structured population model used as the basis for Yield extends the standard Beverton and Holt / Thomson and Bell yield per recruit models by allowing for uncertainty in parameter inputs; by including a stock recruit relationship; and by allowing stochastic variation in annual recruitment rates. The probability distributions estimated for the technical reference points enables their conversion to "precautionary" points (as described in Section 2.5.4), reflecting the uncertainties in the parameter inputs and the risk tolerances chosen by the manager.

While yield per recruit (YPR) models will be familiar to most fisheries officers, the calculation of YPR and related reference points including stock recruitment relationships and allowing for uncertainty is technically much more difficult. The aim of the Yield software package is to allow these calculations to be made with ease and thereby promote the adoption of more precautionary management approaches. FMSP Project R7835 (Wakeford *et al.*, 2004) found that YPR-type analyses formed the basis of 40 percent of fish stock assessments, 64 percent of these based on age-based growth parameter estimates, and 36 percent on length frequency data. Most of these took little account of uncertainty in the inputs.

Simple YPR models look at the trade offs between the loss in biomass due to mortality and the gains in biomass due to the growth of individual fish. Given the balance of these parameters, certain values of fishing mortality and age at first capture will give the maximal yield (per recruit) from the fishery. Catching fish at too small a size will lead to "growth overfishing" (taking too many fish at a smaller than optimal size). The YPR reference points in Yield may thus be used to avoid such growth overfishing.

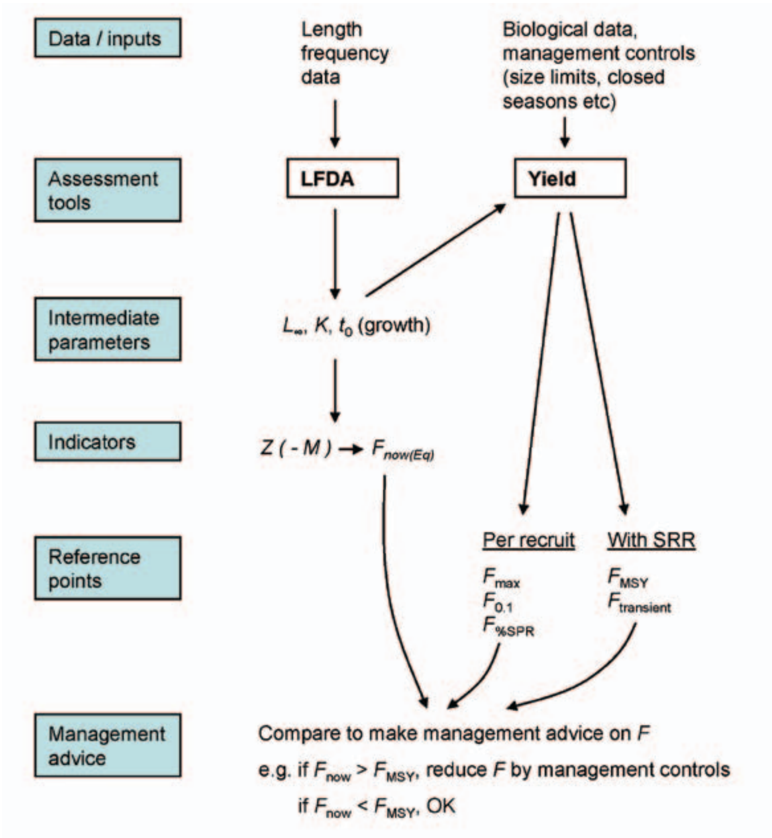
Most "per-recruit" analyses assume that recruitment will remain constant. In practice, one of the greatest sources of uncertainty in fisheries management is the very high year to year variability in the recruitment of young animals to the stock, which can vary by an order of magnitude or more between years. As shown in Section 3.1.6, including a stock recruitment relationship (SRR) in an analytical YPR model changes its predictions dramatically. While YPR often rises asymptotically with increasing fishing mortality, F, a Yield model with a SRR operates more like a "surplus yield" model in that yield will decline when F gets too high, and will eventually reach a point of stock collapse (see Figure 3.1). Including a SRR in Yield enables investigation of "recruitment overfishing" and the estimation of reference points related to both MSY and the protection of the spawning stock (see Section 3.5).

Yield is mainly designed to estimate reference points based on the fishing mortality rate, such as F_{max}, F_{MSY} and $F_{0.1}$. Yield's $F_{SSBx\%}$ reference point is equivalent to the $F_{\%SPR}$ described in Section 3.5. With an age-based, "flexible selectivity", analytical model (Shepherd, 1988) in the background, Yield can also be used to investigate the impacts of size limits and closed seasons on both yield and spawning stock biomass indicators.

Finally, it is emphasized that Yield is not a data-fitting or estimation procedure like LFDA or CEDA. It is a simulation tool that uses intermediate parameters estimated by other tools (e.g. by LFDA or age based methods) to estimate reference points. To be useful in managing the fishery, current estimates of indicators relevant to the reference points must also be estimated using other procedures (see Section 3.4). Managers must for example also be able to estimate the current F to compare with the $F_{0.1}$ or other reference points, in order to decide if that current fishing pressure is too high.

The relative contributions of LFDA and Yield to a simple "analytical" stock assessment process (see Section 3.1.3) are illustrated in Figure 4.1. In this type of stock assessment, LFDA (or an alternative age-based methodology) is first used to estimate the intermediate growth parameters K, L_∞ and t_0. These are then used again in LFDA to estimate the current fishing mortality F_{now}, as the indicator of fishing pressure, found by subtracting M from Z. The growth parameters are further used in Yield along with various other inputs to estimate a range of alternative F-based reference points for comparison with F_{now}. This process assumes that the fishery could be managed using input or output controls relating to the fishing mortality rate, F. Yield may also be used to test the effects of alternative size limits and closed seasons. Changes in these technical measures will give corresponding changes in both the indicators (YPR, %SPR etc) and the F-based reference points ($F_{0.1}$, $F_{\%SPR}$ etc) output by Yield.

FIGURE 4.1
Illustration of the analytical or dynamic pool approach to fish stock assessment, using the FMSP LFDA and Yield software tools (see text)

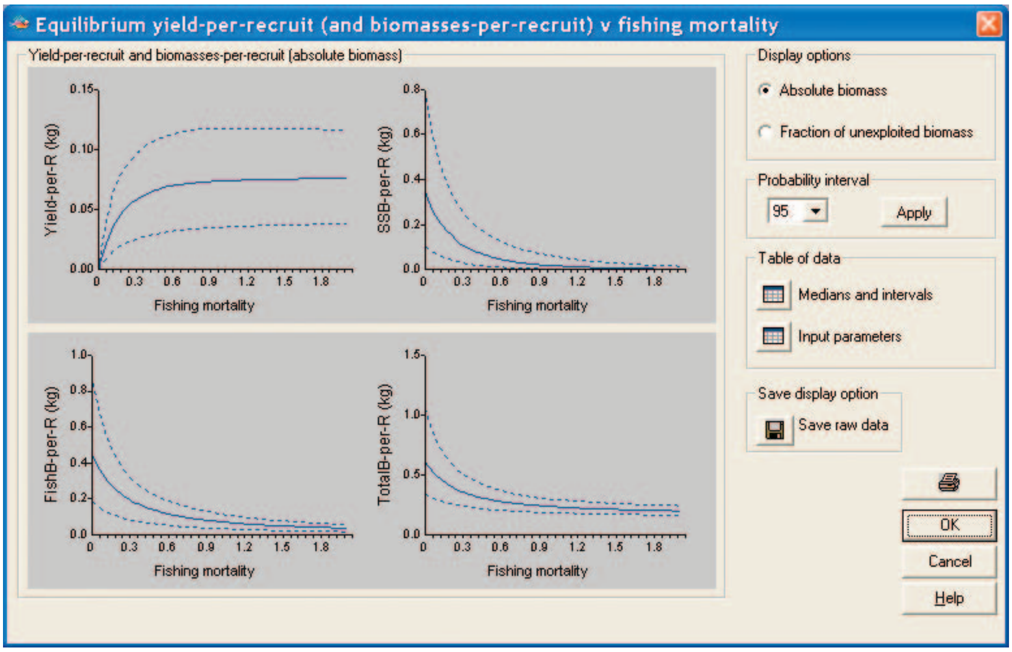


4.3.2 Inputs and outputs

As described in detail in Chapter 7 and the software help files, Yield produces outputs for three types of analysis: per recruit (YPR and biomass per recruit, BPR); absolute yields and biomasses (incorporating SRRs); and "Transient" analyses. Under the "Equilibrium" menu option, both indicators and reference points may be examined for the first two of these analyses. Both of these assume an equilibrium condition in the stock, with constant recruitment, growth, fishing mortalities etc.

For the two equilibrium analyses, Yield may first be used to plot the indicators against F, e.g. as shown in the example in Figure 4.2. These show the average values of each indicator (the YPR and three versions of BPR – spawning stock, fishable and total) at each value of F, and the confidence intervals around the curves. By clicking on the "display option" buttons, the results may either be plotted as absolute values (of YPR, yield, BPR or biomass), or they may be scaled to the fractions of the unexploited values. Different levels of confidence intervals may also be plotted by entering the chosen probability interval.

FIGURE 4.2
An example of the indicator plots produced by Yield

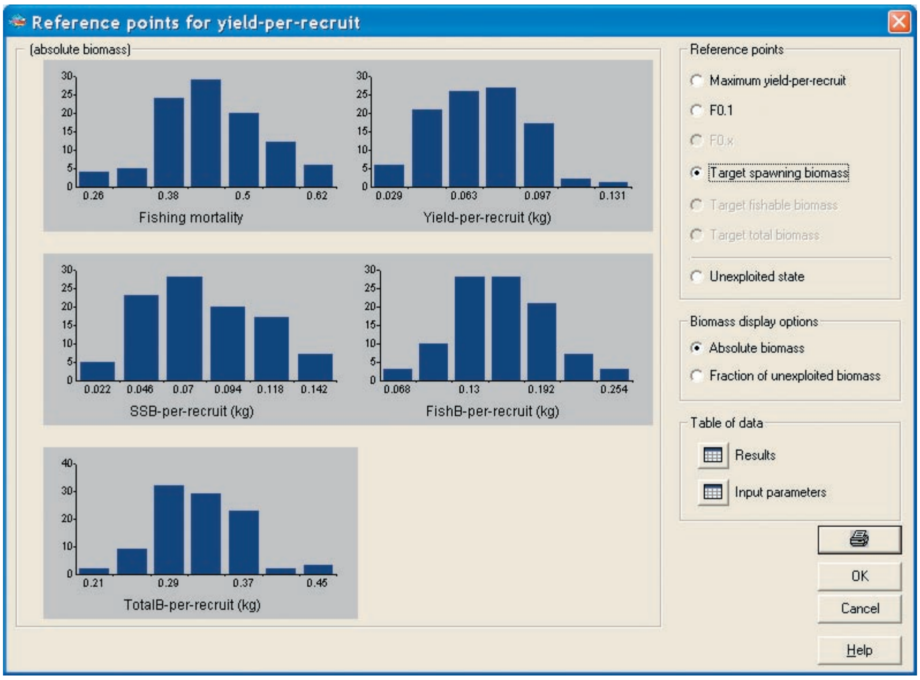


If there were no statistical uncertainty about any of the biological and fishery parameters, i.e. if the user has entered only single values for each of the intermediate parameters (K, L_∞, M, etc.), then there would be just a single certain value of each indicator for each value of F. If, however, there is statistical uncertainty about M or any of the other parameters, then there will be corresponding uncertainty about the indicators and hence the reference points. The primary purpose of the Yield software package is to allow these uncertainties to be quantified.

This is done by the user entering information on the uncertainties (the probability distributions and their coefficients of variation) in one or more of the inputs as entered under the parameters menu. Yield then selects a large number of sets of biological and fishery parameters by sampling from the defined probability distributions of the parameters (i.e. "Monte Carlo" sampling). The quantities of interest are then calculated for each set, giving a distributions of outputs.

As described in Chapter 2, reference points are particular values of fishery indicators, e.g. the fishing mortality rate giving the maximum YPR (the highest point on the curve in the top left plot in Figure 4.2), or the fishing mortality giving a biomass of 20 percent of the unexploited level (estimated from the top right plot in Figure 4.2). Such reference points will be at slightly different values of F for each sampled set of parameters. In Yield, the two reference point options under the Equilibrium menu can be used to plot histograms of the different values obtained from each sampled data set. As shown in Figure 4.3, these plots report the distributions of the fishing mortality rate, the yield per recruit (or yield) and the three versions of the biomass per recruit (or absolute biomass). The values shown in the plots depend on which reference point is selected in the top right menu box in Figure 4.3. In this example, the "Target spawning biomass" reference point is selected (i.e. the fishing mortality rate that would reduce the spawning stock biomass per recruit (SSBPR) to a specified percentage (here 20 percent) of the unexploited biomass). The top left plot in Figure 4.3 thus shows the histogram of fishing mortality rates at which this reference point occurred for the 100 data samples. The middle left plot in Figure 4.3 shows the histogram of the actual values of spawning stock biomasses obtained at the reference point. The other three plots show values of the other indicators obtained at this reference point. The distributions in these reference point plots may thus be thought of as showing the variability around specific points in the indicator plots as illustrated in Figure 4.4. Which plots are most important in each case depend on what reference points are selected in the menu box.

FIGURE 4.3
Examples of the reference point distribution plots produced by multiple stochastic simulations (100 runs in this example) using the Yield software



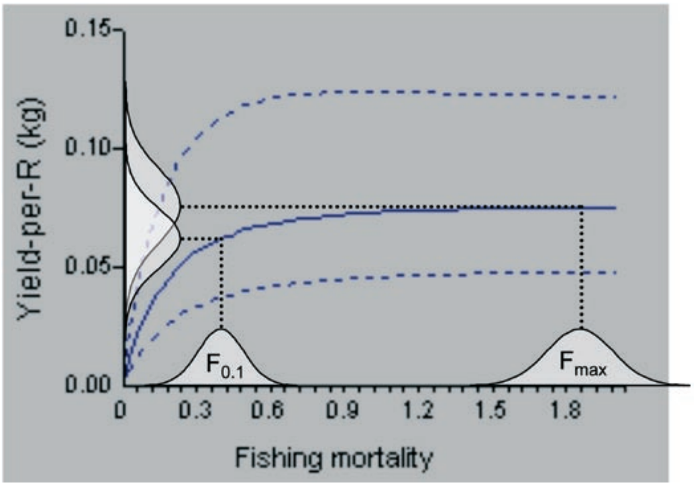
With Yield's histograms of estimates, rather than a single estimated value, the question arises as to how these results should be reported. Most stock assessments end up with a single value calculated for say $F_{0.1}$; Yield gives a histogram of say 100 estimates of $F_{0.1}$. As a "central" value for $F_{0.1}$, either the average or median values may be used. These are easily calculated from the tables of results that accompany the histograms (e.g. by exporting to a spreadsheet). The same table of results may also be used to estimate the precautionary values of the reference points, e.g. as a 5 percent lower percentile of the reference point $F_{0.1}$. To ensure that such points are estimated reasonably precisely, the number of simulations needs to be sufficiently large (e.g. 100 simulations may be made for quick exploratory analyses, and increased to 500-1000 to give the final parameter estimates; see software help file).

The inputs required to produce these analyses are listed in Table 4.3. More data inputs are required in Yield than for the methods based on the Beverton and Holt "invariants" methods (see above section). For all three types of Yield analysis, stock-specific estimates are required of the von Bertalanffy growth parameters (e.g. estimated using the LFDA software, Section 4.1), the weight at length relationship, the natural mortality rate M, and the size (or age) at maturity. Uncertainties may be entered for each of these parameters, as stated coefficients of variation with normal, logarithmic or uniform distributions (see help files). Management control inputs are required on the selectivity of the fishing gear and the seasonality of fishing. For the Equilibrium Yield predictions, the form (Beverton and Holt or Ricker) and parameters of the stock recruitment relationship must also be entered, along with their uncertainties.

As noted above, both the YPR and Yield analyses assume equilibrium conditions in the stock. In contrast, the "Transient" option uses information entered about the inter-annual variability in recruitment strength to estimate "risk-based" reference points (see Section 3.5.4). The Transient analyses make repeated projections over a specified time period, until they find the fishing mortality rate having a user-selected risk that the spawning stock biomass falls below a certain level (e.g. 20 percent of unexploited) over the duration of the projection. Input information on the variability in recruitment strength may be derived from VPAs or simpler methods (see software help files and Section 7.4).

FIGURE 4.4

Conceptual illustration of the connection between Yield's reference point distribution plots (Figure 4.3) and the indicator plots (Figure 4.2). The hypothetical normal distributions shown for the $F_{0.1}$ and F_{max} reference points on the x-axis relate to the histograms in the top left plot of Figure 4.3 (clicking on the top right buttons to respectively select each of the two reference points). The normal distributions on the y-axis indicate the values of the YPR indicators achieved at each of these reference points, as given in the histograms in the top right plot of Figure 4.3. Users should note that the actual distributions of the reference points and indicators will sometimes be non-symmetrical, unlike the hypothetical normal distributions used in this illustration



4.3.3 Applicability and related approaches

YPR-type analytical models such as used in Yield are common and familiar fish stock assessment tools. Simple versions can be easily programmed in spreadsheets (see examples in Haddon, 2001). Extensions of YPR models form the basis of catch at age analyses, which combine data from VPAs, selectivity and SRRs, including versions that use auxiliary data. Many different formulations of these models are possible (see summaries in Hilborn and Walters, 1992; Haddon, 2001). In the opinion of Hilborn and Walters (1992), "when proper consideration is given to the errors introduced in data collection, and to the natural variability in the recruitment and mortality processes, catch at age analysis is the *state of the art* in the analysis of fisheries data". The Yield software goes some way towards such sophisticated analyses while maintaining a simple theoretical basis and a menu-driven format. The inclusion of parameter uncertainties and SRRs enables managers to estimate precautionary reference points both for yield-based targets and those based on preserving the spawning stocks. The "Transient" option also provides managers with a simple but effective means of fitting risk-based reference points that incorporate both parameter uncertainty and the long-term implications of recruitment variability. The Transient option also provides the ability to make projections at different future levels of fishing mortality rates to show the short and medium-term impacts of alternative strategies (see Section 3.6.2).

The YPR models available in the FiSAT software package for making "Fishery Predictions" do not include Yield's three key advantages (allowing for uncertainties in parameter values and levels of future recruitment, and incorporating a SRR). Yield's additional flexibility in fishing seasons also allows investigation of alternative lengths and times of closed seasons, less easily accomplished in FiSAT. FiSAT, on the other hand allows YPR analyses including economic data (predicting equilibrium *values* of the catches in addition to weights). FiSAT is also formulated to estimate indicators for multispecies, multigear models, while Yield is only programmed to carry out single-species assessments.

TABLE 4.4

Summary comments on the alternative approaches for estimating reference points using the FMSP analytical approaches (Sections 4.2 and 4.3)

Assessment Tools	Advantages / application	Disadvantages / comments
Beverton & Holt "invariants" (Section 4.2)	• Useful where only limited data are available (need only K and L_c for simplest version)	• Limited range of reference points available (but including F_{MSY}) • Assume standard growth patterns
Yield (Section 4.3)	• Estimate F-based reference points allowing for uncertainties in inputs • Outputs include probability distributions for indicators and reference points, enabling estimation of precautionary buffers • Includes stock recruitment inputs to enable yield/biomass outputs as well as YPR/BPR • Enables analysis of size limits and closed seasons • Estimates "transient" risk-based reference point allowing for variability in annual recruitment	• Not formulated for economic or multispecies, multigear analyses
FiSAT	• Also able to estimate economic reference points, • Allows multispecies, multigear models	• No consideration of uncertainties or confidence intervals for outputs • SRR not included

4.4 MANAGING FISHING EFFORT IN MULTISPECIES FISHERIES

4.4.1 Purpose and methodology

FMSP project R5484, "Analysis of Multispecies Tropical Fisheries" assessed the effects of fishing on multispecies fish stocks and derived management guidelines (and minimum data requirements for management) applicable to situations where resources for stock assessment are limited. The project focused on biological management of the resource which needs to be placed in the context of local social, economic and livelihood conditions. Whilst not the focus of this project, these issues are discussed in project documentation (see Mees and Rousseau, 1996).

Multispecies fisheries and the interactions within them are complex and not clearly understood (see Section 2.2.2). Whilst multispecies models have been developed, they remain complex and data-hungry (see Table 4.5), and therefore inappropriate where resources are limited. Through a case study and fishery management simulation approach, project R5484 aimed to assess fishing effects, derive biological management guidelines, and describe minimum data requirements for demersal bank and deep reef slope fisheries, a relatively simple multispecies fishery, but with widespread applicability. It explored the question of whether complex multispecies assessment models are required, or whether assessment and management could be achieved with single and aggregate single species models.

TABLE 4.5

A summary of models applied to multispecies fisheries (after Polovina, 1992; see also Cochrane, 2002c, Table 4)

Method	Model	Extension of model to ms situation	Comments	Data requirements
Comparison of like areas	Yield per unit area	Directly compare like areas	Useful first approach. Requires the least data of all to derive first estimate of potential yields	Environmental characteristics, area of habitat, Catch and effort by location for Munro approach (need not be time series data)
		Plot *Y*/area vs *F*/area similar to production models to determine MSY (see Section 4.7.1)		
Single species	Biomass dynamic models (Schaefer / Fox etc.)	Total biomass Schaefer model	Sometimes useful, e.g. for apical predators - not for prey species	Time series catch and effort data by species / location. Must aggregate data to be useful
		Multispecies Schaefer model/ Lotka Volterra models	No useful results to date, Impractical for large numbers of species	
	Analytical Y/R models (Beverton and Holt etc.)	Apply individually to single species and sum yields	Can be useful, but ignore interactions	Demographic variables (K, M, L_∞, R etc) by species. Length frequency data can be usefully applied
		Modified YPR models incorporating interactions	These models are complex. Many parameter estimates are required and the models may need to be simplified to be useful	
		Summation of single species YPR equations		
	Cohort (Virtual Population) analysis	Single species cohort analysis plus regression to evaluate interactions	Very complex. Data intensive. Need species specific variables plus estimates of interaction (predation)	Demographic variables Catch at age, Time series catch and effort, gut content analyses
		Multispecies VPA		
Ecosystem models	Ecosystem box models, e.g. ECOPATH	Designed to incorporate all trophic levels and interactions	Highly complex in that all interactions must be understood. Data intensive. Unreliable due to errors inherent in estimating all variables	Demographic variables, estimates of primary production, catch, effort. Do not need time series data

Case study fisheries were Indian Ocean bank reefs, and Tongan deep reef-slope fisheries exploited principally with hooks and lines using handlines, reels and electric or hydraulic reels. Theoretical studies explored fishing effects, alternative management strategies, and the importance of input parameters (minimum data requirements). A multispecies interactive dynamic age-structured model (MIDAS) was developed for this purpose. This model simulated a number of stocks being fished by a number of gear types. The model follows the dynamics of fish populations as formulated by Beverton and Holt (1957). It is a fully age structured model, and includes biological interactions between species (as competition or predation) and density dependence in the form of any one of a number of stock recruitment relationships. The model was populated using parameters derived from case study fisheries. The MIDAS model has not been packaged for dissemination as it is particularly complex.

Case studies revealed no detectable multispecies responses due to biological interactions and fishing. The theoretical studies indicated that prey release, due to fishing down of top predators, occurred after about 5 years, but that this would be undetectable, as the response was less than the variation in typically available data. Species composition changes due to technical interactions were, however, significant. The results showed that single, and aggregate single species models were adequate to derive management advice, at least for such a single-gear fishery. They also indicated that data need not be collected on all species individually, but only for the most important species and guilds of others.

This project did not develop stock assessment methods or software. Rather, it developed guidelines for management of multispecies fisheries, and for evaluating the status of those resources, based on parameters (reference points) derived through existing stock assessment tools (see Chapter 12). The guidelines for management describe ways of selecting the most important and vulnerable species for analysis (the key indicator species), and give a method for setting overall effort limits for a multispecies fishery, taking into account targeting practices and conservation trade-offs. Having defined the key indicator species, the project also developed rules of thumb, based on biological reference points, which indicate the status of the fishery and the need for further action.

4.4.2 Inputs and outputs

Outputs from existing stock assessment tools (e.g. LFDA, FiSAT, Yield and CEDA) are required to implement the guidelines. In particular it is important to calculate the length at first capture, and the current fishing mortality which is compared to optimum values of fishing mortality for key indicator species. The inputs for these multispecies approaches are therefore the data required for the relevant stock assessment tools (see Sections 3.3.6, 3.4.3, 4.1.2 etc). The project focused deliberately on data that could be collected by a typical developing country fisheries institution with limited resources. Catch and effort data are essential for the key indicator species and for guilds of others, length frequency data are essential for the key species, and biological (life-history) data, whilst useful, is not essential. Details on the required inputs are provided in Part 3 (Chapter 12).

The guidelines for management of multispecies fisheries include criteria for selection of key indicator species, rules for determining the ideal fishing mortality of key species, and a method for determining the appropriate overall effort level for the multispecies fishery. Outputs from application of these guidelines translate into management actions to control fishing effort in the fishery.

4.4.3 Applicability and related approaches

The guidelines for managing multispecies fisheries derived by project R5484 relate to bank and deep reef-slope fisheries for demersal species caught with hooks and lines. The guidelines relate mainly to the use of F-based management since other approaches would be impractical for these fisheries. As described in Chapter 12, the optimum F depends on the size at first capture relative to the size at maturity and the asymptotic length, L_∞. The guidelines have not been validated for other fisheries, but should be applicable to fisheries with similar characteristics. Evidence from another FMSP project, R5024, which examined shallow water multispecies reef fisheries, suggests that the guidelines may also be applicable to those fisheries (Jennings, Marshall and Polunin, 1995).

As noted above, the guidelines are based on the use of single species tools to provide guidance for a multispecies situation. Whilst the management guidelines derived are relatively simple, there is still a requirement for detailed species specific information, and for technically skilled stock assessment specialists for the analyses.

An alternative approach to the analysis of technical interactions in these types of fisheries is the multispecies, multigear YPR model developed by Sparre and Willmann (1992) as "BEAM4". A version of this model allowing up to 19 species (or guilds) and 12 fishing gears (fleets) is now available as the Thomson and Bell yield prediction model in FiSAT. The FMSP ParFish software, described in Sections 4.6.2 and Chapter 9, may also be applied to multispecies, multigear fisheries. These alternative approaches estimate the aggregate yields available from the multispecies complex allowing for the different size selectivities and seasonalities of the gears etc. Although data requirements are high, BEAM4 may be used to investigate the effect of mesh sizes, gear bans and closed seasons as well as changes in fishing mortality rates (see e.g. Hoggarth & Kirkwood, 1996).

TABLE 4.6
Summary comments on the alternative approaches for multispecies stock assessments

Assessment Tools	Advantages / application	Disadvantages / comments
Chapter 12 guidelines	• Set *F* levels to protect most vulnerable species (e.g. highest *q*, L_∞; lowest *M*, *K*) • Use minimum possible data inputs	• Most applicable for deep reef hook and line fisheries where selectivity is hard to control • Conservation-based approach, may not produce maximum overall yield or value
BEAM4 / FiSAT	• Set *F* levels, fishing seasons, selectivities (age at first capture) to maximize overall yield or value in fishery	• Per recruit approach and emphasis on overall optima may lead to extinction of vulnerable (usually valuable) species • Very high data needs

4.5 BIOMASS DYNAMIC / DEPLETION MODELS (THE CEDA SOFTWARE)

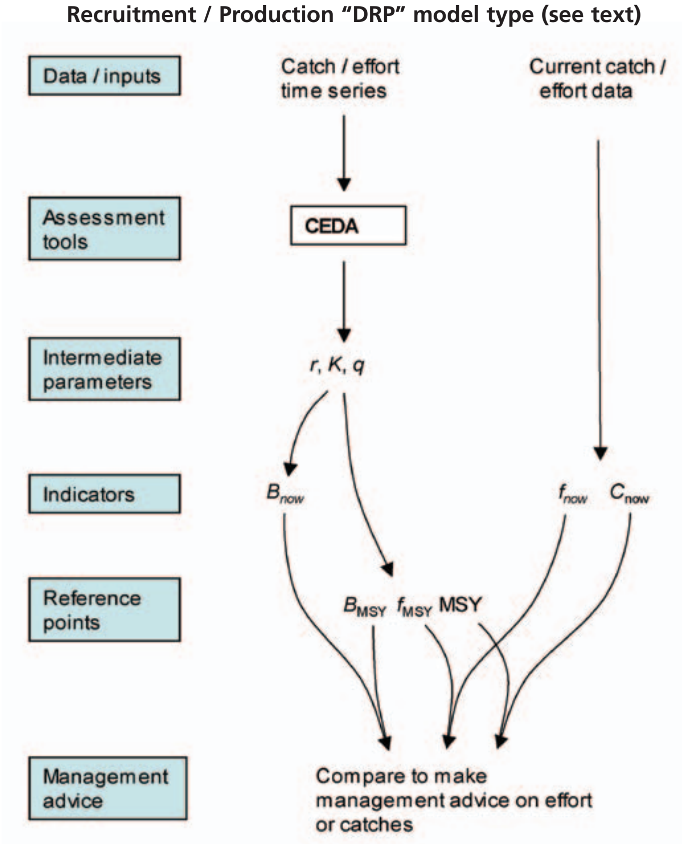
4.5.1 Purpose and methodology

The CEDA package was developed to fit biomass dynamic models to catch, effort and abundance data using non-equilibrium fitting methods. Biomass dynamic models have historically been thought of as ways of analyzing catch and effort data. In the more robust non-equilibrium versions they are better viewed as methods for analyzing catch and *abundance* data. Effort data are not necessarily required, except as used to estimate CPUE *as an index of abundance*. The CEDA models include the well-known "surplus production" or "surplus yield" models (e.g. the Schaefer model) and others that depend on the concept of stock depletion. In recent years, these approaches have been re-phrased as biomass dynamic models to emphasize their focus on a simple biomass function, contrasting with the age- or length-based analytical models (as used in the "Yield" software for example). The concepts of surplus production or yield can also apply to such age or length-based yield models. Surplus production represents the amount by which the stock biomass will grow in the absence of fishing, and hence the catch that could be taken sustainably while maintaining the biomass at a constant level. As described in Section 3.5, biomass dynamic models provide estimates of stock sizes and catch rates relating mainly to the MSY reference point. These models provide management guidance assuming that selectivity (the age at first capture etc) has been constant in the past and will remain so in future.

CEDA is a data-fitting or parameter estimation tool, not a simulation tool like Yield. However, since it is based on the simple biomass dynamic models, the parameters estimated by CEDA may be used directly to give indicators (e.g. the current stock size) and reference points (e.g. the MSY catch level) for managing the fishery, as illustrated in Figure 4.5. A basic projection facility is built into CEDA, so that no additional simulation tools are needed.

The general approach used to fit models in CEDA is to choose a model type and specify any relevant input parameters. CEDA then uses these starting parameters to

FIGURE 4.5
Illustration of the "biomass dynamic" approach to stock assessment using the FMSP CEDA package (see text and cf. Figure 4.1). Parameters shown assume use of the Deterministic Recruitment / Production "DRP" model type (see text)

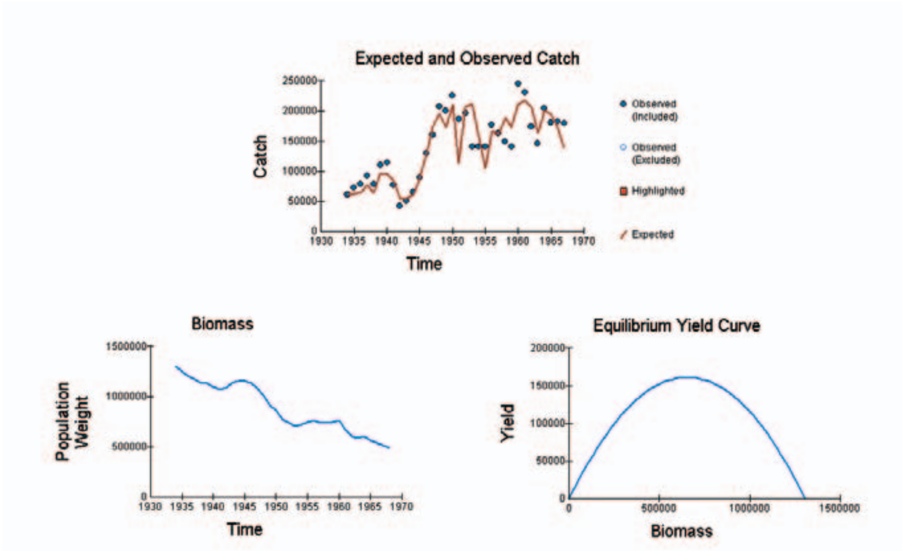


iteratively find the parameters of best fit for the model based on the data set. A variety of graphical and statistical features are provided to determine how well the model has fitted the data set. CEDA also allows the temporary omission of statistical outliers and influential points from the dataset to examine their effects on the fit. Confidence intervals for parameter estimates are calculated by bootstrapping.

The CEDA fitting methods work by adjusting parameter values iteratively until the best fit is achieved between the observed and predicted values of relative abundance or catch data. Different assumptions may be made about the residual errors in both the model and the data. All of the models used are based on non-equilibrium fitting methods. As noted in Section 3.1.4, traditional equilibrium methods for fitting "surplus production" models should be avoided at all costs due to the risks of overestimating sustainable yields, especially if the fishery has been expanding over the period of data collection (as is usually the case).

Once the best fitting set of model parameters has been estimated, they can be used in two ways. Depending on the model used and the type of data, the MSY or other reference points can be calculated. These can be compared with the current catch and estimated biomass levels to see if they are likely to be sustainable. In the example in Figure 4.6 (based on the CEDA tuna tutorial), the biomass can be seen to have declined with the high catches in the late 1940s and in the 1960s, and by 1968 was below the estimated B_{MSY} of 650 000 tonnes shown by the fitted equilibrium yield curve. Secondly, the fitted models may be used to make projections showing the likely changes in future stock size, starting from the current levels, for alternative future catch or effort scenarios, as specified by the user (see Section 8.3). Confidence intervals can be fitted for these projections. For all of these analyses, stock size (in numbers or biomass depending on the model) is thus the main indicator given by CEDA.

FIGURE 4.6
Illustration of a CEDA stock assessment, showing the observed and model-predicted catches (top), the estimated biomass time series, and the fitted equilibrium yield curve (*K* = 1.3m t, MSY = 160 000 t, for a DRP Schaefer model with least square errors, fitted to the tuna tutorial data set)



CEDA allows the use of three different model types, with four alternatives in the final type, giving a total of six different models, as described below. Details of the models are given in Section 8.1 and the software help files. The models offered by CEDA have been described under many different names in the literature, but all are centred around the idea of depletion. The fundamental idea behind all depletion analyses is very simple: if fish are removed from a population, the population size will fall, and this will be reflected by a fall in any abundance indicator such as catch per unit effort. All of the CEDA models assume that the fish population is a single "closed" stock, having no emigration or immigration. The main differences between the six models relate to the assumptions made about recruitment to the stocks. Summary guidance on the selection of a model is given in Table 4.7.

Model type 1: No recruitment

This model assumes that there is no recruitment to the stock after the first data point, but that there is a constant natural mortality rate M, for which the user must supply an estimate. This might apply to a set of data collected at intervals over a short period, certainly less than one year, and to species that would have spawned only before the start of the data collection. The animals are sure to grow over the period when data are collected, so the mean weight of animals in the catch will change. Because the model operates in terms of numbers of animals, rather than weight, catches and abundance indices must either be measured in numbers, or there must be data on mean weight to allow conversion from total weight to total numbers.

This model is used for in-season stock assessments in the fishery for the shortfin squid *Illex argentinus* around the Falkland Islands (as described by Rosenberg *et al.*, 1990, see Section 4.5.3). Short-lived shrimp species and other invertebrates could also be suitable subjects for the no-recruitment depletion model.

The model may also be useful for analyzing the results of experimental fishing, where a discrete population is fished relatively heavily for a short period of time in order to estimate the population sizes (see examples in help files). If the time period is short enough, then natural mortality will be negligible, and the data can be analyzed using M=0.

Model type 2: Indexed recruitment

For data sets stretching over a number of years, it is usually unreasonable to assume that no recruitment has occurred. If some index of relative recruitment (i.e. an index whose value is proportional to the number of new recruits) is available for each data point, it can be used to adjust for the number of recruits entering each year, allowing population sizes and catchability (q) to be estimated. An estimate of natural mortality M is still required, and again all data should either be measured in numbers of animals, or in biomass with mean weights available for conversion. This is not such an important requirement for the recruitment index itself, because recruits will be approximately the same size each year, so that the recruitment index in weight will be proportional to the index in numbers.

Three possible sources for the recruitment index are: larval or pre-survey data; catch data from another fishery operating in the same area, but catching smaller animals; and length-frequency data. The latter method has been used with this model in the analysis of anchovy data from the Mediterranean (Santojanni *et al.,* 2004). In this analysis, the length frequency data were used to estimate the proportion of the catch that came from new recruits aged 0+. Multiplying this proportion by the CPUE gave an appropriate index of recruitment.

Model type 3: Deterministic Recruitment/Production (DRP)

The remaining four models in CEDA assume that recruitment or production is deterministic; that is, controlled entirely by current stock size, without any environmental effects or other sources of "random" variation. The different DRP models have differently shaped production functions, which describe the relationship between current stock size and recruitment or production. They all have in common the idea of a constant carrying capacity or unexploited population size, at which level the population would stabilize in the absence of exploitation. With this assumption, a population whose current size is below carrying capacity will increase towards the carrying capacity, subject to any catches that are taken.

There are two categories of DRP model in CEDA: the constant recruitment model, which operates in numbers of animals (and consequently requires data in numbers rather than weight), and the production models, which operate in terms of biomass.

The constant recruitment DRP model is based on the "modified deLury" method of Allen (1966). This may be applicable in situations where the population is large enough that the stock size has not yet been reduced to a level where declines in recruitment may be expected. In other words, the stock has remained in the area of the stock recruit relationship (SRR) where recruitment is effectively random, above the "sloped" region of the SRR curve found at small stock sizes.

The other three DRP models are based on the standard "production model" or biomass dynamics of the familiar Schaefer, Fox and Pella-Tomlinson methods. These models operate in biomass terms, not in numbers. In CEDA they are fitted using non-equilibrium methods, using an "observation error" formulation, and allowing for three alternative error models: normal, log normal or gamma (see software help files).

TABLE 4.7

Comparison of the different data requirements of the six models available in CEDA

Data series	Recruitment within series?	Have index of recruitment?	Catch data in form of:	Use CEDA model:
Depletion over a single year	No (only once, at start)	Not applicable	Numbers	No recruitment
Covers several years	Yes, each year	Yes	Numbers	Indexed recruitment
		No	Numbers	Constant recruitment
			Weight	DRP (Schaefer, Fox or Pella-Tomlinson)

Comparison of DRP and indexed recruitment models

The DRP concepts that recruitment and/or production are linked to current stock size, and that each stock has a constant carrying capacity, are intuitively appealing, and lead to models with parameters that can be easily interpreted. It is also easy to use these models to predict future stock sizes under different scenarios of catch and effort. However, not all stocks necessarily obey the assumptions of DRP models. The indexed recruitment model does not need to make such assumptions, and may therefore be preferable if even an imperfect series of recruitment indices is available. The deterministic nature of DRP models can cause problems when analyzing stocks with highly variable recruitment. If, for example, the actual recruitment in one year is very much higher than the mean recruitment predicted by the DRP model, then the large cohort of recruits will raise catch rates not just in the current year, but also in subsequent years until it is fished out. Conversely, an abnormally small recruitment will depress catch rates for more than one year. DRP models do not take account of this effect. This situation may cause less of a problem in longer data series (say 20 years or more), if high and low recruitments occur at random. Even then, any trends in recruitment due to exogenous factors (i.e. anything other than current stock size) can cause serious biases.

4.5.2 Inputs and outputs

As outlined above and summarized in Table 4.8, the different models in CEDA have different data requirements. The first requirement for all depletion methods, and indeed most fisheries assessment methods, is a comprehensive record of total catch for the whole time period to be analyzed, preferably with no gaps. The catch data should be extended backwards in time as far as possible, even if no corresponding index of abundance or effort data are available. If the catch data are incomplete, initial population size will be underestimated, and all subsequent population sizes will be underestimated as well.

The other requirement of all depletion methods is a good index of relative population size. A "good" index should be proportional to population size over a wide range. In contrast to total catch data, abundance index data need not cover the whole period of the data set, and there may be gaps in the series. The two most common types of index are research survey data and commercial CPUE data. The CEDA help files discuss the pros and cons of each type of index.

It should be noted that there is no obligation to use catch and effort data from all the boats in the fishery when constructing CPUE. In some cases it may be better to estimate CPUE as the index of abundance for a sub-set of boats which are thought to provide the best index of abundance, e.g. a fleet that has changed little over time and that has fished consistently for the full period of the fishery. Estimates may also be made using different fleets and compared. CEDA allows such analyses when "partial" catch data are entered in addition to the total catches. In this case, the effort data are assumed to refer to the partial catches only. One disadvantage of using only partial CPUE data with the current version of CEDA is that it is not possible to investigate the effects on stock size of different future effort levels, because there will be other boats in the fishery that will be taking unknown catches.

CEDA can also be set to apply relative weights to each of the different data points used in the analysis. Weights are usually assigned in inverse proportion to the variances of each data point, so that information believed to have a high accuracy is given a stronger influence in the fitting process.

The outputs provided by CEDA also vary between the different models (see again Table 4.8). For the "no recruitment" and "indexed recruitment" models, CEDA estimates the initial and final population sizes in numbers and the catchability coefficient, q. These may be used to estimate the fishing mortality rate and the proportional escapement as described in Section 8.1.

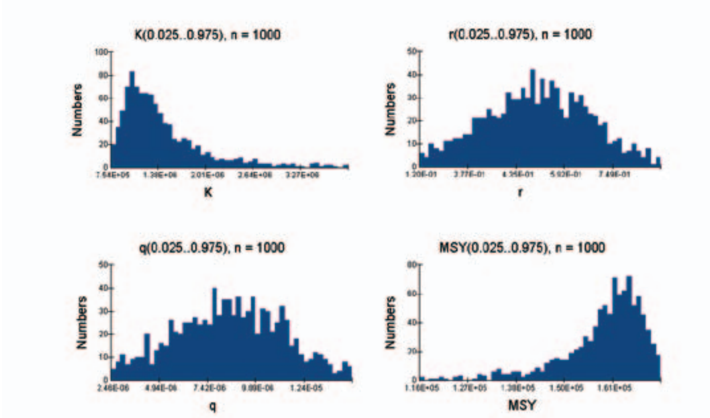
All of the DRP models estimate unexploited population size or carrying capacity, K, along with the intrinsic population growth rate, r, and the catchability, q (see Sections 3.3.2 and 3.3.7). Ideally, K will correspond to the stock size at the start of the catch data series, which should always extend as far back in time as possible. In cases where the collection of catch data only began after a significant fishery had existed for some time, CEDA makes allowance for the prior exploitation by allowing models to be fitted with different ratios of the stock size at the start of the catch data to the unexploited stock size. This ratio is referred to as the "initial proportion".

In most cases, the value of the initial proportion will not be very well known. The best course of action is then to find the range of values between 0 and 1 over which the model fits reasonably well, and to use the values at the ends of the range to give ranges of answers for the other parameter estimates and projections. This procedure, known as sensitivity analysis, is described further in the CEDA help files. It should not be attempted to find a single "best fit" value for the initial proportion.

Confidence intervals and uncertainty

CEDA provides an estimate of R-squared to indicate the goodness of fit of each model (see help files and Section 8.2 for valid uses of R-squared in comparing model fits). Residual plots are provided to visually check the fit between the observed and expected data points. CEDA also estimates the confidence intervals of the model parameters by bootstrapping (re-sampling from the residuals of the C/E data points etc and re-fitting the model each time). Confidence intervals will often be asymmetrical for one or more of the parameters (see examples in Figure 4.7, and CEDA help files for further interpretation). Confidence intervals for the final (current) stock size and for other times are not reported with the other estimates of K, r, q etc, but can be found by making a projection "with confidence intervals" and then clicking on the button to copy the graph source data to a spreadsheet.

FIGURE 4.7
Example distributions of parameter estimates produced by 1000 CEDA bootstraps, showing 95% confidence intervals (P=0.025-0.975) for the tuna tutorial data set



The CEDA help file promotes the use of sensitivity analyses to find likely ranges of values of parameters such as the "initial proportion", which will often not be well known (see help file "Guide to fitting models", and Section 8.2). The CEDA tuna tutorial describes a step by step investigation of the sensitivity of outputs to the choice of error models, outliers, the "initial proportion", time lags in recruitment, and the z shape parameter of the Pella-Tomlinson model. When such sensitivity analyses produce a wide range of equally well fitting estimates for a particular parameter, confidence intervals may be fitted for the two models with the most extreme point estimates. The highest upper limit and the lowest lower limit may then be used to give conservative confidence intervals for the outputs (see help files). Moving beyond the realm of CEDA, more robust estimates of uncertainty, integrated across uncertainties, may also be made with the Bayesian methods described in Section 4.6 below.

TABLE 4.8
Inputs and Outputs of the different models in the CEDA package

	Notation	No Recr.	Index Recr.	DRP Const Recr	DRP Schaefer	DRP Fox	DRP Pella Toml.
Inputs – Ecological							
Natural Mortality	M	Yes	Yes	Yes			
Time lag between spawning and recruitment					Yes	Yes	Yes
Index of recruitment (annual)			Yes				
Initial proportion (fraction exploited at start of data set)			Yes	Yes	Yes	Yes	Yes
Pella-Tomlinson shape parameter	z						Yes
Inputs – Fishery							
Total catches by time period (in weight)					Yes	Yes	Yes
Total catches by time period (in numbers)		Yes	Yes	Yes			
Mean weight of individual fish [1]		(Yes)	(Yes)	(Yes)	(Yes)	(Yes)	(Yes)
Fishing effort applicable to total or partial catches [2]		Yes	Yes	Yes	Yes	Yes	Yes
Partial catches by time period (in weight) [3]					Yes	Yes	Yes
Partial catches by time period (in numbers) [3]		Yes	Yes	Yes			
Abundance index (proportional to biomass only) [4]					(Yes)	(Yes)	(Yes)
Variance of abundance index [5]					(Yes)	(Yes)	(Yes)
Outputs - Parameters etc							
Initial population size (numbers)	N_1	Yes	Yes				
Carrying capacity (unexploited population size)	K			Yes	Yes	Yes	Yes
Population growth rate	r			Yes	Yes	Yes	Yes
Catchability coefficient	q	Yes	Yes	Yes	Yes	Yes	Yes
Outputs - Indicators							
Population size (numbers) at time t	N_t	Yes	Yes	Yes			
Equil. Biomass at time t	B_t				Yes	Yes	Yes
Outputs - Reference points							
Maximum Sustainable Yield	MSY				Yes	Yes	Yes
Replacement Yield	RY				Yes	Yes	Yes
F giving MSY [6]	F_{MSY}				Yes	Yes	Yes

Notes:
[1] Used to convert total weight to numbers in different models
[2] For a single gear fishery, the total fishing effort for the whole fleet. For an analysis where one gear out of several is selected as the most reliable CPUE index of abundance, the effort related to the partial catches.
[3] "Partial" catches correspond to the effort column where the specified effort is not for all gear types.
[4] May be entered as an alternative to supplying a catch and partial effort series.
[5] May be used to weight the fitting of models; i.e. indices with smaller variances are given greater weight than those with larger variances.
[6] Only available if effort entered relates to the whole catch (e.g. for a single-fleet fishery, or one where all efforts are standardized to a standard unit).

4.5.3 Applicability and related approaches

Biomass dynamic models provide one of the simplest possible ways of carrying out a full fish stock assessment. Only data on total catch and an index of abundance (e.g. CPUE) are required. All aspects of production – recruitment, growth and mortality – are pooled into a single function with undifferentiated biomass. Since age and size structure are ignored, however, outputs should clearly be treated with caution, especially for example if the selectivity of the fishery is changing such that fish are increasingly being targeted at sizes smaller than the size at maturity.

All of the CEDA models produce an estimate of the current population size, either in numbers or biomass. This can be used to give a rough estimate of fishing mortality, by comparing catches with population size (i.e. $F = C / B$, or $F = C' / N$ where both B and N should be given as the averages over the year and where C' is here the catch in numbers). Where CPUE data are used as an abundance indicator, the catchability coefficient (q), defined as fishing mortality per unit effort can also be estimated (Section 3.3.7). Having estimated catchability, it is straightforward to predict what would happen to the stock under different levels of fishing effort in the future. The ability to carry out projections using hypothetical catch or effort data is built into CEDA (see Section 8.3).

Use of the CEDA "no recruitment" model

Rosenberg *et al.* (1990) and Beddington *et al.* (1990) provide an example of the use of the "no-recruitment" depletion model for the assessment and management of annual squid stocks in the Falkland Islands. These assessments are based on the use of a target 40 percent proportional escapement, $X_{40\%}$ as the reference point. The proportional escapement, X is defined as the number of survivors at the end of the fishing season divided by the number that would have survived if there had been no fishing, i.e.:

$$X = N_0 e^{-(M+F)} / N_0 e^{-(M)} = e^{-F}$$

where N_0 is the number of squid at the start of the season. For this fishery, the target 40 percent escapement value was chosen based on historical stock and recruitment data as a conservative rate that should, in most years, allow sufficient escapement to maintain a safe spawning stock. Although *absolute* escapement levels (i.e. the actual numbers of squid) would be preferable as management targets, these are harder to use than the proportional escapement target as the allowable levels of fishing or catches could not be set at the start of each season due to the unknown levels of recruitment that year (see Section 2.5.3).

With the target X value directly related to the fishing mortality F as shown in the equation above, and since $F = qf$ (where f = fishing effort), the allowable f and a corresponding fleet size for the coming season is set using the qs from the last season (i.e. $X_{40\%} = e^{-F} = 0.4$, so $-F = \ln(0.4)$, so $F = 0.92 = qf$, so $f = 0.92/q$). Having set what should be a safe fishing fleet size based on last years' catchability, the progression of the fishery is monitored in real time through the season using daily catch and effort reports radioed in from all vessels. These data are supported by mean squid sizes estimated by observers at sea, since catches in numbers are needed by the model, not in weights. Such real time monitoring enables the managers to ensure that the target X is not exceeded to any significant extent by any increases in q due to experience, concentration of the stock, or other factors. The monitoring also allows early closure or extended opening of the fishing season in years of smaller or larger than average recruitments respectively. In the example of Rosenberg *et al.* (1990), a multi-fleet model is used in the assessment, based on the basic concepts outlined above. Only single abundance indices may be used in CEDA. For further details, see the squid fishery tutorial in the CEDA help files.

Depletion modelling can also be used with the primary aim of estimating stock sizes (other possible methods are VPA, tagging, and direct counts; see Section 3.4.2). This is especially useful in circumstances where the assumption of a closed population can be adequately met and where enough depletion can be achieved without endangering the overall stock. Deliberate depletion experiments may for example be used in restricted local areas such as bays, or reefs, and then used to calibrate relative abundance indices collected over wider areas. As another example, in the Turks and Caicos Islands, new lobster recruits are known by fishermen to occupy specific grounds and are targeted each year after the opening of the fishing season. In this situation, the "no-recruitment" depletion model may be used each year to estimate the relative recruitment or cohort strength at the start of each fishing season. These data may then be used as indices of recruitment strength in a multi-year "indexed recruitment" model in CEDA, or to construct a stock recruitment relationship (Medley and Ninnes, 1997).

Use of DRP-model outputs from CEDA

The intermediate parameters estimated by the DRP models in CEDA (K, r and q) may be used to estimate a range of useful reference points. In the case of the logistic (Schaefer) model, where the biomass associated with the MSY, B_{MSY} is found at $K/2$, the MSY catch level may be quickly estimated as $rK/4$. For data sets where the effort inputs relate to the total catches (not the "partial" catches for a selected fleet), the effort giving the MSY, f_{MSY} is equal to $r/2q$ (and thus $F_{MSY} = r/2$). The maximum possible F (the point at which the stock collapses) is equal to r, and the effort at the maximum possible F will be r/q. Equivalent points for the Fox and Pella-Tomlinson models are given in the CEDA Technical Appendix help files.

With these outputs, CEDA is mainly designed to assist fishery management based on catch quotas or TACs. Such catch quotas could be set at the estimated MSY level, or at a catch that would be predicted to rebuild to MSY in a selected number of years (estimated using a CEDA projection). The effort related quantities f_{MSY} and F_{MSY} are best estimated for single fleet fisheries where catch and effort data relate to the whole fleet. Regardless of whether full or partial effort data are used, CEDA may always be used to provide estimates of C_{now}/B_{now} (a proxy for F_{now}) and C_{MSY}/B_{MSY} (a proxy for F_{MSY}). Where overall catchabilities are not known (i.e. for multi-fleet fisheries analyzed with partial abundance estimates in CEDA), f_{MSY} may *not* be known, but simple forms of effort control may still be feasible, based on the relative proportions of F_{now} and F_{MSY}.

In addition to estimating the current size of the fish stock and a range of reference points as described above, CEDA can also be used to make risk assessment projections, for future scenarios of either catches or effort levels. The confidence intervals for such projections are given by CEDA and can be used to estimate precautionary levels of catch or effort associated with defined risk tolerances (see e.g. Haddon, 2001 pp313-5).

Problems with using biomass dynamic models

Potential problems with the use of biomass dynamic models are described in the CEDA help files (and in Hilborn and Walters, 1992, etc). These include problems with sequential distribution of fishing effort over different spatial areas and changes in fishing power (catchability) of vessels over time. Where standardisation of fishing effort is required due to such changes, this should be done before analysis in CEDA. Where several different kinds of gear are used to fish the same stock, it may be possible to standardize effort, but this should only be done where the CPUE trends from the different gears show the same basic trends. If different gears show different trends (and both are thought to be equally reliable as indicators of abundance), sensitivity analysis should be used, by running and reporting separate analyses for each CPUE series.

Another problem with biomass dynamic models is that the parameters r, K and q are usually severely correlated and hard to fit without good data. Hilborn and Walters (1992) describe how good contrast is needed to fit all three parameters well, including data from different combinations of stock size and fishing effort, e.g. at low stock sizes with both low and high fishing efforts (see CEDA "contrast" help file). Where the data show little contrast or exhibit a steady "one-way trip" decline in catch rates over time, biomass dynamic models may be unable to distinguish between a small stock (K) with a high population growth rate (r), and one with a large K and a low r. The CEDA tuna tutorial data set is an example of such a one-way trip. In these circumstances it may be possible to make reasonable estimates of the MSY and the optimum effort, without knowing whether the stock is small but productive or large but unproductive. Depending on the data, management advice may be highly uncertain (e.g. standard deviations for the parameters may be as large as the estimates themselves) or the models may prove impossible to fit. With low contrast in the data, good parameter estimates will always be difficult to obtain. In these situations, either precautionary or adaptive approaches can be adopted or "auxiliary information" e.g. about likely values of K or r may be used to improve the precision of the estimate. Bayesian methods (see Section 4.6) are well suited to this approach, though simpler methods can also be used (see Hilborn and Walters, 1992, p325).

Comparison with other biomass dynamics software packages

Non-equilibrium biomass dynamic models may also be fitted using minimization routines in spreadsheets (e.g. "solver" in Excel) or with other software packages. The BIODYN spreadsheets (Punt and Hilborn, 1996) offer fitting of both process and observation error models for the Schaefer, Fox and Pella-Tomlinson models. These can prove very useful in understanding the fitting of the models. Haddon (2001) also provides spreadsheet templates for fitting such models. Punt and Hilborn's BIODYN manual agrees that the observation-error methods (as used in CEDA) should in most circumstances provide more precise and accurate estimates of parameters. Punt and

TABLE 4.9

Summary comments on the alternative software tools for fitting non-equilibrium biomass dynamic models

Assessment Tools	Advantages / application	Disadvantages / comments
CEDA	• Use "no recruitment" models to estimate abundance over a short depletion experiment or single fishing season. • Use "indexed recruitment" and DRP models for longer time series • Easy menu-driven software • Useful diagnostic tools (residual plots and goodness-of-fit) • Allows "toggling out" of outliers and influential points • Includes projection facility • Estimates distributions of parameters (and confidence intervals) by bootstrapping • Good help files and tutorials	• Limited to six model forms (plus three different error models) • Does not allow analysis of multi-fleet data sets (data may be standardized by GLM first for analysis)
BIODYN	• Spreadsheet approach assists understanding of models and allows for adaptation	• Less automated
ASPIC (also ICCAT BSP)	• Allows more flexibility in form of production model than CEDA • Allows analysis of multi-fleet data sets	
ParFish (see Section 4.6)	• Designed to assist co-management of small and medium scale fisheries • Allows analysis of multigear (fleet) data sets • Can supplement analysis with information from meta-analyses, localized depletion experiments or the local ecological knowledge of fishermen or other experts • Can include "preference" data from fishers and managers giving measure of utility to assist decision analysis	• Only logistic (Schaefer) model available

Hilborn (2001) also give a useful checklist of issues which should be considered when performing biomass dynamic stock assessments, most of which are relevant to CEDA analyses. The help files and tutorials in CEDA cover similar issues and may also be helpful in guiding good stock assessment practices. While the spreadsheet approach used in BIODYN may allow greater flexibility, the CEDA software allows users to test outliers and influential points and fit confidence intervals etc in a simpler, menu-driven environment.

Where CPUE data are available for more than one fleet, biomass dynamic analyses may be made using the ASPIC software published by NOAA (Prager, 1994). Common estimates of *r* and *K* are then made, along with an estimate of *q* for each data series. Different weights may be applied to each data series reflecting their variances or relative confidence. The ASPIC help files advise, however, that analyzing a single standardized abundance index, e.g. fitted by a GLM approach, may be better than analyzing multiple fleets. Such GLM standardization thus removes explainable variation from the data, which would only create noise in a multi-fleet ASPIC model.

4.6 BAYESIAN STOCK ASSESSMENT APPROACHES

4.6.1 Purpose and methodology

Stock assessment tools such as the CEDA and Yield models use standard fishery data to estimate management parameters. Where the data for these methods are limited, as is often the case, parameters can be estimated only with low precision. Data may be limited in new fisheries (having only a few years' data), in fisheries where historical data have not been collected (e.g. due to financial constraints), or in lightly exploited fisheries (having no data on the response of the fishery under heavy exploitation). Given these problems, project R6437 developed methods for Bayesian stock assessment and decision analysis as a way of allowing for the uncertainties and limitations of such data sets. The Bayesian approach is not a new stock assessment model, but an improved way of fitting models to data and making decisions.

Punt and Hilborn (1997) and McAllister and Kirkwood (1998a) give theoretical introductions to the use of Bayesian approaches in fisheries, based on integrated analytical (age based) approaches, and biomass dynamic models respectively. The mathematics involved requires an understanding of probabilities and the statistical concept of a likelihood function of the data. Simple Bayesian analyses can be implemented using a spreadsheet approach (e.g. using Punt and Hilborn's (2001) BAYES-SA software), but the addition of extra levels of uncertainty (more hypotheses) can soon make the analyses complex to the point of requiring days of computer time to conduct analyses.

Combining the guidance of both McAllister and Kirkwood (1998a) and Punt and Hilborn (2001), a Bayesian decision analysis involves the following six steps:

1. identify each of the alternative management actions that could be taken (e.g. a range of TACs for the forthcoming year);
2. specify a set of performance indicators to measure the potential consequences of each management action (e.g. the average biomass or catch in the future, possibly relative to a reference point);
3. identify the alternative hypotheses about the population and the fishery dynamics, also termed the possible "states of nature" (e.g. the alternative plausible combinations of *K* and *r* in the logistic model);
4. determine the relative weight of the evidence (the data and any other information) in support of each alternative hypothesis (expressed as a relative probability);
5. calculate the distribution and expected value of each performance indicator for each management action (i.e. randomly select multiple values of the parameters from their probability distributions, run the model and apply the management action, and calculate the indicators from each set); and
6. present the results to the decision makers.

Details on each of these steps are provided in the references listed above: a few explanatory comments are repeated here. In step 1, the alternative management actions may be simple absolute values such as for TACs or effort levels, or may be specified as fishing mortality rates conditional on stock status as per an agreed decision rule (Section 2.5.3). In step 2, clearly, the more performance indicators that are specified, the more sets of results must be presented to managers as separate decision tables. Unless utility functions are specified giving weights to the different indicators, some subjective analysis of the tradeoffs between indicators must still be made. In step 3, uncertainty may be considered both in the distributions of the parameter values, e.g. for K, r etc; and in the underlying structural model that determines the dynamics, e.g. a Fox or a Schaefer model. The most common approach is to select a single structural model and to consider only the uncertainty in its parameters. This simplifies the analysis but will reflect only part of the uncertainty in the assessment. Where different underlying models are compared as hypotheses, general forms of models may be used (e.g. for both stock recruitment relationship and biomass dynamic models, an extra parameter can be included to give the functional difference between the Ricker and the B-H forms, or between the Schaefer and the Fox forms respectively). Other elements of uncertainty (see Section 3.6.4) can also be included as alternative hypotheses.

Steps 4 and 5 are the Bayesian parts of the analysis. In brief summary, the process starts with “prior probability distributions” for hypotheses (e.g the likely range of values of K) and calculates the “posterior distributions” or relative probabilities taking account of the data used in the analysis. Priors may either be “informative” or “non-informative”. In the latter case, the prior is “flat”, indicating that nothing is really known about the parameter. The posterior distribution is then estimated only on the basis of the data used, so analogous results should be achieved as with a standard fitting method. “Informative” priors allow the incorporation of information from the literature about similar fish populations, or the inclusion of local experience about the fishery (see below).

In presenting the results to the decision makers (step 6), decision tables are used to show the values of the performance indicators for each combination of hypothesis and management action. Where there is uncertainty in several parameters or models, the indicators may be integrated across the hypotheses, weighted by their relative probabilities, to give an overall expected (average) potential outcome from each management action. With such aggregated results, care must be taken not to ignore the possibility of providing bad advice if some of the extreme values for the hypotheses actually prove to be true.

The main advantage of the Bayesian method is that it provides a valid framework for assigning probabilities to different hypotheses (i.e. step 4 above) using both data from the fishery and prior information from other similar stocks or species (Punt and Hilborn, 2001). This is particularly useful where data from the fishery are limited. For long time series with good contrast, e.g., marked drops and increases in indices of abundance that correspond to large and then small catches, Bayesian methods may give more limited advantages over standard fitting of models to the data, e.g. using CEDA. In the more data-limited situations, the uncertainty in the outputs could usually be much reduced by including informative priors. In a biomass dynamics analysis, for example, the model parameters K and r are often strongly negatively correlated, with a ridge of pairs of values giving almost equally good fits (McAllister, Pikitch and Babcock, 2001). In this situation, auxiliary data from demographic analyses, life table equations, or about fecundity or age at maturity could be used to restrict the range of likely values for r and thereby pin down the most likely slice through the ridge of K values (McAllister, Pikitch and Babcock, 2001). Estimates of q may also be available from tagging or depletion studies. An example of an hierarchical Bayesian formulation of the depletion (De Lury) models used to assess Falkland Island squid stocks is given in McAllister *et al.* (2004).

Building on the concept of Bayesian priors, Hilborn and Liermann (1998) and Punt and Hilborn (2001) promote the method of "hierarchical meta-analysis" for including uncertainties in key input parameters in a stock assessment. Real uncertainties in factors such as natural mortality rates and the stock recruitment "steepness" parameter (and many others listed in Hilborn and Liermann, 1998) could potentially be incorporated using these methods. Instead of just assuming that steepness is "0.9" or some other single value, a probability distribution for steepness could be estimated using meta-analyses of stock-recruit data from similar species (Michielsens and McAllister, 2004). This is an active research area at present and the use of sources such as Myers' stock-recruit database may hold some promise. It is clear, however, that the selection of which data to include or what weighting to give in preparing the priors may significantly affect analyses, and that some care must be taken. It may also be re-emphasized that including uncertainty from meta-analyses in this way is different to estimating a single value of say M from Pauly's (1980) model, also derived from one of the earliest examples of meta-analysis (Hilborn and Liermann, 1998). Unfortunately parameter estimates are rarely published in a form appropriate for simple prior formulation.

Another useful method for building informative priors is to synthesize the knowledge of a group of experts, e.g. on the perceived current size of the stock compared to the unexploited state. Most older fishers will have historical experience on changes in their stocks even when no formal data have been written down or collected over time (see ParFish example below). Stock assessment scientists on working groups may also be canvassed to give opinions that can be formulated into priors (Punt and Hilborn, 2001). Where different experts suggest different values for priors (e.g. the opinions of stock assessment experts may differ from those of industry members), they can be weighted equally to give a mixture distribution which may perhaps be recognized as giving a fair balance between the different views, thus encouraging acceptance of the conclusions.

The second main advantage of Bayesian methods is that they provide a statistically rigorous method for integrating all the uncertainties in an assessment, to produce management advice for the key factors of interest – i.e. the probability distributions (the range of likely values) of the performance indicators, for each of the management actions being considered. Where normal "sensitivity analyses" are used instead of Bayesian methods (i.e. by changing a single parameter at a time and re-calculating), the presentation of results can become very cumbersome for multiple combinations of parameter uncertainties. Bayesian approaches estimate (1) the posterior probabilities of each alternative hypothesis (based on the data and the priors), i.e. the relative support given to each hypothesis and (2) the consequences of each management action for each performance indicator under each hypothesis. These two outputs can be presented separately to decision makers, perhaps focusing on the outcomes of the management actions under the most likely hypothesis, while also bearing in mind the outcomes if other hypotheses prove to be true. For more complicated analyses, the two outputs can also be multiplied together and added up to determine the relative consequences of each management action integrated over all the hypotheses. Integration can therefore be used to simplify analytical results.

Under the FMSP, project R6437 developed new Bayesian statistical and decision analysis methods aimed at precautionary management strategies for data-limited fisheries. Both surplus production and age-structured models were developed in this project. Based on an age-structured model with expert judgment-based informative priors for the constant of proportionality or catchability coefficient (q) for the indices of abundance, the method was used in annual assessments of the newly discovered (data-limited) Namibian orange roughy fishery (see Chapter 13, McAllister and Kirchner, 2001). Since the project, the Bayesian surplus production model has also been developed as a software package by the Wildlife Conservation Society, used for ICCAT swordfish, White Marlin and pelagic shark stock assessments (McAllister *et al.*, 1999;

Babcock and McAllister, 2002; Babcock and Cortes, 2004), and "catalogued" as an official ICCAT software tool. The software may be downloaded from the ICCAT web page (http://www.ICCAT.es/downloads.html - as the "BSP" model listed under "Assessment Quality Control").

FMSP project R7947 also developed a Bayesian-based software tool, in this case specifically designed to encourage stakeholder inputs into fish stock assessments, for participatory co-management decision making. Details are provided in the following section and in Chapter 9. A "Bayesian network" modelling approach was also developed by FMSP project R7834 for the empirical analysis of qualitative multivariate fisheries data (see Section 4.7.2 and Chapter 14).

TABLE 4.10
Summary comparison of Bayesian and traditional assessment approaches

Assessment approach	Advantages / application	Disadvantages / comments
Standard methods	• More familiar and easier to understand	• Results of normal sensitivity analyses can be difficult to present with multiple uncertainties
Bayesian methods	• Useful where information on the fishery is limited (e.g. short data series, little contrast etc) • Allows inclusion of "auxiliary" data or knowledge that improves the assessment • Allows for the robust integration of uncertainties to assist decision making	• Higher complexity • Need understanding of Bayesian statistics to apply

4.6.2 Participatory Fisheries Stock Assessment (the ParFish software)

The ParFish software developed by FMSP project R7947 uses a Bayesian approach for making decision analyses based on logistic/Schaefer type models. The usual catch and effort data and parameter inputs of these models can be supplemented with other "prior" information, e.g. from meta-analyses, from localized depletion experiments or from the local ecological knowledge of fishermen. The software is designed to provide guidance on effort control, quotas or refuges (closed areas reserves) for co-managed small and medium scale fisheries (see Chapter 9).

The approach is to estimate parameters for a target simulation model – a model which is thought most likely to represent the behaviour of the fishery in response to a control (effort, catch quota or closed area). The aim of the assessment is to build up best estimates for all the parameters in the target simulation model from what ever information is available. In the current version of the software, the operational model used is the non-equilibrium Schaefer logistic (biomass dynamic) model, selected as being robust in providing advice where few data are available. The Schaefer model requires a minimum of 4 parameters: B_{now}, r, B_{inf} (i.e. the carrying capacity or unexploited biomass "K" in CEDA) and q for at least one gear. Two or more gear types are allowed with separate q parameters for each gear. The model describes changes in stock biomass over time, but does not differentiate between fish ages or species.

The data inputs are defined in a hierarchical structure under the ParFish "Probability model" menu. All probabilities are represented by frequencies of one or more of the parameters used in the target simulation model. Parameter frequencies can be generated internally based on catch and effort or interview data, or loaded from an external source. These frequencies can be combined to estimate the "posterior" probability density function, which is used to generate possible parameters for the target simulation model.

The inclusion of interview priors in ParFish generates outputs that take into account the views of the stakeholders. An interview process is provided (see ParFish toolkit on attached CD-ROM) by which the parameters of the logistic model can be estimated based on simple questions about current, historic and expected catch rates and recovery times. While they may not be correct, they do allow fishers to express current expectation or belief which can be combined with the available catch/effort data (using the Bayesian approach), and which can be tested by scientific research.

The potential management actions being considered, along with the performance indicators and the target and limit reference points, are defined in a control menu. The Schaefer model can use all three of the available controls – effort restrictions, quotas or closed areas (simply set as a percentage of the total stock protected assuming no migration).

The primary aim in ParFish is to set a "best" or optimum level for the desired control, based on a TRP (e.g. f_{opt}, C_{opt}). Such TRPs are defined with a social/economic focus depending on the "preference" data that are input. A second interview proforma is provided in which fishers rank possible outcomes in their fishery, measured as relative changes in their catch and effort, in terms of preference. This is used as a measure of utility for decision analysis (see example in Figure 4.8). It is possible also to define LRPs as specified percentages of the state of the stock compared to B_{inf} (e.g. 50 percent if MSY is used as the LRP in the Schaefer model).

Management advice in ParFish is presented as the selected performance indicators plotted relative to the reference points using integrated, graphical outputs (see Figure 4.9). It is also possible to export results to a Microsoft Excel spreadsheet.

FIGURE 4.8

Illustration of ParFish preference scores (utility) for a range of catch quotas which could be applied. The lower lines indicate the preference for individual fishers. The top line shows the overall preference for all fishers combined, which is proposed as the target reference point as a compromise across all of the individual fishers

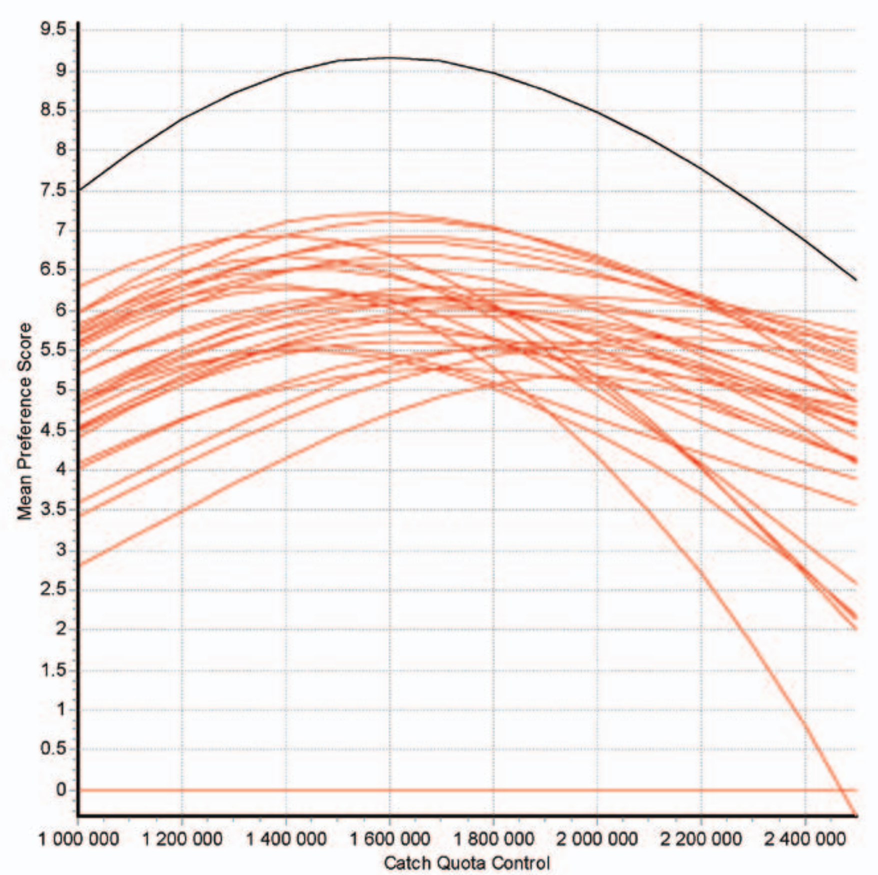
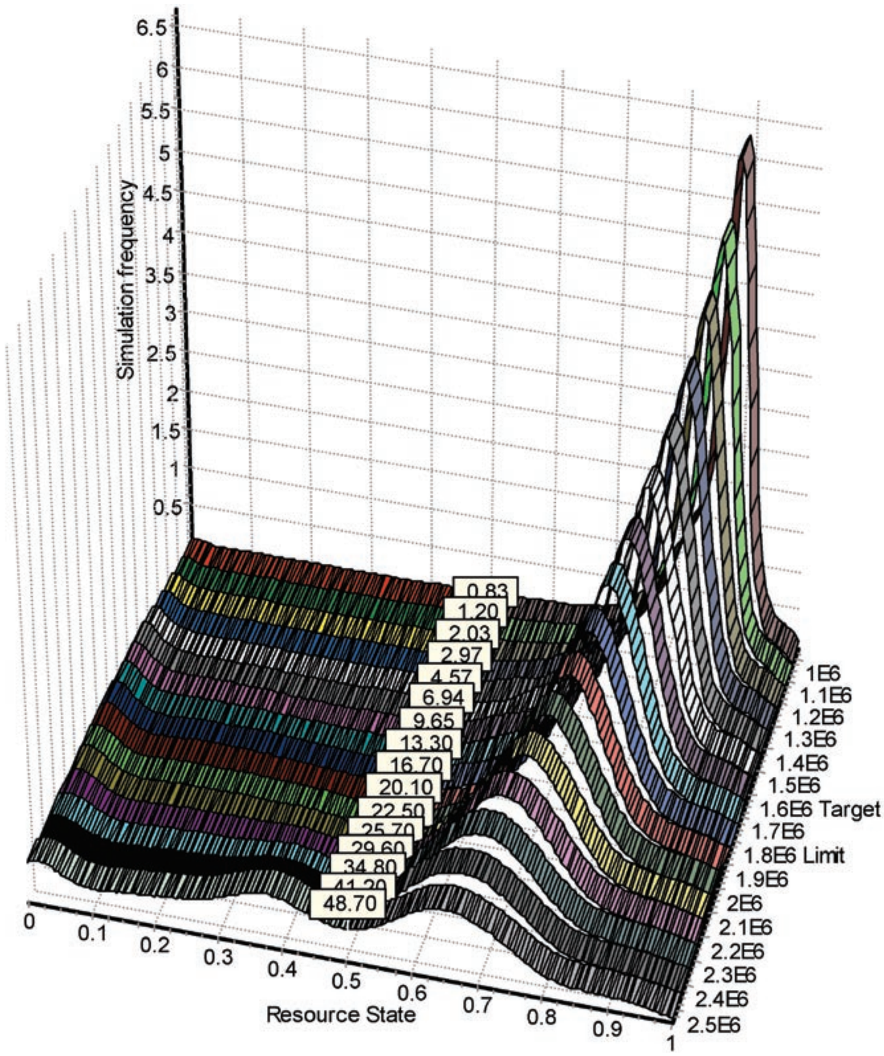


FIGURE 4.9

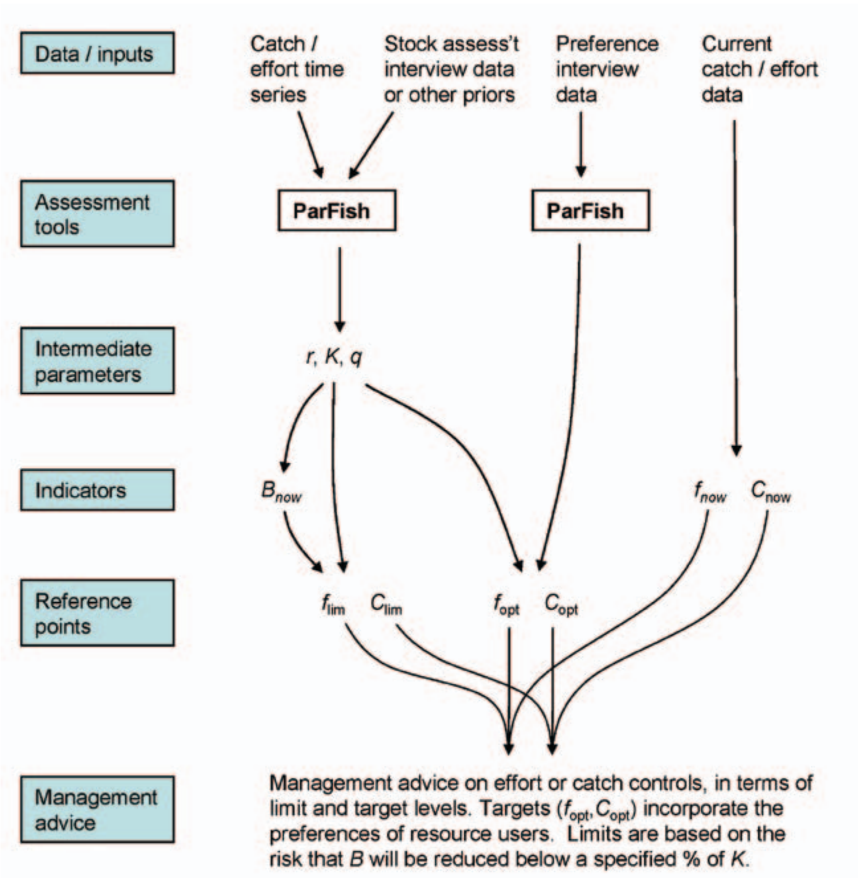
Example output from ParFish showing the stock state as probability functions for different levels of the management control, in this case a catch quota (shown on the right axis). The number labels on each curve give the probability (as a percent) that the stock will become overfished with each quota. Overfishing is defined as the stock falling below an input proportion of unexploited level (50% of B_{inf} is used in this example). As the quota increases, not only does the average stock state (i.e. the peaks of the curves) decrease in size, but the state becomes increasingly uncertain, as illustrated by the flatter probability distributions. The LRP catch in this example is a quota of approximately 1.8m units, having a chance of less than 20% (as selected) of falling below the 50% B_{inf} threshold. The TRP quota, incorporating fishers preferences, at 1.6m units, is safely inside the predicted LRP level



Although this first release of the ParFish software offers less model options than CEDA, its Bayesian formulation also allows the use of a range of other data types, as described above and illustrated in Fig. 4.10. The stock assessment interview, fishing experiments, or other prior data may thus be used to improve the estimates of the performance indicators and reference points. The preference interview data then tailors the management advice to the priorities of the users. Such features make ParFish particularly useful for co-management and data-limited conditions. The software is still under development, with the focus on making the method easier to use and more accessible to fisheries scientists charged with assessing small scale fisheries where extensive data collection and monitoring are not possible.

FIG. 4.10

Illustration of the ParFish approach to stock assessment (see text, and compare with the CEDA process shown in Figure 4.5). In ParFish, advice is given as change relative to the current effort and catch levels. Both targets and limits integrate uncertainty. Advice is also given on refuges / no take zones (not shown here)



4.6.3 Comparison with other Bayesian software

The ParFish software follows the approach of LFDA, CEDA and Yield in being a menu-driven, "front-end" tool designed to do a number of specific jobs. Although the hierarchical probability model can be developed to give many different sub-models (e.g. different error models and data, using various priors for parameters), the possible outputs are still limited to the adopted logistic model, which it may be argued is probably enough to make a reasonable start on fisheries with little previous data. This models and others may alternatively be programmed with Bayesian fitting methods in spreadsheets, e.g. building on the BAYES-SA templates (Punt and Hilborn, 2001), or using the freeware "WinBugs" package (http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml). The particular advantage of ParFish is in involving fishers in the assessment through the incorporation of a specific interview method and allowing more fisheries scientists to access Bayesian methods through simpler procedures. This makes ParFish particularly appropriate for small scale fisheries which rely on co-management to implement fisheries controls.

The ICCAT BSP program fits either a Schaefer model or a Fletcher / Schaefer model to CPUE data using the Sampling-Importance-Resampling algorithm. Thus the generalized version of the Fletcher/Schaefer logistic model presented in McAllister *et al*. (1999) that permits the value for B_{MSY}/ K to deviate from 0.5 can be implemented. An informative prior is required for the shape parameter that governs B_{MSY}/ K, if the Fletcher/Schaefer model is to be run. Required inputs for both the Schaefer and

Fletcher/Schaefer models are catch for all years (missing catch data in the first years of the fishery are allowed), at least one catch rate (CPUE) index of abundance, with CV's if available (missing data are allowed). The parameters that can be fit are carrying capacity (*K*), the intrinsic rate of population growth (*r*), the biomass in the first modelled year defined as a ratio of *K* (*alpha.b0*), the shape parameter for the surplus production function for the Fletcher/Schaefer fit (*n*), the average annual catch for years before catch data were recorded (*cat0*), variance parameters for each CPUE series, depending on the method used to weight the CPUE series in the likelihood function, and the catchability (*q*) for each CPUE series. The program can be used to project the biomass trajectory under any constant catch or constant fishing mortality rate (*F*) harvest policy, with probability intervals for stock biomass also computed. Fishing effort control measures can be evaluated in BSP by inputting and evaluating alternative fishing mortality rate policies. BSP does not permit the evaluation of management methods that involve area closures. Program outputs include decision tables showing the probability of stock rebuilding and other indicators of policy performance at specified time horizons.

ParFish has a different focus and is meant to complement more rigorous statistical analyses. ParFish aims to be robust at the cost of possible accuracy. For data analysis, it offers a non-parametric analytical approach similar to the CEDA assessment tools, which allow analyses to be conducted without extensive statistical knowledge. However, where output from any more rigorous statistical analysis consists of a random draw of one or more relevant parameters from a probability distribution, such as in Bayes-SA, the parameter frequency data can be drawn into ParFish. Otherwise ParFish encourages use of specific interview data, and forms one part of a more holistic assessment being developed for small scale fisheries (see ParFish toolkit on attached CD).

4.7 EMPIRICAL STOCK ASSESSMENT APPROACHES

4.7.1 Predicting yields from resource areas and fishing effort

Where no detailed stock assessment data are available, a common approach has been to estimate the potential multispecies catch of a resource from its size (e.g. the area of floodplain or fringing reef) or other characteristics, assuming that its productivity will be similar to other locations for which data are available. FMSP projects R5030 and R6178 developed such predictive models for river and lake fisheries respectively. Such models are inevitably approximate, being based on reported yields which may or may not be close to the "MSY" of each fishery included in the sample. FMSP project R7834 extended these analyses by including fishing effort as well as resource areas, where available. These new models updated previous analyses to the latest available data for 36 floodplain rivers, 143 lakes and reservoirs, and 79 coral reef fisheries from around the world (Halls, Burn & Abeyasekera (2002)). In almost all cases examined, the best performing model was an empirical variant of the equilibrium Fox production model, which explained up to 82 percent of the variation in CPUA. These models allow initial estimates to be made of the approximate potential catch of a resource and the average levels of fishing effort (per unit area) that maximize yields in other locations. Details of the analyses are summarized in Chapter 14. The data sets used and further information are available at the FMSP website (www.fmsp.org.uk, project R7834).

4.7.2 Multivariate modelling of fishery systems

The predictive models described above assume that fisher density alone provides an adequate index of fishing mortality and that production potential is similar among sites. Of course, fishery productivity may also vary in response to the management strategies used, the levels of compliance with these strategies, the physical and ecological characteristics of the fisheries and the effects of any fish stocking or habitat enhancement efforts. In reality, a host of factors is likely to influence fish yields and related management outcomes beyond the size of the resource and the level of fishing effort. FMSP Project R7834 developed methods for working with such multiple variables and analyzing which ones are most important. In contrast to the standard fishery models (e.g. Yield, CEDA) which assume that only the management controls determine the outcome in the fishery, these multivariate models recognize that many different factors may be important (Halls, Burn and Abeyasekera, 2002). They are most likely to be useful for enhancing the learning process in the context of adaptive management (see Section 2.1.3) where the effects of "treatment" variables (e.g. different management measures) may be confounded by a wide range of other factors.

Two complementary approaches for constructing models of this type are described in Chapter 14. The first, General Linear Modelling (GLM) is appropriate for dealing with *quantitative* management indicators (or outcome variables) such as indices of yield or abundance. The second, Bayesian network models is better suited to more *qualitative* indicators such as equity, compliance and empowerment, that must be *subjectively* measured or scored along with many of the explanatory variables. Methods for such analyses were developed by Project R7834 using data assembled from 119 case studies of co- or community-managed fisheries or management initiatives from around the world. In applying such tools to assist in the management of other fisheries, multivariate data would most likely be collected over smaller spatial scales, such as for different study villages or lakes within a river catchment, country or region.

TABLE 4.11
Summary comments on the FMSP-developed empirical stock assessment approaches (see also Chapter 14)

Assessment Tools	Advantages / application	Disadvantages / comments
Area-based regression methods and surplus production models based upon among fishery comparisons	• Models provide useful estimates of potential yield and corresponding fisher densities that maximize yield in floodplain rivers, lakes and reservoirs and coral reefs, based upon estimates of yield per unit area, resource area and/or fisher density. • Time series of catch and/or effort not required.	• Approximate methods based on observations at other sites, assuming resources and exploitation patterns are similar
General Linear Models (GLM)	• GLM approach suitable for examining the impacts of multiple independent variables on quantitative fishery indicators • Designed to enhance learning process for adaptive co-management	• Independent variables may be continuous or discrete
Bayesian network methods	• Approach for analyzing relationships among multivariate data sets including qualitative dependent and independent variables • Designed to enhance learning process for adaptive co-management	• Require detailed studies from case study fisheries / villages with contrast in variables of interest

4.8 SPECIAL APPROACHES FOR INLAND FISHERIES

Inland fisheries, and particularly floodplain river fisheries are based on complex interactions between the fish, the environment and the fishermen. The resource is usually highly seasonal, and varies greatly between years and between different localities. There are many different habitat types and strong competition for the best fishing locations where fish become concentrated in the migration or dry seasons. Inland fisheries are usually multispecies and multigear and the artisanal fishing communities are usually widely dispersed around the resource, making monitoring and enforcement more difficult. Inland fisheries are potentially highly productive due to the annual input of nutrients with each new rainy season. They are also vulnerable to the competing and often negative impacts of other activities within the catchment, including pollution from various sources, modification of the flood regime due to deforestation, dams and irrigation programmes etc, and the destruction of aquatic habitats. Management of inland fisheries must take particular account of these interactions of the fishery with the wider environment. As described in Sections 4.7.1 and 14, the potential fish yields of lakes and floodplain rivers may be roughly predicted according to the areas of the flooded resource. More detailed stock assessment approaches for assessing alternative management strategies for floodplain river fisheries are discussed briefly below in Section 4.8.1.

Given the semi-enclosed nature of the habitat and in mitigation of the various negative impacts they face, many inland fishery managers attempt to enhance the fish production of their waters. Commonly used methods include the introduction or regular stocking of appropriate fish species, the fertilization of waters, and the modification of aquatic habitats to give better breeding or feeding opportunities or to ensure migrations (e.g. fish passes) (Welcomme, 2001). Such methods involve a range of interventions falling in between wild, capture fisheries and extensive aquaculture. Due to the irreversible nature of introductions of non-native fish species, precautionary approaches are clearly required (FAO, 1996). The regular stocking of indigenous fish species is less controversial although negative genetic impacts may still occur where fish are transferred around their natural range, e.g. into catchments to which they are not genetically adapted. Given the importance of inland fisheries in food security and rural livelihood strategies in many poor countries, the FMSP has placed a major emphasis on the investigation of enhancement fisheries, particularly stocking. A brief summary of this work is given in Section 4.8.2 below.

Inland fisheries are particularly suited to adaptive management and co-management approaches, as outlined in Sections 2.1.3 and 2.4. In floodplain river systems, many fish species survive the dry season in village ponds or other discrete water bodies, each of which may effectively comprise a separate stock unit. These provide excellent opportunities for adaptive management experiments. General guidance on the management of these types of fisheries, arising from a series of FMSP projects, was provided by Hoggarth *et al.* (1999). Specific methods for adaptive co-management in inland fisheries were developed by FMSP project R7335 (Garaway and Arthur, 2002), as summarized below.

4.8.1 Integrated flood management for fisheries and agriculture

Project R5953 outlined the potential benefit of farmers and fishermen working together to manage the flooding regimes of agricultural polders and flood control schemes, that are common in Bangladesh and elsewhere. While some constraints are imposed by the irrigation needs of the crops, flexibility in the timing should be used to ensure that sluice gates are open at the times needed by fish for their migrations (Hoggarth *et al.*, 1999, Part 2). Current FMSP project R8210 has continued these studies. Preliminary results suggest that passage success of fish through the gates is very limited during the ebb phase of the flood. Opportunities to improve passage success are at their greatest during the flooding period when the flow of water into the flood control schemes increases but when turbulence outside the gates remains low. The results also indicate that controlling fishing activities along channels connecting the schemes to the main rivers may be as important for ensuring passage success as keeping the main gates open during times of favourable hydrological conditions (Halls, 2005).

To quantify the potential impacts of alternative management options for floodplain fish stocks, project R5953 also developed an age-structured population dynamics model to examine the effects of flood intensity on fish production (Halls, Kirkwood and Payne, 2001). The analytical model assumes that fish growth, natural mortality rates and recruitment may all be affected by the intensity of flooding, as mediated by its effect on the density of fish. Initial analyses showed that floodplain fish production and therefore catches are most strongly dependent upon recruitment and therefore on the density dependent survival of the spawning stock, especially through the dry season. Including this hydrological sub-model, the model enables the importance of traditional fishery management measures such as fishing effort control and closed seasons to be compared with the management of the hydrological regime (e.g. managing water heights in the flood and the dry seasons). More recently, the model has been used to explore the effects of different dam release strategies on exploitable biomass (see Halls & Welcomme, 2004), and to determine production trade-offs between fisheries and agriculture (see Shankar, Halls and Barr, 2004).

4.8.2 Stocking models and adaptive management

A series of FMSP projects has focused on the use of fish stocking for enhancing production in inland fisheries. The results of project R5958 and others are summarized by Kai Lorenzen in Welcomme (2001). Stocking is usually undertaken either to compensate for the modification of the environment due to the impacts of other sectors (e.g. dams, habitat losses etc); to compensate for recruitment overfishing; to increase the productivity of the resource to better support human livelihoods; or to conserve a threatened species. In some cases, water-bodies are stocked that have no natural recruitment (e.g. some new reservoirs). In other cases, where some natural recruitment of the stocked species still occurs, the relative benefit of the stocking can be quite hard to evaluate. The key biological factors determining the outcome of stocking are density dependence in growth and size dependence in mortality (in combination these processes also result in density dependent mortality). Based on these findings, Lorenzen (1995) concluded that the optimal stocking density depends on the fishing rate, and vice versa. Inappropriate combinations of stocking and harvesting regimes may lead to either overfishing or "over-stocking". The size of fish at stocking and harvesting are also related to the potential production and will affect both the cost of the fingerlings and the value of the harvest.

FMSP Project R6494 (also summarized in Hoggarth *et al.*, 1999 – Part 2) reviewed the experiences of eight development projects, all based in Asian countries, that had used fish stocking to enhance fisheries production. Key lessons were reported for the design of both the technical and institutional strategies. Key technical issues concern the suitability of different locations for stocking, the mix of species to be used, the fish size and densities to stock at, and the commercial aspects of procuring the fingerlings. The institutional strategy must address both the management of the stocking and the wider management of the aquatic resource to ensure the maximum potential. Government, community members, and NGOs can all play important roles (see Section 2.4). A key component of the institutional strategy for stocking is to establish a cost recovery mechanism for the high investment that is needed.

Many of these factors that affect stocking outcomes will vary according to the specific characteristics of the water bodies to be enhanced and the fish species to be stocked. Adaptive frameworks for finding optimal stocking regimes were developed by FMSP Project R7335. As summarized by Garaway and Arthur (2002, and see other papers in the R7335 project web page - http://www.fmsp.org.uk/), the approach involves identifying the main areas of uncertainty associated with the resource system – including both the technical and the institutional aspects – and developing a learning strategy for reducing the key uncertainties. As outlined in Section 2.1.3, the learning strategy may be based on passive and/or active adaptive management strategies. Combinations of passive and active experiments will be useful in most cases and were applied in this case. In project R7335, the experiments that made up the learning strategy were analysed using multiple regression and other methods. The results were shared with all the stakeholder groups at the end of the production cycle, using a number of innovative methods, so that they could clearly see the benefits of participating in the adaptive process and to ensure that the results were available to decision makers in order to guide the next year's stocking strategies.

5. Conclusion

Part 1 of this guide has focused on both the process of managing a fishery and the detailed stock assessment methods and tools that may be used to support decision-making. It has been emphasized that a complete fishery management system must recognize a range of driving forces that provide the "context" for management decisions. Consideration must be given to each of the component parts of the management framework (as given in Figure 1.1) and combined into a clear, logical, feedback-based process for the management of the fishery. Such a process would support the FAO Code of Conduct for Responsible Fisheries, and its requirement for proactive and precautionary decisions to be made, based on the best available science. The processes, standards and measures adopted in each fishery should be clearly stated in a Fishery Management Plan (FMP) so that all stakeholders may understand the rationale for decision making.

Within the various elements of the management framework, there are many different options, between which choices will have to be made. Different tools will be applicable in different fisheries and different reference points and indicators may be selected by stakeholders in different locations. As examples, where use rights are allocated either to a share of the catch or to guarantee future access to the fishery, this will determine the stock assessment outputs that are required, and hence the tools that may be used (see Section 2.3). Alternative systems of co-management and decision making arrangements (see Section 2.4) will clearly affect the selection of the other elements. Where artisanal fishers are to be involved in decision making and to contribute data to the management and feedback process, it may be better to use simpler assessment methods and indicators to ensure that all of the stakeholders can understand the process and participate effectively. Some management measures are more applicable for certain situations and are better estimated using certain tools, as described in Section 2.5.5 There is no point in estimating a catch quota for a fishery, for example, where it is impossible to monitor the catches or the landings of many of the fishers. In these and other ways, the context variables listed in Figure 1.1 determine what will be practical and feasible for the management process in each fishery.

Fishery managers thus have to make many choices, both in the way they will manage their fisheries and in the types of information and advice they need from the stock assessment process. As noted at the start of this document, many different approaches and methods are available. Some of these have been described in the previous sections, including both the FMSP tools and a range of other methods, particularly those that fill important gaps in the FMSP suite (e.g. VPA).

In choosing between these alternative tools, many trade-offs must be considered in their costs and benefits, e.g. in their data needs, the complexity of the analyses, the likely accuracy and realism of the model outputs, the levels of uncertainty in the outputs and the extent to which these are known. The data needs of the different FMSP and other stock assessment tools were considered in Chapters 3 and 4. The needs are summarized again here in Table 5.1 and Table 5.2, in order to provide an at-a-glance guide to their possible application in the management system. Clearly, data needs vary greatly between different stock assessment tools and approaches. Some methods require only one or two parameter inputs, some require hundreds. Some methods can use data from only a single point in time, others require detailed and expensive time series collected over many years. As shown in the tables, the simpler indicators and reference points can be estimated with the empirical methods, biomass dynamic models and the length-based analytical and per-recruit models. The VPA-based methods (the bottom lines in each table) produce the most detailed and valuable outputs but have much higher data needs than the other methods.

The costs of data collection will also vary with the frequency with which assessments are made. For highly valuable fisheries, fully age-based VPA assessments are usually made on an annual basis. With the equilibrium assumptions of some of the other simpler methods (see tables), it may be better to undertake a thorough assessment only once every two or three years, rather than a less precise one every year. Where funds and capacity are limited, rolling programmes may be used to cover different priority species in different years.

Differences in data needs have great implications for the costs of alternative stock assessment and management approaches. No attempt is made here to quantify the costs of the alternative methods in terms of the effort (e.g. sampling days) required to collect the different data for each approach. These will clearly vary with the type and scale of the fishery and the frequency of data collection undertaken. This manual has also attempted to emphasize, though, that the *value* of different tools can also vary significantly, particularly regarding the likely accuracy and precision of the predictions (see e.g. FMSP comparisons of age and length-based methods in Section 3.1.5). With low accuracy, there is a higher chance of being wrong and failing to deliver the objectives of management. With low precision (i.e. higher uncertainty), any precautionary management measures may be very restrictive and may limit the potential contribution of the fishery to society. Fishery managers therefore need to make tradeoffs in the effort and funding that is put into management and the relative benefits that will be obtained from the system used. While it is hard to be completely prescriptive, some guidance on the pros and cons of the different management options and stock assessment tools has been given in the summary tables in several of the preceding sections.

Although the detailed design of a management system must be based on the specific conditions of each fishery, a number of simple criteria can be envisaged that might help managers to decide which management and stock assessment choices to make. These include the relative size and value of the fishery, the capacity of the managing authority for stock assessment and enforcement, and the goals set for the fishery. There are some obvious pointers that smaller, less valuable fisheries will need to be managed with simpler assessment methods than might be used in larger, more valuable ones. Usually correlated with the above, where management capacity is limited, ambitions must be set lower. Quantitative stock assessments are required for all fisheries, but the most technical approaches may only be applicable for the most valuable fish stocks that are heavily exploited and likely to be endangered. A few other obvious or general guidelines are given below.

- Where fish cannot easily be aged (e.g. crustaceans and some tropical fish), only length-based analytical methods, biomass dynamic models or empirical approaches may be possible.
- Where size-limits or closed seasons are considered as management measures, analytical (age or length-based) methods, empirical models or common sense approaches must be used, not biomass dynamic models.
- A highly technical precautionary approach and market-based use rights may be most appropriate for larger, offshore, industrial fisheries, usually based on single species fish stocks.
- An adaptive approach, area-based access rights and co-management will have advantages in fisheries that can be split in to local stock sub-units allowing comparison and learning (e.g. by empirical methods). These may be inland or coastal fisheries that are also often multispecies, multigear resources where single species assessments may be hardest to apply and where input/output rules may be hardest to enforce.

- Where stocks are lightly exploited and data limited, Bayesian methods may be useful for improving assessments.
- Where the environment is highly degraded, first priority should be given to ecological issues rather than the fine details of fishery management rules.

Beyond these basic pointers, it seems hard to offer a comprehensive but simple expert system or flow diagram that will lead to the right choice of all the details in all circumstances. Most of the options have both advantages and disadvantages that must be taken into consideration in a detailed analysis of the circumstances of each fishery.

Recognizing that many changes are afoot in the way that fisheries are managed, it is argued that conventional fishery management, especially when it recognizes uncertainty and applies precaution, has many strengths that need to be carried forward. It can provide efficient outcomes, perhaps especially where management deals with single species and single gears and where the fishery is valuable enough to warrant investment in good monitoring systems and capacity for data analysis. Smaller scale fisheries, especially tropical multispecies fisheries may also apply the conventional management principles described here, but ambitions for stock assessment and technical details of reference points etc. must be tuned down and greater emphasis placed on participatory processes and the use of traditional knowledge (Mahon, 1997). Whether a fishery is large or small, managers must still be prepared to take action in the face of uncertainty and to decide what actions to take on the basis of the best information available.

It should also be noted that in stock assessment, more is not necessarily better – a simple model that fits well may give better advice than a complex model with many inaccurate parameters (Hilborn and Walters, 1992, p74). Usually there will be virtue in trying out several different methods and presenting the results in decision tables outlining the assumptions or uncertainties associated with each case. Where capacity exists, Monte Carlo methods may be used to test which stock assessment approach is more likely to give good advice. The most important answer can also sometimes be found by common sense – if recruitment overfishing clearly exists, the key recommendation (to increase stock size) will be the same regardless of the details of the model used.

Most importantly, the methods adopted should clearly be driven by their ability to achieve the goals set for the fishery, which should themselves be agreed with the key fishery stakeholders. The hardest decisions will often not be about which theoretical assessment method to use, but about what risks should or should not be accepted in the fishery. Clear discussions on this issue between managers, stock assessment scientists and the fishing industry and other stakeholders may provide useful guidance on which methods will be required.

TABLE 5.1
Summary of data needs and intermediate parameters for selected methods for estimating different fishery indicators

Data					**Intermediate parameters**		**Indicators**	
Catch	Abundance (CPUE / survey)	Length Freq	Age Freq	Biological	Software / method	Parameters	Software / method	Indicators
Myr TS							Grainger & Garcia (1996)	Fishery phase (D/M/S)
Myr TS	Myr TS				**CEDA**	r, K, q	**CEDA / ParFish**	B_t, N_t
		1yr TS			**LFDA** Pauly	Growth M	**LFDA**	F_{eq}
		SS	SS		Spreadsheet Spreadsheet Pauly	Age-L Key Growth M	Catch curve	F_{eq}
Average		Average			**LFDA**/FiSAT Pauly	Growth M	FiSAT LBCA	N_{eq}, F_{eq} at length
Myr TS	Myr TS (for tuning)	Myr TS	Myr TS	Mat., Wt/age			VPA Spreadsheet	N_{ta}, F_{ta}, Sel. SSB_t

Notes:
Myr = multi-year, TS = time series of data, SS = single sample, Mat. = maturity at age data, Sel. = selectivity pattern by age
Fishery phases: D = developing, M = mature, S = senescent (see Section 3.4.1). Subscripts: *t* = year, *a* = age, eq = equilibrium.
FiSAT LBCA = length based cohort analysis ("pseudocohorts" method can also estimate N_t etc from time series data for fast growing species)
Current version of ParFish may also be used to fit per-recruit indicators and reference points.

TABLE 5.2

Summary of data needs and intermediate parameters for selected methods for estimating different fishery reference points

Data						**Intermediate parameters**		**Reference points**	
Catch	Abundance (CPUE / survey)	Length Freq	Age Freq	Biological	Resource area	Software / method	Parameters	Software / method	Indicators
		SS		Mat. at size		Spread-sheet	L_{m50}		Size-based (approx.)
					Yes			**Empirical models based on other similar fisheries**	MSY, f_{MSY} (approx.)
Myr TS	Myr TS					**CEDA**	r, K, q	**CEDA / ParFish**	MSY, B_{MSY}, F_{MSY}
		1yr TS		Sel., Mat.		**LFDA**	Growth	**B&H invariants**	YPR_{eq}/BPR_0, F_{MSY}*
						(Pauly)	M		
				DDRecr.				**B&H invariants**	$Yield_{eq}/B_0$, F_{MSY}
		1yr TS		Sel.		**LFDA**	Growth	**Yield**	F_{max}, $F_{0.1}$, $F_{0.x}$
						Pauly	M		
				Mat.				**Yield**	$F_{\%SPR}$
			SS	Sel.		Spread-sheet	Growth	**Yield**	F_{max}, $F_{0.1}$, $F_{0.x}$
						Pauly	M		
				Mat.				**Yield**	$F_{\%SPR}$
Myr TS	Myr TS	Myr TS	Myr TS	Mat., Wt/age		VPA	N_{ta}, SRR	**Yield**	F_{MSY}, F_{crash}
	(for tuning)						R An.var.	**Yield**	$F_{transient}$

Notes: Myr = multi-year, TS = time series of data, SS = single sample, Mat. = maturity at age data, Sel. = selectivity pattern by age or size, DDRecr. = density dependence in SRR (Beverton & Holt "steepness"), F_{MSY}* = F_{MSY} assuming constant recruitment, R An. Var. = annual variability in recruitment (coefficient of variation)

Part 2
Introductory guides to the FMSP stock assessment software

6. LFDA software – Length Frequency Data Analysis

G.P. Kirkwood and D.D. Hoggarth

The LFDA (Length Frequency Data Analysis) package was originally produced by FMSP project R4517 and then extended to a Windows-based environment in project R5050CB. The software allows users to estimate non-seasonal and seasonal growth curves from length frequency data using three alternative fitting methods. Using these estimated growth curves, further analysis allows estimation of total mortality rates from a length converted catch curve and two other methods, and estimation of age frequency distributions based on "age slicing".

6.1 FITTING VON BERTALANFFY GROWTH CURVES

Methods for analysis of length frequency data have tended to fall into two groups. The first group consists of methods that directly estimate growth parameters from the length frequencies, the most well-known of these being the ELEFAN method. The second group consists of what may be called "modal analysis" methods, i.e. methods that attempt to dissect the length frequency distributions into age frequency distributions. These can then be subjected to subsequent analysis using the very wide range of fishery assessment techniques that assume the fish can be aged accurately. The LFDA package includes three methods of estimating von Bertalanffy growth function (VBGF) parameters from the first group.

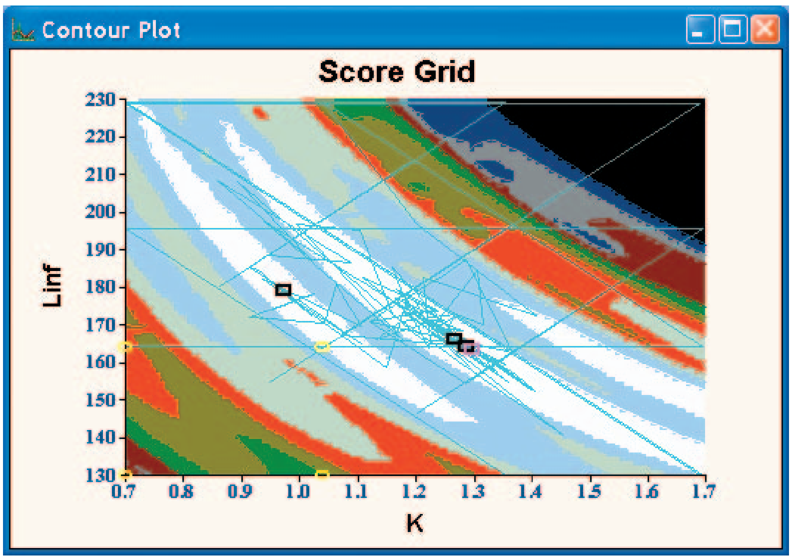
The available methods are Shepherd's Length Composition Analysis (SLCA, Shepherd, 1987), the projection matrix method (PROJMAT, Rosenberg, Beddington and Basson, 1986) and the ELEFAN method (Pauly, 1987). Each of the three methods was originally developed to estimate the parameters of a non-seasonal von Bertalanffy growth curve; however they are all in principle also suitable for estimating the parameters of seasonal growth curves. In practice, it has been found that the SLCA method does not perform well when estimating seasonal growth parameters, and so LFDA allows only the PROJMAT and ELEFAN methods to be used for fitting seasonal growth curves.

The concept behind fitting VBGF models in LFDA using length frequency data is very simple. Given a single length frequency distribution or a set of length frequency distributions, the set of von Bertalanffy parameters is sought that leads to the best description of the distributions. This is done in a slightly different way for each method, and differently for fitting seasonal and non-seasonal curves, as explained in the Technical Appendix help file. In each case, the overall principle is that a "score function" measures the goodness of fit of the length frequency distributions for each combination of von Bertalanffy parameters. The higher the value of the score function – i.e. the better the goodness of fit – the more consistent that set of von Bertalanffy parameters is with the data. The final estimates of the parameters correspond to those that lead to the highest value of the score function.

The non-seasonal von Bertalanffy curve has three parameters: L_∞, the average maximum length, K, a measure of the growth rate (the rate at which L_∞ is approached); and t_0, the time (age) at which length is zero. As illustrated in Figure 6.1, strong correlation is usually found between the parameters L_∞ and K, with one or more ridges of pairs of L_∞ and K values giving almost equally good fits to the data. This problem is most extreme when only a small size range of animals are included in the length frequency data. Two of the VBGF parameters, L_∞ and t_0, relate to the extreme values of the growth curve. With length frequency data for only a restricted range of lengths, very little information is available about these "anchor points" for the growth curve. This means that estimates of t_0 and L_∞ represent considerable extrapolations beyond the range of the data and will be associated with high uncertainty. The parameter estimates obtained from length frequency data are thus those that provide the best fit to the data over the range of lengths available.

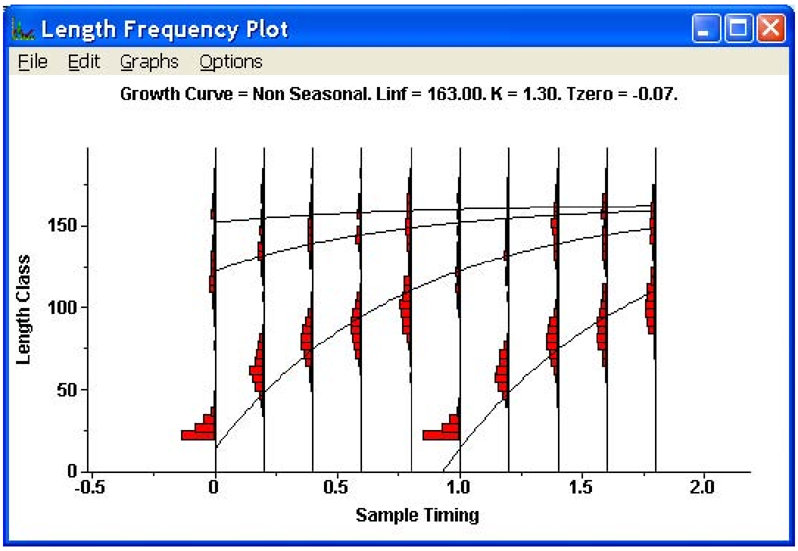
The LFDA help file describes a procedure for searching manually first of all for good combinations of K and L_∞ (the highest scoring ridges), and then using a maximisation algorithm to find the best fit within that range (see Figure 6.1). Users are advised to run the maximisation process from a range of different starting points within the selected region to ensure that consistent values are obtained. It is also good practice to always plot the fitted VBGF curves against the length frequency data to confirm by eye that they give a reasonable tracking of the main modes in the data. As noted by Gulland and Rosenberg (1992), if clear modes are not visible in the data, length-based fitting methods should not be used (see Section 3.1.5).

FIGURE 6.1
Score function grid for different combinations of the VBGF parameters K and L_∞ (based on a Projmat fit of the TUTOR.TXT data set). The white bands represent the highest scoring combinations of parameters. The blue lines indicate the progress of four maximisation searches, starting at the yellow boxes and ending at the black and pink boxes indicating local maxima within the main ridge. The pink box identifies the best fitting combination of K and L_∞ values



A fitted non-seasonal growth curve is illustrated in Figure 6.2. In this case the data from the tutorial were actually generated with a seasonal simulation model. It can be seen that the curve passes through some of the modes nicely, but misses others quite badly. Where this is apparent one may consider fitting non-seasonal growth curves as guided below.

FIGURE 6.2
A non-seasonal VBGF growth curve fitted to the TUTOR.TXT data set



6.1.1 Fitting seasonal growth curves

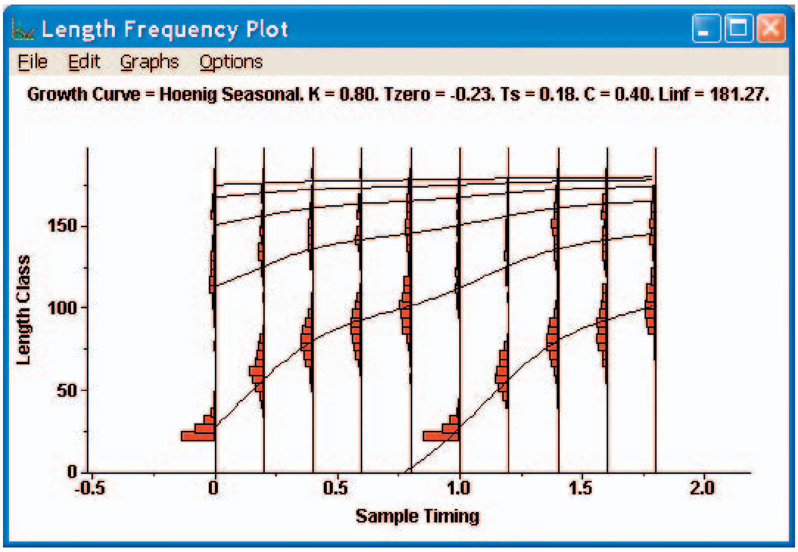
LFDA allows the fitting of seasonal VBGF curves based on the alternative formulations of Hoenig and Hanumara (1982) or Pauly *et al.* (1992) (see LFDA help files). Such seasonal growth curves have five parameters instead of three (the usual K, L_∞ and t_0, plus two further parameters that fix the position and amplitude of the seasonality). Fitting curves with five parameters is much harder than with only three and should not even be attempted unless it is fairly clear from the data that there is evidence of seasonal variation in growth rates (e.g. if there are times of year when a non-seasonal curve consistently underestimates or overestimates the observed modal lengths). Seasonal growth curves should not be fitted in other circumstances because they will nearly always show some degree of seasonal growth even if it is not really there at all. An apparently better fit can always be achieved with five parameters than with three.

In a normal statistical context, five parameters is not very many parameters to estimate. Those familiar with non-linear estimation might expect that one should simply carry out a standard numerical maximisation of the score function with respect to all five parameters simultaneously (actually this only would involve four, since the estimate of t_0 can be determined after the other four have been estimated). Experience has shown, however, that only with almost perfect simulated data is this consistently successful, and the option to estimate the parameters this way is not included in the LFDA package (see help files for further details). Rather, the seasonal growth parameters are estimated two-by-two by LFDA, using an iterative process, as described below.

In the case of the Hoenig and Choudary Hanumara curve, the best fitting pairs of values of L_∞ and K are first sought for fixed values of C and t_s, and then the best estimates of C and t_s are sought for the fixed values of L_∞ and K. This automated process is repeated over and over until convergence is reached. While this iterative process does normally converge, it is by no means certain that it will converge on the global maximum. In particular, because the process starts by fitting a non-seasonal growth curve, if the true growth curve is highly seasonal inappropriate estimates can arise. Users must exercise some independent judgement based on how well the estimated growth curve really fits the data, and some exploration of different ranges of parameters is highly recommended. A seasonal curve fitted to the tutorial data set is shown in Figure 6.3.

A second less automated approach may also be taken to fitting seasonal growth curves, taking advantage of any supplementary information about the parameters that may exist. More reliable estimates may thus be found if it is possible to fix the values of L_∞ or the winter point t_s. If strongly seasonal growth is suspected, it can also be useful to consider only large values of C. Manual grid searches can then be carried out with some of the seasonal growth parameters fixed (see LFDA Tutorial and Reference Guide help files).

FIGURE 6.3
A seasonal (Hoenig) VBGF growth curve fitted to the TUTOR.TXT data set



6.1.2 Uncertainty in the LFDA growth parameter estimates

Confidence intervals for the growth parameter estimates could in principle be calculated using "bootstrap" resampling methods. However, these have not been implemented in the LFDA package, partly due to the difficulty of automatically finding the global maxima of the score function surface, but also because the resampling process itself is extremely complicated statistically and requires knowledge rarely available about the sampling process underlying the collection of the length frequency samples.

In the absence of estimates of confidence intervals, the best approach may be to identify sets of values of the growth parameters that lead to values of the score function that are close to the maximum, and treat these as informal surrogates for possible confidence regions. For example, in most cases, sets of parameters that lead to values of the score function that differ by only a few percent are probably all equally likely. Sets of growth parameters that lead to fits of the length frequency data that are virtually indistinguishable by eye over the length ranges available must also be considered as equally possible. Estimates of growth parameters fitted using length frequency data are always likely to be fairly uncertain (see Section 3.1.5).

6.2 ESTIMATING TOTAL MORTALITY RATES (*Z*)

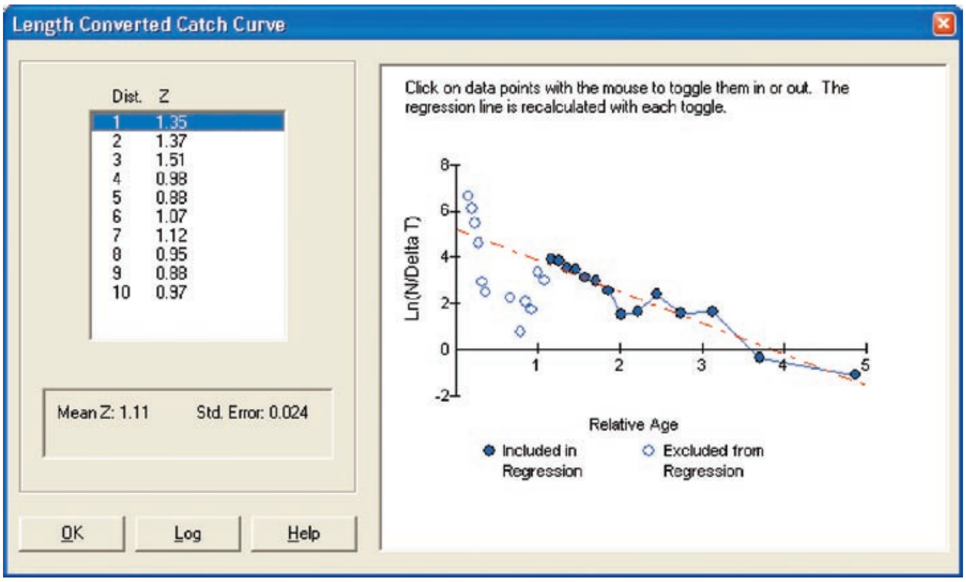
In addition to methods for estimating growth parameters, the LFDA package also includes three methods for estimating the total mortality rate Z (or Z/K), using the estimates of the von Bertalanffy parameters. The routines available in LFDA are the

Beverton-Holt method (Beverton and Holt, 1956), the Powell-Wetherall method (Powell, 1979; Wetherall, Polovina and Ralston, 1987) and a method based on a length converted catch curve. Full descriptions of these methods are given in the Technical Appendix help files. All of the three methods assume that the overall population is in a "steady state", with constant mortality and recruitment over the ages represented by the lengths in the samples.

All three of the mortality estimators available in LFDA are based on non-seasonal von Bertalanffy growth curves, so cannot be used to estimate mortality for a stock displaying strongly seasonal growth. This is not normally a problem since the growth of most fish stocks can be reasonably described by the non-seasonal von Bertalanffy model. The case of strongly seasonal growth is a difficult one, for it is unlikely that such a stock would have non-seasonal mortality anyway. For this reason such stocks should be treated with great care.

The "catch curve" method produces a separate estimate of *Z* for each distribution in a length frequency data file by fitting regression lines through the right-hand side of a length-converted von Bertalanffy catch curve (see help files). The user is required to input values of *K* and L_∞ (e.g. as estimated above). LFDA then presents estimate of *Z* for each of the distributions in the dataset, along with the mean and standard error of the estimates (see Figure 6.4). The user is also required to toggle off any points lying on the ascending arm of the catch curve to give a valid fit (see Technical Appendix help file). This gives a degree of subjectivity to the method that is common to length based approaches. Since the estimates of *Z* may vary over the year as the cohorts grow through the sample, it can be important to have length frequencies from all seasons.

FIGURE 6.4
LFDA fitting of the length converted catch curve method for estimating total mortality rate, *Z*. Separate estimates are made for each of the distributions (ten in the tutorial data file shown here). The fit for distribution "1" is shown in the plot



The method described by Beverton and Holt (1956) for estimating *Z* from length frequency samples is perhaps the most well-known of the three LFDA methods. It relies on a simple algebraic relationship between the mean length in each sample, the length at first full exploitation, the von Bertalanffy growth parameters and the total mortality rate Z. Inputs are this time required for *K*, L_∞ and L_c where L_c is defined here as the first length class which is fully exploited (not the same as the length at 50 percent selectivity). The Beverton and Holt estimator can be quite reliable if the assumptions behind the method are met, and if L_c is well-estimated.

The Powell-Wetherall (1979) method assumes that the shape of the right hand tail of a length frequency distribution will be determined by the ratio between the total mortality rate Z and the growth rate K. Unlike the other methods, it does not directly calculate an estimate of Z; rather it gives a series of estimates of L_∞ and the ratio K/Z. While it thus provides yet another means of estimating L_∞, it is a little more complicated to get estimates of Z with this method (see help file). Users should take particular care if the estimate of L_∞ implied by the Powell-Wetherall method differs substantially from those obtained by the SLCA, PROJMAT or Elefan methods. An estimate of Z should only be made from the predicted K/Z by dividing by K from one of these three methods, if the estimates of L_∞ are similar for both of the methods.

As noted above, each of the Z estimators report a standard error for the Z estimate based on the values obtained from the different samples, perhaps taken over 12 or 24 months. Users should note such standard errors will underestimate the true uncertainty in the parameters, due to the use of constant input values of K and L_∞. More realistic confidence intervals should be calculated by testing out a range of input values for K and L_∞.

7. Yield software

G.P. Kirkwood and D.D. Hoggarth

The "Yield" software estimates target and limit reference points with confidence intervals. The model extends the standard Beverton and Holt yield per recruit models by allowing for uncertainty in parameter inputs and annual recruitment rates, and by including a stock recruit relationship. With these extensions, Yield estimates equilibrium reference points for YPR and biomass per recruit, and for yield and biomass (including a deterministic stock recruitment relationship). With the additional uncertainty in future recruitment, the Yield "Transient" option also calculates a "risk-based" reference point as described below. Examples of Yield analyses are given in the software tutorials and help files. Summary information was given in Section 4.3 and further details are below.

7.1 INCLUDING PARAMETER UNCERTAINTIES

Two types of uncertainty are dealt with in Yield. They are:

- statistical uncertainty about the values of biological and fishery parameters; and
- uncertainty in the annual numbers of recruits arising from stochastic variability about the stock-recruitment relationship.

The first source of uncertainty affects all of the calculations carried out by Yield (both equilibrium and transient), but the second only affects the transient calculations.

The best potential source of variance estimates for Yield (e.g. for the growth and other parameters) obviously is data collected directly for the species and fishery concerned. For the *Lethrinus mahsena* analysis in the Yield tutorial, length frequency distributions and age at length data were collected for each of the main fisheries in the western central Indian Ocean. Estimates of von Bertalanffy parameters were obtained by non-linear regression analysis of the age-length data and using the Elefan method in LFDA on the LF data. The means and CVs used in the tutorial are the means and CVs of the 12 sets of estimates thus obtained. Since no reliable estimates of growth parameter uncertainty are available from any currently-used method for analyzing length frequency data, users may need to collect and analyze such multiple samples (across space or time).

Where no direct estimates are available, the FishBase database will often have recorded estimates of biological parameters for the species concerned or a closely related species. This should allow at least a rough idea as to appropriate mean values and likely ranges of values of the von Bertalanffy growth parameters, though good judgment needs to be applied when using data from related species (see help file).

The natural mortality rate is likely to be one of the hardest parameters to estimate. Pauly's (1980) empirical relationship and FishBase may again be helpful, but users should be aware that many of the values for M in FishBase have themselves been calculated using Pauly's equation. Unless estimates of M are available that are thought to be reliable, users are advised to use the Pauly's equation option available in the Yield software. This is better than entering a single value calculated using Pauly's equation because the uncertainties entered for the von Bertalanffy parameters are then used by Yield to induce further uncertainties in the value of M.

7.2 ESTIMATING EQUILIBRIUM PER-RECRUIT REFERENCE POINTS

Yield estimates equilibrium values of yield-per-recruit (YPR) and biomass-per-recruit corresponding to given values of the fishing mortality rate, F. Yield provides three biomass estimates that may be of interest: the equilibrium spawning stock biomass

(SSB) per recruit, the equilibrium fishable biomass (FishB) per recruit, and the equilibrium total biomass (TotalB) per recruit.

The equilibrium yield-per-recruit (YPR) and equilibrium biomasses-per-recruit are functions of two parameters over which the fishery manager in principle has control: the fishing mortality rate, F and the age at first capture, t_c (or the length at first capture, L_c). While the latter selectivity parameters can be varied by the user, the Yield outputs mainly focus on the variation in the indicators as a function of F, for constant user-specified values of t_c or L_c (see Section 4.3).

The YPR options in Yield provide distributions of the reference points F_{maxYPR}, $F_{0.1}$ and $F_{0.x}$ (where x is an alternative value to the commonly used 0.1, e.g. 0.2). While these YPR reference points are still frequently calculated, it is vital to bear in mind that their means of calculation effectively assumes that recruitment to the fishery remains unaffected, regardless of how low the spawning stock is. For example, it often happens that the maximum yield-per-recruit is taken at very high values of F (sometimes infinitely high values), but the SSB-per-recruit at these values of F may be extremely small relative to its unexploited level. This does not invalidate the calculated F that produces maximum yield-per-recruit, but it does suggest strongly that it may be extremely dangerous to allow fishing to occur at such levels, since the assumption of constant recruitment may be wrong. Because of this, whenever F_{maxYPR} or $F_{0.x}$ reference points are estimated, users are strongly urged to also inspect the histograms of SSB-per-recruit /SSB_0 to check that the reference F does not lead to SSB levels that are very low. Options are also available in Yield to directly calculate the fishing mortality giving a specified spawning stock biomass reference points (the ratio of exploited SSB to SSB_0). Depending on the selected value for the SSB ratio (e.g. 20 percent, 35 percent, see 3.5.3), the associated Fs may be much lower than F_{max}, and may also be lower than $F_{0.1}$.

7.3 ESTIMATING EQUILIBRIUM YIELD AND BIOMASS REFERENCE POINTS

While equilibrium yield-per-recruit reference points are frequently calculated and used when providing fishery management advice, they all suffer from the fact that they assume that recruitment is constant, regardless of how small the SSB becomes. For most fish species, this will be an unwarranted assumption. Equilibrium yield reference points get around this problem by including a specified stock recruitment relationship in the calculations. Equilibrium yield reference points that can be calculated include the values of F that produce a (deterministic) yield equivalent to the MSY, and that leave the population at user-specified levels of SSB, fishable biomass and total biomass, relative to their unexploited sizes.

For any given number of fish recruiting to the fishable population, the formulas given for calculating the equilibrium yield-per-recruit can be used to calculate the equilibrium yield, simply by multiplying the yield-per-recruit by the number of recruits. This of course leaves open the question as to how many recruits there are. This is governed by the stock-recruitment relationship (SRR), which relates the average spawning stock biomass (SSB) in the spawning season in one year to the number of fish that subsequently join the population in the year that those fish recruit to the fishery (see Section 3.1.6).

Yield includes options to estimate the numbers of recruits using a constant SRR or the common Beverton-Holt or Ricker SRRs. The Ricker form, most commonly seen in the context of salmon stocks, is generally thought to apply in circumstances where there is either substantial cannibalism or where there are restricted spawning areas. The Beverton and Holt form is more likely to apply in most cases. Whichever SRR is chosen, two alternative formulations are available in Yield. For each relationship, there is a generally accepted “standard” formulation using the “alpha” and “beta” parameters (see help files). If the user searches the literature for appropriate values of parameters for these relationships, it is likely that these will be estimates of the parameters for these standard formulations. Despite their familiarity, it is by no means a trivial task to calculate from the standard formulations exactly what unexploited levels of SSB or recruitment they correspond to. This is unfortunate, because in many cases rough estimates of these quantities (e.g. from surveys, or calculations of densities per unit area) may be the only information available on absolute stock sizes. Consequently, alternative formulations of these stock-recruit relationships are also available in Yield that allow the user to supply such other information.

For the Beverton-Holt SRR, in the alternative formulation, the user must enter the so-called steepness parameter. Some external information is available on typical values of this parameter, e.g. from the data collated by Myers *et al.* (1995), now included in FishBase. The second parameter is the maximum or unexploited number of recruits (R_0) (the equivalent biomass, SSB_0, may alternatively be entered). This parameter is, of course, entirely stock-specific. Small stocks will have a small maximum number of recruits; large stocks will have a large number. The actual number will be a function of the fecundity of the stock, the productivity of the waters in which it spawns, the size of the available spawning or nursery areas, and so on. Regrettably, such information cannot be gleaned from estimates obtained from related species, or the same species in different areas. In some cases, an abundance survey may have been carried out prior to or shortly after the fishery was discovered, which may provide estimates of the unexploited number of recruits or of the adult biomass. Alternatively, estimates are sometimes available of biomass per unit area (perhaps between certain depth ranges in which the stock is found), which can be used in conjunction with widely-available bathymetric information. Another possible approach is to choose a value for the unexploited number of recruits that produces a maximum sustainable yield that is of the same order of magnitude as the recent catches, or preferably, other estimates of potential yields.

Failing these options, there is little else to fall back on, and an educated guess may need to be made. Fortunately, the absolute values entered for the unexploited number of recruits do not affect the reference points for the fishing mortality rate, but only the indicators for the yields obtained. The results obtained will be simply proportional to the number of recruits entered. In terms of estimating fishing mortality reference points, R_0 does not need to be estimated with precision. However, in terms of estimating the MSY, it is clear that precise values are needed (see example help file for further details).

7.4 YIELD PROJECTIONS AND THE RISK-BASED TRANSIENT SSB REFERENCE POINT

7.4.1 Making non-equilibrium projections under variable recruitment

The options available under Yield's "Transient" menu allow the likely effects of inter-annual variability in recruitment to be investigated. For many fish stocks, these inter-annual variations in recruitment seem to dominate changes in recruitment brought about by changes in SSB. This can easily be seen when plots of annual numbers of recruits against SSB show a cloud of points with no clear relationship. It is, of course, possible that the apparent lack of a relationship results from imprecise estimation of numbers of recruits and/or SSB (see Section 3.1.6), but in many cases it is believed that the effect is a real one; roughly the same SSB can result in widely varying numbers of recruits. Where such a SRR is apparent, then clearly some doubts must be raised about the reliability of basing management on deterministic equilibrium calculations that ignore this inter-annual variability (such as both the "Equilibrium" YPR and Yield methods discussed above).

Yield's Transient analyses require information on the coefficient of variation (CV) of the inter-annual variability in recruitment. In many cases, this will be an elusive parameter. For *L. mahsena* in the Yield tutorial (example analysis), age frequency data were available for a number of years, and it was therefore possible, using an assumed constant value for M, to project backwards and estimate numbers at age 0 in a number of years. The CV of these estimates was 0.25. Estimates may also be possible using length-based cohort analyses if the stock is short-lived. Should such data not be available, then it should be possible to select at least a plausible value using the Myers *et al.* (1995) data in FishBase. Where the values are taken from such other sources, the sensitivity of the analyses to the CVs entered should be tested (see Section 3.6.4).

The first item on the Transient menu is "Yearly projections". These allow the user to examine the likely ranges of population and yield trajectories (and their confidence intervals) that would result from a specified future pattern of annual fishing mortality rates. Choosing alternative options for F in the forward projections can show the effects of inter-annual variability in recruitment, compared with what might have been expected based on the equivalent deterministic equilibrium calculations. In the example in Figure 7.1, the population starts at an equilibrium F of 0.17 and continues with this fishing pressure for the next for 20 years. At this level, the SSB/SSB$_0$ ratio (the middle right plot) stays at an average level of above 40 percent, with the lower 95 percent confidence interval also above 30 percent. If a higher fishing mortality is applied, say F=0.4 (still starting from the same initial F=0.17 equilibrium) as in Figure 7.2, the yield (top right plot) is higher in the first year but then drops down to a new equilibrium level. The mean SSB/SSB$_0$ ratio in this case falls closer to 0.2, with a lower 95 percent confidence interval closer to 10 percent.

For the Transient projections, account is taken of both the statistical uncertainty in the biological and fishery parameters and stochastic variability in annual recruitment. As for the equilibrium calculations, a specified number of simulations are carried out. In each simulation, a set of biological and fishery parameters is sampled independently from the specified probability distributions for the parameters. Forward projections are then carried out for the specified number of years, according to the specified time series of values of F. In each year, the numbers of recruits is sampled independently from a log-normal distribution, with a mean recruitment equal to that which would be predicted by the stock-recruitment relationship, and using the CV set by the user. Results are presented as plots of medians and confidence bands for the annual values of yields and biomasses, as illustrated in Figure 7.1 and Figure 7.2.

FIGURE 7.1
Example projections of fishery indicators as calculated using Yield's "Transient" menu option (example analysis data set for F=0.17)

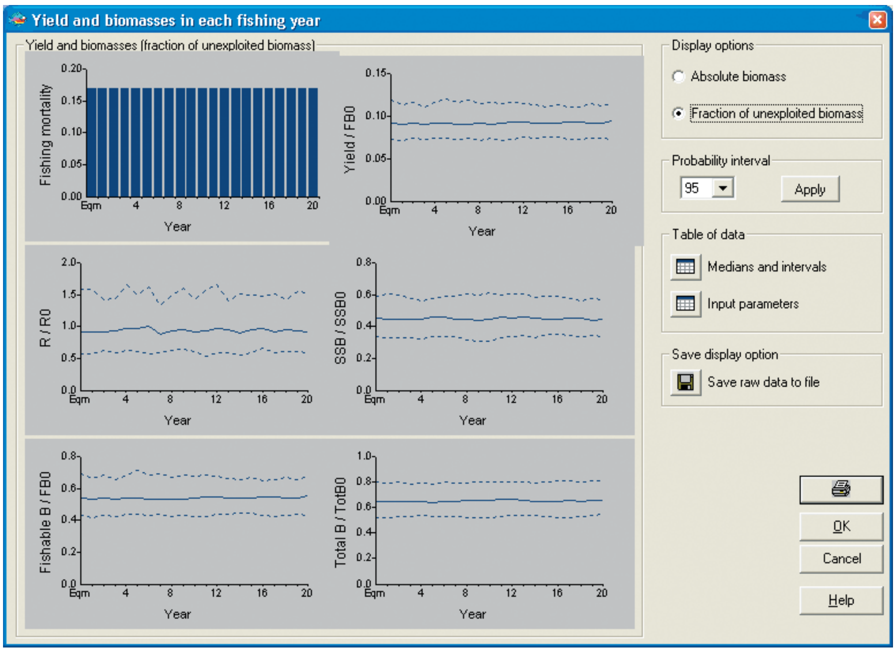
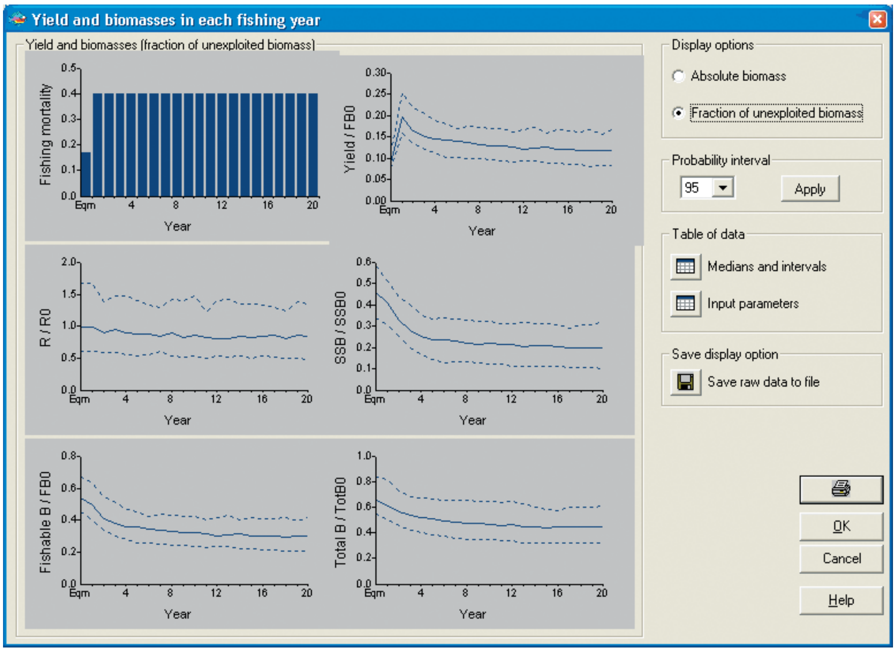


FIGURE 7.2
Example "Transient" projections of fishery indicators for *F*=0.4 from year 1 onwards



7.4.2 Estimating the Transient SSB reference point

Users will recall that one of Yield's equilibrium YPR reference points produces a value of the fishing mortality rate that would reduce the (deterministic) equilibrium SSB-per-recruit to a specified percentage of its unexploited level (e.g. 20 percent). An equivalent reference point can also be selected from amongst the equilibrium *yield* reference points. Such reference points are commonly used as limit reference points below which are "unsafe" levels of spawning stock sizes that expose the population to increased danger of stock collapse.

In fact, if the SRR chosen were really correct, and the stock is really at a deterministic equilibrium (as the above calculations assume), then there is really no danger at all of stock collapse. However, such a statement cannot be made if there is substantial inter-annual variability in recruitment. The chance occurrence of several bad recruitment years in a row thus has a real risk of pushing the stock below the limit reference point and into the "high risk" region. The Transient SSB reference point attempts to quantify this type of risk. If the recruitment variability is substantial, then the values of *F* estimated for the Transient SSB reference point will be substantially less that those for the equilibrium points.

Yield's Transient SSB reference point is that value of *F* that leads to a specified low probability that the relative SSB will fall below a specified "danger" level during a forward projection. To estimate this point, the user must specify three parameters. Firstly, the "danger" level is set as the threshold (limiting) SSB, entered as a percentage of the unexploited SSB_0 (say 20 percent). Secondly, the probability must be entered (say 10 percent) that the SSB will fall below this threshold level. This is where the managers specify the level of risk they are prepared to accept that the SSB may fall into the danger zone. Thirdly, a number of years must be entered (say 20) showing the period over which the projection will be made.

With these inputs, Yield then estimates the Transient SSB reference point by iteratively testing out different values of *F*, making 100 runs[18] for each value, and

[18] The default number of simulations is 100 but this value can be changed by the user. Using a higher number of simulations will increase the time taken to estimate the Transient SSB reference point.

recording the number of runs in which the threshold was broken. Each run uses a different simulated set of biological and fishery parameters. For very low values of *F*, for most of the 100 sampled data sets, the relative SSB levels will remain comfortably above 20 percent with probability equal to or near 1 for each year of each simulation. For high enough *F*, however, the relative SSB will drop below the 20 percent level very frequently. The Transient SSB reference point as defined above will eventually be found as the value of *F* that leads to a probability of 0.1 that the relative SSB will fall below 20 percent of its unexploited level during the forward projections of 20 years. In other words, Yield will give the value of *F* that results in 10 out of 100 of the simulations breaking the defined threshold.

Ideally, one would wish to do this calculation separately for each set of biological and fishery parameters that was sampled from the probability distributions specified by the user, and then to present the results in the form of a histogram, similar to those for the other reference points. Since this would take a very long time, only a single value of *F* is calculated for the Transient SSB reference point.

8. CEDA software – Catch Effort Data Analysis

G.P. Kirkwood and D.D. Hoggarth

The CEDA package developed under FMSP projects R4517 and R5050CB allows for the fitting of surplus production models (e.g. the Schaefer model), indexed recruitment models and depletion models, using catch, effort and/or abundance data. Such models may be used to estimate a range of intermediate parameters (e.g. N_0, K, r and q as listed in Table 4.8), indicators (historical and current stock sizes), and reference points (e.g. the maximum sustainable yield, MSY, and the replacement yield). The CEDA program is based on the standard dynamics of the models, but uses non-equilibrium fitting methods and three different error models. The help files produced for the software package describe the use of sensitivity analyses and diagnostic facilities to find reasonable ranges of model fits where input parameters are not well known. CEDA may also be used to make projections of the stock size into the future, under various scenarios of catch or effort levels, so that different management strategies can be investigated. Bootstrapping is used to estimate confidence intervals, both for the parameter estimates and the projections.

Section 4.5 described the basic operation of the CEDA software. Extensive guidance and technical details are also available in the software help files, including two tutorials describing the step by step analyses of real data sets. This section provides more technical details on some aspects of CEDA. The reader is referred to the software help files for full details and references etc.

8.1 THE CEDA MODELS

CEDA offers six population dynamics models (see Section 4.5.1):

- no recruitment (Leslie depletion model with constant natural mortality rate);
- constant recruitment (modified DeLury with recruitment and natural mortality rate constant and related by an equilibrium assumption);
- indexed recruitment (modified DeLury model with an index of relative recruitment); and
- three stock production models (the Schaefer, Fox and Pella-Tomlinson forms).

The six models make different assumptions about natural mortality and recruitment as described in 4.5.1. The equations and references for each of the models are given in the Technical Appendix help files. Since different authors have used different interpretations of the parameters r, K and z, any reference points such as MSY should only be calculated using the forms of the equations given in the Technical Appendix.

All of the CEDA methods assume that the data refer to a single discrete stock, i.e. a population without any significant immigration from or emigration to other populations not covered by the data. The depletion models include both a population dynamics sub-model (e.g. $N_t = N_1$ – Sum(Catches)) and an "observation" sub-model defining the relationship between population size and the abundance index used. CEDA assumes that the index (e.g. CPUE) is simply proportional to the stock size, according to the catchability q, at least over those time periods where the assumption is believed to hold (see help files describing the removal of data points outside these times). Other more complex assumptions can also be made, as can models for open population depletion estimates with recruitment over several years (see e.g. Hilborn and Walters, 1992, chapter 12 etc). As more assumptions are relaxed, the simpler depletion models are gradually transformed into the "deterministic recruitment/production" (DRP) biomass dynamic models (the last four in the above list).

All of the CEDA models are fitted using "observation error" methods. This means that the models assume that the residual errors are all in the relationship between the true abundance and the index used. Alternative "process error" methods are also available that assume the errors are due to the equations governing the changes in biomass, but these are usually less reliable and less flexible (see Punt and Hilborn, 1996).

Provided suitable data are available, all of the CEDA models can be fitted using three different observation error models: Normal (least squares), Gamma, and log-Normal. CPUE (or whatever relative abundance index is used) is assumed to be directly proportional to population size, with a constant catchability coefficient, q. The three error models deal with the measurement errors in the catch component of CPUE, or, if a single abundance index is being used, in the abundance index itself. The main differences between the error models lie in their assumptions about how the size of the residuals are likely to change as the expected value of the catch changes, i.e. with changing effort and population size; and in the degree of skewness in the residuals. The best form of error model for each data set may be found by examining diagnostic residual plots as described below. Fitting methods (least squares or maximum likelihood etc) differ depending on the error models used (see help files for details). If relative abundance index data (for instance, from surveys) is used in place of CPUE data, and estimates of the variance in each year are available, then a weighted Normal fitting procedure can also be used. Further details on the implications of the different error models and the fitting methods used are given in the Technical Appendix help files.

As described in standard fisheries text books, DRP models can be estimated in a range of different forms. Different values of the parameter z (sometimes denoted p) of the Pella-Tomlinson model give different shapes to the surplus yield vs biomass curve, including the Schaefer and Fox forms (found at $z = 1$ and $z = 0$ respectively). The Pella-Tomlinson model thus gives flexibility in the form of the model (skewed to the left or the right) but it is frequently very hard to fit the extra parameter z. Rather than estimating z from the data, as did Pella and Tomlinson in their original work, CEDA requires the value of z to be specified by the user. In some cases, it may be possible to decide on biological grounds whether the production function should be left or right-skewed (see help files). Where this is not possible, a simpler Schaefer or Fox form should be used, or a sensitivity analysis approach should be used to determine the effects of different assumed values of z, as described in the CEDA "Guide To Fitting Models" and the tutorials. Hilborn and Walters (1992, p304) suggest that "there are few if any data sets on real fish populations for which one can realistically estimate the asymmetry of the production relationship" (i.e. z).

All of the CEDA methods except the "no recruitment" depletion model also require an input to be made of the initial stock size as a proportion of the unexploited biomass or carrying capacity. In CEDA, this is known as the "initial proportion". If catch data are available back to the earliest days of the fishery, the initial proportion may reasonably be set at 1, implying $B_0 = K$. It may also be possible to estimate the starting biomass, B_1 iteratively from the estimated catchability (i.e. $B_1 = C_1 / f_1 q$). However estimated, it is advisable to assess the sensitivity to this and any other parameters as described below.

Since CEDA constrains the initial proportion to values between 0 and 1, it is assumed that the stock was always either at or somewhere below the carrying capacity at the start of the data series. Since fish populations fluctuate naturally, it may be possible for B_1 to have been above the long-term average K at the start of the data set (especially if data are available from the very start of the fishery). Some biomass dynamic models (e.g. the BIODYN spreadsheets of Punt and Hilborn, 1996) can be formulated to allow the first data point B_1 to be greater than K. It may however be argued that an initial biomass anything above normal random variations in K would imply a breakdown in the model. Unexplainably high values of B_1 may thus imply a regime shift in the stock dynamics and may be better modelled with a variable-K formulation (not available in CEDA), or an indexed recruitment model.

8.2 GUIDE TO FITTING MODELS

CEDA's "Guide to fitting models" help files outline the general statistical principles that should be followed when fitting models to data, with specific reference to depletion models. Among other topics, the help files provide guidance on making sensitivity analyses, fitting confidence intervals, using non-linear minimization routines, interpreting residual plots and goodness of fit statistics, and dealing with outliers and influential points. Some of these materials are summarized below. The two CEDA tutorials also demonstrate how a step by step approach should be used to find a range of well-fitting models, noting that there will usually be considerable uncertainty in some of the inputs.

8.2.1 Sensitivity analysis

The single most important point to remember when fitting models to data is: always investigate the effect of varying the model assumptions when there is uncertainty about what is correct. Remembering the precautionary principle, it is better to be honest about the uncertainty in the results than it is to be wrong. The process of checking the sensitivity of the results to the model assumptions is called sensitivity analysis.

Sensitivity analysis can apply at different levels. At the top level, it means trying several different population dynamics models, for instance the three production models and the constant recruitment model, if there is no good reason to prefer one over the others. At the next level, it could mean trying different sets of data: for example, different abundance indices, or catch data with different guesses at missing values. At the more technical level, it means using different error models, including or excluding influential points, and using different values for user-supplied parameters which are imprecisely known, such as the natural mortality rate and the initial proportion.

The problem with this kind of analysis is that a wide range of results (i.e. parameter estimates and projections) can build up, making it difficult to draw clear conclusions. One possibility is to use goodness-of-fit measures to decide which of the results to keep and which to discard, as described below. Judging models by eye using residual plots is equally important. If it is found, for example, that fits using M=0.1 are always much better than those using M=0.2, whatever the values of the other variables, then the latter set of results may reasonably be discarded. Efforts may however be made to find the upper limit of reasonable M-values, by trying M=0.15, etc. Sometimes certain combinations of assumptions will perform very badly; for example, the data may be well fitted by a Pella-Tomlinson production model when both M and z are high, and when M and z are both low, but very poorly when one parameter is high and the other is low. If so, only the combinations that work should be kept.

There is another obvious guideline. If very similar results are obtained when varying one assumption over its "reasonable" range, then the results are said to be insensitive to that assumption. There is then no point in continuing to consider model assumptions at both ends and in the middle of a range if all three give similar results.

After throwing out combinations of assumptions that fit the data badly, and keeping just one set when results are insensitive to an assumption, there may still be a wide range of possible results. Unless there are other good reasons to reject some assumptions or combinations of assumptions on biological grounds, or for reasons not connected with the current data set, nothing further can be done about this. The remaining uncertainties must be presented to managers in decision tables (see Section 3.6.4). However, the sensitivity analysis process will still have been useful in establishing at least two things: firstly, upper and lower bounds on parameters and projections (see the section below about confidence intervals), and secondly, the assumptions to which the results are most sensitive. If the value of M turns out to be the critical factor in deciding whether the unexploited stock size is actually 1 000 tonnes or 1 000 000 tonnes, then it could be more important (and cost-effective) to direct research effort towards getting a better estimate of M than to, say, improve the precision of the relative abundance indices.

Many of the issues raised above can be incorporated into data analysis in a more formal and logical way, using Bayesian statistical techniques (see Hilborn and Walters, 1992, and Section 4.6 for examples). Such methods are particularly useful when making decisions on areas where research should be concentrated, and when trying to make the most effective use of data from outside the current set, e.g. a range of estimates of M. This area is beyond the scope of CEDA.

8.2.2 Choosing the right model

In fitting models, the first step is to start with the right basic model. Usually the choice will be limited by the data available (see Table 4.7) and the objective of the analysis. There are two main situations in which a choice may need to be made between alternative possible models. Firstly, if annual data are available in both weight and numbers without a recruitment index, then either a production model or a constant recruitment model may be fitted. Secondly, if a production model is selected, there is then a choice of the three production functions (Schaefer, Fox and Pella-Tomlinson). In both cases, if there are any really strong reasons why one model should be the most appropriate on biological grounds, then it should be used. Otherwise, all possible models should be tested. If one model gives a noticeably worse fit to the data than the others (using the criteria discussed below), or gives ridiculous parameter estimates, then it may be rejected. If one model fits especially well, it alone may be selected. Usually, however, all or most of the DRP models will perform almost equally well (or badly) when fitting data. If the parameter estimates and projections produced by all reasonably fitting models are similar, then it is evident that the results are not dependent on any one particular set of un-testable biological assumptions. If the results show significant variation, then it is important to show the full range when presenting them to managers.

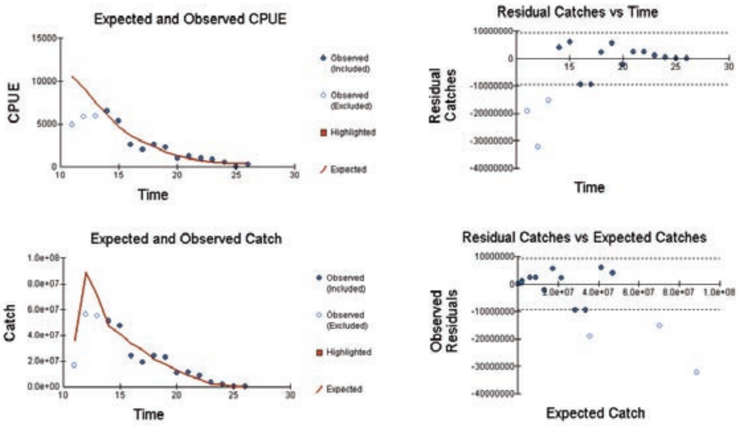
8.2.3 Model diagnostics – residual plots

CEDA's diagnostic facilities provide ways of deciding whether the model being used fits the data satisfactorily and how well the assumptions of the model are met. CEDA provides a range of diagnostics whenever a new model is fitted. The most important diagnostics are the "residuals" graphs of the observed and expected values of catch and CPUE. A "good" residual plot, indicating no major violation of model assumptions, should show points evenly scattered in a horizontal band. Residual plots can be "bad" in three main ways. They may show trends, or runs of consecutive points consistently on one side of the horizontal axis indicating that the model being tested does not fit the data well. Secondly they may show unbalanced distributions of points indicating that the wrong error model is being used. The third type of "bad" residual plot is one that reveals an outlier as described below. Illustrations of good and bad residual plots are shown in the help files.

In the example residual plots in Figure 8.1, based on the squid tutorial data set, three of the data points (the open circles) have been temporarily removed or "toggled out" of the analysis. This is a useful feature of CEDA, but it should be used very carefully. There should always be a good reason for leaving out data from the analysis, in this case because the low points early in the series were believed to be due to the gradual recruitment of squid into the fishery as the season began. Data should not be left out just because they do not appear to fit in with the expected results. If data are left out without good reason, the results might look good but be dangerously misleading. With the three low points toggled out, the remaining points in the residual plots are scattered in reasonable horizontal bands. Two of the points (not including the three eliminated open circles) now fall on or below the lower horizontal dotted lines plotted at the 95 percent confidence intervals for the data. These are discussed in the squid tutorial as potential outliers (see below), but in the end were kept in the analysis.

FIGURE 8.1

Illustration of CEDA fits (left) and diagnostic residual plots (right) for the squid tutorial data set after removing the first three data points, considered low due to incomplete recruitment early in the season



Residual plots are an invaluable tool in data analysis. However, they cannot detect everything. For example, gradual changes in catchability will not be apparent. Also, it is usually difficult to say anything at all from a residual plot with very few points.

When working with the diagnostic graphs it can be useful to know where a data point on the Observed and Expected Catch graph is to be found on the residual plots. CEDA therefore offers the ability to highlight any given data point as a red square simultaneously on all of the diagnostic graphs, allowing the user to decide whether or not the point might be an outlier or a candidate for exclusion. This is particularly useful for the plot of Residual Catch vs Expected Catches, which does not share the same X-axis as the time-series plots (see Figure 8.1).

8.2.4 Outliers and influential points

Outliers in a data set fitted with a particular model are observations that would be extremely unlikely to occur if the model is correct. The main way of detecting outliers is by examining the residual plots as mentioned above. An outlier is a point that lies a "long way" from the X-axis (or the "0.5 line" on the percentile plots used for the gamma function) relative to the other points. The definition of a "long way" depends on the probability of accidentally labelling a perfectly good data point as an outlier. CEDA draws reference lines that should include 95 percent of all of the points in an average sample. If, for example, there are 100 data points, around 5 of them should be expected to fall outside the guidelines even if there are no true outliers in the set. In general, any points that are far outside the 95 percent reference lines should be examined as possible outliers.

The occurrence of an outlier indicates that there is probably a fault with either the model or the data. Because one single outlier can completely distort a fit, leading to poor parameter estimates with wide confidence intervals, any apparent outliers should be subjected to further scrutiny. If an outlier occurs with a model that seems to fit the other data well, the first task is to investigate the offending point. The problem could be caused by unusual conditions at that time or by measurement errors in the abundance index, catch data, recruitment index, or even the mean weight. If conditions were anomalous that year (e.g. unusual sea temperature), then the point should be excluded from analysis.

If the abundance index is likely to be at fault, perhaps due to a very small effort and consequently a small sample on which to calculate CPUE, or due to an unusual distribution of effort in space or time, then it is again reasonable to exclude the point. If the problem is due to sample size, another approach might be to try to obtain an estimate of variance for each abundance index, and use the weighted least squares fit; the point based on the small sample would then automatically be down-weighted. Other possible reasons for outliers and what to do about them are discussed in the help files. It is re-emphasized that data points should never be omitted from the analysis unless there is a good reason to do so.

The CEDA help files also describe how to deal with "influential points", that is, points whose presence or absence in the data set makes a large difference to the results obtained. An influential point is not (necessarily) the same thing as an outlier.

Influential points tend usually, but not invariably, to lie near the extremes of the data set, i.e. near the lowest and the highest stock sizes, where they exert a strong pull on the fitted models. Potential influential points can often be identified from plots of residuals against expected catches: they will be the ones corresponding to isolated large or small expected catches, usually with small residuals. If a point is suspected as influential, it can easily be checked by toggling it out and seeing if the parameter estimates change substantially.

The data for an influential point should be carefully scrutinized, just as for a potential outlier. If there are serious data problems, then the point should be dropped from subsequent analysis. If not, then sensitivity analysis should be used to determine the effects of including or excluding the point. It is definitely wrong to exclude an influential point and then forget about it, as one might for an outlier; the results will then be biased and the precision of the estimates reduced.

8.2.5 Model diagnostics – using the "goodness-of-fit"

Numerical measures of goodness of fit (GoF), such as the well-known coefficient of determination, *R*-squared, are often quoted as evidence of how well a model fits. This is only meaningful for data that accord with the model assumptions, i.e. where the residual plots show no trends or patterns. The *R*-squared statistic is calculated by CEDA but should only be used in comparing fits that both use the same error model. Each error model has a corresponding GoF defined in a distinct way. Therefore, it is not possible to use GoFs to compare fits based on different error models; these should be done with residual plots alone. Under a fixed error model, there are two allowable types of comparison: between different model assumptions when fitting the same data, or between the same model assumptions when fitting "similar" data. Some types of data comparison are more reliable than others, and three examples are given below:

1. The best type of comparison is between different sets of catch or recruitment index data with the same number of points, used to fit the same abundance data. This will not be a very common event, as different catch series should only occur if some values are missing and have been filled in by more than one method.
2. It is also reasonable, but less statistically sound, to use *R*-squared when comparing fits using different series of abundance indices, again of the same length and with missing values, if any, at the same points. The comparisons should not be taken too literally. Graphs of observed and expected values of different abundance indices can often reveal more useful information.
3. It is not reasonable to use *R*-squared to compare two series of different lengths, or with missing data and/or points deliberately excluded in different places.

Subject to the above constraints, *R*-squared (or its analogue for the gamma and log-transform fits) is a useful tool for comparing fits. Rather than following the approach of some packages in using "tests" of dubious validity for deciding when a fit is acceptable, users of CEDA are encouraged to make such decisions by the careful scrutiny of graphs and the application of common sense. Seemingly "high" *R*-squared values should not be trusted if the evidence of the residual plots shows that the fit is in fact poor.

8.2.6 Finding point estimates using non-linear minimization

For many of the population dynamic models used in CEDA, estimates of the parameters are calculated using numerical non-linear minimization techniques. As described in the Technical Appendix section, this is done using a version of the "Simplex" method. The method makes a number of iterative steps, changing the values of the parameters to be estimated and evaluating the function to be minimized, trying to move "downhill" all the time. As the minimum of the function is approached, the step sizes in the parameters (i.e. the amount by which they change between iterations) tend to get smaller and smaller, as do the differences between function values at successive iterations. The minimization process is deemed to have converged when either, or preferably both, the step sizes in the parameters and the function values are sufficiently small. Guidance is provided in the help file on the options in CEDA for judging when minimization has occurred. CEDA provides an option to view the minimization tracks graphically, similar to the plots provide in LFDA (see Figure 6.1). Such plots can be quite useful in showing the strong correlation between K and r in production models. CEDA also allows users to manually set the starting values for the minimizations to ensure that a consistent global minimum is reached. Starting values can also be fixed, e.g. to find the best value of K for a fixed value of r or vice versa. This facility can be useful with poor contrast data sets, where the automatic minimization may converge on unreasonably high values of K or r. Values of r above about 2 imply unreasonable "chaotic" solutions (see Haddon, 2001, p35).

8.2.7 Fitting confidence intervals

One of CEDA's most useful features is the generation of confidence intervals (CIs) for the estimated parameters. The single value obtained for each parameter is known as a point estimate. Because data are never measured exactly and models are never a perfect description of the real world, these estimates will be in error to a greater or lesser extent. The probable magnitude of this error can (and should) be estimated using the discrepancies between the observed and expected values of the data, in terms of the CIs of the parameters. CIs can also be applied to quantities that depend on estimated parameters, such as projections of future stock sizes. They may be fitted for each set of model assumptions that fit the data well enough to survive the sensitivity analysis stage. There is no point in generating CIs for models that fit relatively badly.

It is always preferable to make decisions on the basis of CIs rather than on the point estimates alone. Suppose, for example, that a strategy of subsidizing increased fishing effort on a stock is under consideration, and some idea of the stock size is required to fix the desired level of effort. It would be irresponsible to base the decision about effort levels solely on a single point estimate for stock size; there might be a 20 percent or greater chance that the stock would actually be too small to support such a level of fishing, and would collapse. By examining CIs, the actual risk of this bad outcome could be investigated and an effort level selected, as appropriate to the manager's risk tolerance.

CIs are also useful for deciding whether two different analyses give similar results, for instance when conducting a sensitivity analysis. It may be wrong to conclude that two methods are giving inconsistent results just because the point estimates appear to be "far" apart, since the confidence intervals may actually show considerable overlap.

This kind of check can cut down on the number of different model assumptions one needs to consider at the end of a sensitivity analysis.

CEDA uses a method called bootstrapping to estimate CIs, as explained in the help files. Bootstrapping works by using the set of discrepancies between observed and expected values in the original data to simulate new data sets, or resamples. For each resampled data set, the parameter estimation procedure is repeated. After 1 000 resamples have been simulated, there are 1 000 estimates of, say, initial stock size. Figure 4.7 showed the histograms of estimates of *K*, *r*, *q* and MSY generated by CEDA in this way, within the 95 percent CI boundaries (wider histograms can be plotted by specifying wider CIs).

The size of a CI is related to the probability that the interval contains the true value. It is for the fishery manager to decide whether a 75 percent, 90 percent, 95 percent, or some other CI is appropriate; the choice depends on what level of risk (that the true parameter value will lie outside the CI) is deemed acceptable. CIs can also be two-sided, upper or lower. A two-sided 90 percent CI for, say, the initial stock size is a pair of numbers which defines a range of values of initial stock size which has a 90 percent probability of containing the true initial stock size. CEDA requires inputs for both the upper and lower limits of the CIs and can thus provide either equal-tailed or unequal-tailed CIs. Entering 0.975 and 0.025 for the two limits provides a 95 percent confidence interval. Entering 0.1 as the lower level for the confidence interval range (regardless of the upper level entered) would produce a lower value of MSY with only a 10 percent chance that the true value might be even lower. This would be the value of MSY where 100 of the 1 000 resamples gave a lower result, i.e. the 10th percentile of the bootstrapped distribution of MSY as shown in Figure 4.7.

If a sensitivity analysis has produced a wide range of acceptable point estimates for a particular parameter, CIs should be estimated for the parameter using (at least) the two models that gave the most extreme point estimates. This will of course give two different CIs for the same parameter. The best approach to finding a combined confidence interval would be to use the Bayesian techniques described in Section 4.6. Where this is not possible, a reasonable alternative for, say, a two-sided 90 percent interval is to use the highest upper limit and the lowest lower limit. This will lead to a conservative CI, with a coverage probability likely to be rather more than 90 percent. If the range of model assumptions considered is wide, then the combined CI can be very conservative. In this situation, it may be considered reasonable to reduce the size of the individual CIs to compensate.

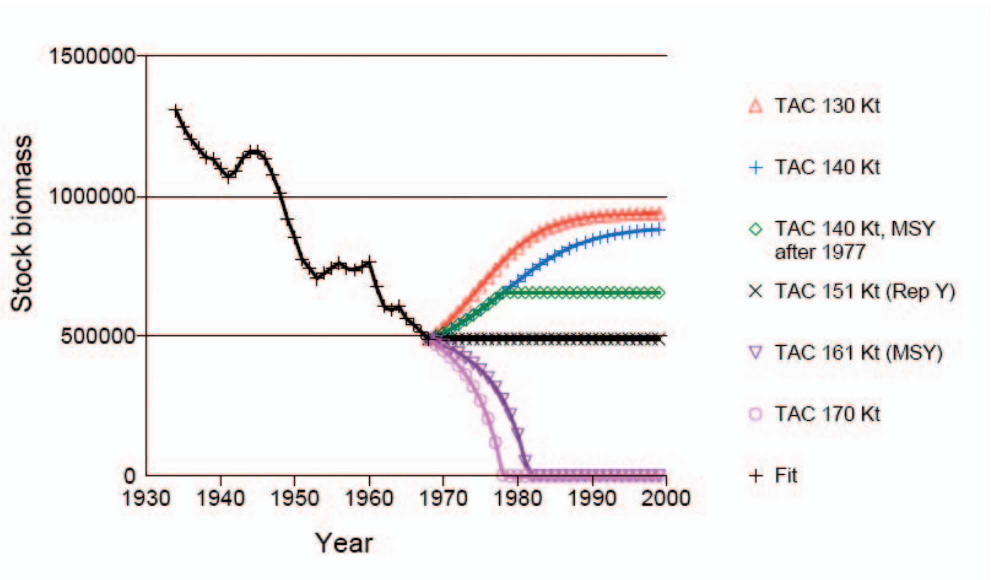
8.3 MAKING PROJECTIONS IN CEDA

A population projection in CEDA is made by applying a selected population model and its estimated parameters to a user-defined scenario of future catches or effort levels. CEDA allows multiple scenarios to be entered and plotted on the screen at the same time for comparison. Scenarios may be entered for three different types of future fishing strategies as appropriate to the different CEDA models. Future catch weights (e.g. set as total allowable catches or TACs) may be entered for the production models; future catches in numbers may be entered for all of the other number-based models. Future fishing effort levels may be entered for all models, though this will only be appropriate if the effort refers to the total catch taken (i.e. not where a "partial" catch effort series is used to compute the abundance index).

Each CEDA scenario consists of a column of either catch or effort data running as far into the future as required (providing the total number of data points, including the original data set, does not exceed 200). Effort or catch levels can be changed between years to evaluate the impact of "stepped" policies on the stock size. Names can be given to each scenario to aid identification, and scenarios may be saved with the dataset for future analysis.

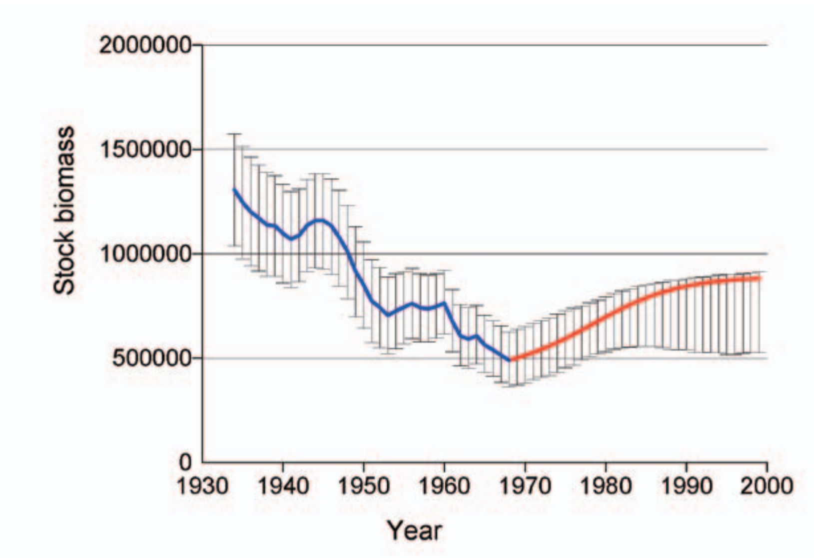
An example of CEDA's projection facility is given in Figure 8.2, based on the tuna tutorial data set, as fitted with a Schaefer production model back in Figure 4.6. It may be remembered that fishing between 1934 and 1967 was estimated to have reduced the stock size from the initial biomass (here assumed equal to the carrying capacity, *K*) of just over 1.3m tonnes, to a 1967 level of just under 500 000 tonnes. This stock biomass was well below the estimated B_{MSY} (=K/2) of 650 000 tonnes. The MSY catch was estimated as 161 000 tonnes. The projections show that future TACs of 130 000 and 140 000 tonnes would have allowed the stock biomass to rebuild up to levels above B_{MSY} over several years. Taking the estimated "replacement yield" of 151 000 tonnes would, as expected, maintain the population at the 1967 level of 500 000 tonnes. Taking the MSY catch of 161 000 tonnes would actually cause the population to decline to zero over about 15 years since such a catch would not be sustainable at the starting 1967 stock sizes that were below the biomass, B_{MSY}, necessary to give the MSY. Taking an annual catch of 170 000 tonnes would cause an even faster decline (see Figure 8.2). Taking a catch of 140 000 tonnes for 10 years up to 1977 would in theory have allowed the biomass to rebuild to B_{MSY}, after which the MSY catch of 161 000 tonnes could have been taken sustainably.

FIGURE 8.2
Stock biomasses as predicted by CEDA's projection facility, for the tuna tutorial data set (1934 to 1967; see also Figure 4.6), for a range of alternative TACs projected from 1968 to 1998



Each CEDA projection is deterministic, as illustrated in Figure 8.2. However, if confidence intervals (CIs) have previously been generated for the model being projected, then CIs can also be produced for the projections. Multiple projections are then made using each set of parameter estimates from the bootstrap resamples, and distributions of population sizes at each point in future are obtained. Fifty percent confidence intervals for the stock projection with a TAC of 140 000 tonnes are shown in Figure 8.3. The bars show that there is less than a 25 percent chance (the lower percentile of a 50 percent CI) that the stock biomass should fall below 50 000 tonnes after returning to equilibrium levels in the future. Different TACs and confidence intervals could be tested to find selected precautionary reference points based on specified limit reference points (e.g. the B_{MSY}) and risk tolerances (e.g. a 10 percent risk that biomass after a certain year will be below B_{MSY}) (see Section 2.5.4).

FIGURE 8.3
Stock biomasses with 50% confidence intervals from CEDA's projection facility, for the tuna tutorial data set, for the 140 000 tonnes TAC from projected from 1968



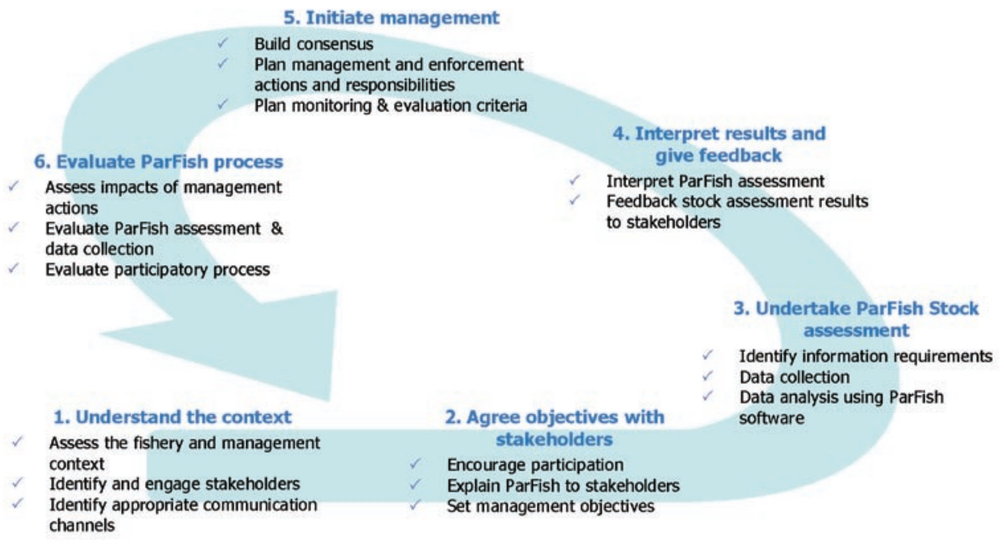
9. ParFish – Participatory Fisheries stock assessment

Paul Medley

9.1 INTRODUCTION

The ParFish approach provides a framework for participatory stock assessment and co-management. In this approach, fishers are actively involved in the management process, and their knowledge may be incorporated into stock assessments alongside more conventional fisheries data. As illustrated in Figure 9.1, the ParFish approach begins with guidance on understanding of the context (Step 1) and setting objectives (Step 2). It then goes on to provide tools and techniques for data collection and stock assessment (Step 3) and to support communication of the results to the stakeholders and the development of management actions (Steps 4 and 5). The final stage (Step 6) is to evaluate the ParFish process to provide feedback and guide future management efforts.

FIGURE 9.1
The ParFish approach



The final outputs of the ParFish process can include:

- improved fisher understanding of the concepts of fisheries management;
- greater involvement of fishers in the management process; and
- agreed management options including control levels, monitoring plans and pilot schemes.

Although ParFish is being developed by the FMSP as a general co-management system, this section looks in detail at Step 3, how the stock assessment is carried out within this participatory framework. More detailed information on the other steps will be provided in a toolkit, and the software manual will provide step-by-step guidance on carrying out the analysis. These tools will be made available shortly at http://www.fmsp.org.uk/.

9.2 BACKGROUND

Small scale fisheries require agreement and co-operation to achieve management objectives. Methods that rigorously capture stakeholder knowledge, objectives and preferences have been generally unavailable in fisheries. However, these are now recognized as being of central importance in establishing successful management.

Although meetings among fishers using participatory approaches can produce better co-operation, any decisions made still need to be informed by scientific advice regarding the status of the fisheries resources, and the consequences of following different management alternatives. The absence of good advice balancing risks and benefits may lead to overfishing and economic hardship. In this context, science can be seen more as a form of independent arbitration among fisher opinions, not as a way of dictating management decisions.

Bayesian statistical methods are particularly well adapted to dealing with situations where there is a lack of good sci.entific information, because they deal with uncertainty in a consistent and rigorous manner. Existing assessment methods often demand detailed time-series of catch and effort data. Expensive data collection activities are inappropriate for many small scale fisheries, and collecting many types of data is often beyond the capability of countries operating under severe financial constraints. While these data should be used where they are available, their absence should not prevent stock assessments and management advice.

A participatory stock assessment method has been developed to address these needs. It applies Bayesian decision analysis, using non-parametric robust statistical techniques and interviews implementing a multi-attribute decision-making method. The analyses can be conducted using specially written software.

ParFish applies standard stock assessment models, but uses new techniques and methods to make the assessment more flexible. The ParFish approach has four distinct differences compared to other approaches:

- The fishing community's views can be incorporated into the stock assessment by using information gathered through interviews. Even if these beliefs are considered unreliable, there is considerable political advantage in involving fishers in an assessment where they can see that their views are being taken into account. It is arguably necessary if co-management is being applied.
- Data can be combined from many sources, and in particular, rapidly collected data can be used as a starting point for an adaptive management system.
- The method applies decision analysis, making use of utility (a measure of the stakeholders' preference for an outcome) and risk to help in deciding management actions. This means the method can be used to give advice even when only limited information is available.
- The method can use any information source as long as information can be reduced to frequencies of possible parameter values for a target simulation model. A number of Monte Carlo techniques are available for producing such frequencies. Separating sources also allows information to be built up from simpler sub-models, making the whole process easier.

9.3 OVERVIEW

The ParFish method allows complex information sources to be organized into a hierarchy describing a target fishery model that is then used to assess fishery controls. Controls are assessed on the basis of the changes in catch rates that they are expected to produce in the fishery over time. Fishers are separately asked to rank and score possible outcomes on their catch and effort in terms of their preference, thereby allowing the assessment to identify the control yielding the greatest preference score. Altogether, this allows information from many sources to be combined, and in particular involves fishers and their community in the stock assessment process.

Information on the fish stock state and behaviour is reduced to sets of parameter frequencies. The parameters are defined by the target simulation model that is thought to represent the possible projected behaviour of the fishery. As long as information can be reduced to a frequency of one or more of these parameters, it can be used in the model.

Parameter frequencies may be generated in a number of ways, including direct draws from a probability distribution (e.g. Markov Chain Monte Carlo), interviews and empirical bootstrapping. The last two are supported within the software. However, complexity in data interpretation often requires non-standard models which generally cannot be supported in simple software. Therefore the software also supports the loading of previously-generated frequencies from Microsoft Excel.

Current components which are supported in the software consist of:

- An interview to get subjective belief from fishers or other persons with relevant knowledge.
- The use of fishing experiments and non-destructive survey methods (such as visual census).
- The use of any catch-effort based stock assessment models and data.

Any number of such frequencies can be combined to produce a posterior probability density function. Sets of parameters can then be repeatedly drawn at random from this posterior and used in the target simulation model to project changes in catch and effort in response to different controls.

Each outcome, a catch effort time series, is converted to a utility score using the relative preference information from the fishers. By ranking and scoring these scenarios it is possible to estimate how much better or worse a fisher would think any particular outcome is compared to the present.

One or more variables under management control must have been identified which have an impact on the objective. For example, in many fisheries the numbers of fishers or fishing days could be limited, whereas catch could not. Fishers or fishing days would be the appropriate control variable. Possible controls are limited to closed area, and catch and effort controls in the current software.

The target and limit reference points are defined in terms of the management control (the action to be taken by management) and should be chosen to be consistent with the management objectives. The main objectives currently supported by the assessment methodology are:

- To maintain fishing so that the probability that the biomass falls into an overfished state is at a particular level. The definition of "overfished" is defined by the limit state, and would be set to 50 percent of the unexploited biomass in most cases. The probability is a measure of management's risk averseness policy.
- To move fishing activity to a target level of fishing which has the highest expected preference for the fisher community based on the current uncertainty (the "Bayes action"). Management may change issues such as whether and how they weight fishers' opinions. They may also set a policy discount rate.

It is important to note that the optimum decision is not the same as a prediction for the outcome. The prediction is represented by the probability distribution, which may be very uncertain. The method chooses the optimum action based on this uncertainty, so if the decision-makers are risk-averse, actions are taken that will tend to avoid the worst outcomes rather than just assume the expected outcome.

9.4 THE TARGET SIMULATION MODEL

Simulation models are used to provide management advice through investigating the effects of applying different potential management contols. A target simulation model must be chosen that represents the behaviour of the fishery, and in particular, its expected response to changes in catch and effort.

The chosen model needs to adequately describe the dynamics of the system and be able to give indications of what might happen under any particular management regime and how this might affect fishers. These predictions can be used to provide management advice.

A fishery will be made up of a number of parts, such as species, fishing grounds, gears and fishing communities. Each fishery should, ideally, have a model developed specifically for it. However, it is pointless trying to use more realistic models unless significant amounts of information are available. Simpler models which encapsulate basic biological behaviour will probably be more accurate in data poor situations.

As the focus in ParFish is fisheries with limited data, a robust simple model was chosen as the starting point for the analysis and as an easy way to introduce fishers to population dynamics. The software currently supports only the logistic (Schaefer) biomass dynamics model, which has simple attributes common to all biological systems. It describes biomass growth and allows estimation of a surplus yield which will not deplete the population.

9.5 CONTROLS

9.5.1 Effort

The effort control is applied through the catch equation used in the simulation model. A new effort is set as the new control and the stock is projected forward from its current state under the new fishing mortality.

9.5.2 Catch quota

The catch quota control is applied as a future limit to catches. A new effort must also be supplied as the maximum effort. This is used to calculate catches. If catches exceed the quota, this maximum effort is scaled back to a level where the catches are met. This allows effort to change, but catches remain fixed if the effort is high enough to reach it and if the stock is not overfished. Setting the quota above the MSY means it will have no effect and the maximum effort control will apply.

9.5.3 Refuge

Management can provide a refuge from fishing by setting up closed areas or no take zones. Such zones may provide many benefits beyond those dealt with in this assessment model, and each of these benefits may be sufficient to justify a closed area. The model considers only the impacts on the fish stock and the resulting catch and effort.

The refuge control indicates what proportion of the stock is protected from fishing. The stock is initially split into protected and unprotected stock in proportion according to the control and it is assumed that there is no adult migration between the two. Migration would reduce the effective refuge size. The two separate stocks are modelled independently. If there has been no previous refuge, both stocks will be at the same level. Once the control is applied the protected stock will rise to the unexploited level. The exploited stock will be subject to the new mortality based on a new effort level defined for this control. The unexploited stock size and the recruitment between the refuge and exploited areas is split according to the control level.

Catch is only removed from the exploited part of the population, although both parts contribute to overall recruitment and growth. This will result in an immediate decrease in catches after the control is introduced and effectively a decrease in catchability. There is a longer term gain in stock size as productivity is boosted by the refuge stock. As the model suggests, refuges are a good way to maintain the stock size above the limit reference point. In combination with effort control, refuges could provide a useful tool for reducing risk.

9.6 CONTROL REFERENCE POINTS

Indicators must be converted to measures of preference, so that risks can be properly assessed. For example, fishers may wish more to avoid low catches rather than make large catches, and hence be risk averse. This requires that indicators be converted to some measure of utility (an economic measure of satisfaction).

The target simulation model calculates the overall catch and effort for the fishery projection. These can be converted to the relative change in CPUE and effort. These relative changes are assumed to apply equally to all fishers, so that if CPUE is 85 percent and effort 80 percent of the initial CPUE and effort, then each fishers CPUE is also 85 percent and 80 percent of his/her current CPUE and effort. The main assumption is that any effort or other control is applied proportionally to all fishers.

The optimum Bayesian decision is to choose the action that maximizes the expected preference. Using the preference data and model (see Section 9.9), the discounted preference score can be summed for each simulation leading to a relative measure of how much that outcome would be preferred. The expected preference score is the average of the simulations where the simulation parameters are drawn at random from their posterior probability distribution.

The maximum is found by interpolating between the control increments using a polynomial function. Finding the maximum by direct means would be very slow and produce an unnecessary degree of accuracy. If greater accuracy is required, the range of the control (minimum – maximum) can be reduced around the optimum point and/or the number of control increments can be increased.

The limit reference point is designed to limit the chance of overfishing to some acceptable level. Overfishing is defined here as forcing the stock biomass below some limit state defined as the proportion of the unexploited biomass. The limit state may be set by the user, but there is a generally accepted point for some models, most notably MSY at 50 percent for the logistic/Schaefer model. The probability of reaching this state is calculated as the chance that a scenario state taken at random from all scenario states combined over time, species and simulations, is below the limit state. This position is found again through interpolation using a polynomial function. The method, as well as working for the current simulations, will work with stochastic simulation models or under more complex management simulations. It could also be interpreted as the expected proportion of time that stocks will spend in the overfished state under each management regime.

9.7 PROBABILITY ASSESSMENT

The ideas for the approach for modelling probability originate with Press (1989), who presented a method to estimate the probability of nuclear war. Nuclear war is similar to overfishing in that we do not want to have several observations before being able to estimate if and how it might occur. Press (1989) suggested using interviews with experts and kernel smoothing functions to generate a prior probability. The approach can easily be extended to dealing with very many other sources of information.

Given a set of frequency data, how can a probability density function be obtained? One option would be to fit a parametric distribution. This would require knowledge of the appropriate shape of the function. While in some cases we would be able to propose a function, such as the normal or log-normal, in many others it would not be possible. There is always a risk of proposing an incorrect function and introducing structural error. Instead, a more general non-parametric technique using kernel smoothers is used.

Kernel smoothers provide the building block for probability density functions. Silverman (1986) provides a detailed description of the use of kernel smoothers in estimating densities in one dimension. This method has been adapted to multiple dimensions. The method is essentially construction of a smoothed form of histogram.

Instead of adding each point to a bin, each point is spread over the real line to smooth the distribution.

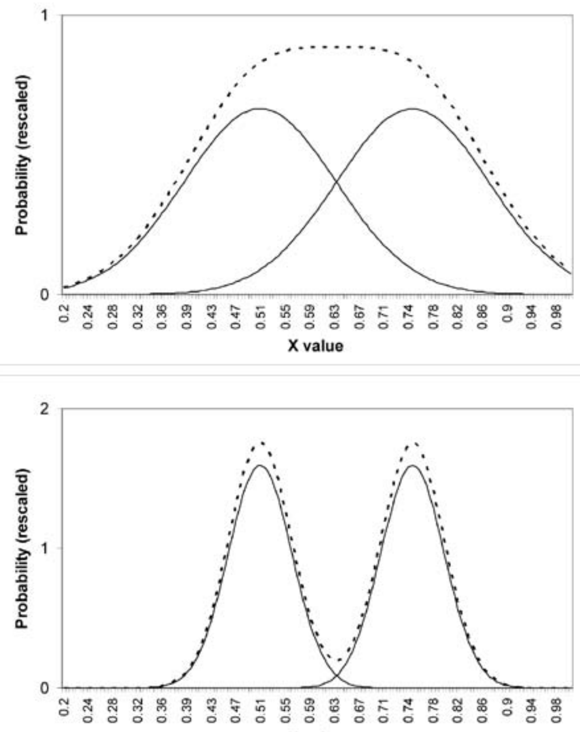
There are two requirements to this method. Firstly, a kernel function must be chosen. It has been shown that the particular choice of function is not particularly important in trying to estimate a density (Silverman, 1986), so the function can be chosen more for convenience than mathematical requirements. The normal or Gaussian function was chosen for the current model for two reasons:

- The multivariate normal offers a simple way to calculate and maintain individual multidimensional kernel models through use of its covariance matrix. In particular, the posterior of a normal mixture can be calculated directly.
- Where very little data is available from interviews, for example, the normal distribution has a natural shape which it is assumed can represent an individual's subjective prior as well as building into a community density function once enough data are available.

The second requirement is a smoothing parameter for each dimension which controls the degree of spread of the density around each point in the frequency. These parameters are important. Not only do they change the look of the density, but it is a measure of the uncertainty associated with each point in the frequency and hence the frequency as a whole.

Each probability density function is represented by a smoothed probability distribution around a set of points. The points can be derived from interview (see Section 9.8.3), and represent the prior belief of interviewees (expert stakeholders / fishers), from bootstrapping a stock assessment model fitted to fisheries data (see Section 9.8.1) or from other means. Frequencies are smoothed by spreading the probability around each point using the normal kernel function (Figure 9.2).

FIGURE 9.2
An example of two points forming a mixture distribution in one dimension. The individual smoothed point densities (—) are added together to produce a joint density (- - -). In the top graph, the smoothing parameter (Sigma parameter or standard deviation in the normal distribution) is large and a single flattened mode is produced. In the bottom, the smoothing parameter is relatively small and produces two modes



Although several frequencies (information sources) might be used, they must be independent. Non-independent parameter estimates must occur within the same frequency, so that their dependence can be represented by the way they occur together. The separate independent smoothed frequencies can be combined to generate a posterior probability density function.

Using frequencies has several advantages and disadvantages:

1. A complex set of parameters can be broken down into simpler subsets which can be assessed separately.
2. Gross errors can be minimized as each set can be checked separately to ensure estimates are reasonable. For example, catch and effort models might be fitted in the normal way, and the observed – expected plots inspected to ensure the fit is reasonable. All other standard checks can be applied to ensure results are valid.
3. The method can be made robust. Non-parametric techniques can be used to obtain frequencies.
4. Given a set of parameter frequencies, computation of the posterior is straightforward, fast and exact.
5. The individual probability density function derived from the frequencies may be inaccurate. If each smoothed frequency represents the source probability density function exactly, the corresponding posterior distribution is also known exactly. However, any inaccuracies between the individual kernel models and the underlying probability density functions will be represented in the posterior. These inaccuracies will have two sources. Firstly a randomly-drawn frequency will contain errors both in precision and bias (precision can be increased through increasing the number of random draws). Secondly, the smoothing parameters will be estimated with error. These parameters allow the kernel to cover regions between the frequencies, but also they will provide the relative weight between information sources.

9.8 MODELS FITTED TO DATA

9.8.1 Approach

Fitted models are structured as a linked hierarchy of sub-models. The structure allows greater flexibility, speeds up the fitting process and will allow easier development in future.

The basic structure is to have a multispecies model at the top level (if appropriate), the single species population models next and then generalized linear models which fit to data. There can be many species populations for each multispecies model and many generalized linear models for each single species model. The generalized linear models (GLM) link the population models to observations. The population models are more likely to be non-linear and more difficult to fit.

The separation of the single species model and GLM is a formal, more integrated approach of what is already commonly done (see Hilborn and Walters, 1992; Lassen and Medley, 2001). In many cases, a GLM is applied to observations to produce a population index. The population index is then used to fit the population model. While this pre-processing may be easier with some complex data sets, it introduces a redundant parameter and ignores possible correlations between the GLM and population model parameters. McCullagh and Nelder (1989) provide a description of generalized linear models as implemented in the current software.

The basic approach is to include the population size as a variable in the GLM. For any set of population parameters, the GLMs can be fitted to the population sizes. This is fast even if a GLM contains many parameters. A slower non-linear minimizer can then be used to minimize the fitted GLM log-likelihood with respect to the smaller number of population parameters.

The GLM approach in the software allows three types of log-likelihood: Normal, Poisson and Log-normal. The default is the Poisson. The quasi-likelihood argument (see McCullagh and Nelder 1989) suggests that, at least for the GLM parameters (as opposed to the non-linear population parameters), only the variance-mean relationship needs to hold to obtain maximum-likelihood estimates. Finally, the software allows parameter frequencies to be loaded directly, so any external model can be used to generate parameter PDFs as required.

An empirical bootstrap method is applied to generate parameter frequencies. This is the same methodology as applied in the CEDA software (Section 4.5). The approach has been found to be robust and is widely used in stock assessments as a measure of uncertainty. The interpretation in ParFish is a little different, however, as the resulting frequency is assumed to approximate the parameter likelihood.

9.8.2 Population models

The logistic (Schaefer) model fitted to the data is the same as that used in the target simulation model and CEDA software. This model is the simplest closed population model encapsulating recruitment, growth and density-dependent mortality. It describes the basic behaviour of populations.

The parameters are given maximum and minimum limits to prevent unrealistic results. The current population state, B_{now}, is defined as the estimated total biomass at the current time as a proportion of the unexploited stock biomass and therefore varies between 0 and 1.0. The intrinsic rate of increase (r) produces erratic behaviour above 2.0. Estimates above 2.0 indicate a shorter time unit should be used. The unexploited biomass must be above the maximum observed total catch in any time period. An upper limit was also placed on the unexploited biomass, at 100 times the maximum total catch. This upper limit is set because if catches do not discernibly decrease the resource size (1 percent mortality probably would not), the resource size estimate can become arbitrarily high. If the estimate drifts to this upper level, we will learn little more than that the resource is lightly exploited. No boundaries are applied to the catchability parameters which are fitted through regression.

A linear depletion population model is also provided for analysing fishing experiment data. This assumes a closed population with changes only coming about through catches and natural mortality. The model is useful for estimating catchability and the current biomass within the area of the fishing experiment, which may then be scaled up to the total area and size of the overall stock.

9.8.3 Stock assessment interview

The interview allows the logistic model parameters to be estimated from information provided by fishers by asking them key questions which can be related to the current state of the resource and its potential yield. Questions are asked in units and terms familiar to the fisher. The following information is obtained from each fisher:

- the main gear used, last year's CPUE and this year's CPUE for that gear;
- the current CPUE for all other gears used;
- the expected catch rate range for the unexploited stock; and
- the time for an overfished stock to recover to the unexploited state.

In addition, the total effort in this fishery over the last year has to be obtained from elsewhere (e.g. from Department of Fisheries' data, personal estimates or key informants in the fishery). The total size of the fishery should form the frame of the sample and allows the individual answers to be raised up to the totals for the whole community.

The individual catch rates are regressed towards the mean of the sample. This is necessary as they are used as an estimate for the mean catch rate for the whole fishery although the question asks for the fisher's own catch rate.

There are considerable political benefits from taking account of fishers' views, but it is not clear how valuable this interview information is in terms of assessing the stock. A positive example of the use of this approach is given in thr Box below.

BOX 9.1

Testing the ParFish approach in the Turks and Caicos Islands

The queen conch fishery in the Caribbean Turks and Caicos Islands provides a useful test of the value of fisher interviews because a long time series of catch and effort data is available for comparison. The fishery consists of small vessels that go out for day trips only. The 2 or 3 crew free dive up to 10m depth to collect conch which are shelled at sea. The meat is landed at the processing plants which keep a record of the vessel, date and amount purchased. These data are used for calculating the catch and fishing effort.

Effort in the fishery has fluctuated naturally over the years as available labour has responded to economic conditions. This has given enough contrast in the time series to get a good fit from a logistic biomass model (Medley and Ninnes, 1999).

The fishery is managed through a quota, so this is the appropriate control. Using the preference information, the stock assessment based upon both the interview and catch-effort model combined and the catch-effort model alone suggest a quota of around 1.53 and 1.38 million pounds respectively. Interviews by themselves were found to be much less accurate (as indicated by the much lower limit control), but nevertheless recommended a target of 1.68 million pounds, reasonably close to but above the other targets.

TABLE 9.1

Target and limit controls (landings quota in pounds meat weight) for the Turks and Caicos Islands Conch fishery based on catch-effort and interview data

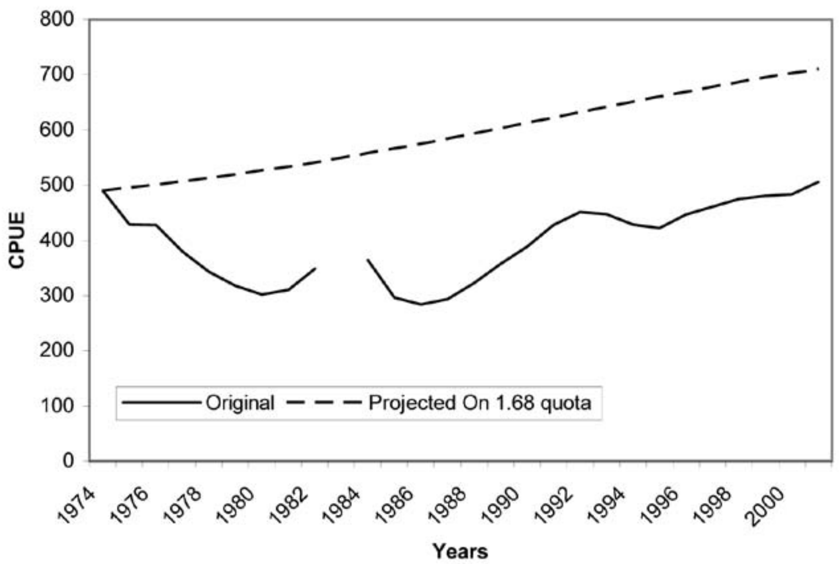
Scenario	Target Control	Limit Control
Interviews and Catch-Effort Model Combined	1 531 254	1 580 855
Interviews Data Only	1 678 103	791 651
Catch-Effort Model Only	1 384 882	1 432 696

If it is assumed that fishers knew as much in 1974 as they do now, the interview data can be used as representative of a sample that would have been obtained had the interviews been conducted at the beginning of the time series. Hence, the interview-only target quota can be applied at that point to see what might have happened to the fishery had this stock assessment method been applied, assuming that the logistic and maximum likelihood parameter estimates are correct.

The actual total catch over the period 1975–2002 was 45.47 million pounds. Had the 1.68 million pound quota been applied, the results suggest a total catch of 47 million pounds. This quota would realize higher catches in the longer term by foregoing catches in the late 1970s. A discount rate of around 5 percent yields approximately the same net present value between the two options.

The real gain, however, would have been the rise in catch rate (Figure 9.3). The catch-effort model suggests the stock was in an overfished state in 1974 and an enforced quota would have led to stock recovery. In other words, the catch would have been met with much less work and costs than has been applied (from 3 300 boat days down to 2 500 boat days to realize the same catch). This case study suggests that there are considerable benefits to be made using just interview data if no other data exist about the fishery. This would need further testing to make the case as a general statement. However it is clear that an initial quota set on the basis of interview, but updated as other scientific information came available would have led to much better economic benefits from this fishery over the last 30 years.

FIGURE 9.3
Expected catch per boat day (CPUE) from the fitted logistic model and the projected CPUE with 1.68 million pound quota



The cost of applying the quota is that, without the depletion in the mid-1980s, less information would now be available on the behaviour of the stock, so that the current stock assessment would be less reliable. This would need to have been addressed through alternative research activities.

9.9 UTILITY

9.9.1 Overview

Economics in fisheries assessments have mostly been dealt with by assessing costs and prices and constructing an economic model of the fishery profit. This is probably the best way to assess commercial fisheries, although it has problems:

- Such assessments are expensive and could not be extended to each small scale fishery,
- Data may be inaccurate and fishers may be unwilling to co-operate,
- There may be unobserved variables connecting data to utility (for risk etc.),
- The non-commercial aspects of fishing are not accounted for.

For small scale fisheries, a direct approach is more appropriate. In this case, the assessment tries to identify the situation fishers would prefer, so that managers can try to target this. This may not directly lead to greater understanding of the economics of the fishery, but should give the fishers the opportunity to select management targets more similar to their own needs or priorities.

Obtaining information on preferences for outcomes in the fishery has several significant advantages for small scale fisheries:

- It is simpler and faster to assess potential changes in the fishery.
- It is probably more robust to consider changes directly. This does not require an accurate model of the economics of the fishery, but does require fishers to be able to assess how changes in catch and effort might affect them.
- Asking fishers their preferences among outcomes gives them power over management objectives, but still allows independent scientific advice to make a contribution. This is consistent with all the advantages of community based management.

- The questions make fishers think more clearly about possible outcomes for the fishery. If community management is to be successful, it is important fishers understand possible management outcomes and can weigh up the impact of these on themselves and the community. This assessment approach not only obtains data for assessment, but starts fishers thinking about what might happen and what they would prefer to happen.

A main disadvantage is that it is left to the fisher to assess and balance complex issues. However, although imperfect, fishers are probably the best at assessing their own circumstances and the effect of changes in the fishery and will get better with practice.

The main source of error is the fishers' inability to assess accurately how they might react to changes in the fishery. This is exhibited in the narrow choice offered in scoring (see below) as fishers were unable to finely discriminate between outcomes. This error would probably decrease with practice.

A second source of error is in the way the utility model is used. The utility is averaged over respondents, so all are assumed to react in the same way, that is reduce or increase their fishing or catch by the same proportion. In practice, each individual will react separately to maximize their own utility. This makes the assessment pessimistic and the community utility curve will be flatter than that suggested in most assessments. It is unclear whether the maximum point would be much affected by this issue.

The general method can be extended in future based on the hierarchical model structure. For example, the overall catch variable can be calculated as the weighted average of the changes in individual species. The more important a species is to a fisher the higher the weight this species catch gets in the utility model.

9.9.2 Preference interview

Although utility theory is well defined and methods for practical utility estimation are available (Keeney and Raiffa, 1993), they need considerable adaptation and simplification to be used for assessing fishers' utility. Not only does the method need to be simple to understand, it has to be rapid to allow a broad cross-section of the community to be represented and to avoid interview fatigue.

Simplification is achieved by:

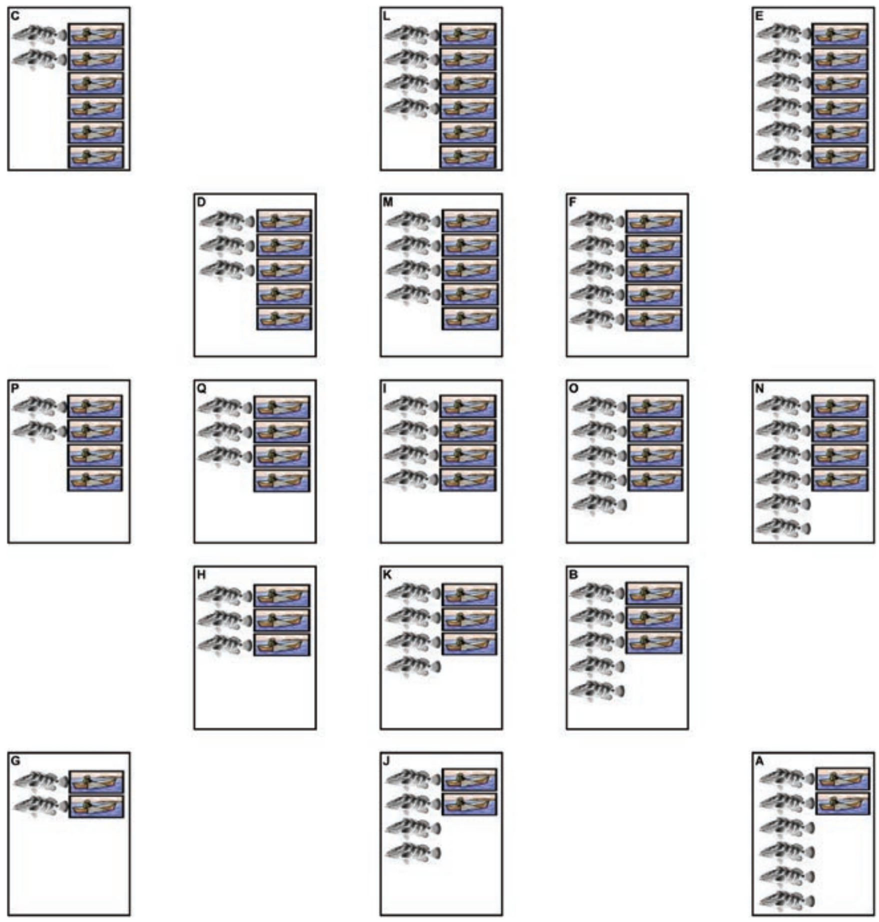
- The variables examined are simple and consistent. The assessment focuses on catch (earnings) and effort (work done).
- Comparisons are made as relative changes from the present situation.
- Scenarios representing changes from the present situation are ranked, then the difference between them scored. The total score for each scenario is the cumulative sum of these scores.
- The number of comparisons are minimized as "dominance" was automatically taken into account in the method.
- All comparisons are "pairwise", so fishers only have to consider two scenarios in any comparison.
- Interviews are based on households as the fundamental economic unit.

It is worth noting that standard utility and multi-attribute decision making techniques have been tried. These techniques were not found to be suitable for fishers in the context of the interview, because they require sophisticated interviewees who have a clear understanding of the issue and are prepared to spend considerable time building up the information necessary to support the method. Such methods are useful in analysing decisions, and this is probably the primary way they are used in decision-making. This analytical capability could be re-examined as a tool to help a small group of fishers representing the fishing community come to some decision on the community's behalf.

9.9.3 The catch-effort scenarios

Scenarios represent possible changes in the catch and effort as they relate to the fisher. Changes are represented as +/-25 percent steps relative to the present and are constructed to maximize the information obtained for a regression information matrix. The scenarios, which have been given a letter for easy identification, can be laid out in relation to the current catch and effort (scenario **I** in Figure 9.4).

FIGURE 9.4
The different scenarios are used to assess fisher preference. The central scenario I represents the current situation with 4 fish and 4 boats representing the current catch and effort respectively. Effort and catch are decreased and increased by 25% and 50% around this current value



One scenario will dominate another where it is clearly better. If we assume higher catches for the same effort is always better and higher effort for the same catches is always worse, any scenario where the catch is higher than or equal and effort is lower than or equal to another scenario will always be preferred. For example, **O** will always be preferred to **I**, as catch is higher and effort is the same. These dominance relationships can be used to rank all 17 scenarios more rapidly with the fewest number of comparisons. **A** represents the best, and **C** the worst scenarios, so it is only necessary to place all other scenarios between these two.[19]

[19] It should be pointed out here that the individual fisher's preference to maximize his or her own CPUE may not be consistent with the community or policy preference which may be to maximize employment. With the latter goal, options **N** and even **E** may be preferable to **A**.

9.9.4 Scoring

The score for each scenario is calculated as the cumulative sum of the difference scores between the ranked scenarios. The scores between ranked scenarios are additive, as they are assumed to measure the relative distance along a utility line. So, by ranking and then asking for a score as an indication of preference between consecutive scenarios (0 – no difference, 4 large difference), all scenarios can be scored.

There are a few useful assumptions which can be made about catch and effort utility curves. Firstly, the curves are monotonically increasing for catch and probably mostly monotonically decreasing for effort. The effort curve is less certain as some fishers complained they would become bored if they could not fish at least some days per month. Given the interest in sports fishing, this does not seem unreasonable. Secondly, they are bounded at zero as fishers would never go fishing if they did not expect to catch something, so utility should never fall below the point where they stop fishing altogether. The CPUE or catch at which they abandon fishing should set the lower bound on the utility.

There are also upper limits to the utility curve. There are logistical limits to the amount of catch that can be handled and the effort which can be applied. Excluding religious days, the number of days fishing a month is probably limited to 25. The amount of fish which a vessel can handle is likewise limited. Changing these limits, such as employing more crew or purchasing larger vessels would change the nature of the fishery and hence the assessment would have to be undertaken again.

9.9.5 Errors and feedback

If the results from the preference assessment are used without feedback to the interviewee, results may not accurately represent true preferences. By their very nature, questions are abstractions and may draw out abstract or inconsistent answers. The way to avoid this is to present back to the interviewee the implications of their answers which they can adjust interactively.

The rank order provides a method to check consistency of replies. Basically, the interviewer can check the reasoning of the fisher for the order chosen. Originally this was intended to see whether a fisher understood the object of the exercise and perhaps exclude those that did not. In practice, consistency was used as a tool to help fisher understanding rather than test for it.

Firstly, dominance is assumed and used in ordering the scenarios. However, fishers should be given the opportunity to change this order. Secondly, the fisher's current activity can be assumed to be optimum. So, the scenarios with the same catch rate but fishing more or less than now are presumed to be less preferred than the current level of catch and effort. If it is not, the fisher should be able to explain why not. The aim was to get the fishers to think as clearly as possible about what the scenarios would mean to them in reality.

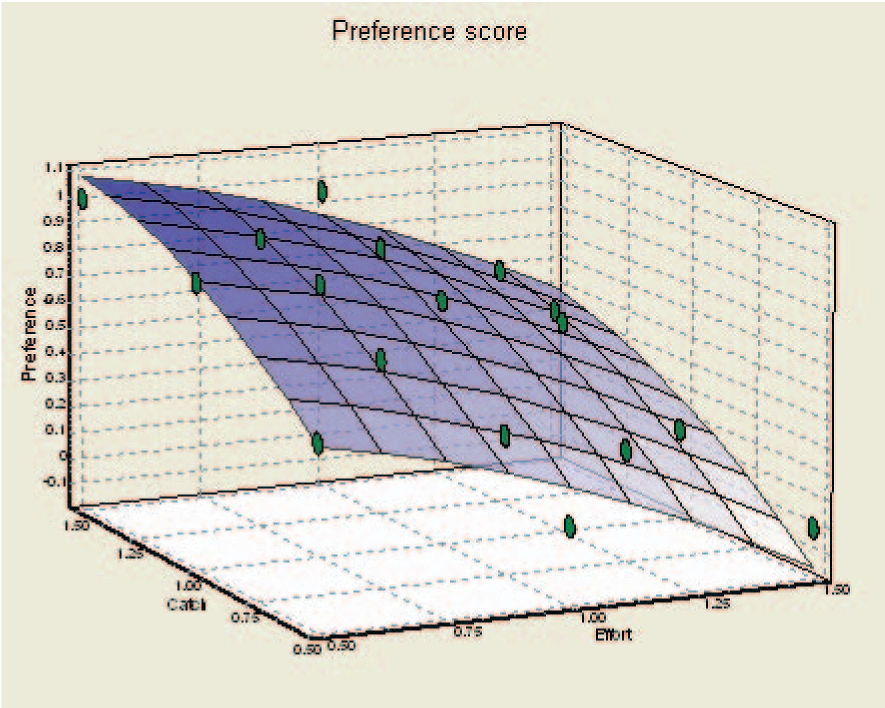
The method works through contrasting catch and effort variables and forces the fisher ranking the scenarios to define an exchange rate between them. Whereas the ranking works well, it was less certain that the scoring was as accurate. Scoring nevertheless gives the fisher the opportunity to draw a distinction between small and large differences between scenarios.

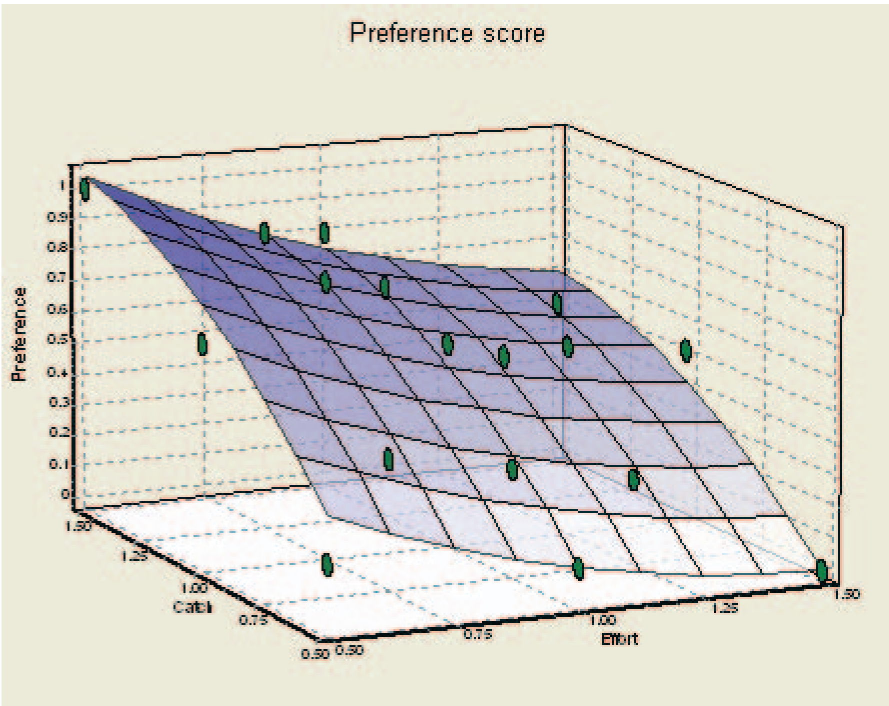
9.9.6 Preference model

The additive nature of the scoring technique suggests that a quadratic model of each variable together with a single interaction term should be adequate in modelling the score (Figure 9.5). The model interpolates the score and smoothes through errors. Pure interpolation is too sensitive to errors. As an alternative to the interview preference, a simple linear price-cost function is also provided in the software.

FIGURE 9.5

Example preference curves fitted to interview data (points). In cases of point outliers, the interviewer could check with the interviewee that the scenarios are in the right order. They may also be evidence that the model is too inflexible for good individual curves





Part 3
Other FMSP analyses and guidelines

10. Comparisons of length- and age-based stock assessment methods

Graham M. Pilling, Robert C. Wakeford, Christopher C. Mees

10.1 INTRODUCTION

Length-based methods for the assessment of growth have, in the past, been the primary method used in tropical countries. The results, however, are only as good as the data to which they are applied (e.g. Majkowski *et al.*, 1987). Many commercially important species in the tropics are relatively long-lived and slow growing, with highly variable individual growth trajectories and protracted spawning periods (Manooch, 1987). These life history characteristics result in the super-imposition of successive modal classes, limiting the information used in length-based methods to estimate growth (Langi, 1990). Despite the historical perception that tropical fish would not show regular marks in hard parts (e.g. otoliths), an increasing number of studies have successfully validated increments deposited on a regular time scale (see Fowler (1995) for review). Therefore, potentially improved estimates of growth may be derived using length-at-age data.

Estimation of growth parameters cannot be examined in isolation. They are commonly used as inputs into a suite of biological and fishery assessment methods, as described in Chapter 3. Indeed, a major source of uncertainty in length-based stock assessments is the use of potentially biased growth parameter estimates to convert length into age. However, as there may be compensatory biases later in the stock assessment process, the use of more accurate growth parameter estimates may not necessarily result in more appropriate assessments, and hence management.

In this study, the performance of length- and age-based methods of growth parameter estimation was first assessed through computer simulation. Secondly, the performance of management based upon simple stock assessments derived using these growth parameters, and of more complicated age-based approaches such as VPA, were examined through management strategy simulation. Simulations were based on data from two species in the central Indian Ocean exhibiting different life-history strategies; a relatively long-lived, slow growing species of emperor (*Lethrinus mahsena*) and a moderately short-lived, fast growing species of rabbitfish (*Siganus sutor*). Conclusions are drawn on the performance of age- versus length-based methods for both tropical fish species.

10.2 METHOD

10.2.1 Growth parameter estimation

Monte Carlo simulations were performed to test the accuracy of length- and age-based growth parameter estimation methods for *Lethrinus mahsena* only. The approach used to model the population was comparable to the individual-based model described in Hampton and Majkowski (1987). In the current model, however, growth was described using a non-seasonal von Bertalanffy growth equation (Table 10.1). Estimates of individual growth variability within the population of *L. mahsena* were also incorporated (Pilling, Kirkwood and Walker, 2002). Recruitment was specified as a normal distribution and the variability as a lognormal distribution. The population was initiated at equilibrium with a set fishing mortality level. Individual fish were randomly assigned values from both growth and recruitment parameter distributions at birth. At each simulation step (approximately 1 month), whether each individual had survived or died was assessed, based upon their probability of survival. If they had died, the probability of capture (i.e. death due to fishing rather than natural mortality) was calculated based on the gear selectivity pattern (Table 10.1). If caught, the length and age of the fish was added to a catch matrix.

Length-based assessment of growth

Four hundred individuals were sampled from the simulated annual catch for five consecutive years to generate a time series of length frequency data for length-based growth parameter estimation. Growth parameters (L_∞, K and t_0) were estimated using the ELEFAN method (Pauly and David, 1981) within LFDA. The growth parameters with the highest score function identified using the amoeba search were accepted.

Age-based assessment of growth

A length-structured catch sampling design was simulated. Ten individuals were randomly sampled from designated 2 cm length classes. A von Bertalanffy growth model was then fitted to the length-at-age data through least squares methods.

For both length– and age-based approaches, simulations of *L. mahsena* were performed for a range of equilibrium fishing mortality levels seen in the field (F=0.05, 0.25, 0.7 and 1.2). For each mortality level, 100 sets of growth parameter estimates were developed for each approach through Monte Carlo simulation. A frequency distribution of parameter estimates was derived, and the mean value calculated. The bias in this mean, compared to the true "seed" population value (cf. Table 10.1), and coefficient of variation (CV) of the distribution were calculated as percentages.

10.2.2 Management strategy simulation

A management strategy simulation approach (Powers and Restrepo, 1998; see also Section 3.6.5) was used to investigate the knock-on effects of using alternative growth parameter estimates within different stock assessment approaches upon which management decisions were based. This approach models the underlying system (an operating model, based on parameter values in Table 10.1) and the perception of that system based upon catch data sampled from it (the assessment model) (see Figure 10.1). The key is that the entire management process relies on imperfect information. The simulation incorporates a range of uncertainties in the perceived model (Rosenberg and Restrepo, 1995), including process error (variability in growth) and model error (simplifying assumptions made in modelling biological processes).

The analysis was performed for both study species; *Lethrinus mahsena* and *Siganus sutor* (Table 10.1). Starting fishing mortalities for *L. mahsena* were identical to those described above. Those for *S. sutor* were F = 0.5, 0.75, 1.25 and 1.5.

Estimation of fishing mortality

Stock assessments provided estimates of current fishing mortality upon which management decisions could be based. Two assessment approaches were used.

The first was based upon estimates of total (Z) and natural mortality (M), which were then used to calculate F (F=Z-M; Figure 10.1a). Total mortality (Z) was itself estimated through three methods; Beverton and Holt's Z estimator (Beverton and Holt, 1956), a length-converted catch curve, and an age-based catch curve. The last approach did not require the use of growth parameter estimates, and hence eliminated one source of uncertainty. Two empirical estimates of natural mortality (M) were applied: Pauly (Pauly, 1980); and Ralston (Ralston, 1987).

The second approach used to estimate F was through direct application of either length- or age-based VPA models (see Wakeford *et al.*, 2004; Figure 10.1b).

Management rule

The selected management target level was $F_{0.1}$ (Caddy and Mahon, 1995). A management rule was used to define annual changes in fishing mortality which moved it toward $F_{0.1}$. Fishing mortality in the following year $F_{(y+1)}$ was determined by the relative values of the estimate of current fishing mortality ($F_{(y)}$) and of $F_{0.1}$:

If $F_{(y)} < 0.8{*}F_{0.1}$, then $F_{(y+1)} = F_{(y)}{*}1.2$,
else if $F_{(y)} > 1.17{*}F_{0.1}$, then $F_{(y+1)} = F_{(y)}/1.17$,[20]
else $F_{(y+1)} = F_{0.1}$.

The resulting change in fishing mortality directly affected the operating model; i.e. it modified the true underlying F (Figure 10.1). Twenty years of management were then simulated for each starting F level and each species. The 20 year simulation process was then repeated 100 times using each pair of estimated von Bertanaffy growth parameters. Pairs of L_∞ and K estimates and values of the other key parameters (e.g. M, $F_{0.1}$) used within the assessment were assigned at the start of the simulation and kept constant throughout the 20 years.

Performance measures

Performance of management based on different growth parameter estimation and assessment methods was examined using the following criteria:

- Ratio of exploitable biomass in year 20 of simulation relative to unexploited equilibrium levels.
- Frequency with which spawning stock biomass fell below a threshold value of unexploited levels during each of the 20 years.
- Fishing effort in the final year. Management target was $F{=}F_{0.1}$
- Average catch over the simulation period. Large fluctuations in total annual catch were identified at the start of the management period during VPA simulations (cf. Figure 10.1b). The average was therefore calculated from the last 10 years of management (i.e. 10-19 years) in this case.

Where VPA was not simulated, initial runs showed that the use of age-based parameters resulted in under-exploitation of the stock, while length-based parameters either under- or over-exploited the stock, dependent on starting fishing mortality. To compare performance directly, target fishing mortality was tuned so that $F_{0.1}$ was reached on average (see Pilling *et al.* (1999) for more details). No tuning was required for simulations using VPA assessment models (see Wakeford *et al.*, 2004).

10.3 RESULTS

10.3.1 Growth parameter estimation

Statistics for the distributions of 100 length- and age-based L_∞ and K estimates obtained at each of the four fishing mortality levels for *L. mahsena* are shown in Figure 10.2. Length-based methods over-estimated both L_∞ and K, compared to the mean input parameter values (Figure 10.2a). By comparison, at lower fishing mortalities, estimates of both growth parameters from age-based methods were less biased, and more precise. With increased levels of fishing mortality, however, the accuracy of length-based estimates of L_∞ improved, while performance of age-based estimation methods deteriorated. At higher fishing mortalities, therefore, estimates of L_∞ derived through

[20] Note that if F is increased by 20 percent when below the target, the equivalent is to decrease by 17 percent if above the target (e.g. the opposite of doubling effort (F*2) is to halve it (F/2)).

age-based methods were more biased, and less precise, than those from ELEFAN. Age-based estimates of K remained more accurate and precise than ELEFAN estimates (Figure 10.2b and d), which showed increasing over-estimation with increasing levels of fishing mortality.

10.3.2 Management strategy simulation

Particular combinations of total (Z) and natural mortality (M) estimation methods resulted in consistently more accurate and precise estimates of current fishing mortality dependent on the growth parameter estimation method. Where length-based growth parameter estimates were used, subtracting Pauly's M estimate from the Beverton and Holt Z estimate resulted in the best estimate of F, while subtracting Ralston's M from the length converted catch curve estimate of Z performed best where age-based growth parameter estimates were used.

Estimated values of current fishing mortality and $F_{0.1}$ after the first year of management were compared to examine the likely performance of annual management using length- or age-based growth parameter estimates. If the true fishing mortality was F=0.05, effort should be increased to reach $F_{0.1}$ (F=0.4 for *L. mahsena*). In contrast, if F=1.2, effort should be decreased drastically. For *L. mahsena*, the use of age-based growth parameters and the "best" performing combination of total and natural mortality estimates described above resulted in the most appropriate decisions at each starting fishing mortality level (Figure 10.3). Decisions showed the correct trend from confident to more cautious management decisions with increasing fishing mortality. In contrast, decisions based on length-based growth parameter estimates were less sensitive to increases in fishing mortality. Decisions were more cautious, calling for decreases in effort or drastic action at all levels. However, decisions also called for no change in effort in a high proportion of cases when fishing mortality levels were very high.

The comparison described above represents management decisions based upon the first year's assessment, when the population was essentially still at equilibrium with the fishing mortality level. The results of the management strategy simulations, which modelled the whole fishery assessment and management process over 20 years, were less clear cut. Performance resulting from the use of the two alternative growth parameter estimates for *L. mahsena* were compared at a starting fishing mortality level equal to $F_{0.1}$ (F=0.4), using the "most appropriate" total mortality estimation combination described above. Both sets of growth parameter estimates performed comparably in terms of the level of final year exploitable biomass and the number of years that spawning stock biomass was reduced below a threshold value (20 percent) of unexploited levels. However, results spanned a wide range of possible outcomes when using either set of growth parameter estimates. Age-based growth parameters resulted in a slightly narrower range of final year fishing mortality levels, and achieved the target level (F=0.4) in 25 percent of cases, as opposed to 15 percent of cases where length-based parameters were used. However, the range still spanned F = 0.1 to 0.9 (Figure 10.4). Age-based methods also performed slightly better for the average catch performance measure (not shown).

The use of age frequency distributions (age-based catch curves) in the estimation of fishing mortality for *L. mahsena* further improved the performance of management. The optimum in each performance measure was achieved in a greater proportion of runs, and the range of outputs was slightly narrower. However, the range of outcomes was still large, indicating that assessment outputs remained uncertain.

The use of either the length- or age-based VPA approaches (Figure 10.1b; Wakeford *et al.*, 2004) did not produce a notable improvement in management performance for *L. mahsena*. In addition, management performance was impaired by bias in growth parameters used to estimate natural mortality and the target fishing level ($F_{0.1}$) derived from the yield per recruit curve. This bias was notable for all starting fishing mortality levels with length-based methods but only at higher levels for age-based approaches (see Figure 10.2a and b).

The performance of length- and age-based VPA approaches was also examined for *Siganus sutor*. In contrast to *L. mahsena*, the use of age-based VPA, along with age-based growth parameters to estimate $F_{0.1}$, resulted in remarkable improvements in management performance. Age-based VPA achieved average catches at the MSY level in a greater number of cases (40-50 percent, dependent upon the starting fishing mortality) while the range of values was narrower and centred on the optimum value (Figure 10.5). A similar pattern was seen in the level of exploitable biomass. The use of age-based VPA also conferred benefits in terms of reducing the number of years in which SSB fell below a threshold level (22 percent of unexploited levels), although the result was highly influenced by the starting fishing mortality level. As for *L. mahsena*, management performance was often defined by biases in the estimate of $F_{0.1}$ (as a result of biases in the growth parameters) rather than the estimate of current F.

10.4 DISCUSSION

The results of this study are predicated upon the assumptions made within the operational model, and the values used to parameterize it. It is expected that results and conclusions will differ according to the geographic location of species and their particular life history strategy. Furthermore, it should be noted that the aim of this study was not to establish an optimum management strategy. Hence only one strategy was examined here ($F_{0.1}$ as target). Alternative management rules and targets may achieve different results in terms of management performance for these and other species, and might improve the performance of VPA approaches.

10.4.1 Growth parameters

Age-based growth parameter estimates for *L. mahsena* were generally more accurate and precise than those estimated through the use of ELEFAN, particularly at lower fishing mortality levels. The ELEFAN estimate of L_∞ was strongly influenced by the largest individuals present in the length frequency distribution. Although the seed mean value of L_∞ was 48.5 cm, individual growth variability resulted in individuals over 70 cm in length being present in the catch at low F levels. This positively biased the resulting L_∞ estimate. This bias reduced as fishing mortality increased, since larger individuals were preferentially selected out of the population. ELEFAN consistently overestimated K. Given the relatively slow growth of *L. mahsena*, modes in the length frequency data are comprised of a large number of age classes, and hence growth curves fitted through those modes will overestimate K. Negative correlation between the two parameters meant that as the value of L_∞ decreased, K became further overestimated. Age-based estimates were also influenced by the selection pattern of fishing. Relatively fast growing individuals survived through length classes, so that at high fishing mortalities, the larger length classes were comprised of relatively young individuals. This decreased the information available on L_∞, and indirectly affected the estimate of K.

Results suggest that age-based methods should be used to estimate growth in species like *L. mahsena*. There is benefit in sampling a population early in its exploitation, to ensure older, larger individuals are present, providing more information on L_∞. Smaller, younger individuals should also be sampled to improve estimates of K. Specific sampling gears may be required to do this.

10.4.2 Assessment of management performance

Under equilibrium conditions, use of age-based growth parameter estimates and accompanying estimates of current fishing mortality appeared to result in the best management decisions for *L. mahsena*. However, the management strategy simulations considered the inter-annual performance of management, and incorporated additional uncertainties compared to the simple study. It showed that while there was benefit for management performance in using age-based growth parameter estimates, there was still considerable uncertainty in outputs, and benefits were less clear cut. This, in part, was the result of using length-based total mortality estimation methods in the assessment process, since they required uncertain growth parameter estimates. Use of age-based catch curves further improved the performance of management for *L. mahsena*, while the use of VPA approaches appeared to confer little additional benefit. Normally, the derivation of age frequency distributions for catch curves would require reading of a large number of otoliths, or derivation of an age-length key. However, there is the potential to use otolith weight to derive realistic age frequency distributions for such a purpose (Pilling, Grandcourt and Kirkwood, 2003). If age-based catch curves cannot be derived, the use of age-based growth parameters and length-based methods appears the next best course. However, catch curves will not be appropriate for all situations. At high fishing mortality levels where stock age range is reduced, for faster growing species with few age classes, or where a species shows high recruitment variability, the accuracy of catch curves estimates is likely to be poor.

In contrast to *L. mahsena*, the use of age-based VPA resulted in considerable improvements in management performance for *Siganus sutor*, when compared with that of length-based VPA.

In all cases, uncertainty in management arose since the estimate of $F_{0.1}$ from the yield per recruit curve is strongly affected by the value of natural mortality. In this study, natural mortality was derived through empirical formulae based upon growth parameter estimates. Natural mortality is notoriously difficult to estimate, and is likely to vary between ages. However, its influence on assessments should be considered when deriving management. Indeed, it is sensible to treat the analytical assessments performed in the simulations as one piece of the assessment process. Other approaches, such as the use of catch per unit effort data, should be used to support the findings.

A final issue for the use of age-based methods of assessment is cost. However, cost-benefit analyses detailed in Pilling *et al.* (1999) indicated the higher costs of age-based methods when compared to length-based approaches was offset by additional benefits in terms of management performance (e.g. improved sustainable yields). This was particularly true if preparation of otoliths was outsourced. Alternatively, costs of age-based growth estimation may be reduced by establishing a regional otolithometry centre. This would reduce the high initial expenditure required for age-based methods, while opening an additional income stream preparing otoliths for other regional organizations. A cost-benefit analysis of the use of potentially more data-intensive approaches such as VPA has yet to be performed.

TABLE 10.1
Parameter values used to simulate *L. mahsena* and *S. sutor* populations

Parameter	*L. mahsena*	*S. sutor*
L_∞ (cm)	48.5	36.6
K	0.14	0.42
t_0	-0.78	-1.36
Length weight a	0.0000806	0.000059
Length weight b	2.74	2.75
M	0.4	0.93
L_{m50}	27.5	18.0
L_{m75}	27.5	18.0
Stock recruitment	Shepherd SRR	Beverton & Holt R = 25 million h = 0.879
Recruitment CV	61%	82%
Recruitment peak	Oct – Feb	Nov – Mar
T_{c50} (L_{c50})	3.75 yrs (22.8 cm)	1.49 yrs (18.0 cm)
T_{c75} (L_{c75})	4.17 yrs (24.3 cm)	1.57 yrs (18.6 cm)

FIGURE 10.1
Flow diagrams presenting the simulated assessment processes. Method for estimating fishing mortality using (a) total and natural mortality estimates (Pilling *et al.*, 1999), or (b) VPA approach (Wakeford *et al.*, 2004)

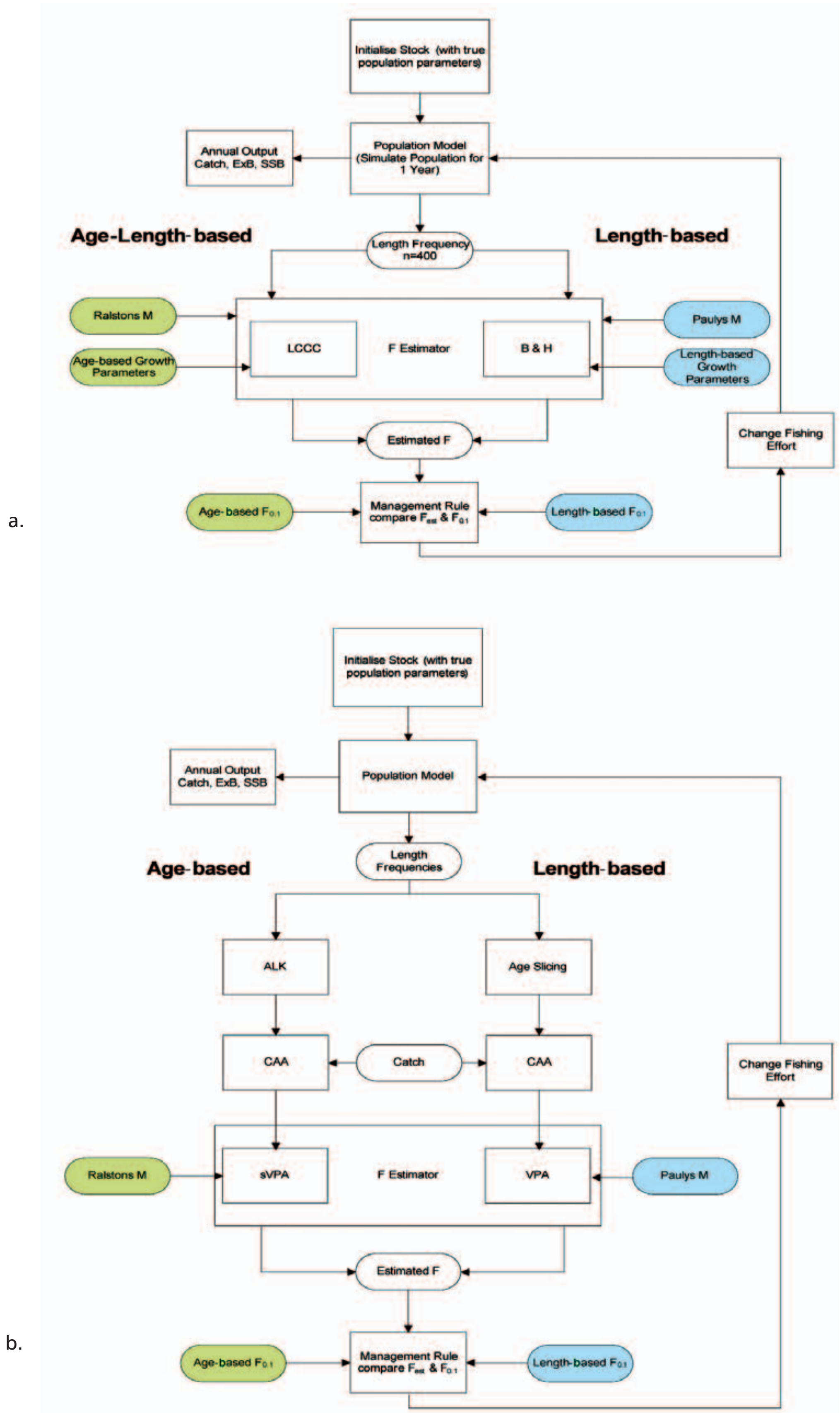


FIGURE 10.2

Statistics for length- and age-based von Bertalanffy growth parameter estimate distributions for *L. mahsena*. Bias (%) in the mean growth parameter estimate of L_∞ and K relative to the true "seed" value used in the simulation (L_∞=48.5, K=0.14) is displayed in graphs a and b respectively. Coefficient of variation (CV%) for L_∞ and K estimate distributions are in graphs c and d respectively

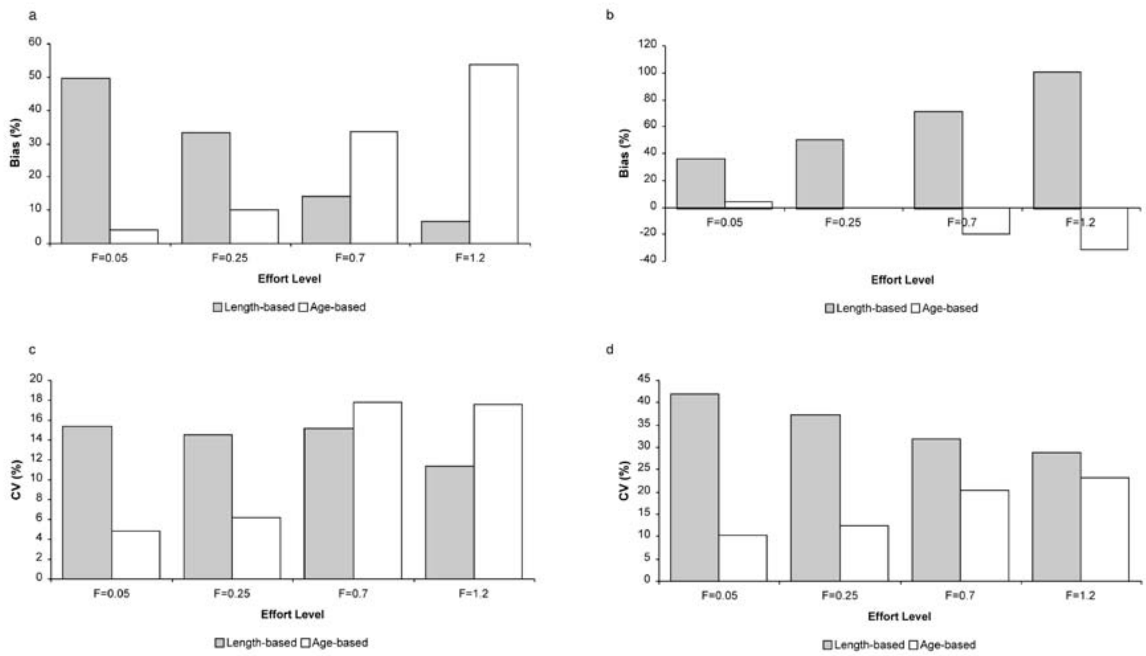


FIGURE 10.3

Distribution of management actions based on estimates of $F_{0.1}$ and current F derived for *L. mahsena* using length- and age-based growth parameter estimates, by initial fishing mortality level

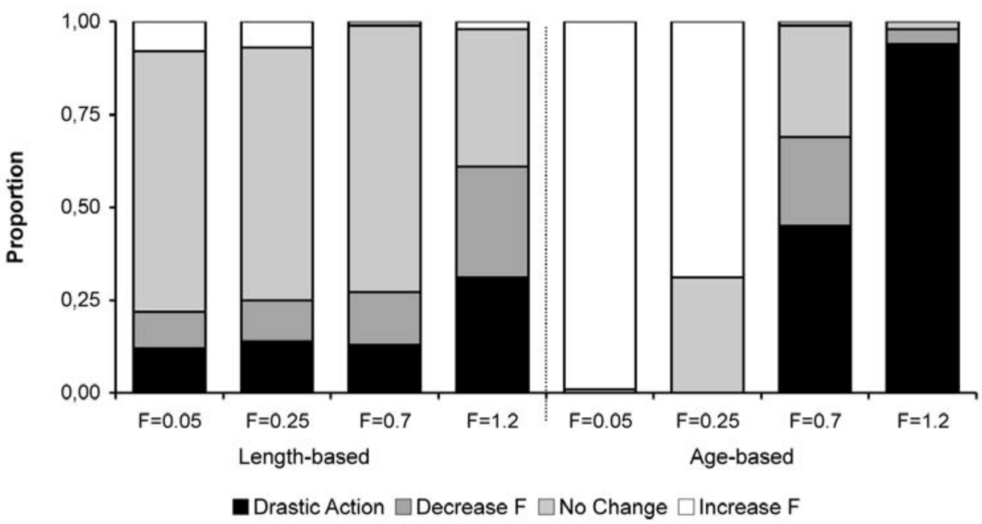


FIGURE 10.4
Final year fishing mortality level achieved using age-based and length-based parameters of *L. mahsena* for a starting fishing mortality of F=0.4. (Target=$F_{0.1}$=0.4)

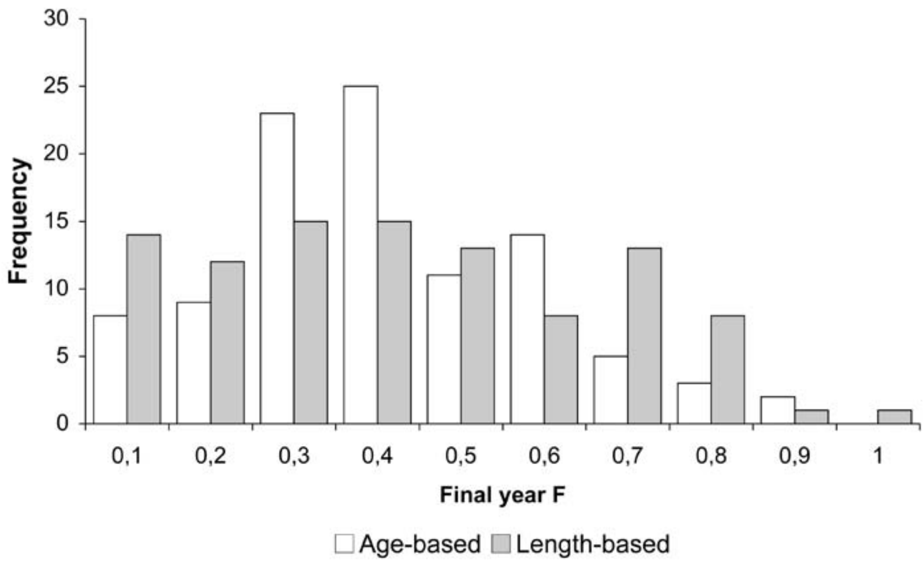
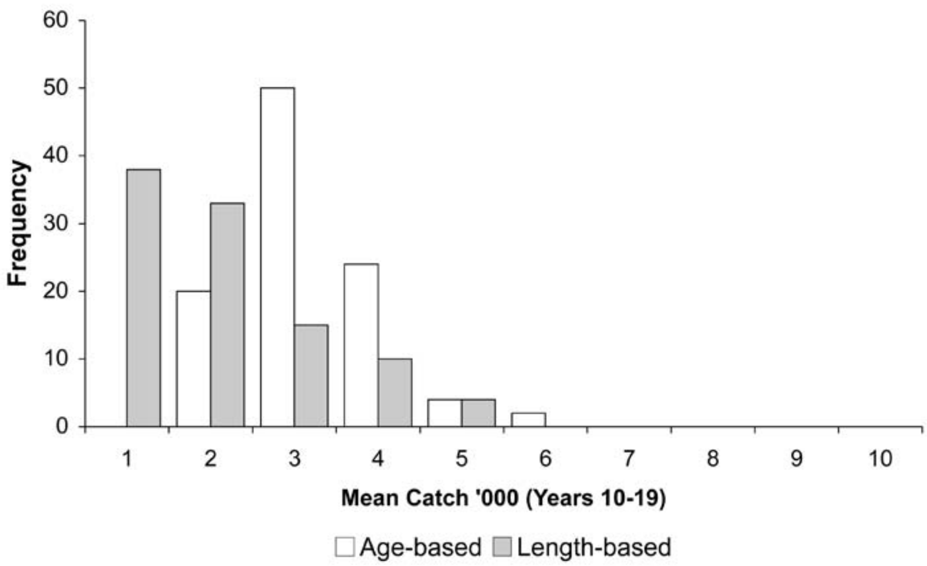


FIGURE 10.5
Histogram of the average catch for both length- and age-based methods for *Siganus sutor* for a starting fishing mortality of F=0.75 (MSY is 3 081 units)



11. The estimation of potential yield and stock status using life history parameters

J.R. Beddington* **and G.P. Kirkwood**

SUMMARY
Using life-history invariants, this paper develops techniques that allow the estimation of maximum sustainable yield and the fishing mortality rate that produces the maximum yield from estimates of the growth parameters, the length at first capture and the steepness of the stock recruitment relationship. This allows sustainable yields and fishing capacity to be estimated from sparse data, such as that available for developing country fisheries.

11.1 INTRODUCTION

Fisheries science has developed substantially in the last two decades, primarily due to the large increase in computing power, which enables complex statistical calculations to be performed relatively quickly and cheaply. Two central problems of the science are:

1. To estimate the potential yield of a stock or stocks.
2. To estimate the current state of a stock or stocks.

The scientific apparatus for solving these problems is well developed. The potential yield of a fish stock can be readily estimated from its demographic parameters and these in turn can be estimated using well-understood methods of sampling, experimentation and statistical estimation. The current state of a stock can be estimated in a variety of ways, both directly via research surveys and indirectly using information on catch levels, their age composition and the effort levels associated with taking those catches.

However, this is a picture of science that is relevant to temperate and high latitude fisheries in the developed world. It has much less relevance to tropical fisheries in the developing world where, even when the scientific methodology is applicable, its use is heavily constrained. Institutions in developing countries, with few exceptions, do not have the resources to conduct the substantial sampling and research that is necessary to apply the methodology and much work is conducted that, although properly executed, is fundamentally flawed because it is incomplete.

What is needed is a development of a scientific methodology that is tailored to the requirements of developing country fishery management and that in particular can be based on data and research findings that are within the capability of their institutions. The scientific analyses described in this paper are therefore aimed at allowing the estimation of potential yield and the maximum sustainable rate of exploitation directly from the parameters of size and growth. Such parameters are readily estimated from relatively simple data obtained by standard sampling and estimation procedures. The results mean that, armed with estimates of growth parameters K and L_∞ of the von Bertalanffy (1938)

* E-mail address for correspondence (j.beddington@imperial.ac.uk)
Note: This paper was also published in a 2005 special issue (360) of the *Philosophical Transactions of the Royal Society B: Biological Sciences* entitled “Fisheries: a future?”, compiled and edited by John Beddington. It is reproduced here with the kind permission of the Royal Society and the authors.

growth curve and an estimate of stock abundance, potential yield and hence capacity can be calculated, and the current status of the stock can be determined.

11.2 POTENTIAL YIELD

The estimation of potential yield is not an abstract problem of interest only to fisheries scientists and biologists; it is arguably the most important problem for fisheries management in the developing world. The reason is that once an estimate of potential yield can be made, the key management information on the capacity of the fishery can be deduced. Knowledge of a fisheries capacity is crucial to its management, whether in small scale localized artisanal fisheries or larger commercial ventures. Management needs to know how many fishers (and their families) can be supported by a fish stock or stocks without eroding the productive capacity of the resource.

It is an intuitively plausible idea that long-lived, slow-growing species provide relatively lower sustainable yields than short-lived, fast-growing species. This idea was first encapsulated in a simple formula by Gulland (1971). The formula directly related the potential maximum yield of a species to its instantaneous annual natural mortality rate, M, in the equation:

$$Y = 0.5\ M\ B_0 \tag{1}$$

where B_0 is the unexploited population biomass.

The argument used by Gulland to support this formula was a simple mix of a theoretical consideration, that the biomass level at which maximum sustainable yield can be obtained occurs at half the unexploited level in a simple logistic model, and an observation from experience of fisheries worldwide that the maximum yield appeared to occur when the fishing mortality rate was roughly equal to the natural mortality rate (see Clark, 1991).

Gulland's formula was never intended to provide anything other than a simple rough guide to potential yield. However, because of its potential usefulness, it was revisited by Beddington and Cooke (1983) and then again by Kirkwood, Beddington and Rossouw (1994). In both cases, the aim was to develop refinements to the formula that improved its accuracy, while still retaining as far as possible its essential simplicity.

In order to achieve these refinements, it was first necessary to take account of another key life history process, growth. In fisheries models, almost universally the relationships between length, $l(t)$, or weight $w(t)$ and age t are assumed to be described by the von Bertalanffy (1938) growth equations

$$l(t) = L_\infty\,(1 - e^{-Kt}) \tag{2}$$

$$w(t) = W_\infty\,(1 - e^{-Kt})^3 \tag{3}$$

where L_∞ and W_∞ are respectively the asymptotic maximum length and weight of the fish, and K is a growth rate parameter measuring the rate at which the asymptote is approached. Note that the von Bertalanffy growth equations usually include a third parameter, t_0, which measures the theoretical age at which length and weight are zero. For ease of presentation, we follow Beddington and Cooke (1983) and assume that t_0 is zero.

It is also well known that the yield from a fish stock is directly related to the length (or age) at which a fish first becomes vulnerable to the fishing gear. Accordingly, we further define L_c to be the length at first capture of the fish stock, measured relative to L_∞.

Beddington and Cooke (1983) and Kirkwood, Beddington and Rossouw (1994) both developed simple relationships between the potential maximum yield Y and the parameters M, K, and L_c. In particular, Kirkwood, Beddington and Rossouw (1994) showed that, for fixed values of M/K and L_c, the maximum yield as a proportion of unexploited fishable stock size is either exactly or very nearly directly proportional to M. In summary, they showed that, if the potential yield is considered as a proportion of unexploited stock biomass

1. Yield is higher for higher M.
2. Yield is higher for higher K (for fixed M).
3. Yield is higher for larger length at first capture L_c.

The major difficulty in applying these results to developing country fisheries is that for very few fisheries has it been possible to reliably estimate the natural mortality rate M. Other parameters have been routinely estimated for many stocks, but the sampling necessary and the complexity of estimation mean that estimation of natural mortality is beyond most developing country fishery institutions (a remark that also applies to the developed world). This is a serious problem, as from the results derived it can be seen that yield is in fact proportional to the natural mortality rate and if it cannot be estimated then neither can the potential yield (at least using this methodology).

The key life history parameters of fish species (M, K, L_m, the length at sexual maturity relative to L_∞, and t_m, the age at sexual maturity) have been estimated for a reasonably large number of species and various authors have noticed that there appear to be some rather simple relationships between them that appear to be similar across different species and for different populations of the same species. The pioneering work in this area was carried out by Beverton and Holt (1959) and was largely empirical in its analysis. In effect, they and a number of subsequent authors (e.g. Pauly, 1980; Froese and Binohlan, 2000), have used simple statistical techniques to derive empirical relationships between the parameters. That such relationships exist is surprising in that the parameters have been estimated using a large variety of sampling methods and sample sizes and using many different estimation techniques. They are thus subject to different kinds of statistical uncertainty (including bias) and the existence of clear empirical relationships with high statistical significance suggests that there are likely to be fundamental evolutionary and ecological processes involved.

A completely different approach to looking at the relationship between the life history parameters has been taken by authors who have sought an explanation of the empirical relationships using life history optimization techniques (Roff 1984; Charnov and Berrigan, 1990; Charnov, 1993; Jensen, 1996).

The implications of these studies are that three fundamental relationships are to be expected amongst the parameters. These are known as the Beverton-Holt invariants and are

a. The product $M\ t_m$ is constant
b. The ratio M/K is constant
c. The value of L_m is constant

Following the development in Jensen (1996), it is possible to show that when growth is of the von Bertalanffy form, $M\ t_m = 1.65$, $M/K = 1.5$ and $L_m = L(t_m) / L_\infty = 0.67$.

Jensen checked these relationships empirically using data published in Pauly (1980) and other sources and they are largely corroborated by this statistical analysis. He also showed that similar results could be obtained for different growth functions, although the empirical estimates of the invariants were slightly different. Mangel (1996) took a slightly different approach to considering these invariants, which would imply a somewhat more species-specific value for L_m, which is in any case estimable relatively easily from field data.

The implications of these results for the estimation of potential yield in developing countries are highly encouraging. They imply that if standard techniques can be used to estimate K and L_∞, simple manipulation of the last two of the invariant relationships above can give the other parameters necessary to estimate potential yield. The natural mortality rate M is equal to $1.5K$ and the length at maturity is equal to two thirds of the asymptotic length, L_∞. With these results, it is possible to revisit the analysis of Kirkwood, Beddington and Rossouw (1994).

11.2.1 Constant recruitment

If annual recruitment is assumed to be constant, Kirkwood, Beddington and Rossouw (1994) derived a simple expression for the maximum yield as a proportion of the unexploited fishable biomass ExB_0 in terms of M/K and L_c and showed that for fixed values of M/K and L_c, the relationship is linear with the maximum yield being directly proportional to the natural mortality rate.

Using the Beverton-Holt invariant $M/K = 1.5$, it follows that:

$$Y/\,ExB_0 = a(L_c)\,K \tag{4}$$

where the parameter $a(L_c)$ is a constant for a given value of the length at first capture L_c. The results are illustrated in Figure 11.1.

FIGURE 11.1
Yield as a proportion of unexploited fishable biomass plotted as a function of K for different values of L_c

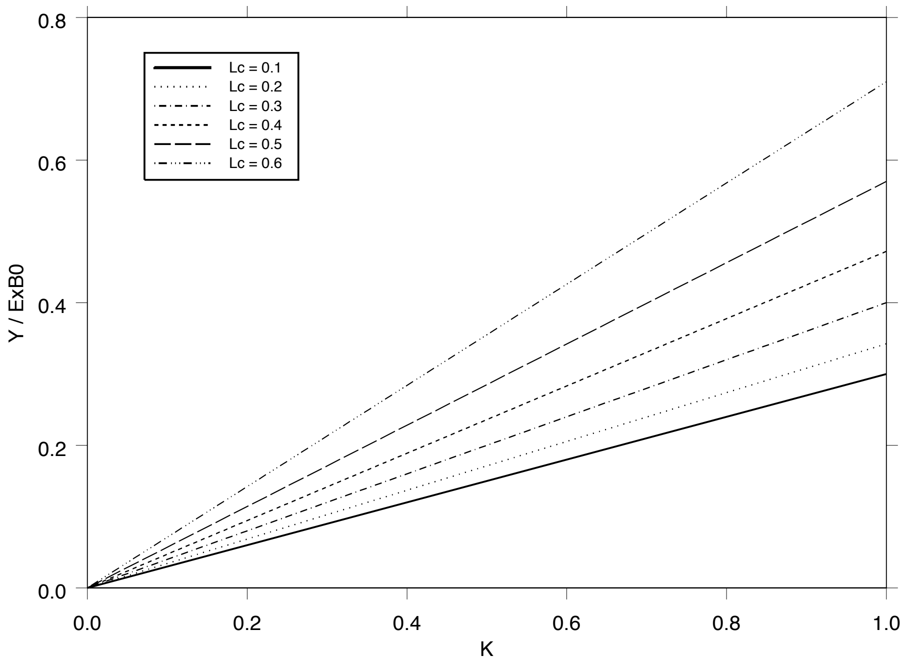


Figure 11.1 indicates that the potential yield increases with both the size at first capture (L_c) and K., as is well known (e.g., Beverton and Holt, 1957). Furthermore, the rate of increase in potential yield with L_c also increases as K increases. However, it is important to remember that situations where both the growth rates and sizes at first capture are high are likely to be relatively uncommon. The exploitable biomass as a proportion of total biomass becomes smaller as L_c and K increase. Hence, although in principle potential yields as a proportion of exploited biomass are higher, the absolute yields are smaller and thus unlikely to be commercially attractive unless there are special circumstances.

In Figure 11.1, results have been presented only for values of L_c up to 0.6. In the case of constant recruitment, it is well known that as L_c approaches the eumetric length (L_e), the fishing mortality rate that produces the maximum yield approaches infinity (Beverton and Holt, 1957). The eumetric length (relative to L_∞) here is given by (Beddington and Cooke, 1983).

$$L_e = \frac{3}{3+ M/K} \tag{5}$$

and from the Beverton-Holt invariants $M/K = 1.5$ and $L_m = 0.67$, it follows that

$$L_e = L_m = 0.67 \tag{6}$$

A simple equation that captures to a good degree of accuracy the relationship illustrated in Figure 11.1 is as follows:

$$Y/ExB_0 = 0.2\ K\ (1\text{-}ln(0.67 - L_c)) \tag{7}$$

There is an attraction in using an assumption of constant recruitment as the mathematics are simple and it has been argued that it is a reasonable assumption as long as the SSB is not reduced to low levels. A number of authors have suggested that when the level of exploitation is such that SSB is greater then 20 percent of its unexploited level, then the assumption of constant recruitment is reasonable. However, it is well known that levels of exploitation are often higher that this (Garcia and Grainger, 2004) and hence the results for constant recruitment are called into question. We explain the more general case in § 2 b.

11.2.2 Recruitment varying with stock size

Constant recruitment is effectively the limiting case of strong density dependence. A more realistic and conservative approach is to assume that recruitment varies with stock size, with reduced recruitment occurring when the stock size is low.

There is a large literature on stock and recruitment in fish and a variety of models have been proposed; see for example Quinn and Deriso (1999). In practice, however, it is rarely possible to distinguish between the different models in terms of how well they fit available stock and recruitment data and Kirkwood, Beddington and Rossouw (1994) chose to use a modified form of the Beverton and Holt (1957) stock-recruitment relationship. They argue that the various stock and recruitment relationships vary between the extreme density dependence of the Ricker (1954) relationship, through constant recruitment to the more conservative form of the Beverton-Holt relationship. This choice seems sensible in the context of developing country fisheries and it has the added advantage that the mathematics are slightly simpler.

According to the Beverton-Holt stock-recruit relationship, the number of recruits first increases rapidly as the spawning stock biomass (SSB) increases from zero. As the SSB increases further, the rate of increase in the number of recruits declines, until for very high SSBs, recruitment approaches an asymptote.

The standard formulation of the Beverton-Holt stock-recruit relationship is

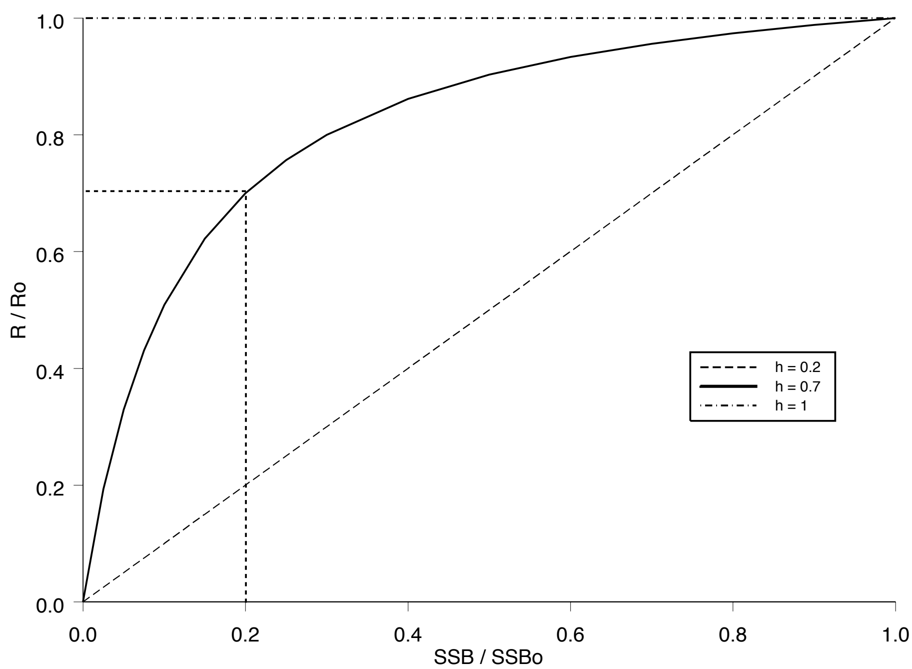
$$R = \frac{\alpha B}{1+ \beta B} \tag{8}$$

where R is the number of recruits arising from an SSB of B, and α and β are parameters. In this formulation, α/β is the asymptotic number of recruits, and β is a productivity parameter measuring the rate at which this asymptote is reached.

This formulation is useful when pairs of corresponding estimates of SSB and recruitment are available, as it is a relatively simple matter to estimate the parameters using regression techniques. Estimates of the parameters α and β are also often reported in the literature when Beverton-Holt relationships have been fitted to stock and recruitment data. In many cases, however, and particularly for developing country fisheries, such data are absent, and it is then very difficult to select realistic values for the parameters.

An alternative formulation incorporates a parameter characterizing the "steepness" of the stock-recruitment relationship at low stock sizes. As illustrated in Figure 11.2, the steepness (*h*) is defined as the recruitment (as a fraction of the recruitment in an unexploited stock) that results when SSB is 20 percent of its unexploited level, SSB_0 (Mace and Doonan, 1988). As *h* approaches 1, the Beverton-Holt relationship approaches a form in which recruitment is constant; when *h* is 0.2, recruitment is linearly related to SSB. The great advantage of this formulation is that *h* is a dimensionless parameter characterising the shape of the relationship and it is unaffected by the actual size of the stock.

FIGURE 11.2
The characterisation of the Beverton-Holt stock-recruit relationship using the steepness parameter, *h*, for *h* = 0.2, 0.7 and 1.0



One further parameter needed for this analysis is the value of L_m. This, it will be recalled, is the third Beverton-Holt invariant, so that $L_m = 0.67$.

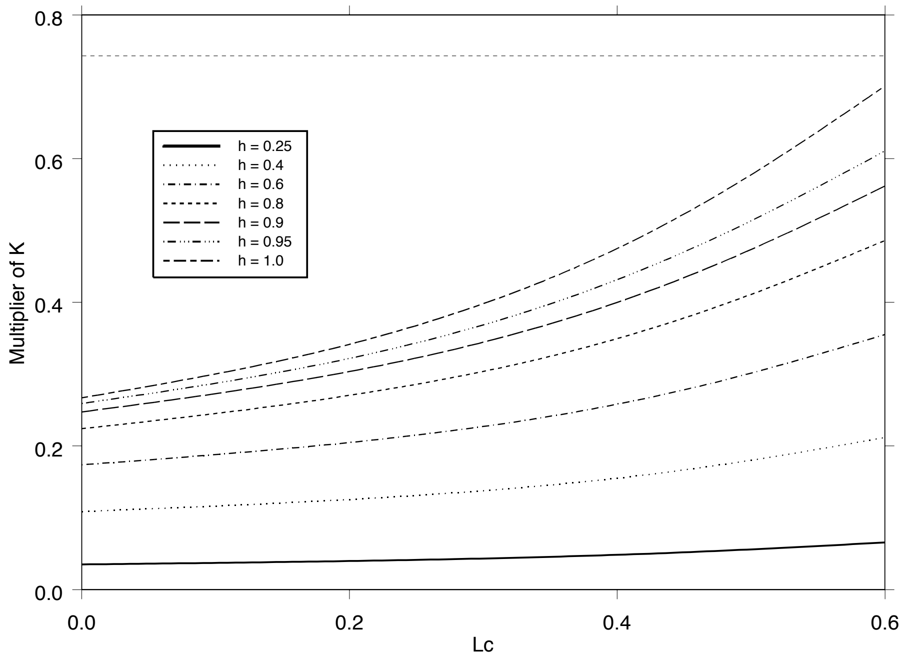
Kirkwood, Beddington and Rossouw (1994) illustrated an empirical relationship between potential yield and the natural mortality rate that was almost linear for large areas of parameter space, but varied with L_m, M/K, the degree of density dependence and the length at first capture (L_c). The use of the Beverton-Holt invariants significantly simplifies that analysis so that, as in the constant recruitment case, the potential yield as a proportion of unexploited fishable biomass is given (to a close approximation) by the linear relationship:

$$Y / ExB_0 = a(L_c, h)\, K \qquad (9)$$

where $a(L_c, h)$ is a constant multiplier of K determined by the length at first capture L_c and the degree of density dependence (steepness) in the stock-recruitment relationship *h*.

The results are summarized in Figure 11.3.

FIGURE 11.3
Multiplier of *K* to determine yield as a proportion of unexploited fishable biomass, plotted as a function of L_c for different values of *h*. The horizontal dotted line is at a level of 0.75, corresponding to the Gulland (1971) formula Y = 0.5 M B_0



As expected, the multiplier of *K* increases with increased length at first capture and with an increasing degree of density dependence, with constant recruitment being the limiting case as the steepness parameter *h* approaches 1.

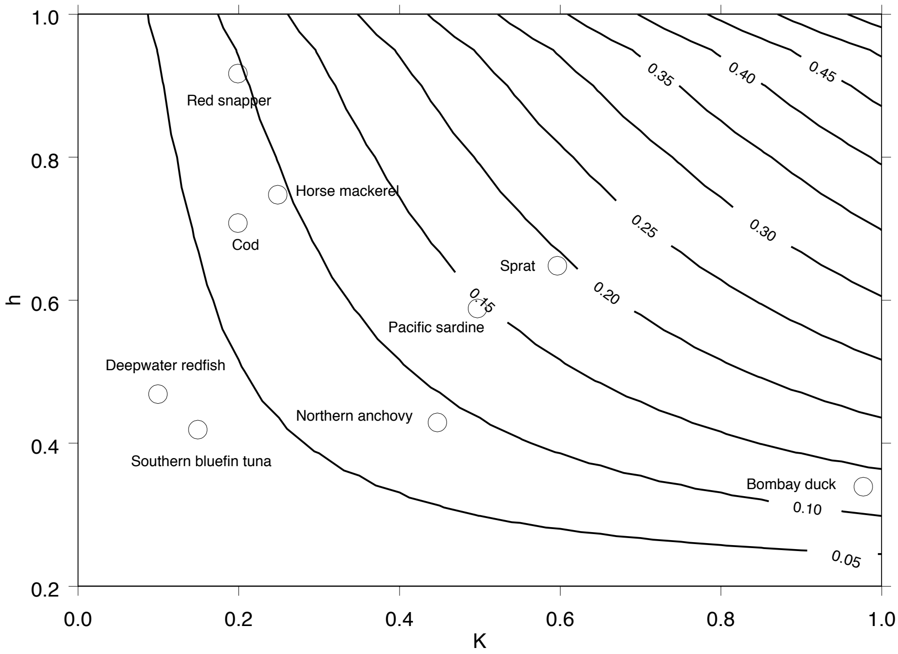
Of particular interest is how quickly yield decreases as the steepness drops below 1, especially for larger values of L_c. Given its definition, it is obvious that reliable estimates of *h* close to 1 will only be available in cases where the spawning stock size has been reduced to very low levels (i.e. it has been severely overexploited). For many stocks, recruitment appears on average to be constant over the observed range of spawning stock sizes. In such cases, it is often possible to identify a reasonable lower bound for the steepness, but the data would be consistent with any steepness between that and 1. Prudence would therefore indicate that in assessing yield, it would be wise to assume lower values of *h* (weaker density dependence) until data accumulate to provide evidence to the contrary.

Figure 11.3 also illustrates clearly the strong bias associated with the use of the Gulland (1971) formula in assessing potential yield. The horizontal line depicting the Gulland relationship lies well above the other contours even for combinations of high density dependence, growth and length at first capture.

Given the comprehensive collection of stock-recruitment data drawn together by Myers, Bridson and Barrowman (1995), there is a reasonable literature on estimates of the steepness parameter *h*. In particular, Myers, Bowen and Barrowman (1999) summarize estimates of *h* for a variety of fish species. Combining this information with estimates of the growth parameter *K* obtainable from FishBase (Froese and Pauly, 2004), it is possible to illustrate our results by looking at a few typical species. A more exhaustive analysis will be reported elsewhere. The summary results for selected species are shown in Figure 11.4.

FIGURE 11.4

Contours of yield biomass ratios (Y/ExB_0) for different values of K and h. Also shown are estimates of yield biomass ratios for selected fish species, based on estimates for those species of h from Myers, Bowen and Barrowman (1999) and of K from FishBase (Froese and Pauly, 2004). A constant value of L_c of 0.5 has been assumed for each species



The results presented in Figure 11.4 for individual species are for illustrative purposes only, as there is manifestly substantial uncertainty around the estimates of K and h. Furthermore, we have assumed a constant L_c of 0.5 for each, when in practice the actual lengths at first capture for particular fisheries are likely to be different from this value. Nevertheless, the positioning of the species within the contours illustrates well the general pattern to be expected from the life history of the species concerned.

Estimates of the ratio between potential yield and unexploited fishable biomass for the individual species, and indeed most species, are arguably of historical interest only as almost all have been subject to substantial periods of exploitation. They are nevertheless indicative of the relatively low levels of sustainable yields that are possible and point to the basic reason why so many stocks are over-exploited. In practice, estimates of the original unexploited biomass ExB_0 are rarely available, although for certain species and populations some estimates can be made when long time series of catch and relative abundance data are available. For new fisheries, particularly where some estimate of biomass has been made, the results can provide useful guidelines for the likely levels of sustainable yields. Recent exploitation of deepwater species, for which growth is known to be very slow, would have been arguably less intense if such preliminary results were available. Similarly, the exploitation of newly discovered or relatively lightly exploited stocks can be guided by this analysis to provide an assessment of sustainable yields and hence the level of sustainable fishing capacity.

Of more immediate interest to fishery managers is an idea of whether the current level of exploitation of a stock is sustainable. In Section 11.3, we explore this issue using similar techniques to those for the estimation of sustainable yield, but this time we focus on the fishing mortality rate that produces the maximum sustainable yield. If this is known and the current fishing mortality rate can be estimated, then the sustainability of current levels of fishing can be assessed.

11.3 STOCK STATUS

In addition to comparing recent and current catches to estimates of potential yield, the status of a fished stock can also be assessed by comparing an estimate of the current fishing mortality rate with an estimate of the fishing mortality rate that produces the maximum yield, F_{max}.

Both Beverton and Holt (1957) and Gulland (1971) observed that in many situations, F_{max} was related to and often close to the level of the annual instantaneous natural mortality rate, M. Other authors have also made similar observations, but to our knowledge no studies have been carried out to elucidate this relationship. The above analysis would appear to have two implications. First, whatever relationship exists between F_{max} and M, it is likely to hold only for a particular length at first capture L_c. Second, it is likely that $F_{\max}$ (for particular L_c) may be a simple fraction of the growth parameter K.

11.3.1 Constant recruitment

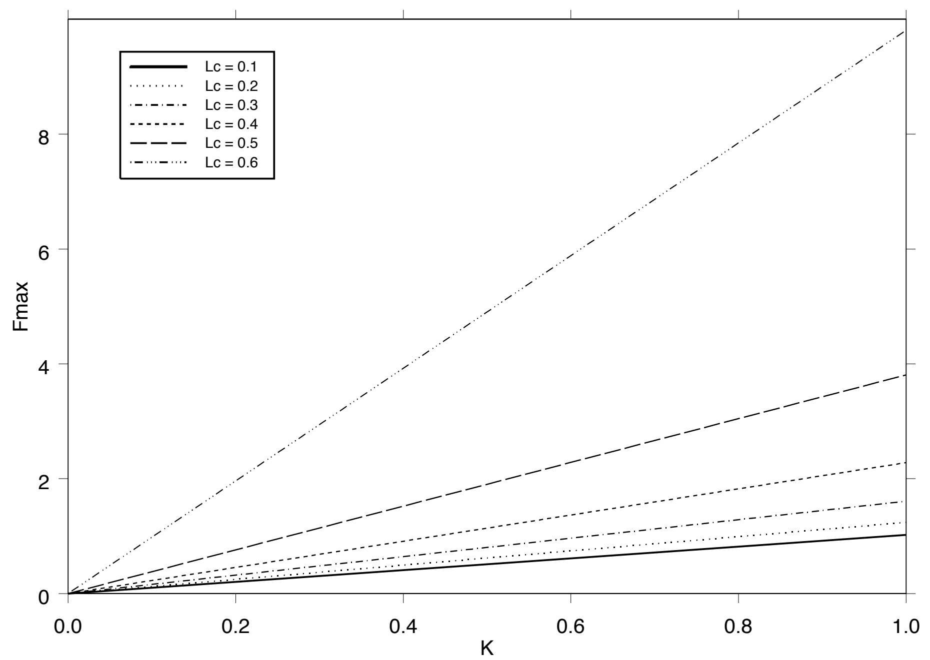
Confirming that suggestion, using the techniques of Kirkwood, Beddington and Rossouw (1994) and the Beverton-Holt invariants, it can be shown that for $L_c < L_m$, in the case of constant recruitment a linear relationship holds between F_{max} and K. Specifically:

$$F_{max} = a(L_c)\, K \qquad (3.1)$$

where the coefficient $a(L_c)$ varies with the length at first capture. The results are illustrated in Figure 11.5.

FIGURE 11.5

$F_{\max}$ as a function of K for different values of L_c, when recruitment is assumed constant



As with the comparable relationship between yield biomass ratios and K discussed earlier, F_{max} increases with increasing K and increasing L_c. Now, however, the relationship is L_c is much more non-linear for larger L_c, reflecting the fact that F_{max} approaches infinity as L_c approaches 0.67.

Because of the extreme density dependence implicit in an assumption of constant recruitment, the F_{max} predicted in this case is almost certainly an upwardly biased estimate of the true F_{max}. It follows, therefore, that if the current fishing mortality rate is estimated to be close to or above this F_{max}, then it is likely that the stock is being overexploited.

A simple equation that captures to a good degree of accuracy the relationship illustrated in Figure 11.5 for $L_c < L_m$ is as follows:

$$F_{max} = \frac{0.6K}{0.67 - L_c} \tag{3.2}$$

11.3.2 Recruitment varying with stock size

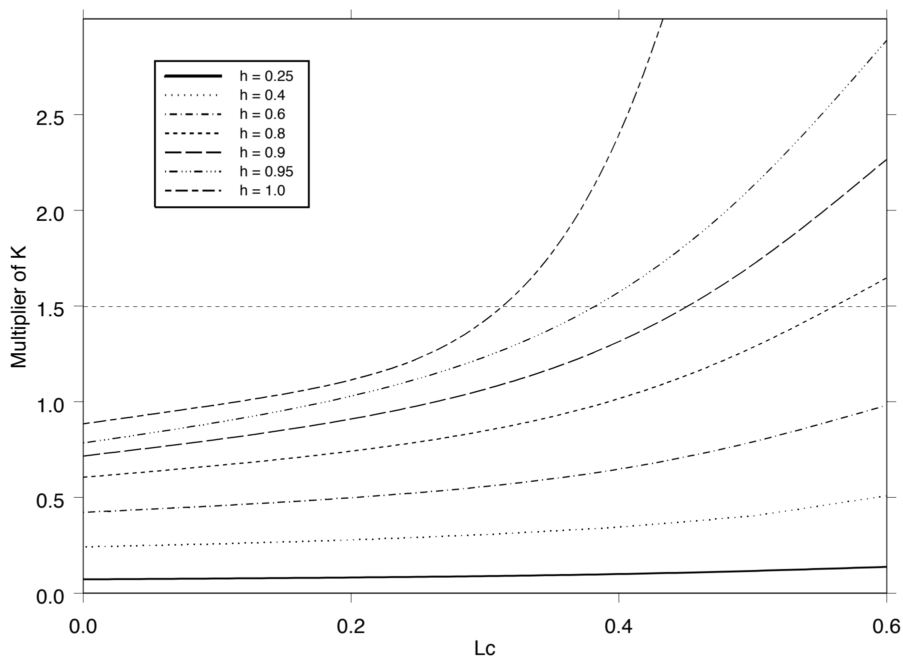
If, as before with potential yield, we make the more prudent and realistic assumption that recruitment varies with SSB according to a Beverton-Holt stock-recruitment relationship, then to a close approximation F_{max} is linearly related to K. In this case, however, the equation is

$$F_{max} = a(L_c, h)\, K \tag{3.3}$$

where $a(L_c, h)$ is a constant depending on the values of L_c and the degree of density dependence h. The results in terms of values of the multiplier of K are summarized in Figure 11.6.

FIGURE 11.6

Multiplier of K to determine F_{max}, plotted as a function of L_c for different values of h. The horizontal dotted line corresponds to a K multiplier of 1.5, when $F_{max} = M$

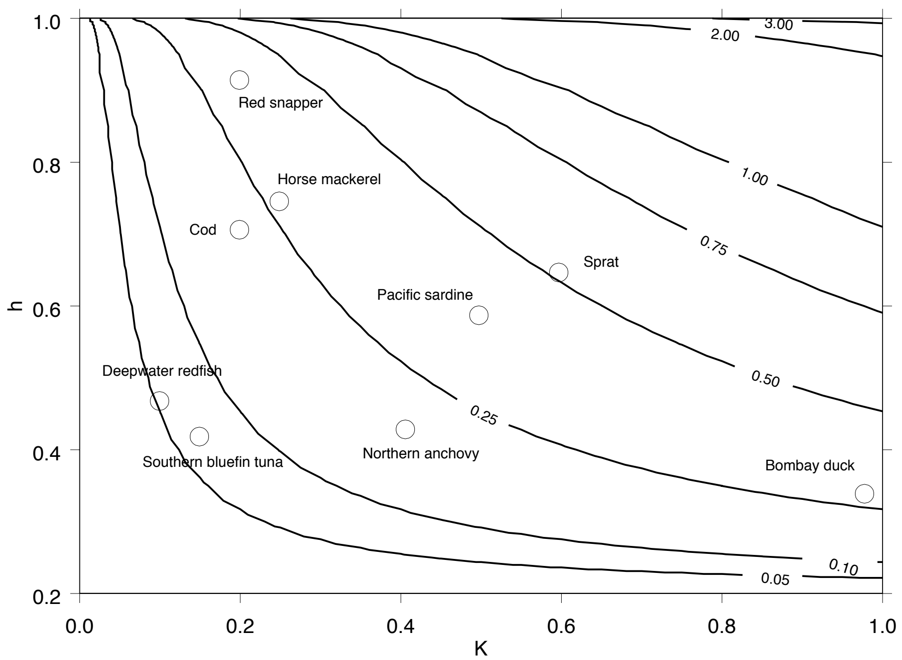


The results shown in Figure 11.6 indicate the very strong influence that the steepness h has on F_{max}. In practice, h is a relatively difficult parameter to estimate reliably, requiring at least a substantial time series of stock and recruitment data corresponding to a wide range of spawning stock sizes. Because of this, it is not surprising that the estimates reported in Myers, Bowen and Barrowman (1999) are predominantly for temperate species subject to substantial fisheries. For developing country fisheries, it may therefore be rather difficult to obtain reliable direct estimates of h, though it may be possible to infer possible ranges from published estimates for similar species elsewhere. In such circumstances, a relatively low choice of h would appear to be prudent.

The horizontal line in Figure 11.6 corresponds to a multiplier of K of 1.5, which is equivalent to F_{max} being equal to M. It will be recalled that a number of authors since Beverton and Holt (1957) have observed that for certain species F_{max} was approximately equal to M. While this is true for certain combinations of K and h, it seems likely that the relationship claimed is an artefact of the choice of species examined, as the region close to a multiplier of K of 1.5 is only a very small part of feasible parameter space.

The results obtained from the set of selected species used in the previous section are presented in Figure 11.7.

FIGURE 11.7
Contours of F_{max} for different values of K and h. Also shown are estimates of F_{max} for selected fish species, based on estimates for those species of h from Myers, Bowen and Barrowman (1999) and of K from FishBase (Froese and Pauly 2004). A constant value for L_c of 0.5 has been assumed for each species



As noted before, the results presented for individual species are for illustrative purposes only, given the uncertainties associated with them. Again, however, the positioning of the species within the contours illustrates well the general pattern to be expected from their life histories.

11.4 CAVEATS

In order to produce the results presented here, it has been necessary to make a number of simplifying assumptions. The first is that all fish with lengths greater than L_c are equally vulnerable to capture. Manifestly, real fisheries do not operate in this manner; typically they are prosecuted using a variety of fishing gears that have different selection patterns with size (and age). Usually, for each gear it is possible to identify an average length at first capture. If one gear dominates catches, then setting L_c equal to the average length at first capture for that gear should be sufficient. If there are many gears catching a wide range of sizes, then setting L_c equal to the smallest average length at first capture would be prudent. The hardest case is when there are two substantial gears catching over quite different size ranges (e.g. purse seine and longline fisheries for tunas), but even here selecting an L_c based on the smaller average length at first capture seems the most sensible course of action.

The Beverton-Holt invariants and their various derivations produce an estimate of the relationship between M and K with growth assuming that the natural mortality rate is constant over the relevant part of the lifespan. However, in a number of species, age- or length-specific patterns of natural mortality have been observed. Kirkwood, Beddington and Rossouw (1994) were able to show that in this case, a simple Heincke estimator (Heincke, 1913) will give a reasonable estimate of the average natural mortality rate that relates well to the natural mortality rate involved in the derivation of the invariants.

By ignoring stochastic effects, the analysis presented here fails to account for a ubiquitous characteristic of fish stocks, namely that they fluctuate constantly. Such fluctuations are difficult to quantify and in most circumstances they are impossible to predict. However, again Kirkwood, Beddington and Rossouw (1994) showed that their deterministic analysis still provides a reasonable guide to the average behaviour of stocks that are exploited in fluctuating environments.

In some species, there is evidence that density dependence operates on both growth and mortality of post-recruits, as well as via the stock recruitment process (e.g. Beverton and Holt, 1957, Lorenzen and Enberg, 2002) In this situation, the analysis is substantially more complicated, but the estimate of potential yield at F_{max} obtained on the assumption that density dependence only occurs via the stock-recruitment relationship is likely to be conservative (Kirkwood, Beddington and Rossouw, 1994).

11.5 ASSESSING STOCK STATUS

The results above have a useful practical implication for the assessment of the status of fisheries where data are sparse. Given an estimate of growth parameters for the species concerned, an estimate of $F_{\max}$ can be obtained simply by application of equation 9. For data-rich fisheries, there is a large number of methods available for estimating the current F that are routinely used in annual stock assessments, but it is often not possible to use these methods when data are sparse. Fortunately, however, several other (albeit rather imprecise) methods for estimating the current total mortality rate ($F + M$) that rely simply on availability of catch length frequency samples and estimates of growth parameters have been incorporated into stock assessment software packages commonly used in developing countries (e.g. FiSAT, Gayanilo and Pauly, 1997). It is then a simple matter to estimate F by applying the Beverton-Holt invariant $M = 1.5\ K$. Alternatively, if an estimate of current biomass is available, for example from a survey, then a simple approximate estimate of F is available from the ratio of current catch to current biomass.

If the current estimate of F is substantially higher than $F_{\max}$, then the stock is clearly being overexploited and action may be needed to avert a stock collapse. If it is close to $F_{\max}$, then any increase in fishing effort should be discouraged. In the situation where the estimate of F is well below $F_{\max}$, then some simple guidelines for expansion of the fishery may be used. Increasing catch levels by increasing effort can be permitted as long as the new F is still below F_{max}. Clearly, prudence will require that it is a reasonable level below.

11.6 CONCLUDING REMARKS

In this paper, we have developed simple relationships that can be used to estimate potential yield and the maximum sustainable fishing mortality rate given information on the growth curve and size at which fishing starts. In both cases, this information can be obtained relatively easily from standard sampling procedures well within the capability of developing country fisheries institutions. The level of potential yield and the corresponding fishing mortality rate depend also on the steepness (the degree of density dependence) in the stock-recruit relationship, which is much less easy to estimate. However, the results in this paper still allow estimates to be calculated for a reasonable range of possible values of steepness, thereby allowing prudent management decisions to be made when only sparse data are available.

ACKNOWLEDGEMENTS

The research reported in this paper was funded by grants from the UK Department for International Development as part of its Fishery Management Science Programme. All calculations of yields and fishing mortality rates were made using the Yield software also funded by this programme.

12. Managing fishing effort in multispecies fisheries

Christopher C. Mees

12.1 INTRODUCTION

FMSP Project R5484 derived guidelines for the management of demersal bank and deep reef-slope fisheries exploited principally with hooks and lines, a relatively simple multispecies fishery, but with widespread applicability (Mees and Rousseau, 1996). Section 4.4 outlines the approach used to derive the guidelines. The guidelines describe appropriate management controls for multispecies fisheries, and in particular they define how to set overall levels of fishing effort applicable across all species. A rule of thumb for evaluating the status of key indicator species within the fishery was also developed. Outputs from existing stock assessment tools (e.g. CEDA for catch and effort data, LFDA or FiSAT for length based data to derive biological reference points, and Yield software to evaluate optimum values of effort) applied to data typically available in developing country situations are required to implement the guidelines. Minimum data requirements to achieve effective management were also derived.

The guidelines for management of multispecies fisheries derived through this study were based on fisheries with particular characteristics as listed below. The applicability of the guidelines to fisheries with other characteristics has not been evaluated, and therefore the reader should be aware of these limitations.

- Hooks and lines represent a selective method of fishing (compared to nets, for example) and the study was confined to examining interactions between target species (including predator-prey responses between them or between age classes of the same species). Any effects on their predator or prey species was not examined. However, for one of the case study locations, Seychelles, the inshore reefs are exploited by small boats using a variety of methods including traps, nets and hook and line. In a fishery independent survey, Jennings, Marshall and Polunin (1995) indicated that fishing depleted the top predators (lutjanids, serranids and lethrinids) but there was no evidence for prey release or an increase in abundance of fish at other trophic levels related to fishing following their removal. It may be assumed that this observation will also apply to the offshore banks of the present study, and suggests that the lack of information on non-target species was not important.
- A poor relationship exists between hook size and fish size (Ralston, 1982, 1990; Bertrand, 1988), which limits management responses, and has implications for data collection.
- Target species, members of the families Lethrinidae, Lutjanidae and Serranidae, are long lived, slow growing species with relatively low rates of natural mortality. Length at maturity as a proportion of the asymptotic length tends to be high, and they have limited reproductive capacity and are vulnerable to overfishing.

12.2 SOME KEY FINDINGS FROM THE STUDY

No detectable multispecies responses due to biological interactions and fishing were found. Species composition changes due to technical interactions were, however, significant. The results indicated that single species and aggregate single species models were adequate to derive management advice for the study demersal fisheries without the need for more complex ecosystem models accounting for all multispecies interactions. However, standardisation to account for technical interactions was essential.

In relation to minimum data requirements, the finding that single species and aggregate single species models are adequate to describe and manage multispecies demersal bank and deep reef slope fisheries has important consequences. The results indicated that it is sufficient to obtain catch and effort data from the most important species and aggregations of other species without the need for detailed information on every species. However, due to the importance of technical interactions, catch and effort data collection must include a number of other details, particularly those relating to technological changes in fishing methods – vessel and gear characteristics must be recorded. Sampling strategies for catch and effort data, and species specific length frequency and biological data, also need to capture fishing depth and spatial information to enable standardisation for variation in these factors.

For length frequency and biological data collection, the management guidelines require that the number of species from which data is collected need only be confined to the most vulnerable and economically important. For individual species length frequency data and age and growth assessment were essential. The more costly biological data to provide parameters such as length at maturity, whilst useful, was not seen as essential for management. An estimate of density dependence in stock recruitment would be very useful for refining management thresholds. A key deficiency in existing data collection related to uncertainty in growth parameter estimates from length based methods. This prompted further studies to investigate the importance of growth parameter estimation (see Section 10).

The effect of a range of potential management controls on study multispecies fisheries was examined. Whilst it is theoretically possible to set management controls for individual species, and for different depth bands, relating to one source of technical interaction, this was considered to be too complex. Management controls based on a combination of effort controls and closed areas is recommended. A simple rule was derived for determining the ideal fishing mortality of single species, based on the effect of controls on effort and length at first capture. A set of criteria was formulated for selecting critical (or key) species for which such a single species analysis should be performed. From this analysis of some of the component species, a method was developed for determining the appropriate overall effort level for the multispecies fishery. Although the guidelines for management are conservative, the method enables informed choices to be made about the risks and benefits of allowing some species to be overfished in order to optimize yields of others.

12.3 GUIDELINES FOR DATA COLLECTION AND MANAGEMENT OF MULTISPECIES FISHERIES

12.3.1 Data collection

Catch and effort data need only be collected on key species (defined by the management guidelines) and guilds of others. Length frequency and biological data need only be collected for the key species. Length frequency data are essential, but biological data are less important. Table 12.1 provides a summary of data collection requirements that may feasibly be implemented by resource limited developing country institutions.

Studies of the predicted effects of management suggested a prioritisation for data collection and research subject to the characteristics of tropical demersal reef bank and deep slope species. The following highlights the information required to implement the management guidelines, some of which are parameters derived from original data.

- It is assumed that length at first capture (L_{c50}) cannot be controlled in a handline fishery. The best that can be done is to measure it, and set effort levels accordingly. Therefore, deriving estimates for L_{c50} for key species is a high priority. When a fishery is new or lightly exploited, the L_{c50} is initially high and drops as the large sizes of fish are removed. In such fisheries where L_{c50} has not stabilized yet, it is wiser to use an estimate of future likely L_{c50} than to use the real measured value.

- It is assumed that catch limitation is impractical. Therefore, it is more important to know the effort range within which yield is maximized, than to be able to predict the maximum sustainable yield that would be so obtained. This means that it is not necessary to estimate length at maturity (L_{m50}) (but see 12.3.2, point 4).
- The study species all have estimated M/K close to 2. This characteristic contributes to the simplicity of the management guidelines. It is therefore important to monitor that this ratio does not deviate significantly from 2. M and K must be estimated for key species. In the case study examples, M was estimated empirically (Pauly, 1980).
- M is also necessary for setting the desirable fishing pressure, since all F's are scaled to M.
- The only requirement for K is the ratio M/K, but L_∞ will be needed in order to derive L_c (defined as the ratio of L_{c50}/L_∞), so growth parameters are required. The growth parameter t_0 is not necessary, so simplified growth curve fitting procedures may be used.
- It is particularly important to have an estimate of the relative catchabilities of species which are to be measured and/or managed as a guild. Similarly, relative catchability of guilds should also be known. Fish which are treated as a guild should have similar catchability and L_c. This does not necessarily require data analysis for all species - where fish are of similar size and habits and are homogenously distributed, it can be assumed their catchabilities are approximately the same.
- Absolute catchability will be needed for key species.
- Length weight parameters are not very important, and are not required for the implementation of the management guidelines.
- Details of a selection ogive for the gear are not nearly as important as a good estimate of L_{c50}.
- If an estimate of virgin biomass is available, it will enable the expected yield to be predicted, to within the tolerance represented by unknown parameters such as L_m and absolute catchability.
- An estimate of density dependence in stock recruitment would be very useful for refining management thresholds.

The influence of unknown or uncertain parameters on resulting management advice can be investigated through sensitivity analyses. One example is provided by Mees and Rousseau (1997), who examined the sensitivity of single species management outputs to uncertainty in growth parameter inputs and the stock recruitment relationship parameter, d. Effort targets set to be slightly more conservative than maximum sustainable yield (MSY) were found to provide security against uncertainty, at relatively low cost to the fishery. The Yield software also allows examination of effort targets for single species.

12.3.2 Summary of biological guidelines for management

A number of alternative management controls for multispecies fisheries were investigated, summarized in Table 12.2.

The guidelines are designed to result in an overall effort limit for a multispecies fishery which will ensure the maximum return from the fishery while protecting all the species within it.

1. Estimate relative catchability for the major species or guilds (guilds may be comprised of similarly sized species which school together or otherwise present a homogeneous profile to the gear).
2. Estimate L_c and M for the following species:

- the most catchable one
- the biggest one (highest L_∞)
- the longest lived (lowest M)
- the slowest growing (lowest K)
- any that is caught with a wide range of lengths, particularly juveniles.

3. If the fishery is new or lightly exploited and $L_c > 0.5$, then work with a projected long term value of L_c=0.5 until it appears that L_c has stabilized at the higher value.
4. From L_c, estimate F_{opt} for these species, using Figure 12.1. Note that in Figure 12.1, F_{opt} is assumed to be $F_{MSY.}$ Yield Software, however, offers the potential to derive alternative values of F_{opt} (e.g. $F_{0.1}$, F_{SSB20}). Thus, if possible, apply yield per recruit analysis to derive F_{opt} based on the selected management target. It is important that the estimated SSB at the target effort is higher than the minimum necessary to maintain long-term average recruitment.
5. Estimate absolute catchability q for:
   - the most catchable species and
   - the one with the lowest F_{opt} as calculated above.
6. Calculate $E_{opt} = F_{opt} / q$ for the above species.
7. Choose the smallest of the two E_{opt}s and set overall effort $E = \min(E_{opt})$

This method identifies the various categories of most vulnerable species, and sets effort to protect the most vulnerable one. If economic or sociological considerations place priorities on a certain species, E_{opt} can be calculated for it, and the effect of such an effort on the more vulnerable species can be estimated. Informed choices can then be made about the risks and benefits of overfishing some species in order to optimize yields of others.

12.3.3 Rules of thumb for evaluating the status of key species and management response

Having defined the key species for a particular fishery, a manager needs to establish the current status of exploitation (i.e. the current fishing effort F_{cur}) and take appropriate management action. Mees and Rousseau (1996) derived rules of thumb based on certain biological reference points, that may be used as indicators of the need for management action.

L_{c50} and fishing mortality (F_{cur}) are key parameters which should be established. Length at maturity (L_{m50}) is also useful, but where unknown, management may be based on knowledge of L_{c50}.

Where length at maturity (L_{m50}) is known and L_{c50} is about L_{m50}, fishing mortality (F) should not exceed twice the natural mortality (M, see also Polovina, 1987). Where L_{c50} is greater than L_{m50} effort controls are less important and overfishing is unlikely to occur. However, where the reverse is true, careful control of the level of effort is required. Yield per recruit analyses may be used to derive the optimum level of fishing mortality (F_{opt}) at any given L_{c50}. These rules are summarized below.

Where L_{m50} is known:

If $L_{c50} = L_{m50}$ then set $F \leq 2M$

If $L_{c50} > L_{m50}$ then effort controls are less critical

If $L_{c50} < L_{m50}$ then calculate F_{opt} from YPR analysis

Compare F_{cur} to F_{opt} to determine the appropriate management action, based on the relationship between L_{c50} and L_{m50} .

Where L_{m50} is unknown, a scale of fishing mortalities has been derived, as a guideline to management, appropriate for different values of L_{c50} (Figure 12.1). However, conservatively it was suggested that where L_{c50} was greater than $0.5L_\infty$ then effort should be determined for $L_{c50}=0.5L_\infty$ rather than current values (see guidelines point 3) and at this point fishing mortality should not exceed natural mortality (i.e. $F/M \leq 1$).

Where L_{m50} is unknown:

If $L_{c50} > 0.5L_\infty$ then manage conservatively assuming $L_{c50}=0.5L_\infty$, setting $F=M$

If $L_{c50} = 0.5L_\infty$ then set $F=M$

If $L_{c50} < 0.5L_\infty$ then calculate F_{opt}/M from Figure 12.1.

Compare F_{cur}/M to F_{opt}/M to determine the appropriate management action, based on the relationship between L_{c50} and L_∞.

Mees, Pilling and Barry (1999) provide an example of the application of these indicators to the banks fishery in the Chagos Archipelago.

TABLE 12.1

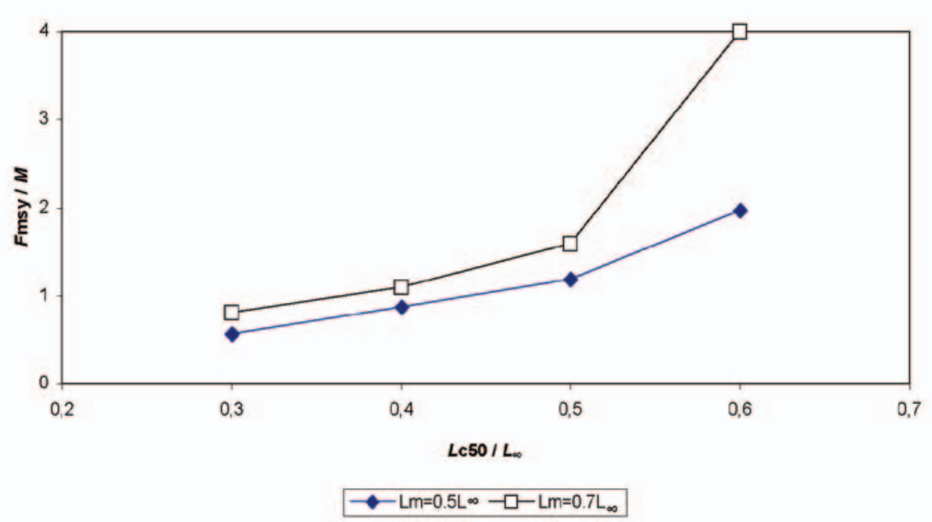
Summary of data collection requirements feasible for resource limited developing country fisheries institutions, for the management of demersal fisheries

Details	Data type		
	Catch and effort data	**Length frequency data**	**Biological data**
Collected for	- Key species plus guilds of others (essential) - All fishing grounds and potential fishing areas	- Key species (essential)	- Key species only if resources available, (not essential)
To estimate	- catch, - effort, - biomass-prodn models - catchability	- L_c - growth K, L_∞ - mortality (M & current F) - Apply guidelines	- (L_m) - (growth from hard parts) - (length-weight relationship) - (Location and time of spawning)
Must monitor	- Technical interactions - Depth - Gear - vessel power - fishing practices - Location specific	- gear size (hooks); - location specific data essential- must relate to heavily fished locations	
Strategies for data collection	- Prioritize to optimize cost/benefits for limited resources - Aim for large sample size (consider logbooks) - Implement targeted sampling strategy - Decide most appropriate guilds (more research?) - Add technological data requirements to logbooks	- Prioritize - Targeted sampling strategy (concentrate on heavily fished locations if cost is limiting) - Increase sample size from lightly fished locations where possible	- Collect biological data from successive key species where funds permit - Collect hard parts for ageing - Use informal interview techniques to get additional information e.g. spawning time /location

TABLE 12.2
Summary findings of the simulated effects of alternative management controls on multispecies demersal bank and reef-slope fisheries, indicating management recommendations

Management Control	Project findings
Catch	Direct catch controls and quotas not recommended for multispecies fisheries, but catches should be monitored, and SSB should not be allowed to fall below 20-30% of initial SSB (refer to Yield software)
Effort	Effort controls are recommended as the primary management control. Effort must be appropriate for L_c Guidelines give appropriate effort for multispecies resource Given potential for uncertainty in parameters upon which effort targets are based, effort controls should be used in combination with permanently closed areas.
Length at first capture	Difficult to apply in hook and line fisheries Minimum size controls not appropriate Essential to monitor this parameter
Closed seasons	No benefit indicated Protection of known spawning aggregations should be encouraged
Closed areas	Benefit to spawning stock biomass, but unknown if loss of yield to fishery is compensated by increased yields Useful buffer against stock collapse
Pulse fishing	No benefit to yield Disruptive to fishing activities Benefits SSB Recovery 8% pa for deep slope, 12%pa for banks
Resource manipulation	Results in reduced overall yields Elimination of species possible Sometimes appropriate to maximize economic yield

FIGURE 12.1
The value of F_{MSY} / M at different lengths at first capture, L_{c50}, expressed as a proportion of the asymptotic length, L_∞(L_c=L_{c50}/L_∞ calculated for Length at maturity equal to 0.5L_∞, and 0.7L_∞ (see 12.3.2, point 4). Note that for lutjanids, Grimes, 1987, indicated that sexual maturity occurs in the range 43%-51% of the maximum length



13. Bayesian stock assessment of the Namibian orange roughy (*Hoplostethus atlanticus*) fishery

Murdoch McAllister

13.1 INTRODUCTION

Bayesian stock assessment can be useful for developing scientifically based fisheries management advice in developing fisheries for a variety of reasons (McAllister and Kirkwood, 1998a, b). For example, in developing fisheries, data on abundance and the biological characteristics of a newly exploited population are nearly always sparse. Yet, it is often the case that other populations of the same and similar species have been exploited elsewhere and studied by biologists. Bayesian approaches offer a variety of methods to harness such data, knowledge and experience to help assess and manage the newly exploited fish stocks. Such previous experience for example can help to quantify plausible ranges of values for growth, natural mortality rates, catchability, and stock-recruit function parameters for the stock of interest.

Bayesian methods offer a coherent probabilistic modelling methodology that permits estimation of key population parameters and abundance using a wide variety of data. Hierarchical modelling methods, for example, can estimate the distribution of values for a parameter across populations based on an analysis of datasets from several different populations (Gelman *et al.,* 1995; Liermann and Hilborn, 1997; Michielsens and McAllister, 2004). Bayesian stock assessment methods can utilize as inputs prior probability distributions for model parameters that incorporate the uncertainty in the input values but also what is known based on previous studies and analyses, e.g., from hierarchical analysis of stock-recruit data for several similar previously studied populations (McAllister *et al.,* 1994). After fitting the Bayesian models to data, output distributions convey what is known about the modelled quantities of interest following the analysis of data. These output distributions can serve as inputs to decision analysis modelling which evaluates the potential consequences of alternative fisheries management actions that could be taken (McAllister *et al.,* 1994; McAllister and Pikitch, 1997). Thereby, the potential outcomes and risks of alternative management actions can be evaluated taking into account all available information and the key uncertainties about the state of the stock.

This section provides an illustration of a recent application to demonstrate how the Bayesian approach was recently implemented and how the stock assessment advice was actually applied in the management of the Namibian orange roughy fishery. For further detail on the application, please see Boyer *et al.* (2001) and McAllister and Kirchner (2001, 2002). In the first part, a brief background to Namibian orange roughy is provided. The second part illustrates how expert judgment and experience from other fisheries for orange roughy were utilized within the Bayesian stock assessment and how the methodology applied evolved as new data were acquired. Third, the manner in which the decision analysis was carried out is outlined. Fourth, some results of the assessment are shown. Fifth, the various pros and cons of the Bayesian methods applied are outlined.

13.2 NAMIBIAN ORANGE ROUGHY: BIOLOGY, EXPLOITATION AND SCIENTIFIC RESEARCH

Orange roughy is found at depths of 500m - 1 500m. It has world-wide distribution and is found in temperate to subtropical waters. It is believed to be very long-lived with some specimens aged over 100 years (Boyer *et al.,* 2001). The age at maturity for Namibian fish has been estimated at 20 to 30 years. Growth is very slow with fish reaching a maximum of 1-4 kg. Fecundity is also low at 20 000-60 000 eggs per year. Mature fish form dense spawning aggregations often over pinnacles and gullies in the austral winter. Spawning orange roughy are harvested by deepwater trawlers that use specialized deep-water trawl gear and modern electronics. Hauls of 20-70 tonnes are possible. Fish are headed and gutted and iced or frozen at sea. On-shore processing plants produce fillets which are exported to the US. The resource has a landed value of about US$2 750 per green-weight ton (Branch, 1998).

Biomass estimation of orange roughy with the use of trawl survey, hydro-acoustic and commercial catch rate data is problematic for the following reasons. Deepwater fisheries resources such as orange roughy (*Hoplostethus atlanticus*) are physically less accessible than other fisheries resources. They are more difficult to locate and map in spatial extent because of their extreme depth and highly patchy distribution. They are more difficult to assess for their biological characteristics, abundance and changes in abundance because of low hydro-acoustic target strength, difficulties in ageing specimens, highly aggregating behaviour, and the inability to apply mark and recapture tagging methods (Clark, 1996). Mature fish migrate to and from spawning grounds and aggregations, required for hydro-acoustic biomass estimation, can form and break up rapidly (Kirchner and McAllister, 2001).

In New Zealand, where orange roughy has been assessed since the late 1980s, an age-structured stock assessment model had been fitted to research trawl survey indices of abundance, mean lengths of fish from these surveys and in some instances commercial catch rate data (Francis, 1992; Francis *et al.,* 1992). The estimation procedure allows for historical deviates from the Beverton-Holt stock recruit function and assumes that these are lognormally distributed with a relatively large standard deviation in the natural logarithm of the deviates of 1.1. The estimation procedure also treats the constant of proportionality, q, between the abundance indices and stock size as estimated parameters. The model therefore relies entirely on historical declines in the abundance indices and the observed catch removals to make inferences about stock biomass and trends in stock biomass. A time series of 6 years showing a consistently decreasing trend provided fairly precise stock biomass estimates (Francis 1992; Francis *et al.,* 1992).

13.3 INITIATION OF THE FISHERY AND STOCK ASSESSMENT OF NAMIBIAN ORANGE ROUGHY

An exploratory orange roughy fishery began in 1994. Catches rose from 29 tonnes to about 13 000 tonnes between 1994 and 1996 (Table 13.1). By 1996, four major fishing grounds, i.e., Johnies, Rix, Frankies and Hotspot had been discovered within the 200 nmi EEZ. From 1997 onwards the fishery progressed beyond its exploratory phase and was managed by a total allowable catch (TAC). The fishery management objectives were to maximize net economic yield and not to deplete the resource below the maximum sustainable yield (MSY) level. The management strategy adopted was to fish down the accumulated biomass for 7 years with TACs set larger than the MSY and then a 7-year transition in TACs to the MSY.

The TAC was obtained from the Johnies, Rix, Frankies and Hotspot fishing grounds. In 1997, the virgin biomass was estimated using commercial catch per unit effort (CPUE) data since these were the only data available (Branch, 1998). Branch (1998) developed a swept area methodology to convert the tow by tow CPUE data

TABLE 13.1
Orange roughy catches from each fishing ground, the total catch and total TAC from 1995-1999 (From McAllister and Kirchner, 2001)

Year	Johnies	Frankies	Rix	Hotspot	Total	TAC
1995	4 111	--	12	2 620	6 743	--
1996	1 905	7 757	1 445	785	11 892	--
1997	2 825	8 773	3 307	612	15 517	12 000
1998	5 954	1 244	4 249	345	11 792	12 000
1999	1 495	80	721	202	3993	9 000

to a single swept area biomass estimate. With only a single abundance estimate, other methodologies such as Francis (1992) which requires a time series of relative abundance indices could not be applied. The only way to use this swept area estimate was to use expert judgment to construct a scaling parameter (q') that could rescale this swept area estimate (I) to absolute biomass (B) such that $B = q'I$. Branch (1998) adopted a Bayesian-like approach to construct a probability density function for q'. q' was assumed to be a function of nine different "bias" factors which could affect the relationship between the commercial swept area estimate and the total mature biomass. These included factors such as the catchability of orange roughy by commercial trawl gear inside aggregations, and the extent to which trawls were directed at known aggregations. Density functions were constructed for each of these factors based on consultation with experts (for more details see Branch (1998) and Boyer *et al.,* 2001). A Monte Carlo approach was applied using the nine individual density functions for the bias factors to develop a probability distribution or "density function" (pdf) for the average unfished biomass, B_o. The stock assessment procedure applied then took draws from this pdf for B_o and projected a deterministic age-structured model 14 years forward to the year 2010 to evaluate the potential consequences of alternative fishing down policies. The population dynamics model was very similar to those applied in New Zealand and the values for its input parameters, except for B_o, were set at the values used in New Zealand because of lack of biological details on Namibian orange roughy (e.g., Francis 1992).

Unlike more conventional stock assessment methods, the initial Bayesian-like stock assessment procedure did not require a time series of relative abundance to estimate B_o and stock biomass. The validity of this method which relies on expert judgment to construct a prior pdf for q is based on the following three assumptions, among others:

1. The spatial positions of individual trawls within each spatial stratum were determined on a random or systematic basis in the first few years of the fishery. This condition is unlikely in any commercial fishery but could sometimes be approached in an exploratory fishery when fishermen are searching for fish. However, once fish are located, this assumption will no longer be valid. Factors to correct for this source of bias were identified and applied in the first assessment (Boyer *et al.,* 2001).
2. The positions of aggregations were stationary over time, i.e., from 1994-1996. Later analysis found this not to be the case. In these years, large catch rates were extrapolated to large, scarcely sampled areas giving positively biased swept area estimates. A recalculation in 2000 that allowed for non-stationarity in aggregation position and stratum definition produced much lower swept area estimates (Kirchner and McAllister, 2001).
3. The pdf for the constant of proportionality, q', was not seriously biased in central tendency and not too narrow (Walters and Ludwig, 1994; Adkison and Peterman 1996). If the central tendency was seriously biased, being too narrow could exclude the true bias correction. This could then result in seriously biased estimates of B_o and stock biomass. In retrospect, it appears that the pdf for the original bias correction was too narrow. The initial coefficient of variation (standard deviation

(SD)/mean) (CV) for *q'* was about 0.25. This was updated to about 0.3 at the 1997 stock assessment meeting. However, this was later updated to about 0.6 for the 1999 assessment.

The result of applying a positively biased swept area estimate of biomass and a pdf for *q'* that was too narrow was a markedly biased commercial swept area estimate of B_o for Namibian orange roughy in the first two years of stock assessment, 1997 and 1998 (Table 13.2). In 1997 hydro-acoustic and research trawl surveys were conducted on the three southernmost fishing grounds. The estimate of biomass obtained from these were about half of the value obtained from the commercial swept area time series. In 1998, the stock assessment procedure was also run using a pdf for B_o based on the hydro-acoustic swept area estimate of stock biomass and pdfs for bias factors for this swept area estimate. The calculated risks of different TAC policies were much higher using this latter estimate of B_o and alarm was raised in 1998 over the possibility that the initial assessment with the commercial swept area estimate was too optimistic. The estimates of B_o and risks and management decisions based on the risks in each year from 1997 to 1999 are summarized in Table 13.2.

TABLE 13.2
The history of scientific advice for the management of Namibian orange roughy up until 1999. The biomass estimates are the median values given by the hydro-acoustic (a) and commercial swept area (c) estimates. The % risks for the TAC policies shown are computed in terms of the probability that the biomass in the final projection year shown drops below 20% of virgin stock size. + two more Companies indicates that two additional companies were allocated TAC (From McAllister and Kirchner, 2001)

Year	Biomass Estimate (tonnes)	Risk Criterion	Management Decision Adopted
1997	300 000 (c)	20 000 tonnes TAC < 10% in 2010	12 000 tonnes TAC + two more Companies
1998	230 000 (c) 150 000 (a)	12 000 tonnes TAC < 10% in 2001	12 000 tonnes TAC for 1998 only
1999	75 000 (c) 25 000 (a)	9 000 tonnes TAC < 10% in 2000	9 000 tonnes TAC for 1999 only + close Frankies

13.4 THE 1999 REVISED BAYESIAN STOCK ASSESSMENT PROCEDURE FOR NAMIBIAN ORANGE ROUGHY

By 1999, the fishery and scientific research program for orange roughy had operated for four years. This enabled the construction of commercial swept area, hydro-acoustic and research trawl swept area time series for each of the four fishing grounds. All time series from 1995-1998 showed a decline, especially following 1997 on the three southern grounds (Table 13.3). The existence of a four-year time series of catch and CPUE indices and a two-year series for hydro-acoustic and research trawl swept area indices opened up the possibility of fitting a stock assessment model to these data for model parameter and biomass estimation. However, the time series were very short. Fitting a time series model to such data and treating them as relative abundance indices with the value for the constant of proportionality, *q*, (that scales stock biomass to the value of the index) allowed to vary from 0 to infinity could be expected to produce highly imprecise estimates (Smith 1993; McAllister *et al.*, 1994). Other studies have indicated that constructing informative prior probability distributions for the constant of proportionality for abundance indices with the use of expert judgment could help to improve the precision in biomass estimates (McAllister *et al.*, 1994; McAllister and Ianelli, 1997). This would occur because the informative priors restrict the range of possible values for *q* so that they no longer range without constraint between 0 and infinity. Moreover, the initial assessments already had produced a pdf for *q'* for the commercial swept area and hydro-acoustic estimates of biomass, albeit too narrow and other work had already constructed prior pdfs for *q* for research trawl survey swept area estimates (McAllister and Ianelli, 1997). It was thus possible to do so for the estimates for Namibian orange roughy.

The revised stock assessment approach fitted the same age-structured population dynamics model used in the previous two assessments to the available relative abundance series (Table 13.3) but also used informative prior pdfs for their constants of proportionality and incorporated process error in the stock-recruit function (Francis *et al.*, 1992; McAllister *et al.*, 1994). The general steps for the revised Bayesian stock assessment procedure are as follows:

1. *Formulate prior probability distributions for the estimated model parameter*s. The prior distribution for a set of parameters summarizes the information about those parameters from all knowledge except data used in the likelihood calculations of the stock assessment (Punt & Hilborn, 1997). Prior pdf's were constructed individually for each parameter. Priors were applied for the long-term average value for unexploited biomass, B_o, the rate of natural mortality, M, and the annual deviates from the Beverton-Holt stock-recruit function (McAllister and Kirchner, 2001). For each trial, the prior for B_o was uniform over the interval [1 000 tonnes, 2 000 000 tonnes]. The prior for M was lognormal with a median 0.055, and standard deviation for the logarithm of M of 0.3 (Clark *et al.*, 1999). The assumed value for the prior SD in annual stock-recruit function deviates was set at 1.1.

Informative prior pdfs were also constructed for the constants of proportionality (q) for each relative abundance index based on the same pdfs for "bias factors" identified in the previous assessments and the relationship $I_y = qB_y$ where I_y is the model predicted

TABLE 13.3
Orange roughy relative abundance indices. Model input coefficients of variation (CVs) are given in parenthesis (from McAllister and Kirchner, 2001)

Year	Hydro Acoustic	Research-Swept-area	Commercial-Swept-area
Johnies			
1995			17 417 (0.40)
1996			16 177 (0.42)
1997	32 171 (0.29)	57 650 (0.32)	25 471 (0.41)
1998	4 733 (0.31)	6 980 (0.30)	17 210 (0.38)
1999	-	2 137 (0.42)	6 924 (0.38)
Frankies			
1995	-	-	
1996	-	-	21 893 (0.39)
1997	19 804 (0.25)	30 995 (0.37)	36 319 (0.38)
1998	6 551 (0.34)	2 400 (0.60)	12 509 (0.38)
1999	1 751 (0.30)	3 055 (0.35)	4 143 (0.42)
Rix			
1995	-	-	
1996	-	-	12 339 (0.41)
1997	17 500 (0.29)	-	16 254 (0.42)
1998	10 041 (0.31)	-	13 697 (0.38)
1999	-	1 006 (0.59)	5 902 (0.40)
Hotspot			
1995	19 838(0.39)		
1996	3 892(0.39)		
1997	2 939(0.42)		
1998	2 112(0.39)		
1999	2 364(0.42)		

index of abundance in year y and B_y is the model-predicted stock biomass in year y. An additional lognormally distributed prior uncertainty factor with a prior CV of 0.5 and a median of 1 was also incorporated into the priors for q. This was because recent work (McAllister and Kirkwood, 1998a) had shown that risks of overfishing could be substantially increased if the prior CV for parameters such as q in developing fisheries is set too low, e.g., < 0.5, as in the 1997 and 1998 assessments. The values for the other model parameters (e.g., the age at maturity and growth parameters) were fixed at values that were assumed to be known without error. These values were obtained from ageing studies of Namibian orange roughy (Clark *et al.*, 1999). The weight-length relationship constants were estimated from research samples taken in 1998 and assumed to be the same for the three grounds, Johnies, Frankies and Rix, but were different for the Hotspot ground (Dalen *et al.*, 1998). The value for the Beverton-Holt steepness parameter (0.75) was taken from Francis (1992).

Individual stock assessments were done on the orange roughy stock on the four grounds separately. It was shown by ageing analysis that orange roughy at Hotspot are more similar to the New Zealand orange roughy and therefore biological parameters for New Zealand orange roughy were used (McAllister and Kirchner, 2001).

2. *Formulate the likelihood function of the data for each relative abundance series*. This function provides a formalized probabilistic measure of the goodness of fit of the model to the stock assessment data. It gives the probability of obtaining the data for each possible combination of values for the estimated model parameters. A set of parameter values that provide a very close fit of the model to the data will yield a very high likelihood of the data and vice versa. The likelihood function chosen was a lognormal density function indicating that the deviate between each observation and the value predicted for it by the model and its parameters is lognormally distributed (McAllister and Kirchner, 2001). In stock assessment, this is a very commonly applied likelihood function for relative abundance data. The product of the prior probability and the likelihood function for a given set of values for the estimated model parameters is directly proportional to the posterior probability for these values.

3. *Calculate the joint and marginal posterior probability distributions for model parameters and stock biomass in each year and the other management quantities such as the ratio of stock biomass in each year to B_o*. The numerical algorithm applied for these calculations was importance sampling (Berger, 1985, Rubin, 1988, Gelfand and Smith, 1990; West, 1993), a commonly applied algorithm for Bayesian stock assessment (Francis *et al.,* 1992; Punt, 1993; McAllister *et al.,* 1994; Raftery, Givens and Zeh ,1995; Kinas, 1996; McAllister and Ianelli, 1997).

4. *Evaluate the potential consequences of alternative management actions*. This was achieved by randomly sampling values for model parameters from the joint posterior probability distribution obtained in the previous step and projecting the population dynamics model into future years using these values. The combined steps of 3 and 4 are typically called the sampling importance resampling (SIR) algorithm (Rubin, 1988).

5. *Present the results*. The posterior probability distributions for B_o, stock biomass in 2000 (B_{2000}), and B_{2000}/B_o were graphed for each fishing ground. Also graphed were 95 percent probability intervals for stock biomass over time. For the 2000 stock assessment, the potential consequences of alternative constant TAC policies were projected for the period 2001-2010 and presented in decision tables.

13.5 SOME KEY FEATURES OF THIS APPLICATION

One key feature of this application of Bayesian stock assessment is its use of an informative prior probability distribution for q for each of the three different indices of abundance to deal with the very short time series of relative abundance. The independent construction of each prior allows the comparison of the resulting prior stock biomass estimates from three different sources to check for overlap in probability intervals and to ground-truth each individual prior for q. The effect of implementing these informative priors is illustrated below by also producing results with non-informative prior probability distributions for q that were uniform over the natural logarithm of q (McAllister *et al.,* 1994).

A second feature of this assessment is its advocacy of Bayesian probability analysis to identify precautionary reference points for fishery management (FAO, 1995). An important management reference point for many species including orange roughy is the ratio of population biomass at maximum sustainable yield (MSY) to the long-run average unexploited biomass (B_{MSY}/B_o). This can be either used as a target reference point (a system state to achieve and maintain) or a limit (threshold) reference point (not to be dropped below), depending on the situation. In past studies of orange roughy, MSY-based reference points have been computed using an age-structured model with all parameters except for B_o and recruitment deviates fixed and uncertainty from data analysis accounted for (Francis 1992; Francis *et al.,* 1992). The stochastically derived estimates used the average value of 0.3 B_o as the reference point.

While the method of Francis *et al.* (1992) was rigorous in its treatment of uncertainty, it still assumed parameters such as the rate of natural mortality, M, were known without error. Methods that even more rigorously account for uncertainty can allow more thorough assessments of the reliability of estimates and the potential for error in them. Bayesian estimation of a pdf for B_{MSY}/B_o would permit managers to be more precautionary because more parameters could be treated as uncertain. Using the mean value for B_{MSY}/B_o as the reference point also ignores uncertainty in the estimate of B_{MSY}/B_o. Uncertainty in B_{MSY}/B_o could be more rigorously taken into account and a more precautionary reference point could be formulated by the use of values higher than the average. For example, a pre-specified percentile for B_{MSY}/B_o that was acceptably high could be applied to set a management reference point based on B_{MSY}/B_o. Bayesian probability distributions for B_{MSY}/B_o were thus computed to identify such a reference point (McAllister and Kirchner, 2001).

A third feature of this application is that in the fourth year, the procedure was extended to formally account for uncertainties in population dynamics model assumptions (i.e., structural uncertainty) rather than only uncertainty in the values of parameters such as B_o and M. The large drop in the biomass indices could not be easily explained by the relatively small catch removals. Thus four structurally different models for resource decline were developed.

1. The catch removal model. The observed declines occurred mainly because of catch removals and the priors for q are centred too low.
2. The fishing disturbance model. The observed declines occurred because of successive disturbances of the orange roughy aggregations by fishing. Orange roughy have responded by failing to reaggregate on the fishing grounds. If fishing is stopped, the fish may reaggregate.
3. The intermittent aggregation model. The observed declines occurred because of temporary factors unrelated to fishing. Orange roughy may aggregate on an intermittent basis depending on various environmental conditions. Fish will reaggregate on the fishing grounds but the timing of this remains unpredictable.
4. The mass emigration or mortality model. The observed declines have been caused by either a mass mortality event or a mass emigration and the original large abundance recently observed on the fishing grounds is unlikely to re-establish in the near future.

The mathematical features of these models are outlined in McAllister and Kirchner (2002). Each model was fitted to the same data (Table 13.3) and a marginal posterior probability was computed for each model. To obtain these probabilities, Bayes' factors were computed for each alternative model based on the prior pdf for model parameters and likelihood function of the data with the use of an importance sampling algorithm

(Kass and Raftery, 1995; McAllister and Kirchner, 2002). The Bayes' factors were combined with a prior probability for each model to give Bayes' marginal posterior probabilities, i.e., the total weight of evidence in support of each alternative model. Each model was assigned an equal prior probability. This was because it was believed that before analysing the stock assessment data there was no other rational basis that could be applied to rate the credibility of each model (Butterworth, Punt and Smith, 1996). This procedure allowed the probability distributions for management quantities such as stock biomass to be combined across models with the weighting for each distribution given by the associated model's marginal posterior probability. The resulting estimates could thereby more formally account for uncertainty in both the values for model parameters and the structure of the stock assessment models for Namibian orange roughy.

13.6 RESULTS

Prior medians and probability intervals for abundance indices

In order to check whether the priors for q gave consistent biomass estimates, the biomass indices were rescaled by the prior median value for q and 95 percent probability intervals for q (incorporating the prior coefficient of variation (prior standard deviation / prior mean) (CV) and the survey CV for each index, Table 13.3). The results are shown in Figure 13.1. Where there is more than one abundance index per year all of the 95 percent probability intervals overlap considerably indicating that there are no serious inconsistencies among the prior biomass estimates and trends given by the indices. However, the trends in the commercial swept area estimates appear to give smaller declines than the other two indices on the three southern grounds where all three types of indices are available. Moreover, on each ground, the indices suggest high stock biomass in the initial years of the fishery and then a large decline.

The use of non-informative versus informative prior distributions for q

If the approach of Francis *et al.* (1992) which effectively used non-informative priors for q was applied, the results would suggest that considerably fewer orange roughy are left on the fishing grounds than if informative priors were applied (Figure 13.2). The wide probability distributions for stock biomass in both cases indicate that uncertainty in the estimates is very large.

To evaluate whether the models applied could fit the data adequately, the posterior 95 percent probability intervals for stock biomass from 1994 to 1999 are plotted in Figure 13.3. The relative biomass indices rescaled by the posterior median value for q are also shown on these plots. Median values for the biomass indices falling outside of the posterior 95 percent probability intervals for annual stock biomass would indicate that the model and the prior assumptions do not fit the data very well. When both the informative and non-informative priors for q are applied, some of the rescaled biomass indices fall outside of the posterior 95 percent intervals for each of the grounds except for Rix.

When structural uncertainty was accounted for, the only model that encompassed the rescaled indices within its posterior 95 percent probability intervals for stock biomass on all of the four fishing grounds was the mass emigration / mortality model (Figure 13.3). This model also suggested that current biomass on each of the four fishing grounds was very low.

The use of decision analysis results in decision making

The key results for fishery managers of orange roughy were presented as the risks associated with alternative TAC policy options (Table 13.2). These were given in terms of the probability of stock biomass dropping below some level of virgin biomass in some future year. In the first stock assessment in 1997, when alternative fishing down

FIGURE 13.1

Prior medians and 95% prior probability intervals for stock biomass given by dividing the abundance indices by the prior median *q*, and the prior 2.5th and 97.5th percentiles for *q* with the CVs in the abundance indices also incorporated. Results are shown for the Johnies, Frankies, Rix, and Hotspot fishing grounds. (a) Intervals produced using prior CVs for *q* of about 0.6 (used in 1999 and 2000); (b) intervals produced using prior CVs for *q* set at 0.3 (similar to values used in the 1997 and 1998) (from McAllister and Kirchner, 2001)

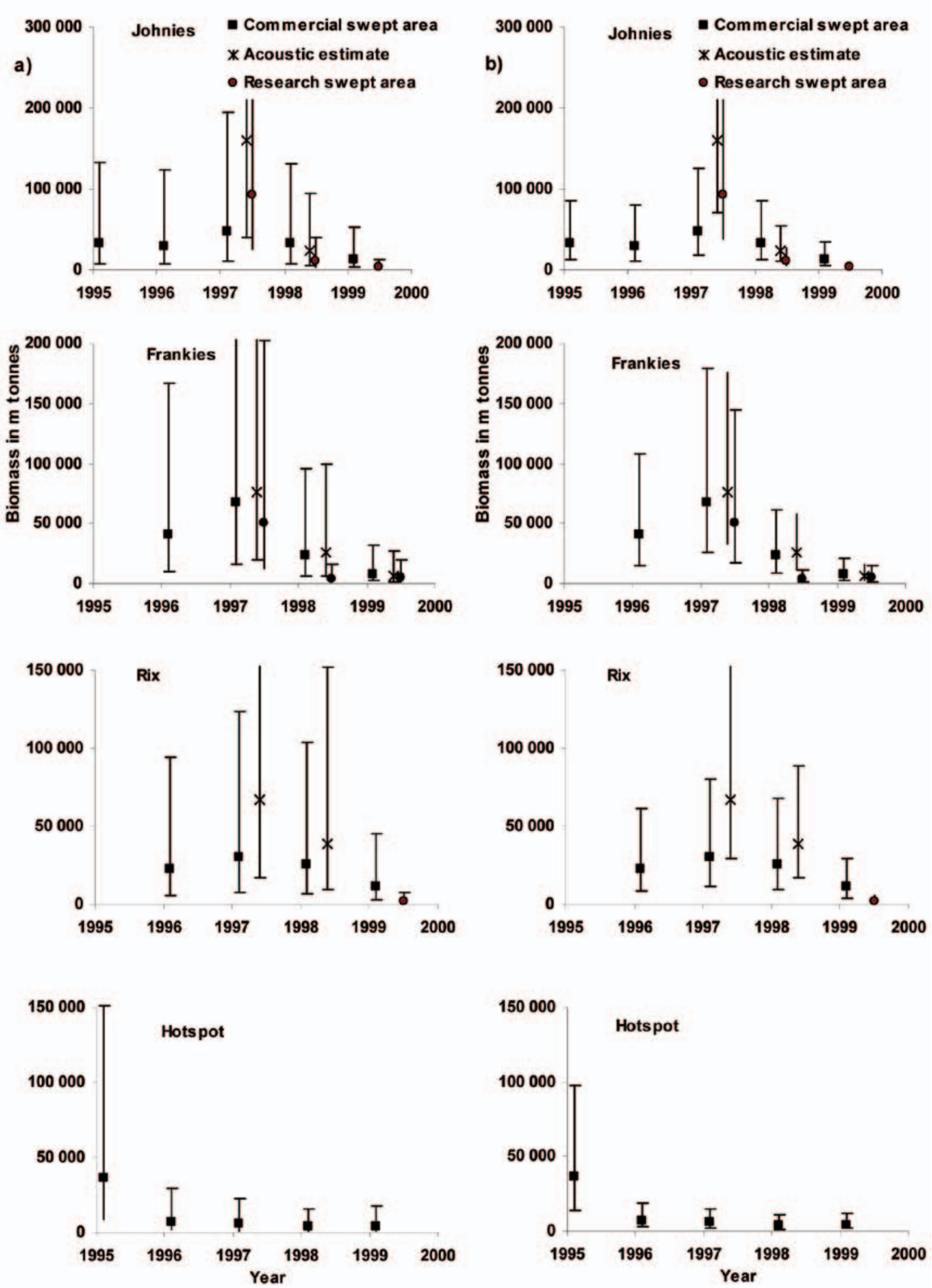
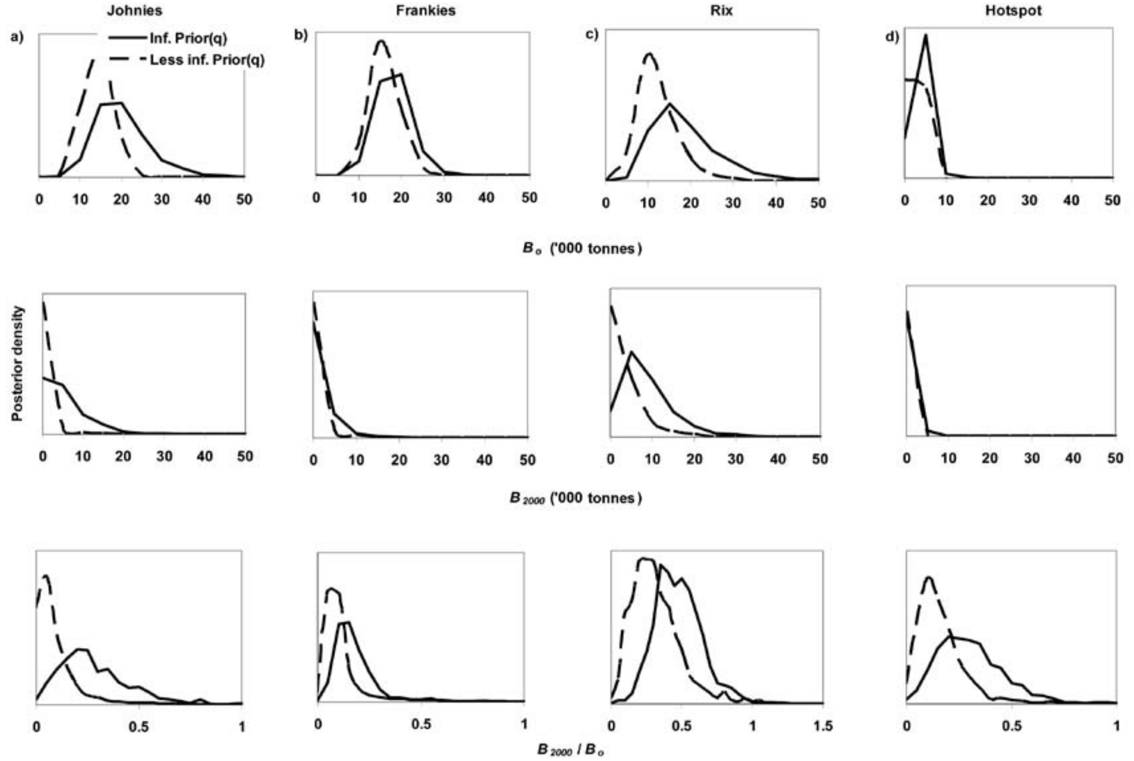


FIGURE 13.2
Marginal posterior probability distributions for the average unfished mature biomass (B_o), mature biomass in 2000 (B_{2000}) and depletion (B_o / B_{2000}) for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. Results are shown with non-informative priors for *q* and informative priors for *q* (from McAllister and Kirchner, 2001)



TACs were considered, the horizon was 14 years until 2010 (Table 13.2). TAC policies that began at no more than about 20 000 tonnes had less than a 10 percent chance of dropping stock biomass below 20 percent of B_o in 2010. The Cabinet adopted a 12 000 tonnes TAC option but allowed two more fishing companies into the fishery to share the same TAC. In the next assessment in 1998, when the much more pessimistic 1997 hydro-acoustic estimate was used to produce a pdf for B_o, only a three-year horizon until 2001 was applied to evaluate the potential consequences of alternative TAC options. TAC policies of no more than about 12 000 tonnes had less than a 10 percent risk in 2001. The Cabinet approved a 12 000 tonnes TAC but only for the 1998 fishing season. In 1999, when the revised stock assessment procedure was applied, a 9 000 tonnes TAC had less than a 10 percent risk with only a one-year projection to 2000. The Cabinet approved a 9 000 tonnes TAC and closed the Frankies fishing ground where the observed decline was the most severe.

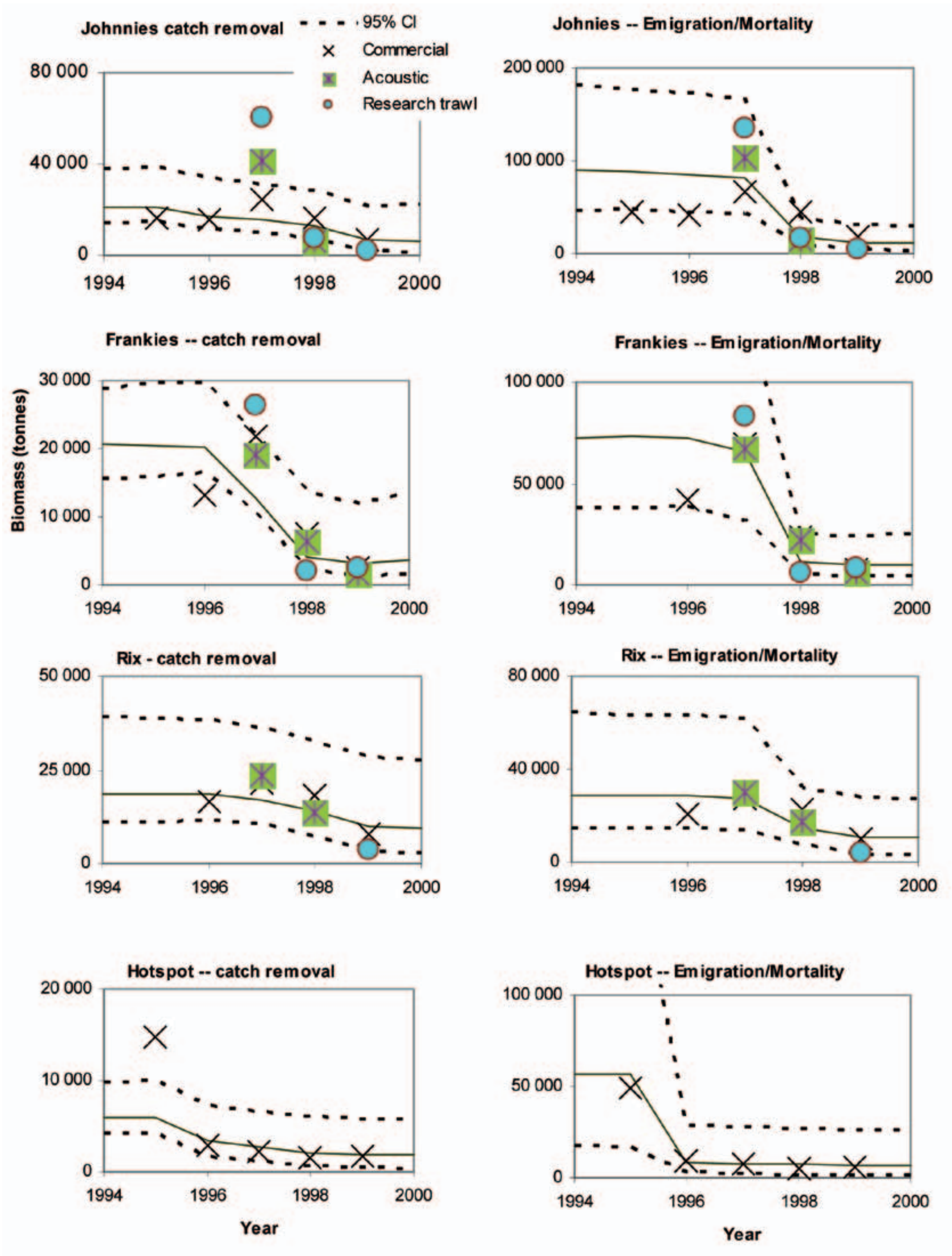
In the 2000 assessment, the declines had continued on the grounds remaining open. Only much smaller TACs, e.g., 1 500 tonnes combined across grounds, had less than a 50 percent chance of causing further decline on all of the fishing grounds. The cabinet followed this advice but made the provision that the TAC could be increased if orange roughy appeared to be re-aggregating. Although preliminary results were presented from the analysis of structural uncertainty that suggested that stock biomass might not be so severely depleted, these results were considered too preliminary to be given any weight in the provision of management advice.

Results from the analysis of structural uncertainty

More recent updates of the methodology to account for structural uncertainty provided the following results (McAllister and Kirchner, 2002). The probability distributions for stock biomass given by the different structural models suggested far larger uncertainties

FIGURE 13.3

Posterior medians and 95% posterior probability intervals for mature stock biomass from 1994 until 2000 for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. The abundance indices rescaled by the posterior median q are also plotted. Results are shown for the catch removal and mass emigration / mortality hypotheses with informative priors for *q* (from McAllister and Kirchner, 2001)



in stock size than any one of the models considered by itself (Figure 13.4). For some of the grounds, such as Frankies and Johnies, these probability distributions were non-overlapping (Figure 13.4). Given these widely differing results across structural models, the key question was how should each model be weighted? This weighting was obtained by computing a posterior probability for each structural alternative (Table 13.4). For Rix, none of the four alternative models had very low probability. For Frankies, only catch removal had very low probability. For Johnies and Hotspot, the catch removal and fishing disturbance models had low probability. On all of the four fishing grounds, only the mass emigration/mortality hypotheses retained moderate to high probability. If the same mechanism for decline is operating on the four grounds, these combined results give most credibility to the mass emigration/mortality hypothesis but still convey considerable uncertainty over the mechanisms for decline. The probability distributions for stock biomass that result from using these model probabilities to combine the distributions from the different models were much flatter for most of the fishing grounds (Figure 13.4). In some cases, such as for Frankies and Hotspot, the combined distributions were bimodal, suggesting that the stock was either lightly exploited or heavily depleted.

TABLE 13.4

Posterior Probabilities for the 4 different Hypotheses for the four major orange roughy fishing grounds (from McAllister and Kirchner, 2001)

	Hypothesis			
	Catch removal	**Fishing disturbance**	**Intermittent aggregation**	**Mass emigration/ mortality**
Rix	25%	45%	13%	17%
Frankies	<1%	37%	25%	37%
Johnies	<1%	<1%	2%	98%
Hotspot	<1%	1%	12%	87%

The estimates of risk from each of the structural alternatives could be presented in a single decision table (Hilborn, Pikitch and Francis, 1993; McAllister and Kirkwood, 1998b). For the sake of illustration, results are shown only for the Rix fishing ground (Table 13.5). This shows the four structural hypotheses along the top and the marginal posterior probability for each hypotheses in the next row down. In the following rows the potential consequences resulting from each TAC policy under each structural hypothesis are shown. In the table shown, this is in terms of the 10th percentile for mature stock biomass in the year 2010 relative to B_o. This indicates that there is about a 10 percent chance that stock biomass will drop below the values shown. The final column integrates the results under the different hypotheses for each TAC policy and thereby accounts for both parameter and structural uncertainty. The table indicates that the largest TAC for which the risk of dropping below 20 percent B_o < 10 percent depends strongly on the model assumed, with the highest risks being given by the catch

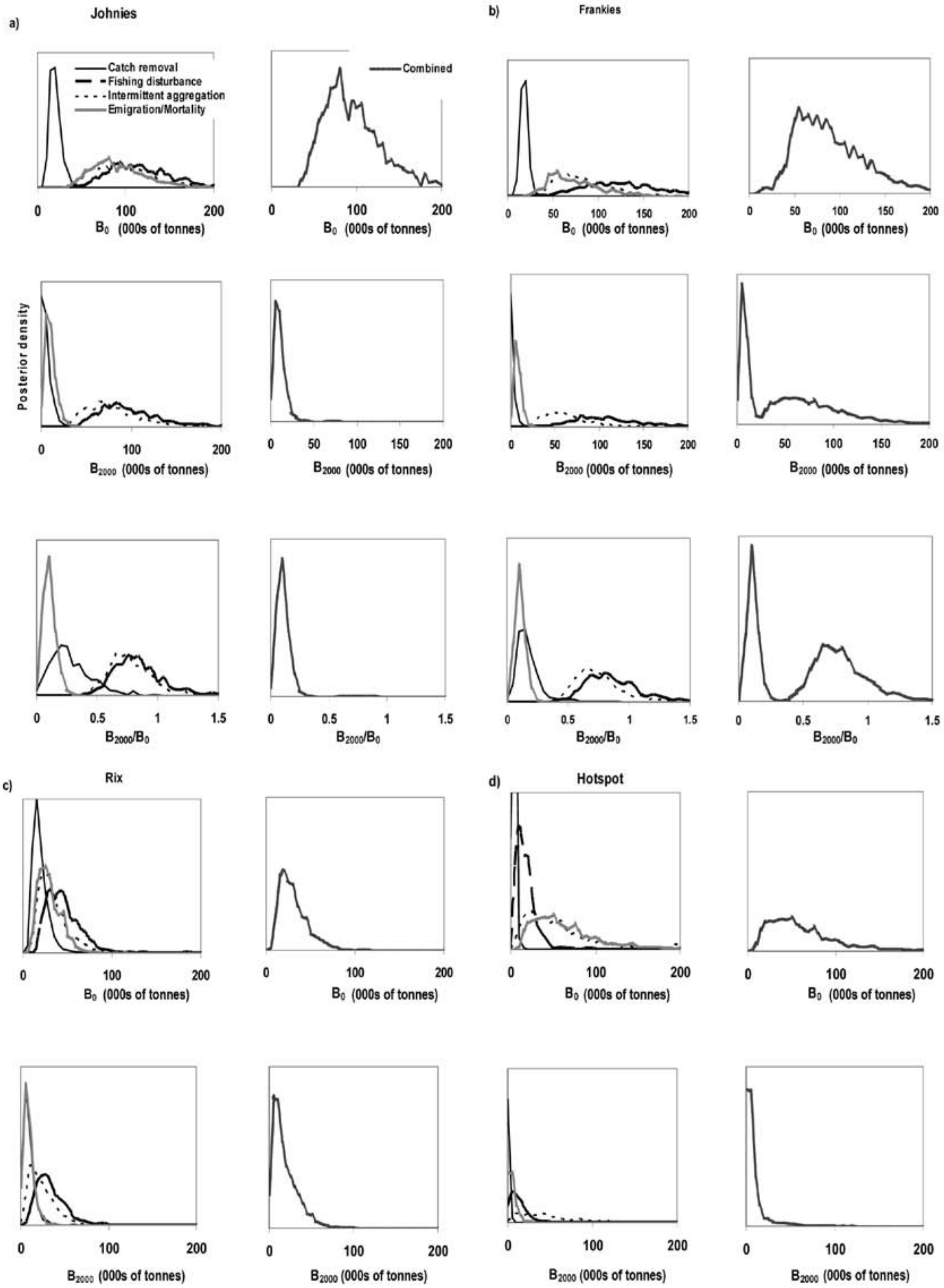
TABLE 13.5

Decision table of alternative TAC policy options for the Rix ground for the years 2000 to 2010. The 10th percentiles are shown for total mature biomass in the year 2010 relative to B_o. This indicates a 10% probability that biomass will fall below the indicated proportion of unexploited biomass. CRH refers to the catch removal hypothesis, FDH refers to the fishing disturbance hypothesis, IAH refers to the intermittent aggregation hypothesis, MEH refers to the mass emigration/mortality hypothesis (from McAllister and Kirchner, 2001)

	CRH	FDH	IAH	MEH	
Prob.	0.25	0.45	0.13	0.17	
TAC					Combined
500 t	0.21	0.52	0.40	0.14	0.36
1000 t	0.02	0.41	0.22	0.01	0.22
1500 t	0.01	0.28	0.06	0.005	0.14
2000 t	0.01	0.16	0.02	0.004	0.08

FIGURE 13.4

Marginal posterior probability distributions the average unfished mature biomass (B_o), mature biomass in 2000 (B_{2000}) and depletion (B_o/B_{2000}) for the (a) Johnies, (b), Frankies, (c) Rix, and (d) Hotspot fishing grounds. Results are shown separately and combined for the catch removal model, fishing disturbance model, intermittent aggregation model, and the mass emigration and mortality model (from McAllister and Kirchner, 2001)



removal and mass emigration / mortality hypotheses. When structural uncertainty is accounted for, and the results are integrated across the different models, the lowest TAC evaluated, 500 t, would have a risk of less than 10 percent (as there is an estimated 10 percent chance that the stock biomass will fall below 36 percent of the unexploited biomass; see Table 13.5).

13.7 DISCUSSION

The management of the developing fishery for Namibian orange roughy posed some difficult challenges for stock assessment. The Ministry of Fisheries, as in many other developing countries, had relatively few scientists trained in the development and application of stock assessment methods. Yet the scientists were provided with financial support to collect biological data on the resource and to bring in overseas expertise to help develop and apply a stock assessment methodology for the management of this resource. Data on abundance were scarce at first and were initially established from the contribution from industry of detailed commercial catch rate information. Even after three different sets of indices of abundance were established, the time series was too short for established methods for stock assessment (e.g., Francis, 1992; Francis *et al.,* 1992; Smith, 1993) to be of use. Scientific and industrial expertise from orange roughy fisheries in New Zealand and Australia were also available to facilitate the rapid development of the resource. As the fishery developed with a single exploratory licence holder and catch rates and profits grew quickly, other companies demanded entry into the fishery.

Because one of the general guidelines for the management of the fishery was to maintain a precautionary approach to its development in the face of the large uncertainty over resource potential, scientific advice was needed on the resource potential and the potential consequences of alternative harvesting policies. A long-term fishery management strategy was suggested that would fish down the resource over seven years and then allow a smooth transition to catches that might maintain the resource at or above the MSY level. A fundamental question for the first stock assessments was how large should be the initial TACs? Even then, it was recognized that some adjustments might be necessary as estimates of abundance were updated.

A stock assessment methodology to provide such advice thus was required to do the following:

1. Incorporate and integrate sparse data from diverse sources.
2. Estimate resource abundance and its potential responses to exploitation as the fishery proceeds.
3. Explicitly account for uncertainty in estimates of abundance and trends in abundance.
4. Quantitatively evaluate the potential consequences of alternative fishing down policies.
5. Provide precautionary fishery management advice so that the TAC options adopted had an acceptably low risk of depleting the resource below the MSY level.
6. Be sufficiently transparent, understandable and credible to the various parties to the fishery management system.

The Bayesian methodology applied addressed these various requirements to varying extents but some difficulties in implementation were encountered. The stock assessment methods developed for the management of the Namibian orange roughy fishery have helped to facilitate the fishery's management, although some drawbacks were noted and subsequent revisions required, for the following reasons (from McAllister and Kirchner, 2001).

1. The methods have helped to integrate diverse sources of information, contributed by industry members and government scientific research, to provide estimates of stock biomass and trends in stock biomass, and to predict the potential outcomes of alternative management outcomes.

2. The probabilistic modelling methods applied have taken uncertainties into account and provided fishery managers with estimates of biological risks of alternative TAC options. This has served as a basis for the provision of precautionary fishery management advice.
3. From 1997 to 2000, the Namibian Minister of Fisheries actively sought the probabilistic stock assessment results computed for Namibian orange roughy and studied them carefully in making his TAC decisions. The assessment results were used to identify those TAC policies that had acceptably low biological risk. The Minister of Fisheries adopted only TAC values that had less than a 10 percent chance of depleting stock size to less than 20 percent of B_o.
4. Subjective judgments about stock assessment model formulation and inputs in the 1997 and 1998 assessments led to underestimates of uncertainty in stock biomass, over-estimates of stock biomass, and underestimates of the risks of alternative TAC management options. Two judgments in particular appear to be largely responsible for this. The first was the requirement for a consensus among industry members and scientists in developing probability distributions for the bias correction factors for the commercial swept area biomass estimate. This lead to distributions applied being too narrow conveying far too much certainty. The second was the assumption that fish aggregations are spatially stationary from year to year and clusters of high catch rate values can therefore be extrapolated to large poorly sampled areas. This led to the gross overestimation of stock biomass. In later assessments, these judgments were questioned and replaced with more rigorous ones but by then the apparent abundance had diminished very considerably.
5. The revised Bayesian assessment method applied in 1999 and 2000 more adequately accounted for uncertainty in bias factors for the abundance indices, stock biomass and risk but ignored structural uncertainty, particularly over whether the catchability of orange roughy on the fishing grounds had changed. Because of this, the methodology could not easily account for the large drop in the biomass indices and lost credibility before industry.
6. A Bayesian method was developed in 2000 to account for uncertainty in the structural formulation of stock assessment models and considered a set of plausible alternative models that was balanced with respect to conjectures about catchability and the remaining stock biomass. Some of the alternatives considered more adequately accounted for drops in the biomass indices. Because this methodology accounts for both parameter and structural uncertainty in a statistically rigorous and balanced manner, it provides a more scientifically defensible basis for precautionary fishery management.
7. Bayesian posterior probability distributions for biological reference points for Namibian orange roughy such as B_{MSY}/B_o were computed and indicated that mean values from previous analyses could easily be too low. This enabled the identification of more precautionary reference points, e.g., the 90th percentile for B_{MSY}/B_o of about 40 percent of B_o instead of the previous mean estimate of 30 percent.
8. The methods developed need to be refined and simplified to make versions of them more accessible to developing country fisheries scientists.

In contrast to the case study in this paper, a number of articles advocate the use of Bayesian surplus production models for stock assessment in data-poor and developing fisheries (McAllister and Kirkwood, 1998a, b, McAllister, Pikitch and Babcock, 2001; McAllister and Pikitch, 2004). These age aggregated stock assessment models also have relatively few parameters to estimate (e.g., the intrinsic rate of increase (r), carrying capacity (K or B_o), and q). To be advantageous over non-Bayesian methods, informative prior probability distributions would be needed for the estimated parameters. No reliable methods have yet been developed to obtain informative priors for *K* or B_o. Thus an informative prior would be needed for either *q* or *r*. The current paper has indicated that credible methods exist to obtain an informative prior for *q*, providing that the prior CV is not made too small. However, even with an informative prior for *q*, it is not clear whether the typical sparse relative abundance data available could enable statistical discrimination between sets of parameter values that included high values for *K* and low values for *r*, and vice versa.

Thus, it would appear that to be useful, Bayesian surplus production models should incorporate an informative prior for *r*. Bayesian hierarchical modelling could be applied to obtain an informative prior for *r*, provided that data for other populations with similar life history characteristics were available (Myers, Bowen and Barrowman, 1999; Michielsens and McAllister, 2004). Demographic modelling methods could also be applied to provide a prior for *r* (McAllister, Pikitch and Babcock, 2001). However, the latter method would require considerable life history information, for example, spawner biomass per recruit, natural mortality rate at age, fecundity at age, that might not necessarily all be available. Tagging studies would be useful in order to help estimate some of these inputs. However, for some species, such as orange roughy, tagging studies are not possible. Thus, age-structured population dynamics that incorporate informative priors for *q*, may be the only stock assessment option for some developing fisheries where it is difficult to acquire precise data on life history characteristics and relatively few studies exist on other similar populations.

ACKNOWLEDGEMENTS

M. McAllister's contribution to the research reported in the reported research was funded by the Namibian Government and the Fisheries Management Science Programme of the U.K. Department for International Development. The authors are indebted to B. Oelefson, D. Boyer, A. Staby, T. Branch, D. Butterworth, A. James, M. Clarke, B. Vaske and many others for their frankness and willingness to express their opinions and contribution to the material presented in this section.

14. Empirical modelling approaches

Ashley S. Halls, Robert W. Burn, and Savitri Abeyasekera

This section describes a number of approaches adopted or developed under FMSP projects for constructing empirical models to support fisheries management and development planning and evaluation. Unlike the *explanatory* or *process* types of models described in many of the previous sections, the models described here are purely *descriptive*,[21] providing, in most cases, a deterministic output for a given input. In spite of this distinction, the selection of variables was typically guided by established theories, models and frameworks.

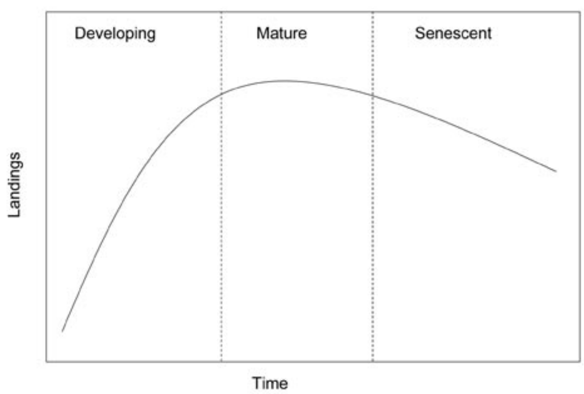
The approaches are generally suited to data poor circumstances, or when among fishery comparisons are possible, for example under adaptive approaches to (co-) management (see Section 2.4). The models and approaches are described below in ascending order of their data requirements and complexity.

14.1 A SIMPLE MODEL TO PREDICT POTENTIAL YIELD FROM CATCH TIME SERIES

Empirical approaches to estimating potential yield of a fishery in the absence of any catch and effort data have been described in Section 4.2. Often, however, it is not uncommon to have a time series of total annual catches but, due to resource limitations, not supported by any corresponding effort data. In these cases, the application of biomass-dynamic modelling approaches (Section 4.5) for estimating potential yield and related reference points is not an option. However, the *theoretical potential yield* of the fishery, together with some indication as to when it might be achieved can be estimated following the approach described by Grainger and Garcia (1996). This approach was adopted by FMSP project R7040 (MRAG, 2000) to determine the exploitation status of Large Marine Ecosystems (LMEs) and is therefore briefly described here.

Time series of catches from fisheries typically follow a similar trend or generalized fishery development model (GFDM) comprising three or four main phases or periods (Figure 14.1).

FIGURE 14.1
A simplified version of the Generalized Fishery Development Model (GFDM) after Caddy (1984); Grainger and Garcia (1996)



[21] see Haddon (2001) for an explanation of the differences between explanatory and empirical models.

Catches increase rapidly as the fishery expands during the initial stage of development. Catches are maximum during the mature stage before declining during the senescent stage as resources become depleted. The relative rate of increase in catch, r during successive time periods, t, during this cycle is given by:

$$r = (C_{t+1} - C_t) / C_t \qquad (1)$$

where t = 1 year.

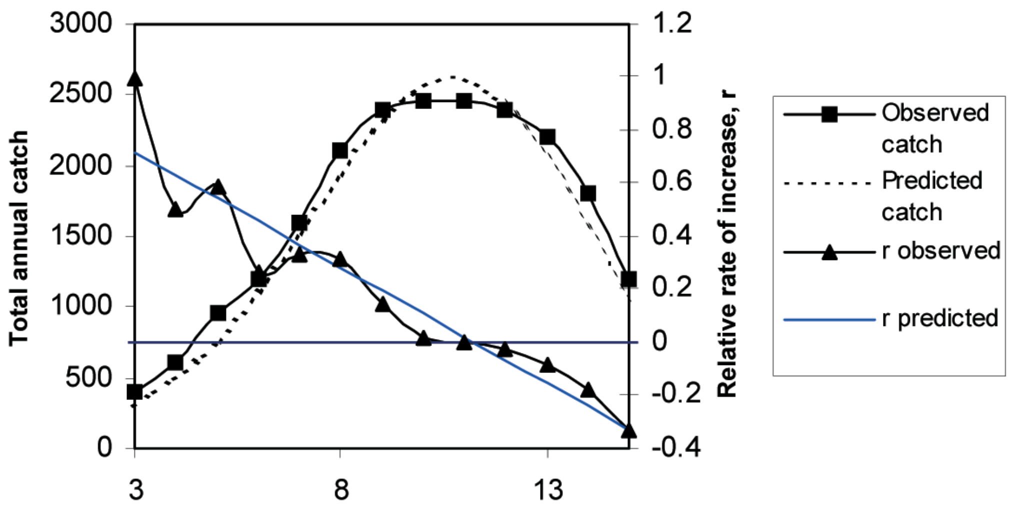
The value of r declines continuously as the fishery begins to develop, and eventually drops to zero when the fishery reaches its maximum production during the mature phase before becoming negative corresponding to the senescent stage as the stock is depleted or collapses. The year when theoretical maximum production is likely to be achieved can therefore be estimated from the abscissa intercept ($t_{\text{max prod}}$ = -a/b) of the linear regression of rate of increase in catch, r and year, t, (Eq .2) where the catch in year t, $C_{t,}$ is a three year moving average value (Figure 14.2):

$$r = (C_{t+1} - C_t) / C_t = bt + a \qquad (2)$$

Maximum production can then be estimated by predicting the evolution of catches with time iteratively, based upon the estimates of a and b of the linear regression model and the catch value in the first year of the modelled time series using Eq.3:

$$C_{t+1} = C_t\,(bt + a + 1) \qquad (3)$$

FIGURE 14.2
Estimation of maximum production potential and predicted year of achievement

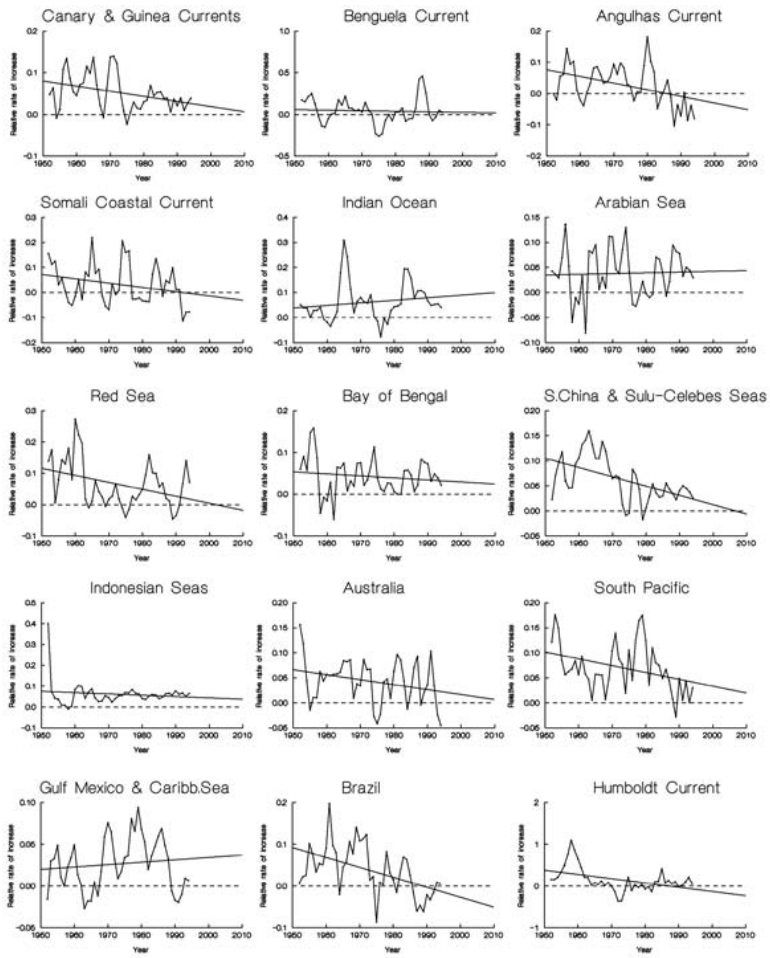


The modelling approach assumes that fishing mortality (effort) increases with time driving the fishery from one phase to the next (Grainger and Garcia, 1996).

Application

Figure 14.3 below illustrates model fits to the LMEs examined under project R7040. The same methodology can be applied to fisheries operating at other scales for example, on a national, regional or even local scale providing a long enough time series is available exhibiting marked changes in landings. However, it is important to note that due to the typically imprecise nature of catch data and the large residual components of fitted models, predictions will themselves be imprecise and therefore should be treated with caution. Potential yield predictions based upon this method are particularly sensitive to catch variability during the initial three years of the time series.

FIGURE 14.3
Time series (1952-1995) of rate of relative increase, r of total landings of finfish, molluscs and crustaceans in the 15 LMEs with fitted GFD model (MRAG, 2000)



14.2 EMPIRICAL MULTISPECIES YIELD MODELS

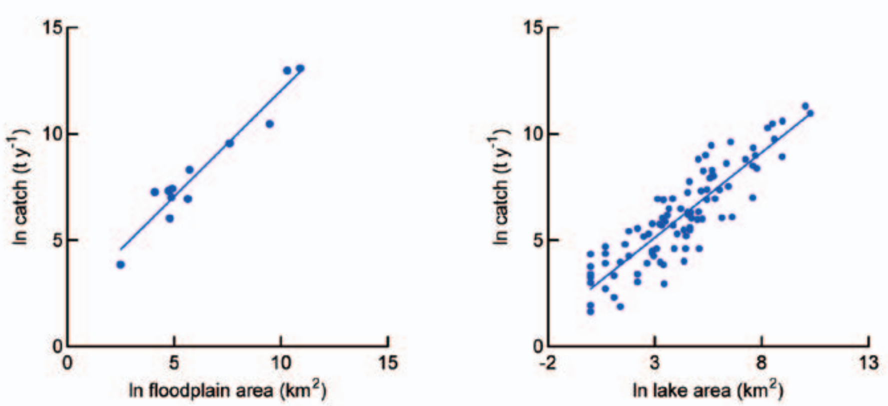
A number of multispecies empirical models have been developed under the FMSP programme to help support management planning and evaluation, as well as to help guide policy level decision-making with respect to fisheries resources. These have been constructed on the basis of among fishery comparisons of yield and either simple descriptors of the resource habitat eg resource area, or some relative measure of fishing effort. Whilst the examples illustrated below are based upon comparisons across wide geographical scales, their application may be equally, if not more, relevant on a more local scale, particularly in the context of adaptive co-management (see Section 4.8.2).

14.2.1 Models based upon habitat variables

These models were developed under two FMSP projects R5030 (MRAG, 1993), R6178 (MRAG, 1995) and by FAO/MRAG (Halls, 1999) primarily as a means of providing planners and policy makers with some approximate indication of the potential yield of lake or river fisheries when catch (and effort) data are unavailable or when alternative empirical approaches (eg Section 4.2) are inappropriate. All the models were generated from among fishery comparisons of easily measurable habitat variables, including relevant measures of resource area, indices of primary productivity and hydrological variables, and corresponding estimates of potential yield. A “Lakes and Rivers Database” developed as part of this research containing data for these and other variables is available on a CD-ROM published by FAO (see Dooley *at al*., 2005).

Simple and multiple backward stepwise regression methods were used to fit linear models to the covariates after appropriate log-transformations to ensure that the normality assumptions of the method were met. The most promising models were those that employ estimates of resource area as the explanatory variable (Figure 14.4). Details of these and other best fitting models are given in Annex 1 including guidelines for estimating confidence intervals around model predictions. Full details of all the models are described in MRAG (1993; 1995) and Halls (1999).

FIGURE 14.4
Potential yield from (a) Asian floodplain rivers; and (b) African lakes and reservoirs plotted as functions of resource area with fitted regression lines on $\log_e$ transformed scales. For (a) $\log_e$ catch = 2.086 + 0.996 $\log_e$ area (R = 0.97; P<0.001); and (b) $\log_e$ catch = 2.668 + 0.818 $\log_e$ area (R = 0.90; P<0.001)



Application
Generally speaking, these types of models provide only very imprecise predictions because of the significant measurement error associated with the potential yield estimates used to *fit* the models. Potential yields were estimated using (i) the GFDM approach described above, (ii) as the average annual catch value, or worst (iii) from a single observation, all of which are subject to potentially significant measurement error. The utility of these estimates is therefore restricted to providing a rough indication of the likely potential of the fishery for policy and development planning purposes.

The model for predicting potential yield from African lakes (see Figure 14.4 above) has recently been incorporated into the FAO African Water Resources Database (Dooley *et al.*, 2003) that includes a routine for calculating the confidence intervals around the predictions.

14.2.2 Models incorporating fishing effort [22]
Despite enforcement difficulties, particularly in highly dispersed artisanal fisheries, the control of fishing mortality via fishing effort remains fundamental to most fisheries management strategies even at the local community or co-management level.

Decisions concerning the control of effort to maximize yield require knowledge of the underlying response of the catch to changes in effort. Under adaptive management strategies (Section 2.1.3), even imprecise knowledge of the response is likely to help

[22] A.S. Halls, R.W. Burn, and R.L. Welcomme.

accelerate the adaptive learning process. Several multispecies biomass dynamics and age-structured models have been developed to elucidate such responses to guide the setting of fishing effort levels to achieve common target and limit reference points (See Section 3.5). However, the data and institutional capacity requirements to employ these models invariably render their use impractical particularly in the developing world (Hilborn and Walters, 1992).

The most rudimentary approach to elucidating the relationship between catch and effort in multispecies fisheries is to ignore any species interactions and fit some form of production model to catch and effort data aggregated across all species (eg Ralston and Polovina, 1982). Such an approach assumes that any species interaction effects are captured (at least statistically) in the overall empirical relationship between yield and effort. Even aggregated production models of this type require a long time series of (aggregated) catch and effort data exhibiting plenty of contrast to achieve reliable models describing the response.

When little or no data are available for a particular fishery, among fishery comparisons may provide an indication of the likely response. This comparative approach assumes that observations from discrete fisheries or units can treated as samples from a hypothetical fishery. Assuming the fishery covers the entire area, differences in scale are accounted for by standardising both yield and effort by area.

This type of among fishery comparisons may be particularly relevant when data and information sharing among discrete local fisheries is promoted as part of an adaptive management strategy (see Section 2.1.3 for further explanation). Building on earlier work described by Bayley (1988), Project R7834 adopted this approach using aggregated species catch data and estimates of fishing effort assembled from the literature and the "Lakes and Rivers Database" described above.

The expanded data set contains 258 estimates of CPUA and corresponding fisher density estimates for floodplain-rivers (36), reservoir and lakes (143) and coastal reef-based fisheries (79). Similar to Bayley (1988) up to two observations for each river corresponding to different years are included in the floodplain-river dataset. The data sets are downloadable from FTR ref.no.7834 at http://www.fmsp.org.uk/FTRs.htm.

Relative fishing effort (intensity) was expressed as the number of different fishers active during the year divided by the surface area of the resource; the same area as that used to calculate aggregated catch per unit area (CPUA) estimates. For reef-based ecosystems, few estimates of the number of active fishers were available. Instead, estimates of the total human population size associated with each fishery were used assuming that the proportion of fishers is approximately equal among the observations. After testing all possible combinations of untransformed, log-transformed and square-root transformed variables, the best performing model for all ecosystem categories was described by the following empirical variant of the Fox model (Equation 4).

$$\ln(Yield + 1) = i^{0.5} \exp(a + bi^{0.5}) + c \qquad (4)$$

in which i = fishing intensity and a, b and c are fitted constants.

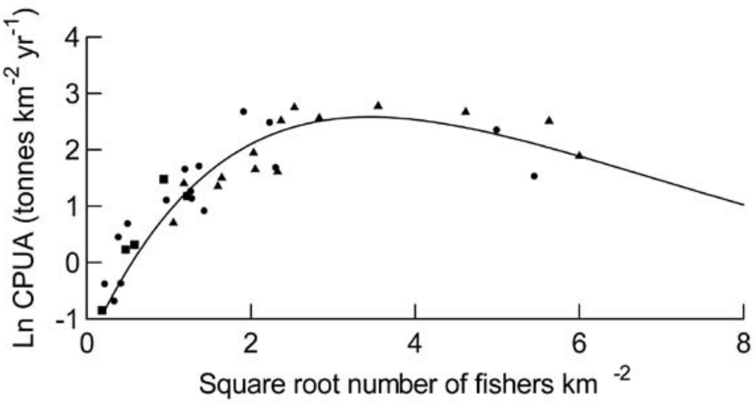
Floodplain rivers

Based upon a combined data set for floodplain-rivers from all major continents examined,[23] the fit of Equation 4 is remarkably good (Figure 14.5). Fishing intensity explained 80 percent of the variation in CPUA (corrected $R^2 = 0.80$). The model predicts a maximum yield (MY) of 13.2 tonnes km^{-2} yr^{1} (95 percent CI [1.9, 225]) or 132 kg ha^{-1} yr^{1} at a fisher density, i_{MY} of approximately 12 fishers km^{-2} (95 percent CI [8.8, 17]).

[23] Separately fitting the data for floodplain-rivers from Africa and Asia resulted in very similar curves whose coefficients could not be distinguished at P = 0.05. Insufficient data were available to test for differences between South American floodplain-rivers and those of other continents.

FIGURE 14.5

CPUA vs. fisher density for floodplain rivers (all continents). Curve is least squares fit of Eq. 4 to 36 floodplain rivers in Africa (●); Asia (▲); and South America (■); R^2 = 0.8



Lakes and reservoirs

The parameters of Equation 4 were found to be significantly different for African and Asian lakes and reservoirs. The resulting curves (Figure 14.6 and Figure 14.7) imply that much higher yields (MY=880 kg ha^{-1} y^{-1}) are achieved in Asian compared to African lakes (MY=172 kg ha^{-1} y^{-1}) and they appear to be able to sustain much higher levels of fishing effort (i_{MY}=78.3 fishers km^{-2}) and (i_{MY}=10.9 fishers km^{-2}) respectively. This may reflect one or a combination of different factors including the common practice in Asia of stocking lakes and reserves to augment natural recruitment, a greater proportion of part-time fishermen in Asia compared to Africa, and natural differences in production.

FIGURE 14.6

CPUA vs. fisher density for African lakes and reservoirs. Curve is least squares fit of Eq. 4; n = 97; R^2 = 0.61

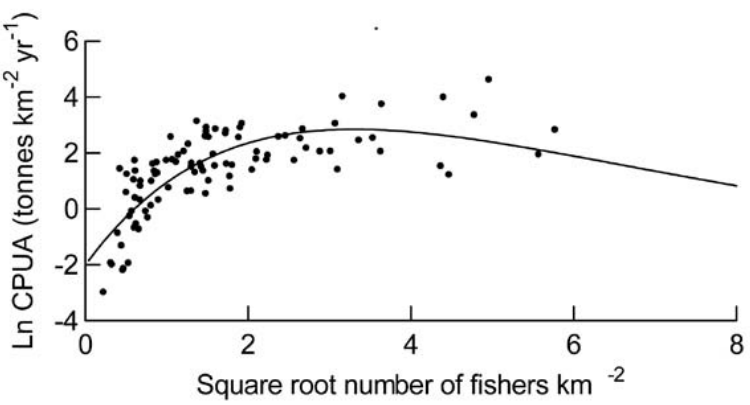
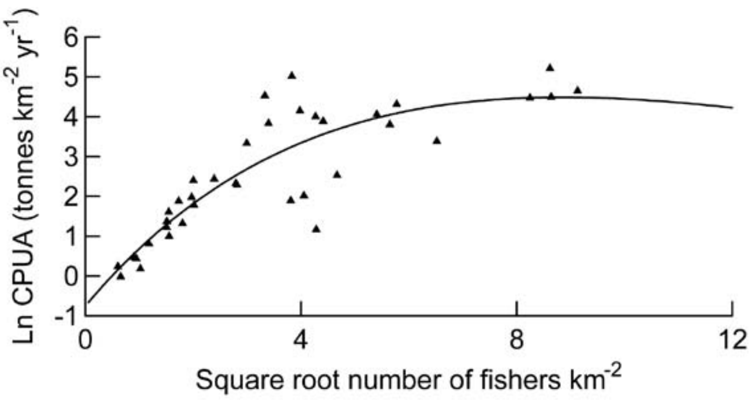


FIGURE 14.7

CPUA vs. fisher density for Asian lakes and reservoirs. Curve is least squares fit of Eq. 4; n = 37; R^2 = 0.76

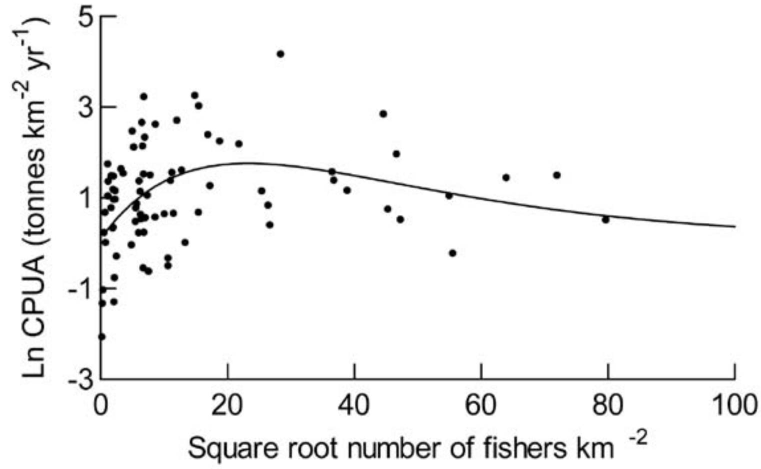


Reef-based fisheries

For reef based-fisheries, fisher density was found to explain only 18 percent of the variation in CPUA (Figure 14.8). The maximum yield for these systems is predicted to be in the order of 6 tonnes km^{-2} yr^{-1} (95 percent CI [1.3, 265]) at 540 fishers (total population) km^{-2} (95 percent CI [287, 1372]). This relatively poor fit is likely to reflect imprecise estimates of (i) fisher density based upon estimates of total population number rather than numbers of fishers; (ii) the surface area of the resource; and (ii) variation in the habitat covered by the term “reef”.

FIGURE 14.8

CPUA vs. fisher density for reef-based fisheries. Curve is least squares fit of Eq. 4; n =79; R^2 = 0.18



Application

For floodplain rivers, the estimates of optimal fishing intensity (i_{MY}) and maximum yield compare well with earlier predictions made by Bayley (1988) and Welcomme (1977). However, estimates for African lakes are generally much greater than those reported by Bayley (1988) of 2.4 fishers per km^2 and 98 kg ha^{-1} y^{-1} compared to 10.9 fishers per km^2 and 172 kg ha^{-1} y^{-1} reported here.

The i_{MY} prediction for reef-based fisheries compares well with that reported Dalzell and Adams (1997) of 581 people km^{-2} (n = 41, R^2 = 0.44) based upon a subset of the same data. Although their corresponding prediction of maximum yield of 16.4 tonnes km^{-2} y^{-1} is significantly higher than the 5.8 tonnes km^{-2} y^{-1} predicted here, Dalzell (1996) suggests that maximum yields are more likely to be in the region of 5 tonnes km^{-2} y^{-1}.

The models described above were fitted to data from fisheries located across a very wide geographical scale. Whilst they provide tentative guidance on approximate levels of fishing intensity that maximize yield within different ecosystems, the reliability of model predictions is likely to improve as the scale over which comparisons are made is reduced.

14.3 MULTIVARIATE MODELS [24]

The above models described in Section 14.2.2 assume that fisher density alone provides an adequate index of fishing mortality and that production potential is similar among sites. In reality, (age-dependent) mortality rates may also vary in response to any management strategies, i.e. the combination of management rules and regulations such as closed seasons and areas, gear controls, minimum landing sizes… etc, implemented to improve or sustain yields and associated management outcomes. Compliance with these rules and regulations, often influenced by the prevailing institutional or management arrangements, may also be important in determining mortality rates. Production potential is also likely to vary among sites either naturally or in response to any stocking or habitat enhancement activities. In other words, a host of factors is likely to influence yield and related management outcomes beyond just simple measures of fishing effort.

Passive adaptive management approaches (Section 2.1.3) may seek the best management strategy in a haphazard way rather than by the application of explanatory models of the type described below. This approach can be wasteful and it can take many years to achieve success. Appropriate institutional arrangements may also be sought in this way. However, where opportunities exist to share knowledge and compare outcomes among fisheries, empirical *multivariate* models can be constructed to help managers understand and predict the performance of different management strategies and institutional arrangements whilst also taking account of any natural variation, thereby potentially accelerating the passive adaptive learning process.

Two complementary approaches for constructing models of this type are described below. The first – the application of the General Linear Model (GLM) is appropriate for dealing with *quantitative* management performance indicators (or outcome variables) such as indices of yield or abundance. The second – the application of Bayesian network models is better suited to deal with more *qualitative* performance indicators such as equity, compliance and empowerment that must be *subjectively* measured or scored along with many of the explanatory variables. The application of both approaches in the context of adaptive management was developed under project R7834 using data assembled from case studies of co- or community-managed fisheries or management initiatives undertaken during the last two decades. These studies documented a total of 119 discrete local management units or areas under national (government) control among 13 different countries in Africa, Asia and Melanesia. The

[24] A. S. Halls, R.W. Burn and S. Abeyasekera.

units represented a range of different ecosystems and management arrangements. Each management unit was treated as a separate observation for the model development. In practice, it is likely that the data will be assembled over a much smaller spatial scale such as a country, region or district.

Mutidisciplinary model variables

For the purposes of methodological development, indicators of management performance (outcome variables) and corresponding explanatory variables were selected on the basis of various established fisheries models, and the Sustainable livelihoods (SL) and Institutional Analysis and Development (IAD) frameworks (see Oakerson, 1992; Pido *et al.*, 1996; DFID, 1999). However, other frameworks could serve as a basis for model development or hypothesis formulation. Examples of these variables and their indicators are summarized in Table 14.1 below.

TABLE 14.1
Examples of Multidisciplinary Model Variables

(a) Management Performance (Outcome) Variables

Category	Outcome Variables	Indicator	Units	Notes
Production/Yield Sustainability/ Biodiversity	Annual production per unit area	Catch per unit area (CPUA)	tonnes/km^2	or tonnes/km (specify)
	Annual production per unit area	CPUA - Trend	0;1;2	Total landings: increasing (0); stable (1); declining (2)
	Sustainability (Resource)	Catch per unit effort (CPUE)	Tonnes/ fisher/year	All species combined or specify for each target species.
	Sustainability (Resource)	CPUE -Trend	0;1;2	Declining (0); static (1); rising (2)
	Biodiversity	Species richness	Number of species	
Well-Being (Fishers/ Households)	Household income from fishing	Household income from fishing	\$/year	
	Assets eg TV, Bikes, Tin Roofs…etc	Assets eg TV, bikes, tin roofs…etc	0;1;2	Low (0); medium (1); high (2)
	Savings and investments	Savings and investments	0;1;2	Low (0); medium (1); high(2) or state mean value(s)
	Food security	Number of fish meals/ week	0;1;2	Declining (0); static (1); rising (2)
Institutional Performance	Empowerment	Participation in management	0;1;2	Low (0); medium (1); high (2)
	Equity	Distributional among community members	0;1;2	Low (0); medium (1); high (2)
	Compliance with rules and regulations	Compliance with rules and regulations	0;1;2	Low (0); medium (1); high (2)
	Conflicts	Frequency of conflicts	0;1;2	Low (0); medium (1); high (2)

(b) Explanatory Variables

Category	Explanatory Variables	Indicators	Units	Notes
Resource	Production potential	Water transparency (Secchi depth)	m	May not be valid indicator in rivers
	Production potential	Primary production	0;1;2	g/C/m^2/year:Low <150 (0); medium 150-300 (1); high >300 (2)
	Abundance/Biomass	(Total annual catch)/ (Numbers of fishers)	Tonnes/ fisher	All species combined or specify for each target species.
	Ecosystem Type	Ecosystem Type	0;1;2..n	River (0); fringing floodplain (1); beel (2); lake (3); ….etc
	Waterbody type	Permanence	0;1;2	Seasonal (0); perennial (1); both (2)
	Rule enforcement potential	Area under co-management per fisher	km^2/fisher	or km of coastline/ fisher (specify)

table 14.1 cont.
(b) Explanatory Variables

Environment	Environmental health of habitat	Health of critical habitat	0;1;2	Low (0); medium (1); high (2)
	Nutrient recycling	Depth of reserve, lake, fishing area ...etc	m	
	Habitat descriptors	% Coral cover	%	
Technological	Exploitation intensity	Fisher density	N / km^2	or km of coastline (specify)
	Exploitation intensity	Number of villages	N	
	Exploitation intensity	Number of fishers	N	
	Exploitation intensity	Mean size of fish caught in Month x, with gear x	cm	
	Stocking density	Stocking density	kg/ha	
	Habitat alteration activities	Habitat alteration activities	0 - 5	Destructive (0); none (1)……beneficial (5)
Market Attributes	Economic value of resource	Mean unit value of target species	US$/kg	
	Market facilities/ infrastructure	Transport/infrastructure/ landing sites...etc	0;1;2	Poor (0); medium (1); good (2)
	Cost of marketing (market fees)	Cost of marketing (market fees)	0;1;2;3	None (0); low (1); medium (2); high (3)
	Price control mechanism	Price control mechanism	0;1	No (0); yes (1)
Fisher/Community Characteristics	Social cohesion	Social cohesion	0;1;2	Low (0); medium (1); high (2)
	Dependence on fishery for livelihood	% of household income derived from fishing	%	
	Level of local (ecological) knowledge	Level of local (ecological) knowledge of fishers	0;1;2	Low (0); medium (1); high(2)
Management Strategy & Decision-making Arrangements	Legitimacy / widely accepted	Legitimacy of local decision-making body	0;1;2	Low (0); medium (1); high (2)
	Membership to decision-making body	Democratically elected?	0;1	No (0); yes (1)
	Clear access (property) rights	Clear access (property) rights	0;1	No (0); yes (1)
	Management plan	Present/implemented	0;1	No (0); yes (1)
	Management measures (operational rules)	Mesh / gear size restrictions	0;1	No (0); yes (1)
	Management measures (operational rules)	Gear ban(s)	0;1	No (0); yes (1)
	Management measures (operational rules)	Closed seasons	0;1	No (0); yes (1) if yes specify month(s) closed
	Management measures (operational rules)	Reserve area as a % of total management area	%	
	Representation in rule making	Representation in rule making (fishers)	0;1;2	Low (0); medium (1); high (2)
	Formal performance monitoring?	Formal performance monitoring by community?	0;1	No (0); yes (1)
	Sanctions for non compliance	Sanctions for non-compliance	0;1	No (0); yes (1)
External Decision-Making Arrangements	Enabling legislation for co-management	Enabling legislation for co-management	0;1	No (0); yes (1)
	Local political/institutional support	Local political/institutional support	0;1;2;3	Anti (0); Weak (1); indifferent (2); strong (3)
	Effective coordinating body	Nested structure of co-management arrangements	0;1	Absent (0); Present (1)
Exogenous Factors	External financial assistance	Expenditure on community	$/year/ fisher	
	Capacity building support from NGO's	Support for community from NGO's	0;1;2;3	none (0); weak (1); medium (2); strong (3)

It is important to note that these are only examples of the types of variables that may be employed and represent only a small subset of potentially appropriate variables identified by project R7834. In applying the method in a specific fishery, the choice or variables and their indicators should be identified in a participatory manner with resource users and managers. These multidisciplinary variables are typically recorded on a variety of different measurement scales, including quantitative, binary and categorical (nominal and ordinal), and either measured empirically or subjectively scored. Details of all the model variables and data used to develop the methodological approaches can be downloaded from www.fmsp.org.uk (FTR Report R7834).

Hypothesis Matrix

A convenient way to summarize variables for initial inclusion in models is by means of a hypothesis matrix that summarizes which explanatory variables are believed to affect management outcomes either directly or indirectly (see Annex 2). The construction of the matrix may be guided by appropriate frameworks and/or through consultation and discussion with resource users and managers.

Preliminary Data Screening and Variable Selection

Before either approach is applied, assembled data sets of variables should be scrutinized, checked, and reduced and transformed as necessary. Annex 3 of this manual gives recommendations for field applications of the methods including guidelines for data collection, variable selection, minimum sample sizes, and model validation and updating. An FAO manual entitled "*Guidelines for Designing Data Collection Systems for Co-Managed Fisheries*" is currently being prepared which provides further guidance for designing data collection and sharing systems to support models of this type.

Data Scrutiny and Checking

When data are assembled from a number of fisheries that vary substantially from each other, various types of errors in the data are inevitable and these have to be corrected before the full data set is ready for analysis. Any inconsistencies found in the data should be resolved. The data should therefore be first listed and scrutinized. Simple summary statistics (for quantitative variates) and frequency tables (for qualitative variates) should be produced and examined for any inconsistencies and data errors.

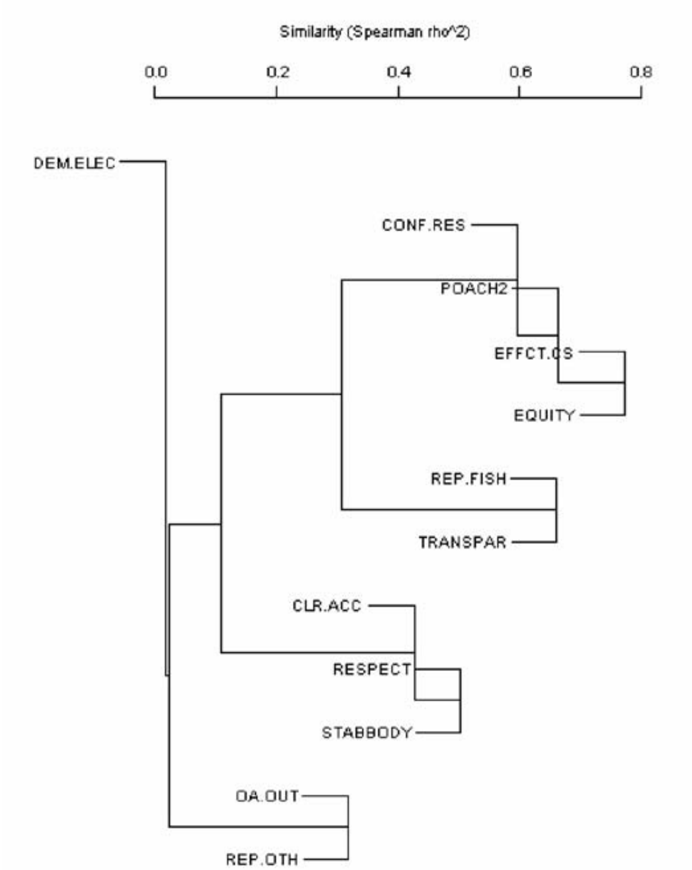
Dimension Reduction

To be useful, most statistical models should be parsimonious and not overloaded with redundant variables. It may therefore be necessary to reduce the number of variables in the dataset for inclusion in the models described below. Replacing the original set of variables with a smaller set is called "dimension reduction" and is reasonable to attempt in cases where there are possible redundancies among the variables. These redundancies would occur, for instance, when two or more variables are highly correlated and can be regarded as measuring essentially the same thing. Often, such variables can be regarded as "proxies" for some unobservable latent variable.

Two statistical methods are recommended for dimension reduction: variable-clustering and principal components analysis (PCA). The idea of clustering variables is similar to the more familiar clustering of cases, except that a more appropriate measure of "distance" is used. In fact it is more usual to think of "similarity" between two variables, the converse of distance. It is natural to base this on some measure of correlation between variables. Because the data types are typically mixed, some being measurements on an interval scale while others were ordinal or binary, the square of Spearman's rank correlation similarity measure derived from rank correlation is suitable. The package S-PLUS 6 (Insightful Corp., 2001) can be used for this analysis; the S-PLUS function for variable clustering is *varclus*, which is part of the *hmisc* library.

To illustrate the method, we present the results of analyses undertaken by project R7834 for one set of explanatory variables selected from the Decision-Making Arrangements group of variables. An outcome variable EQUITY (distributional equity among community members) was included with a view to having a prior look at how it might depend on the attributes in this group. The dendrogram below summarizes the results.

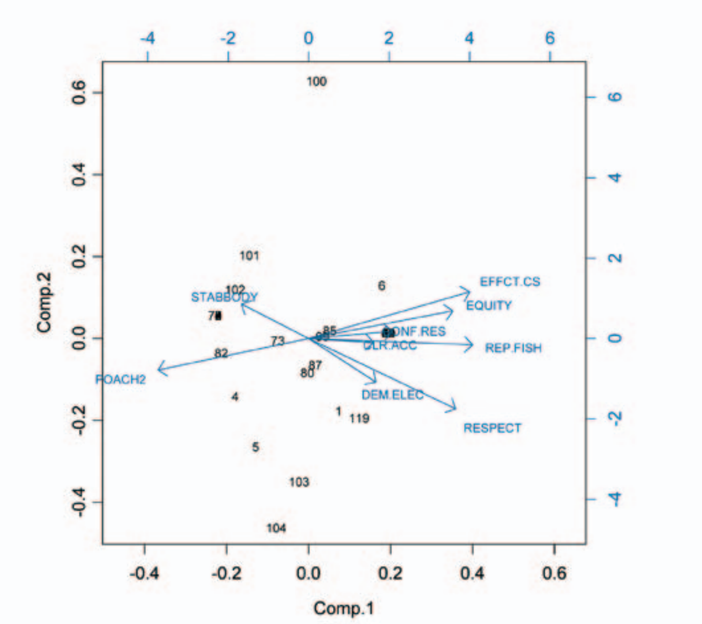
FIGURE 14.9
Dendrogram illustrating similarities among variables



The figure shows that the variables REP_FISH (representation of fishers on the decision-making body) and TRANSPAR (transparency of rule making) are closely related, and probably contain similar information. In the interests of parsimony, only one of these variables should be retained. In some cases, variables may be retained for modelling even though they are closely related statistically. This may occur when the contextual meanings of the variables were different and model interpretation would benefit from retaining them all.

With some of the groups of variables examined, it may be possible to gain further insights into the complex relationships between them by using PCA. Given the varied data types (especially with ordinal variables taking values 0, 1, 2) we should not perhaps expect great success with this approach (which generally works best with measurement variables). However, as an exploratory tool, it may be useful, at least to further explore possible relationships. As an example, PCA was tried on the variables EQUITY, RESPECT (respect for decision-making body), STABBODY (stability of decision-making body), CLR_ACC (clear access rights), REP_FISH (representation in rule making), DEM_ELEC (democratically elected decision-making body), CONF_RES (conflict resolution mechanisms), EFFECT_CS (effective control and surveillance) and POACH2 (incidence of poaching). The first two components accounted for 85.5 percent of the variance. A biplot (Figure 14.10) of the first two components is shown below.

FIGURE 14.10
PCA Biplot



Biplots like this are very useful summaries of PCA because they simultaneously represent the data points and the variables. Their interpretation is extensively described by Gower and Hand (1996), but for our purposes it suffices to note that the length of a vector represents the variance of the corresponding variable and that the angle between two vectors is a measure of the correlation between the variables (a small angle indicating a high correlation). The numbers on the plot are the ID numbers of the fisheries in the R7834 project database. (Note the direction of the STABBODY variable is unexpectedly opposite to that of RESPECT, but this is because of the way numeric codes were assigned to the former variable, 0 representing "stable".)

Taken together, these two exploratory tools, variable clustering and PCA with biplots, can be very helpful in selecting sets of variables for inclusion in models, especially the network models described below.

Exploratory Data Analysis

Following data checking, cleaning and reduction, exploratory data analyses using graphical and data summary procedures should be undertaken. Such exploratory and descriptive methods of analysis are essential at the first stage of data analysis since they form a valuable tool for identifying important features of the data and further scrutiny of the data for any unexpected patterns or extreme observations. They are also useful for getting a preliminary idea of the behaviour of the data and the distributional patterns exhibited by individual variables and to guide appropriate data transformations to meet the assumptions behind the methods described below.

14.3.1 The General Linear Model Approach [25]

The use of multiple linear regression techniques is common in research investigations. A typical objective is to explore the dependence of a key quantitative outcome, often called the dependent variable (y), on one or more explanatory variables that are believed to have a potential influence on y. Sometimes there is also interest in using the model equation as a predictive tool.

[25] S. Abeyasekera and A.S. Halls

When dealing with multidisciplinary data sets, we are often confronted with a mix of different data types, e.g. quantitative measurement variables, binary responses and categorical variables such as those in Table 14.1. The appropriate model for dealing with these different measurement variables is then the general linear model (GLM). This is essentially a more general version of the model used in a multiple linear regression analysis. The aims of model development remain the same, i.e. to explain, via a series of potential explanatory variables, the variation in *y*, or as a predictive tool. It must be recognized however that variables, which contribute to explaining the variation in *y*, are not necessarily implying causation. Non-statistical considerations will help in determining whether or not causality is likely.

Model description

To illustrate the form of the model equation for a GLM, we consider a situation where the aim is to study the influence of two explanatory variables x_1 and x_2, and two categorical variables R (with 3 levels) and S (with 4 levels) on a response variable y when measurements on y, x_1 and x_2 are made on n co-managed sites or units. The model equation is then:

$$y_{ijk} = \mu + \beta_1 x_{1i} + \beta_2 x_{2i} + r_{ij} + s_{ik} + \varepsilon_{ijk}\ , \qquad i = 1,2,...n;\ j = 1,2,3;\ k = 1,2,3,4$$

In this equation, μ represents a constant, similar to the intercept in multiple linear regression, while ε_{ijk} represents the residual component and reflects the random (or residual, or unexplained) variation in y after the effect of x_1, x_2, R and S have been taken into account. The parameters β_1, (and β_2) give the change in y for a unit change in x_1, (and x_2) when all other explanatory variables are held constant. The parameters r_{ij} and s_{ik}, show changes in the overall model constant in accordance with changing the levels of R or S respectively. We draw attention to the fact that when the model is fitted, the underlying mathematics requires a constraint to be imposed upon the model parameters. The constraint used depends on the software. In SPSS (2001) for example, the default setting fixes the last level of R and the last level of S to zero, i.e. $r_{i3} = 0$ and $s_{i4} = 0$, in the example above.

When the categorical variables are nominal (e.g. type of ecosystem, or type of gear used), their inclusion in the model allows a test of whether the mean values of the outcome differ significantly across the different levels of the factor. So for example, if catch per unit area (CPUA) is the dependent variable being modelled, and the explanatory variables include the type of gear being used (GEARTYP2) with four levels, i.e. (i) gillnets; (ii) hook & line or speargun; (iii) nets; (iv) traps or other, then the overall significance level for GEARTYP2, obtained via the modelling process, indicates that the mean CPUA differs across the different gear types used.

When a particular categorical variable considered for inclusion in the model is ordinal (e.g. level of ecological knowledge or wealth variation among fishers, recorded as low, medium, high), there is a choice to be made. The categorical variable can either be regarded as a quantitative variate (1 d.f. in the corresponding analysis of variance (anova) table which results from the GLM), or it can be regarded as a nominal variable (d.f. = number of levels-1). The former poses some difficulties. First, it assumes that the effect of the ordinal variable is a monotonic increase or decrease. Secondly, most of the ordinal variables in the profiled data set were scored on a 0,1,2 scale. So even if the effect was linear, the number of levels can be too low to identify this linearity. Moreover, it assumes that the “distance” from the “low” category to the “medium” category is the same as the “distance” from the “medium” category to the “high” category. We have therefore initially regarded all ordinal variables as nominal since this accounts for the total contribution to variation in the outcome from each such variable.

Our procedure has been to determine the subset of attributes (explanatory variables) that best explains the variation in the outcome variable (y) of interest and then investigate whether the main contribution from the ordinal variables in the model was due to a linear effect. If this was found to be the case, the model was refitted with just the linear component. However, we have found that for purposes of interpretation and reporting, regarding the ordinal explanatory variables as nominal was the most effective in the majority of cases. A binary variable (only 2 categories) can also be included in the model as nominal or as a quantitative variable, but the choice is less crucial here since the results of the tests of significance will be identical in either case. Some care is needed however in interpreting the corresponding model parameters since this can vary according to the software package being used.

Model assumptions

The model carries some assumptions that need to be checked for their validity at the data analysis stage. The assumptions strictly relate to the residual components ε, but practically they require that the y values are independent of each other, have a constant variance, and follow a normal distribution. It is this last assumption that restricts the outcome variable y in a GLM to a quantitative measurement variate. Although inferential procedures associated with GLMs are quite robust to small departures from normality, management performance measures such as equity, compliance, empowerment etc that are often subjectively measured with, for example, a three-point ordinal scale (low, medium, high) are non-normal and therefore not suitable as the key outcome variable in GLM models. The GLM-based approach we describe here should therefore be restricted to genuine measurement data such as the catch per unit area or the catch per unit effort as the dependent (outcome) variables. The Bayesian network modelling approach described in Section 14.3.2 below offers an alternative approach to modelling these more subjectively measured, non-normally distributed management performance variables to complement the GLM approach described here.

The variance homogeneity assumption and the assumption of independence are both very important to ensure the validity of model-based results. Independence would normally be assured by collecting the data according to some well-defined random sampling procedure. Checking the validity of the variance homogeneity assumption for each model investigated is possible through a residual analysis. This analysis involves looking at a series of plots where the residuals, i.e. the deviation of model predictions from observed value, are plotted in different ways. The most useful is a plot of residuals versus model predicted values. This will show a random scatter if the assumptions underlying the model are reasonable. This is illustrated in the example below. Residual analysis is also useful for identifying outliers, i.e. observations far removed from the pattern exhibited by the remaining data.

Example application

Here we illustrate the application of the GLM approach for constructing models of catch per unit area (CPUA) measured in tonnes per km^{-2} - a key quantitative variable from the dataset described above. The analysis was carried out using SPSS version 11 (SPSS, 2001).

Using the hypothesis matrix, a total of 35 explanatory variables were identified as having a potential influence upon CPUA. Since it is impractical to include so many variables in the model simultaneously, subsets of these variables were considered in turn, e.g. sets of attributes corresponding to categories of explanatory variables given in Table 14.1. The subset of variables from each set, contributing significantly to the outcome variable CPUA, were first selected through a backward elimination procedure. The contributors thus selected from each set were then considered together and a variable selection procedure applied to determine a range of suitable alternative models. Interactions between these effects were also examined, e.g. to examine whether the effect of ecosystem type was different across the different waterbody types. It was not possible however, to examine all interaction effects due to the non-availability of sufficient cases within all 2-way combinations of the categorical variables.

With respect to CPUA, we began with the following set of key identifiers.

PERMEN -Waterbody type: Seasonal (0), perennial (1), both (2).
ECOTYPE -Ecosystem type: Rivers(1), beels(2), lakes(3), reefs(4), others(5).
VILLAGES -Number of fishing villages.
FISHERS1 -Number of fishers of all types.

The significance of each variable in influencing the value of CPUA was judged on the basis of the ANOVA table (Table 14.2) generated by the SPSS software. Since the variable VILLAGES appears to be the least significant variable when added to a model containing the remaining three variables, it was dropped from the model and the model refitted with the remaining variables. The resulting probabilities for the remaining attributes were then 0.017, 0.453 and 0.420 for ECOTYPE, PERMEN and FISHERS1 respectively. At the next step, PERMEN was dropped and the model re-fitted giving probabilities of 0.015 and 0.536 respectively for assessing the significance of ECOTYPE and FISHERS1. Since FISHERS1 was still non-significant, ECOTYPE alone was fitted giving a significant probability of 0.013 (Residual df=25; R^2=39 percent).

TABLE 14.2
An example of an ANOVA table for CPUA

Explanatory variable	d.f.	Type III MS	F	Sig. Prob.
ECOTYPE	4	1526.9	1.81	0.177
PERMEN*	1	338.8	0.40	0.536
FISHERS1	1	313.4	0.37	0.551
VILLAGES	1	0.13	0.00	0.990
Residual	16	845.6		

* only 1 d.f. since there were no data corresponding to the "seasonal category

At this stage, explanatory variables discarded during stage 1, in this example VILLAGES and PERMEN, were brought back into the model to assess whether the removal of FISHERS1 would now indicate their importance. This was found not to be the case in this example and therefore ECOTYPE alone was regarded as the only variable from the subset to contribute significantly to variation in CPUA.

Repeating the above process for each of the remaining sets of categories of explanatory variables (Table 14.1) resulted in seven alternative models. They are described in Table 14.3 and Table 14.4.

The probabilities quoted in Table 14.3 reflect the relative importance of each model attribute. Table 14.4 shows the magnitude and direction of the effect of each attribute. In the case of each categorical variable, the parameter corresponding to the base level (first or last level according to which is easier for interpretation) is set to zero. Values for the remaining parameters show changes from the base level. Although ECOTYPE was a highly significant factor in all the models, it is not shown in Table 14.4 since it acts as a stratification variable whose effect must be eliminated before exploring the effect of other variables.

Each of the models in Table 14.3 were subjected to a residual analysis before they were regarded as being acceptable. We provide in Figure 14.11, an illustration of a residual plot for the second model shown in Table 14.3, i.e. the one where explanatory variables entering the model are ecosystem type, gear type and fisher density. There is no obvious pattern or outliers in this data, and hence the model seems acceptable.

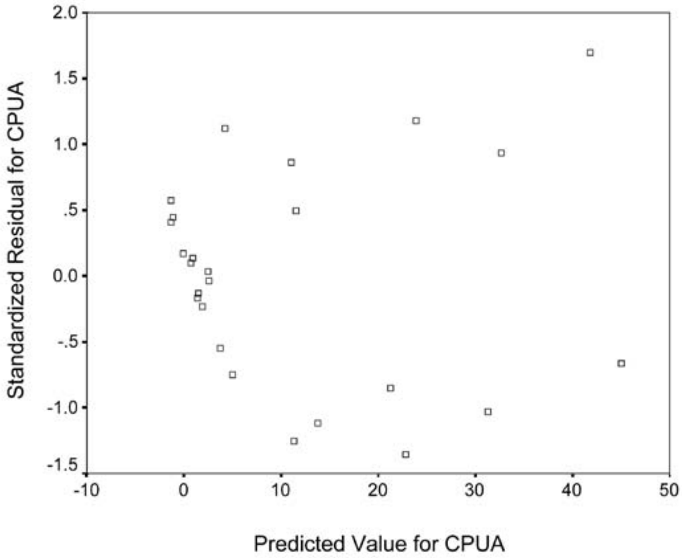
TABLE 14.3
Model summaries for CPUA

Model	Explanatory variable	Variables in model	Prob. for sig.	Residual d.f.	Residual M.S.	Adjusted R^2
1	PRIM_PRO, i.e. Primary Production (g/C/m²/year), with ecotype and fisher density	ECOTYPE PRIM_PRO FISH_DEN	0.000 0.014 0.033	12	36.2	85%
2	GEARTYP2, i.e. Type of gear, with ecotype and fisher density	ECOTYPE GEARTYP2 FISH_DEN	0.000 0.006 0.004	16	33.3	85%
3	HARM_GR, i.e. Destructive fishing practices, with ecotype and fisher density	ECOTYPE HARM_GR FISH_DEN	0.000 0.000 0.013	13	28.1	88%
4	BAN_DRIV, i.e. Ban on fish drives, with ecotype.	ECOTYPE BAN_DRIV	0.000 0.000	18	25.7	89%
5	SIZE, i.e. landing size restrictions, and NUMB_RES, i.e. number of reserves, with their interaction, and with ecotype.	ECOTYPE SIZE NUMB_RES SIZE x NUMB_RES	0.000 0.000 0.001 0.013	14	12.1	93%
6	MANG_TYP, i.e. Type of management and OA_COMM, i.e. if open or restricted access, with ecotype and fisher density.	ECOTYPE MANG_TYP OA_COMM FISH_DEN	0.000 0.005 0.018 0.043	17	32.6	85%
7	LOC_BODY, i.e. Local decision making body, and OA_COMM, i.e. if open or restricted access, with ecotype and fisher density.	ECOTYPE LOC_BODY OA_COMM FISH_DEN	0.000 0.001 0.015 0.011	18	30.8	85%

TABLE 14.4
Predicted Changes in CPUA from a base level of each significant explanatory variable

Model	Explanatory variable	Variable Levels	Changes from base level	n
1	PRIM_PRO, i.e. Primary Production (g/C/m²/year) (with ecotype and fisher density)	Low Medium High	0 5.6 20.8	7 7 4
2	GEARTYPE2, i.e. Type of gear (with ecotype and fisher density)	Gillnets Hook & Line or Speargun Nets Traps or other	0 –2.5 16.4 –0.91	10 9 3 3
3	HARM_GR, i.e. Destructive fishing practices? (with ecotype and fisher density)	No Yes	19.8 0	11 9
4	BAN_DRIV, i.e. Ban on fish drives (with ecotype)	No Yes	0 23.6	19 5
5	SIZE, i.e. landing size restrictions, and	No Yes	0 15.5	19 3
	NUMB_RES, i.e. number of reserves, according to SIZE.	"Slope" for size=No "Slope" for size=Yes	–0.57 -2.90	-
6	MANG_TYP, i.e. Type of management and	Govt. Co_mgt Self/Trad.	0 15.4 12.4	6 5 15
	OA_COMM, i.e. if open or restricted access. (with ecotype and fisher density)	Open Restricted	0 6.4	11 15
7	LOC_BODY, i.e. Local decision making body and	Absent Present	0 15.0	6 20
	OA_COMM, i.e. if open or restricted access. (with ecotype and fisher density)	Open Restricted	0 6.4	11 15

FIGURE 14.11
Residual plot from modelling catch per unit area (tonnes per km^{-2}) on ecotype system, type of gear and fisher density (km^{-1} yr^{1})
(The random scatter is indicative of non-violation of model assumptions)



The effect of quantitative variates, e.g NUMB_RES and FISH_DEN is shown in Table 14.4 in terms of the corresponding model parameter, i.e. the "slope" in standard multiple regression models. This reflects the increase in CPUA (negative values imply a decrease) for a unit change in the attribute.

The results in Table 14.4 are indicative of the way in which a number of explanatory variables can affect CPUA. For example, a fishery with a high level of primary production is likely to have a CPUA that is 20 tonnes km^{-2} yr^{-1} higher than a fishery with low primary production. Using nets (other than gillnets) can give 16 tonnes km^{-2} yr^{-1} higher CPUA compared to using gillnets. Banning destructive fishing practices or banning fish drives can increase CPUA by about 20 tonnes km^{-2} yr^{-1}.

The "slope" coefficient for the number of reserves depends on whether or not there are landing size restrictions. In the absence of landing size restrictions, the number of reserves has no effect ("slope" = - 0.57 is non-sig). However, if there are landing size restrictions, then results of Table 14.4 indicate that an increase in the number of reserves by 1 unit can lower CPUA by approximately 3 tonnes km^{-2} yr^{-1}. However, it is important not to place too much emphasis on this particular result because approximately 50 percent of the observations had no reserves whilst three had very high values. The aim here (and that of project R7834) is to demonstrate the approach, rather than draw specific conclusions from the data.

14.3.2 Bayesian Network (BN) models [26]

Bayesian Network (BN) models (Jensen, 2001; Cowell *et al.*, 1999; Pearl, 2000) are not statistical models in the usual sense, but rather, probabilistic expert systems that are specifically designed to model complex patterns of causality in the presence of stochastic uncertainty. A BN can be a powerful tool for analysing "what-if" scenarios and for identifying combinations of conditions (for example management strategies and institutional arrangements) that tend to lead to successful outcomes. BNs have been successfully applied in many diverse fields including medical diagnosis, forensic

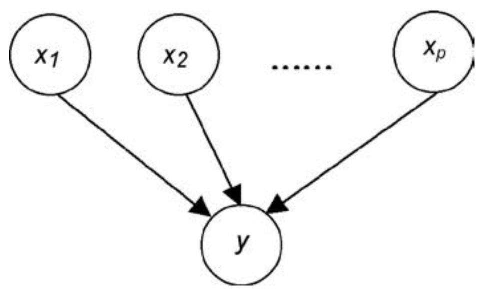
[26] R.W. Burn & A.S. Halls

science and genetics (Jensen, 2001); an interesting application to fish and wildlife population viability under different land management strategies is presented by Marcot et al (2001).

An overview of Bayesian Networks

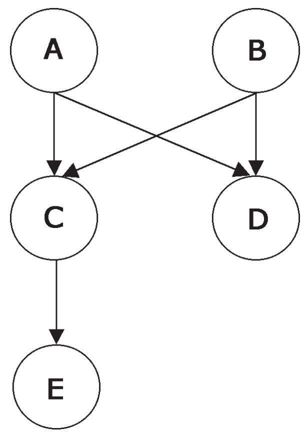
Perhaps the most familiar and general class of statistical models comprises those that seek to account for variation in a response variable *y* (which may be multivariate) in terms of a set of explanatory variables. This class includes all regression and generalized linear models. The relationships between the variables can be represented graphically as in Figure 14.12, an example of a graphical model.

FIGURE 14.12
Explanatory and response variables



It often happens, however, that the relationships between variables are not as simple as this model allows. The effect of one x-variable on the response y may be mediated through another x-variable, or through two or even more x-variables. It could also happen that some of the x-variables affect some of the others. The roles of "response" and "explanatory" variables become blurred, with variables taking on each role in turn. In the simple example in Figure 14.13, variables E and D could be regarded as "responses", and A and B as "explanatory". But C seems to play both roles. It looks like a response with A and B acting as explanatory variables, and it is an "explanatory" variable for E.

FIGURE 14.13
Indirect mediation of effects of explanatory variables



It is customary for statisticians to warn that a significant correlation between variables (or a term in a regression model) does not necessarily imply any causal relationship. In contrast, the network models presented here deliberately set out to model patterns of causality. The arrows in the above diagram represent causal links. A rigorous discussion of the role of causality in scientific inference is presented by Pearl (2000). The causation does not have to be deterministic and can incorporate a degree of uncertainty. Indeed, the variables are modelled as random variables and the links are probabilistic. A link from A to C would be interpreted as meaning that the value of A affects C by influencing its probability distribution. A BN consists of a set of nodes (variables) connected by directed (causal) links without cycles (see Jensen, 2001 for an introductory account, or Cowell *et al.*, 1999 for a more rigorous treatment). Most of the currently available software for analysing BNs requires all nodes to be discrete variables. Continuous variables can be accommodated by grouping their values into intervals. The causal links between nodes are formally quantified by conditional probability tables (CPTs). As an example, Table 14.5 shows the structure of the CPT for the node C in Figure 14.13, assuming, for simplicity, that all nodes are binary, taking values F or T.

TABLE 14.5
CPT for Node C

		C		
		F	*T*	*Total*
F	*F*	p_{000}	p_{001}	*1*
F	*T*	p_{010}	p_{011}	*1*
T	*F*	p_{100}	p_{101}	*1*
T	*T*	p_{110}	p_{111}	*1*

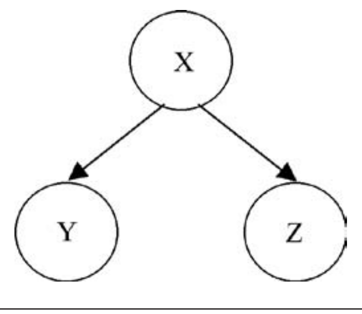
If sufficient data are available, estimates of the entries in the CPT of a node can be obtained by simply cross-tabulating the variables representing its parent nodes. Alternatively, they can be subjective probabilities or degrees of belief, ideally encoded from expert opinions. Formal procedures for eliciting prior beliefs from panels of experts and building probability distributions from them are described by O'Hagan (1998). For Project R7834, most CPTs were estimated by cross-tabulations of the dataset, but where data were too sparse, reasonable subjective estimates were used, although without using the above formal procedures.

In the simple example of Figure 14.13, if the states of the nodes (i.e. the values of the variables) A and B were known, then it would be possible to use the rules of probability to calculate the probabilities of the various combinations of values of the other nodes in the network. This kind of reasoning in a BN can be called "prior to posterior", in the sense that the reasoning follows the directions of the causal links in the network. Suppose now that the state of node E were known. What could be said about the other nodes? The updating algorithm of Lauritzen and Spiegelhalter (1998) allows us to calculate the posterior probabilities of all other nodes in the network, given the known value at E, or indeed, given any combination of known nodes. In the jargon of expert systems, "knowing" the value of a node is called "entering evidence". This is "posterior to prior" reasoning and allows us to infer something about the states of nodes by reasoning against the direction of the causal links. The updating algorithm is a very powerful tool in BNs and enables us to make useful predictions and examine "what if" scenarios with ease. Various software packages are available which facilitate the construction of BNs and implement the updating algorithm. Project R7834 used the Netica program (Norsys, 1998) which is very user-friendly and there are no great demands or pre-assumed knowledge to be able to use it.

In addition to its analytical capabilities, it has facilities for designing and editing network models and for maintaining files of data. It is also inexpensive and a free version can be downloaded from the world-wide-web (www.norsys.com/netica) and so is suitable for use in low-budget situations.

An important property of BNs is conditional independence. Consider the network fragment in Figure 14.14.

FIGURE 14.14
Conditional independence



Knowledge of the state of Z would enable us to infer something about the possible states of X (i.e. calculate the posterior probabilities of X), using the updating algorithm, or in this simple case by using Bayes' rule from probability theory. From this we could estimate the probabilities of the states of Y. However, if the state of X were known then knowledge of Z would tell us nothing about Y in addition to the what we deduce from knowing the state of X. Y and Z are said to be conditionally independent given X. Conditional independence is a fundamentally important property of BNs without which the updating algorithm would not work. It is also important at the stage of building a BN model because it implies that at any stage of development of the model, we can focus just on one node and its parents without having to consider the joint effect of all possible interacting nodes. This amounts to a great simplification in the model building process.

Building a Bayesian Network

Network construction is generally an iterative process. The first step is the qualitative stage of specifying the nodes and the causal relationships between them. To begin with, this is a tentative specification representing a hypothesis (or a collection of related hypotheses) perhaps drawn from a hypothesis matrix (see section 14.3) and subject to modification after closer investigation of the validity of the links. Usually we would start by focusing on a particular outcome or set of outcomes and then propose nodes representing immediate (proximate) causes. Then we decide whether there should be any causal links between the nodes representing these immediate causes and then look for causes of theses causes, if there are any, and so on. At each stage, we again insert any possible causal links between the nodes so far included. In principle, this process could be continued for several stages of causality, but a good model should be parsimonious and represent the principal features of the patterns of causality that exist among the variables. Further guidance on methods for constructing BN models is given by Jensen (2001).

When sufficient data are available, cross-tabulating the data for a node and its parents leads to a multi-dimensional contingency table. The strength of the joint effects of parent nodes on a child node can be assessed by fitting log-linear models to this table, or alternatively, in the case of binary nodes, by fitting logistic regression models (McCullagh and Nelder, 1989). A consequence of conditional independence is that there is no need for concern about the simultaneous effects of nodes other than the parent nodes of the node. It should be stressed that this model-building process is not based on statistical criteria alone, but also involves judgements based on contextual knowledge of the data. In those situations where little or no hard data are available, the causal links and their CPTs will be derived from a process of elicitation of expert knowledge alone.

Once the BN is constructed, it can be used for investigating the effects of given states of one or more nodes simultaneously by "entering evidence" into those nodes. Often, the focus of interest is the effect of combinations of nodes on particular "outcome" nodes. It is possible to quantify these effects by computing the corresponding reduction in entropy (Jensen, 2001) in the network (called "mutual information" in the Netica documentation). Roughly speaking, this compares the change in the amount of uncertainty in the model before and after entering the evidence. Although the absolute numeric values of this measure may not be directly meaningful, it does enable a ranking of nodes according to the importance of their effect on other nodes.

Example model construction

Using the same dataset described in Section 14.3, we illustrate below the construction of a BN model for exploring the principal determinants of "successful" management where "success" is modelled by the joint behaviour of three outcome variables intended to represent sustainability, compliance with management rules and equity of distribution in the community. In addition to these three main outcome variables, it turned out that secondary outcome variables could be added to the model at virtually no cost in terms of complexity and performance. These additional outcomes were stability (the stability of the decision-making body), respectability (the perceived respectability in the community) and poaching.

Variables representing proximate causes of the outcome variables, followed by secondary causal effects, were added to the model after following the general procedure outlined above. A representation of the resulting BN is shown in Figure 14.15.

The strength of the association between each node and its parent nodes was assessed by fitting logistic regression models. The results of this analysis are summarized in Table 14.6.

FIGURE 14.15
The initial qualitative stage of BN model development

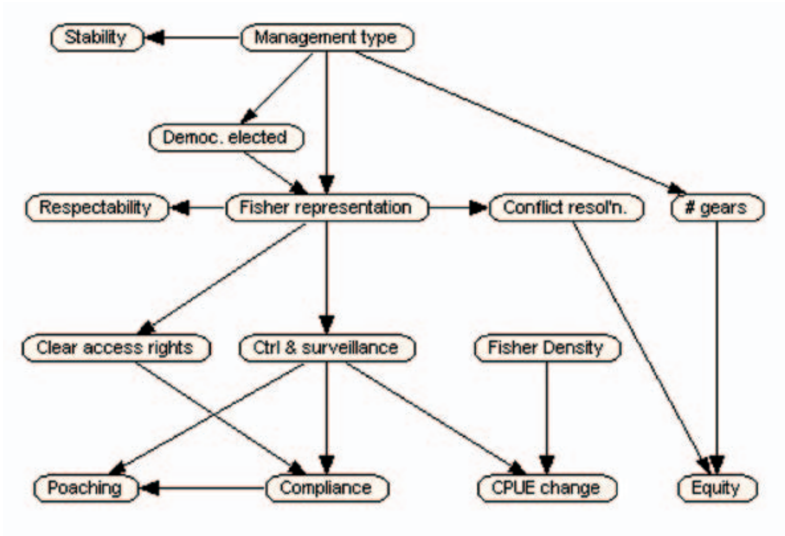


TABLE 14.6
Results of logistic regression analyses

Child node	Parent nodes	Deviance	d.f.	Signif., *P*
Equity	*Conflict resolution*	10.11	1	0.001
	# gears	4.98	1	0.026
CPUE chg.	*Fisher density*	7.13	1	0.008
	Ctrl & surveillance	6.29	1	0.012
Compliance	*Clear access rights*	19.10	1	<0.0001
	Ctrl & surveillance	13.08	1	0.0003
Poaching	*Compliance*	20.13	1	<0.0001
	Ctrl & surveillance	3.90	1	0.048
Ctrl & surveillance	*Fisher representation*	41.87	1	<0.0001
Clear access rights	*Fisher representation*	18.10	1	<0.0001
Fisher representation	*Management type*	12.67	2	0.002
	Democ. elected	20.89	1	<0.0001
Conflict resolution	*Fisher representation*	43.05	1	<0.0001
# gears	*Management type*	17.58	2	0.0002
Democ. elected	*Management type*	30.87	2	<0.0001
Respectability	*Fisher representation*	12.47	1	0.0004
Stability	*Management type*	7.13	2	0.028

Having completed the qualitative specification of the model (i.e. the nodes and causal links), we need to specify the conditional probabilities that govern the links between parent and child nodes. For most of the nodes these conditional probabilities were estimated by cross-tabulating the original data. In the event, some of these estimates were based on quite small numbers of cases in the cross-tabulation, resulting in extreme estimates (1 or 0). When it was judged to be possible, but unlikely, that such an extreme occurs, these probabilities were subjected to small adjustments (0.95 or 0.05, for example). As examples of probabilities estimated in this way, Table 14.7 shows the conditional probabilities for the node Conflict resolution and Table 14.8 represents the conditional probabilities for the node Fisher representation.

TABLE 14.7
Conditional probabilities for Conflict resolution

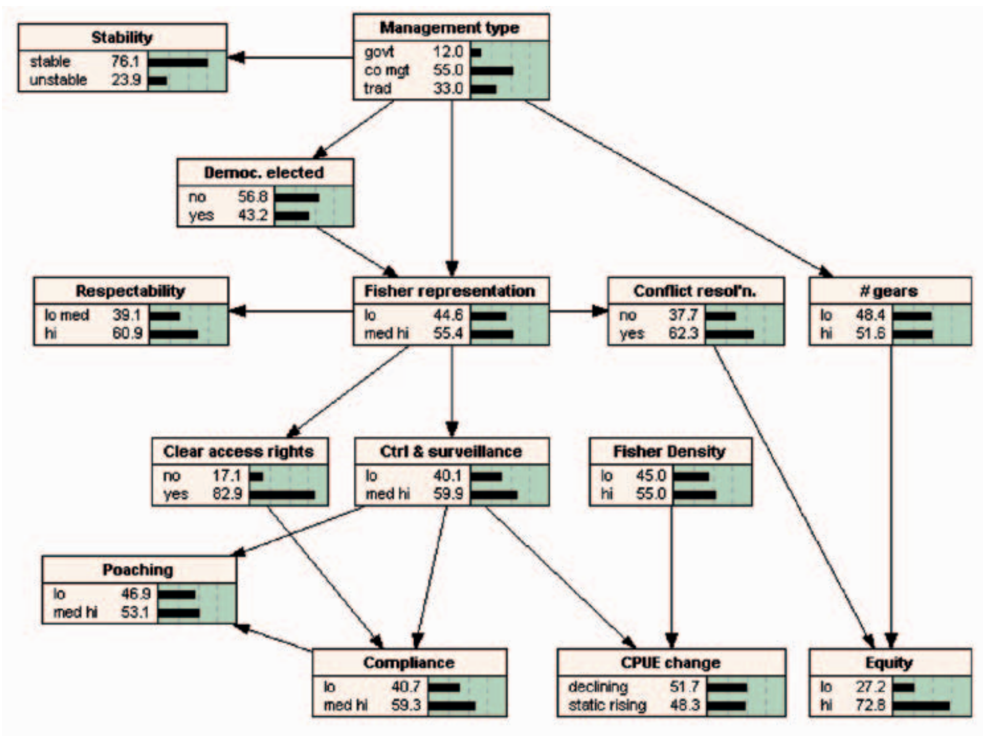
	Conflict resolution	
Fisher rep.	*No*	*Yes*
Low	0.77	0.23
Med/high	0.06	0.94

TABLE 14.8
Conditional probabilities for Fisher representation

		Fisher representation	
Mg't. type	**Dem. Elec.**	*Low*	*Med/ high*
Gov't.	*No*	0.95	0.05
Gov't.	*Yes*	0.95	0.05
Co-mg't.	*No*	0.91	0.09
Co-mg't.	*Yes*	0.11	0.89
Trad.	*No*	0.33	0.67
Trad.	*Yes*	1.00	0.00

The representation of the model (output from the Netica software) in Figure 14.16 shows each node with probability bars (on a percentage scale). The initial values of these probabilities are the overall average "posterior" probabilities of the states of the nodes, as estimated from the data. The exceptions are the nodes with no parents (Management type and Fisher density), where they are "prior" probabilities, in this case simply the proportions of occurrences of the levels of the variables in the data (so for Management type, 12.0 percent of cases were "government", 55.0 percent "co-management" and 33.0 percent "traditional").

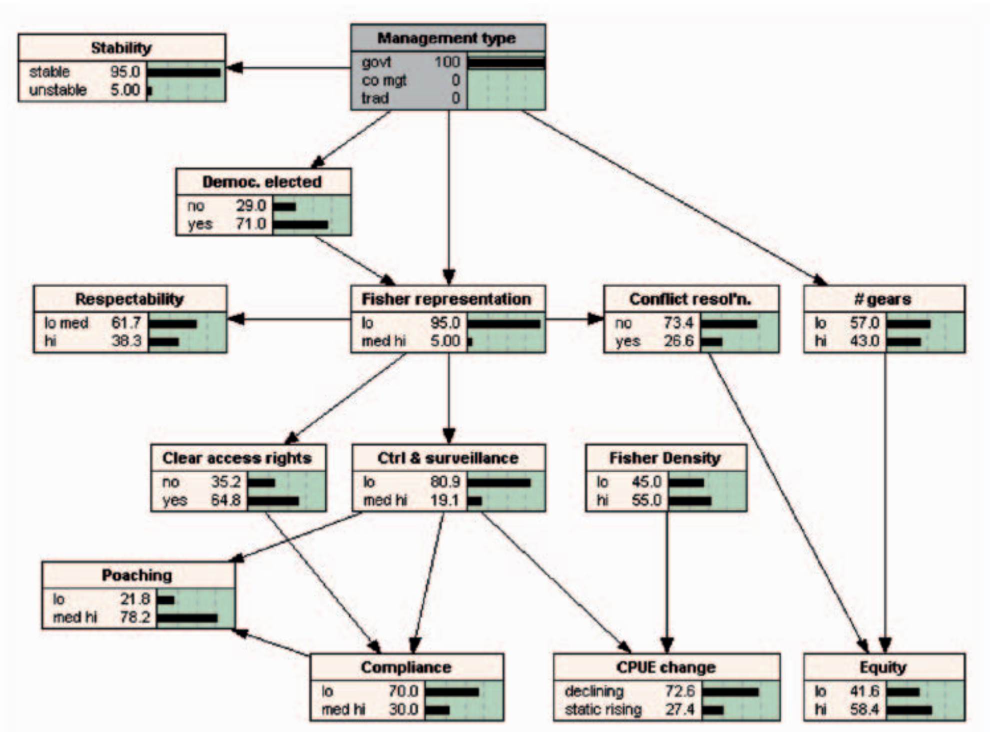
FIGURE 14.16
Bayesian network model for the outcomes *Equity, CPUE change* and *Compliance* (see the text for an explanation of the contents of the boxes)



Using the Model

As a first example, we use the model to investigate the effect on the outcomes of Management type. If we set this node (or "enter evidence") to, say "government", the resulting posterior probabilities in all nodes are updated with the result shown in Figure 14.17.

FIGURE 14.17
Exploring the effects of government management on outcomes



Compare the probabilities now displayed in the nodes with the overall average probabilities in Figure 14.16. We see, for example that the posterior probability of high Equity has changed from 72.8 percent to 58.4 percent. Note also the effect on the subsidiary outcomes: the probability of med/high Poaching, for example has changed from 53.1 percent to 78.2 percent. By successively entering the three possible management types, the effects on the main outcomes can be compared and these results are summarized in Table 14.9.

TABLE 14.9
Posterior probabilities of favourable (main) outcomes by management type

Outcome		Management type		
	Overall	*Gov't.*	*Co-mg't.*	*Trad.*
Equity (high)	73%	58%	80%	67%
CPUE change (static/rising)	48%	27%	50%	53%
Compliance (med/high)	59%	30%	62%	66%

In the same way we can obtain the posterior probabilities of the subsidiary outcomes (shown in Table 14.10).

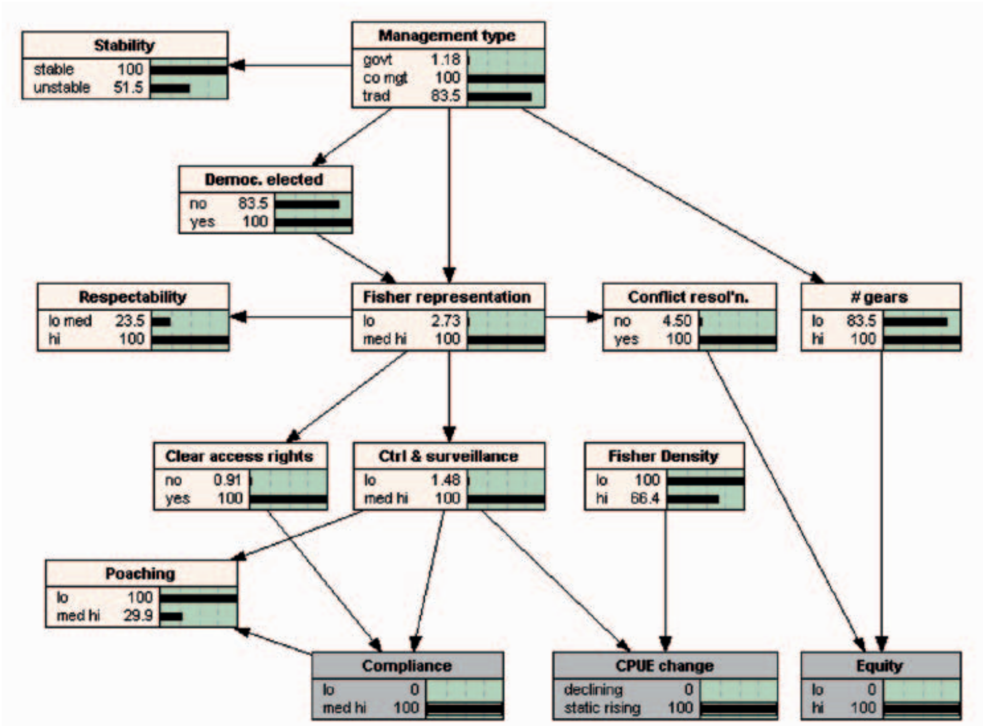
TABLE 14.10
Posterior probabilities of favourable (subsidiary) outcomes by management type

Outcome		Management type		
	Overall	*Gov't.*	*Co-mg't.*	*Trad.*
Poaching (low)	47%	22%	49%	53%
Stability (stable)	76%	95%	66%	86%
Respectability (high)	61%	38%	63%	66%

Evidence can be entered into any node, or indeed any combination of nodes simultaneously, and posterior probabilities for all remaining nodes in the network obtained by applying the updating algorithm. To illustrate this, we can examine the posterior probabilities resulting from setting all three main outcomes to their "favourable" states: med/high Compliance, static/rising CPUE change and high Equity. The resulting posterior probabilities could be obtained as in the previous example, but for the purposes of illustration, Figure 14.18 shows the result in a slightly different form.

FIGURE 14.18

The configuration of states that are most likely to achieve favourable states in all three of the main management outcomes simultaneously



It gives what is called the most probable explanation. This is the configuration of states that are most likely to be conducive to favourable results in the three outcomes simultaneously. The bars in the nodes no longer represent probabilities, but the required favourable state of each node is indicated by 100 percent. The lengths of the bars for the other states in the same node now represent the relative importance of those states, in the sense that a high percentage (close to 100 percent) would indicate that the actual state is probably not critical. We are thus able to deduce which nodes are critical for favourable outcomes. For example, referring to Figure 14.18, we see that Fisher representation appears to be an important feature because the "low/med" state scores only 2.73 against the preferred state "high". Note also the Management type node, where although "co-management" is the state most likely to produce favourable outcomes, "traditional" fisheries score 83.5, which indicates that the corresponding posterior probabilities of the main outcomes would also be quite high. The relative importance of attributes to outcomes can be assessed by measuring the entropy reduction. Table 14.11 summarizes the results of this analysis.

TABLE 14.11
Relative importance of attributes to outcomes as measured by reduction in entropy

Outcome	Important attributes	Entropy reduction
Compliance	Ctrl & surveillance	0.3427
	Fisher representation	0.2636
	Clear access rights	0.1377
	Management type	0.0357
	Democratically elected	0.0225
Equity	Conflict resolution	0.0918
	# gears	0.0524
	Fisher representation	0.0490
	Management type	0.0221
	Democratically elected	0.0170
CPUE change	Ctrl & surveillance	0.1944
	Fisher representation	0.1276
	Fisher density	0.0967
	Management type	0.0185
	Democratically elected	0.0110

Application
These probabilistic expert systems offer a powerful tool for managers and decision makers to identify combinations of conditions or factors that tend to give rise to desirable management outcomes or performance and provide a powerful visual tool for analysing "what-if" scenarios to guide changes to future management activities or plans. Indeed, the very process of constructing the model itself is a useful exercise in the elucidation of characteristics of the situation being modelled.

We wish to re-emphasize that the purpose of including the model described above is to illustrate the general methodological approach, rather than to report specific conclusions from the data. These global-scale comparisons were principally designed to ensure that, during the methodological development stage, consideration was given to a wide range of variables that might be postulated to have an important influence on different aspects of management performance, and whilst these results may encourage further investigation into traditional management practices, these comparisons have, perhaps more importantly, served to illustrate that management performance is likely to be mediated through a number of interacting factors that should be taken into consideration when forming appropriate institutional arrangements, and formulating and implementing management plans.

This approach should hold promise in the context of refining adaptive management strategies pursued at a national or local scale where similar, but more context-specific models can be constructed from among fishery comparisons of a subset of relevant variables. Lessons generated by the formulation and exploration of such models could then be used to iteratively adapt management plans or institutional arrangements. As more evidence become available through time, improved estimates of the conditional probabilities can be derived. The qualitative structure (the nodes and links) can also change adaptively in response to this "learning" process (Cowell *et al.*, 1999). Another development that may turn out to be important in adaptive management is the "dynamic BN". This incorporates the time dimension so that the model evolves. It consists of a series of snapshot models, one for each time period, with links between appropriate nodes at time t to nodes at time t+1. This may be useful for supporting the adaptive management of a single fishery over time.

ACKNOWLEDGEMENTS

We thank Kuperan Visawanathan of the WorldFish Centre and members of the Fisheries Co-Management Research Project (FCMRP) for their help in compiling the modelling dataset and formulating hypotheses concerning factors affecting management outcomes described in Section 14.3.

Annex 1

TABLE A1

Summary of the best fitting regression models for predicting multispecies potential yield from river, lake, coastal lagoon and reef fisheries where *a* and *b* are the constant and slope parameters of the linear regression model: Y = *a* + *b*x, and where *n* is the number of observations, R is the correlation coefficient, and P is the probability that the slope parameter, *b* = 0. S_b is the standard error of the estimate of the slope coefficient, *b*, $s^2_{Y.X}$ is the residual mean square, and $\bar{X}$ is the mean value of the observations of the explanatory variable.

River Fisheries

Relationship	Continent	*a*	*b*	S_b	*n*	$\bar{X}$	$s^2_{Y.X}$	R	P	Reference/Project
ln catch vs ln FPA	Asia	2.086	0.996	0.083	13	4.31	0.531	0.97	<0.001	MRAG (1993) /R5030
ln catch vs ln length	Asia	-14.88	3.234	0.585	5	8.06	0.680	0.96	0.01	MRAG (1993) /R5030
ln catch vs ln DBA	S. America	-3.60	0.936	0.218	15	12.87	1.457	0.77	0.001	MRAG (1993) /R5030

Lake Fisheries

Relationship	Continent	*a*	*b*	S_b	*n*	$\bar{X}$	$s^2_{Y.X}$	R	P	Reference/Project
ln catch vs ln Area	Africa	2.668	0.818	0.042	94	4.34	1.131	0.90	<0.001	Halls (1999)
ln catch vs ln Area (NS)	Africa	2.761	0.786	-	88	-	-	0.90	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (NS)	Asia	2.895	0.856	-	39	-	-	0.76	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (S)	Asia	4.545	0.552	-	25	-	-	0.76	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (NS)	S. America	2.646	0.665	-	12	-	-	0.60	0.040	MRAG (1995) /R6178

Reservoir Fisheries

Relationship	Continent	*a*	*b*	S_b	*n*	$\bar{X}$	$s^2_{Y.X}$	R	P	Reference/Project
ln catch vs ln Area (NS)	Africa	2.274	0.876	-	45	-	-	0.91	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (S)	Asia	3.048	0.413	-	54	-	-	0.50	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (NS)	Asia	2.278	0.823	-	57	-	-	0.70	<0.001	MRAG (1995) /R6178
ln catch vs ln Area (NS)	S. America	2.767	0.726	-	70	-	-	0.73	<0.001	MRAG (1995) /R6178

Lake and Reservoir Fisheries

Relationship	Continent	*a*	*b*	S_b	*n*	$\bar{X}$	$s^2_{Y.X}$	R	P	Reference/Project
Ln CPUA vs ln Rainfall (NS)	Asia	-13.73	2.113	-	12	-	-	0.72	0.009	MRAG (1995) /R6178
Ln CPUA vs ln Total P (S)	Asia	0.507	0.821	-	27	-	-	0.74	<0.001	MRAG (1995) /R6178
Ln CPUA vs ln Total N (S)	Asia	-3.969	1.302	-	25	-	-	0.62	0.001	MRAG (1995) /R6178
Ln CPUA vs ln surface Chla (NS)	Asia	-3.468	2.183	-	8	-	-	0.90	0.002	MRAG (1995) /R6178
Ln CPUA vs ln Zoo prod (NS)	All	4.822	-0.984	-	8	-	-	0.80	0.020	MRAG (1995) /R6178

Lagoon Fisheries & Floodplain Lakes*

Relationship	Continent	*a*	*b*	S_b	*n*	$\bar{X}$	$s^2_{Y.X}$	R	P	Reference/Project
ln catch vs ln Area	Africa	2.583	0.953	-	31	-	-	0.73	<0.001	MRAG (1995) /R6178
ln catch vs ln Area	Asia	2.016	0.871	-	4	-	-	0.99	0.002	MRAG (1995) /R6178
ln catch vs ln Area	S. America	1.626	0.920	-	32	-	-	0.72	<0.001	MRAG (1995) /R6178
ln catch vs ln Area*	Asia	3.165	0.847	-	13	-	-	0.95	<0.001	MRAG (1995) /R6178

Key S – stocked, NS - not stocked), FPA – Floodplain area (km^2); length – river length (km); DBA, drainage basin area (km^2); Area – lake or lagoon surface area (km^2); Rainfall – Mean annual rainfall (mm y^{-1}); Total P – total surface phosphorus concentration (μgl^{-1}); Total N – total surface nitrogen concentration (μgl^{-1}); surface Chla – chlorophyll a concentration in the surface waters (μgl^{-1}); Zoo prod- zooplankton production (g dwt m^{-2} y^{-1}).

Prediction intervals for yield corresponding to new observations of X, $\hat{Y}_{new}$ is given by:

$$\hat{Y}_{new} \pm t(1-\alpha/2; n-2) \times s\{\hat{Y}_{new}\} \quad \text{where}$$

$s\{\hat{Y}_{new}\}$ is the standard error of the estimate given by:

$$s\{\hat{Y}_{new}\} = \sqrt{s^2{}_{Y.X}\left(1+\frac{1}{n}\right)+\frac{(X_i-\overline{X})^2}{\dfrac{s^2{}_{Y.X}}{(S_b)^2}}}$$

where $s^2{}_{Y.X}$ is the residual mean square (the variance of Y after taking into account the dependence of Y on X), and S_b is the standard error of the estimate of the slope coefficient, *b* (Zar, 1984, p272-275).

Annex 2
Example hypothesis matrix for guiding multivariate empirical model development (see section 14.3)

		Outcome Variables										
Variable Group	**Explanatory Variable**	**Annual production per unit area**	**Sustainability (Resource)**	**Biodiversity**	**Average household income**	**Assets**	**Savings and investments**	**Food security**	**Empowerment**	**Equity**	**Compliance with rules and regulations**	**Conflicts**
Resource (Group I)	Production potential	Y	Y					Y			2	
	Abundance/Biomass	Y	Y		Y	Y	Y	Y		10	Y	Y
	Rule enforcement potential	1	1	1				1		Y	Y	Y
Environment (Group I)	Environmental health of habitat	Y	Y	Y	3	3	3	4			2	2
	Nutrient recycling	Y	Y	Y	3	3	3	4			2	
	Habitat descriptors / factors	Y	Y	Y	3	3	3	4			2	2
Technological (Group I)	Exploitation intensity	Y	Y	Y	Y	Y	Y	4			2	Y
	Stocking density	Y	Y		Y	Y	Y	4			2	
	Habitat alteration activities	Y	Y	Y	3	3	3	4		Y	2	Y
Market Attributes (Group II)	Economic value of resource	9	9	9	Y	Y	Y	Y			Y	14
	Market facilities/infrastructure	9	9	9	Y	Y	Y	Y			11	
	Cost of marketing (market fees)	9	9	9	Y	Y	Y	5			11	Y
	Price control mechanism	9	9	9	Y	Y	Y	Y			Y	Y
Fisher/Stakeholder/ Community Characteristics (Group III)	Social cohesion	1	1	1				1		Y	Y	Y
	Dependence on fishery for livelihood	Y	Y	Y				Y		Y	Y	Y
	Level of local (ecological) knowledge	Y	Y	Y	Y	Y	Y	4			Y	Y
Decision-making Arrangements & Management strategy (Group IV)	Legitimacy / widely accepted	1	1	1				1	Y	Y	Y	Y
	Respectability	1	1	1				1	Y	Y	Y	Y
	Traditional decision-making body?	1	1	1				1	Y	Y	Y	Y
	Stability of decision-making body	1	1	1				6	6	Y	Y	Y
	Membership to decision-making body	1	1	1				7	Y	Y	Y	Y
	Clear access (property) rights	1	1	1				1		Y	Y	Y
	Management measures (operational rules)	Y	Y	Y				4		Y	Y	Y
	Reserve area as a % of total management area	Y	Y	Y				4			Y	Y
	Representation in rule making	1	1	1				1	Y	Y	Y	Y
	Level of transparency in rule making (general)	1	1	1				1	Y	Y	Y	Y
	Formal performance monitoring by community?	1	1	1					Y		Y	Y
	Sanctions for non compliance	1	1	1				1		Y	Y	Y
External Decision-Making Arrangements (Group V)	Enabling legislation for co-management	1	1	1				1	Y	Y	12	Y
	Local political support for co-management	1	1	1				8	Y		12	Y
	Effective coordinating body	1	1	1				8	Y		Y	Y
Exogenous Factors (Group VI)	External financial assistance	Y	Y	Y				8			Y	Y
	Capacity building support from NGO's	Y	Y	Y				8	Y	Y	Y	Y

Key
Y - Direct dependence
1 - Indirectly through compliance
2 - Indirectly through abundance/biomass
3 - Indirectly through production potential
4 - Indirectly through CPUA
5 - Indirectly through income
6 - Indirectly through institutional sustainability
7 - Indirectly through empowerment
8 - Indirectly through improved management
9 - Indirectly through exploitation intensity
10 - Indirectly through conflict
11 - Indirectly through economic value
12 - Indirectly through legitimacy

Annex 3
Recommendations for field applications of the methods described in Section 14.3

Sampling Requirements

The case study data used by project R7834 were drawn from studies carried out in several countries and therefore the sampling procedure for selection of co-management units can be described as being purposive. Although strict random sampling is not always crucial, the "global" setting to which the results may tentatively apply is inappropriate for recommendations at a local level. The data collection approach was merely intended to demonstrate the general approach to model-based inferential procedures.

In real field applications, it is recommend that the population of interest is clearly identified at a regional or national level and the modelling approaches applied to data from all, or an appropriately selected sample of management units within that region or country. The relevant sampling unit for this work must be a fisheries management unit with a clear specification of what the unit consists of in terms of its community members and fisheries sources.

Variables for inclusion in future monitoring programmes

It is recommend that the attributes identified in Chapter 6 of the R7834 project final technical report as being important in determining outcomes be included. Consideration should also be given to excluding those variables found to be redundant or unhelpful for a variety of reasons (Annex VI of the same report). A pilot or frame survey employing PRA techniques may provide a more efficient means of establishing the range of potentially important model variables and hypotheses for testing.

A common problem encountered when "profiling" the management units was the need to assign a single value to inherently multivariate or multi-dimensional variables. For example, the variable Gear Type allows only one gear to be recorded whilst, in reality, several gears may be used in the fishery. In this case, the most important gear in terms of catch weight was recorded. This problem could be overcome by adding additional variables to record other important gears in order of importance (eg Gear Type 1, Gear Type 2, Gear Type 3…etc) particularly when the focus of analysis is at a more local scale, and when many other attributes are likely to be constant and can be excluded. Another way might be to score gears according to important attributes or characteristics such as their catchability, habitat destructiveness, by-catch...etc. Selecting additional variables from those remaining should, therefore, be undertaken judiciously taking into consideration available resources and local conditions. Other, alternative variables should also be considered.

For example, many variables such as *Representation in Rule Making* were "scored" in a subjective manner with three point ordinal scales eg low (0); medium (1); high (2). Explicit guidance notes for scoring these variables need to be developed to make these subjective assessments more objective. These guidance notes could be used to generate "composite scores" for the variable where the variable score is the sum of scores assigned to a number of variable indicators. For the variable *Representation in Rule Making* these indicators may include the presence or absence of a forum for discussion and dialogue, the involvement of women in decision-making and whether the decision-making body has been democratically elected or not. In the example below (Table A2), representation in rule making is lowest at site 3 and highest at site n. This type of approach is commonly employed in marketing research and was adopted for elements of the World Bank (1999) study. This approach has the added advantage that it will reduce the total number of potential model variables without loss of any valuable information.

TABLE A2
Example of the calculation of a composite score for Representation in Rule Making

Variable Indicators		Site 1	Site 2	Site 3	Site n
Forum for discussion	Yes (1); No (0)	1	0	0	1
Women involvement	Yes (1); No (0)	1	0	0	1
Democratically elected body	Yes (1); No (0)	0	1	0	1
Representation in rule making – composite score		**2**	**1**	**0**	**3**

Data collection
The validity of results from the application of the model-based approaches described in Section 14.3 depend, of course, on the reliability of the data being used. We strongly recommend that primary data be used where possible in using these models. Since many of the variables of interest depend on the perceptions of fishers and other stakeholders, we recommend that primary data are collected through an approach similar to that adopted by Pomeroy et al (1997) where a 15 rung ladder was used to score attributes on a 0 to 15 scale. This is particularly beneficial for scoring outcome variables such as CPUE change or changes in the well-being of households, because the resulting variable, suitably aggregated to the co-management unit level, can then be regarded as a quantitative variate suitable for use in general linear models. The more specific requirement that the aggregated variable follows a normal distribution, is also satisfied through this approach because of a basic theorem in statistics (the Central Limit Theorem) which says that an average (mean value) over a sufficient number of observations gives rise to a normal variable.

Data at different hierarchical levels
Our fourth recommendation relates to the need to distinguish between various hierarchical levels at which the data may be collected. Some of the variables in the case study data set, for example, involved variables such as household income, number of months fished per year and depth of reserve, which were aggregated over households or fisheries sources (lower levels of the hierarchy), to the co-management unit level – at a higher level. This aggregation was necessary because the model-based approaches developed in the project assumed that all data reside at a single level. If this is not the case, then other modelling approaches, e.g. multi-level modelling techniques, are needed.

Some care is also needed in avoiding any confusion with regard to a stratification variable being considered as a variable at the higher level. For example, the case study data came from different countries and different types of ecosystems. Although the data could be considered as arising from within each country or within each ecosystem, neither country, nor ecosystem type can be regarded as making the data hierarchical since there were no specific variables that were measured at the country level (e.g. type of government) or at the ecosystem level (e.g. size of the river, beel, lake or other).

Selection of outcomes and explanatory variables
The first step in this process should be the preparation of a list of all potential variates that are believed to have an affect, directly or indirectly, on management outcomes (e.g. sustainability or equity), and a list of all variates that could be regarded as proxy indicators of them. The latter set comprises the outcome variables and should be clear

indicators of whether the performance of a fishery is good or bad, e.g. catch per unit effort, household income from fisheries. A selection of explanatory variables from each of these lists is then needed, to give subsets of variates which can be measured relatively easily by a fisheries scientist or other person who has a good understanding of the processes concerning the fishery of interest, and knowledge of the underlying environmental and resource conditions.

The next step would involve a consideration of the chosen set of outcome variables, and select those explanatory variables thought to have a possible influence on each chosen outcome. This step again requires expert opinion and was adopted in our work here through the development of the hypothesis matrix see Section14.3 and Annex 2. Although not undertaken by project R7834, it was realized retrospectively, that this step should have been followed by an identification of the relative importance of each explanatory variable in terms of its potential effect on the chosen outcome variable. A simple ranking exercise should be adequate for this purpose. Consideration should also be given to the ease with which each variable can be measured in the field. This would lead to a much reduced, and more manageable set of variables for analysis purposes.

Data Cleaning and exploratory analysis

The data collection stage must naturally involve collecting information on variables identified from above as appropriate for investigating and identifying the way in which changes in co-management outcomes are influenced by a host of multi-disciplinary attributes associated with the community and with the fishery sources comprising the management unit.

The data would then normally be computerized using appropriate database software (e.g. Access) and checked for possible errors and other oddities. Simple data summaries in the form of summary statistics and graphical procedures are recommended at this stage. Any suspect data has to be checked with the original source and corrected or some decision made whether to discard the erroneous value(s).

The next stage is exploratory data analysis. Such analysis procedures form a key component at initial stages of data analysis and are strongly recommended. This step is very important in understanding the behaviour of the data, identifying patterns of association between different variables, identifying odd observations (outliers) and determining whether any scored attributes demonstrate sufficient variability to be appropriate for inclusion in the modelling procedures. Errors in the data may also emerge at this stage and must be dealt with in an appropriate manner (see also section 14.3).

Data analysis

Initial stages of modelling require further screening of attributes to ensure that the explanatory variables share a sufficient number of cases in common with the outcome variables being modelled. The guideline employed by project R7834 was to ensure that at least 15 cases are available for both. However, the total number of cases, i.e. (co-)management or fishery units included in the analysis must be considerably more during the model development process since the greater the number of variables in the model, the greater is the number of sampling units needed for analysis. A very rough guideline for the GLM approach is to have at least 25 cases more than the total number of quantitative explanatory variables plus the sum of the number of category levels corresponding to each classification variable. For example, if GLM modelling is to be undertaken with 2 quantitative variates (e.g. fisher density and the number of reserves) and 2 qualitative factors (e.g. ecosystem type – 5 levels and gear type – 4 levels), then about 36 cases will be needed for a sensible application of GLM modelling with just the main effects of each of these attributes. However, if two-way interactions between the attributes are also to be investigated (i.e. ecotype by fisher density, ecotype by gear type, etc), then many more cases are needed (e.g. about 75 cases) to minimize the chance of empty cells within the two-way categories identified by these interactions.

For the Bayesian network models, the sample size requirements are based on ensuring, as far as possible, that all category combinations corresponding to each node and its parents have sufficient numbers of cases so that the relevant conditional probabilities can be calculated to give meaningful results. BNs are less vulnerable to missing data provided reliable expert judgements are available which can be suitably encoded.

Both modelling approaches are quite advanced techniques, made more complex by missing data. Although the final set of results reported here, and in the Final Technical Report of Project R7834 may appear straightforward, they were the result of many months of hard work by experienced statisticians. We therefore strongly recommend the involvement of well-experienced and qualified statisticians in the application of the methodological model-based approaches described in Section 14.3 of this manual.

Model validation and sensitivity analysis

A commonly used technique for checking the adequacy of statistical models in general is cross-validation. The idea is to fit the model to a subset of cases in the dataset, use the fitted model to predict outcomes for the remaining cases and then compare the predicted with the actual values. A model which succeeds in predicting outcomes with low error can be regarded as performing well. A variant of this method omits each case, one at a time, fits the model to the remaining cases and again compares predicted with actual outcomes for the omitted case; the entire procedure is repeated for each case. Although this latter method appears to be fairly computer-intensive, there are computational "tricks" which achieve the required comparisons in an efficient way.

In practice it would be important to assess the extent to which a BN depends on the evidence encoded in it. The Netica software has provisions for carrying out a closely related analysis, namely sensitivity to findings. This provides a quantitative assessment of the extent to which each node is affected by entering evidence into a given node. Ideally, an approach along the lines of the cross-validation described above would be used. However, in BNs validation and "learning", that is, the adaptive development of a model as new observations become available, are activities that overlap to a large extent.

Opportunities for rigorous validation under Project R7834 were severely limited by the problem of missing data. In spite of this, it is strongly recommended that in future work, serious consideration is given to model validation.

Updating models

Both modelling approaches described in Section 14.3 can be adapted to deal with further data that may become available over time. How this is done depends on the regularity of updating the database. We consider each approach in turn.

GLMs: Additional information that becomes available on an ad hoc basis would probably be best accommodated by repeating the analysis from scratch. If, however, it is anticipated that data are to be collected at regular intervals (the same set of variables, of course), then it would be possible to incorporate the time dimension in the analysis. Eventually, given sufficient time, this would enable the estimation of trends. The methods of analysis would have to be extended to cope with correlated data structures. There are various statistical approaches to dealing with this situation (Diggle, Liang and Zeger, 1994).

BNs: There are two ways in which BNs can accommodate updated information. The first is learning in BNs. This is a feature which makes them particularly attractive in the context of adaptive management. There are procedures for updating the conditional probabilities in the model based on information provided by new cases (evidence) as they become available (Cowell et al, 1999). The other approach is to use a dynamic BN. In this model, each period of observation is represented by a "static" network model similar to what was described in Section 14.3.2. Dependencies between time periods are modelled by links between appropriate nodes. The Netica software has capabilities for constructing and analysing dynamic models.

References

Adkison, M.D. & Peterman, R.M. 1996. Results of Bayesian methods depend on details of implementation: an example of estimating salmon escapements. *Fish. Res.* 25: 155-170.

Allen, K.R. 1966. Some methods for estimating exploited populations, *J. Fish. Res. Bd. Can.* 23: 1553-1574.

Anderson, J.A., Mees, C.M., & Cowan, V.J. 1999. *The performance of customary marine tenure in the management of community fishery resources in Melanesia. Volume 5. Guidelines towards effective co-management of coral reef fisheries in the Pacific region*. FMSP Project R6436. MRAG Ltd. 16 pp. (http://www.fmsp.org.uk/)

Babcock, E.A. & Cortes, E. 2004. Surplus production model applied to the data for blue and mako sharks availalble at the 2001 ICCAT bycatch working group and other published data. *International Commission for the Conservation of Atlantic Tunas (ICCAT) Scientific Document*. Madrid. Document SCRS/2004/109.

Babcock, E.A. & McAllister, M.K. 2002. Bayesian methods for accounting for data contradictions in stock assessment of Atlantic white marlin (*Tetrapterus albidus*). *ICCAT Scientific Document* SCRS/02/067.

Baland, J-M. & Platteau, J-P. 1996. *Halting degradation of natural resources: is there a role for rural communities?* Clarendon Press, Oxford.

Bayley, P.B. 1988. Accounting for effort when comparing tropical fisheries, river-floodplains, and lagoons. *Limnol. and Oceanogr.* 34(4 part 2): 963-972.

Beddington, J.R. & Cooke, J.G. 1983. The potential yield of fish stocks. *FAO Fish. Tech. Pap.* 242. 47 pp.

Beddington, J.R., Rosenberg, A.A., Crombie, J.A. & Kirkwood, G.P. 1990. Stock assessment and the provision of management advice for the short fin squid fishery in Falkland Islands waters. *Fisheries Research* 8: 351-365.

Benda-Beckmann, F. von, Benda-Beckmann, K. von & Spiertz, H.L.J. 1996. Water rights and policy. In H.L.J. Spiertz and M.G. Wiber (eds.) *The role of law in natural resource management.* VUGA, Netherlands.

Berger, J.O. 1985. *Statistical decision theory and Bayesian analysis.* (2nd Ed). Springer-Verlag, New York, NY, 617 pp.

Bergh, P.E. & Davies, S. 2002. Chapter 8. Fishery Monitoring Control and Surveillance. Pp 175-204 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper.* No. 424. Rome, FAO. 231 pp.

Berkes, F., Mahon, R., McConney, P., Pollnac, R. & Pomeroy, R. 2001. *Managing small-scale fisheries: alternative directions and methods*. International Development Research Centre, Canada. 320 pp.

Bertrand, J. 1988. *Selectivity of hooks in the handline fishery of the Saya de Malha Banks (Indian Ocean).* Fish. Res. 6, 249-255.

Beverton, R.J.H. & Holt, S.J. 1956. A review of methods for estimating mortality rates in fish populations, with special reference to sources of bias in catch sampling. *Rapp. P-v. Reun. CIEM.*, 17A: 1-153.

Beverton, R.J.H. & Holt, S.J. 1957. *On the dynamics of exploited fish populations*. Fisheries Investigation Series 2, Vol. 19. U.K. Ministry of Agriculture and Fisheries, London.

Beverton, R.J.H. & Holt, S.J. 1959. A review of the lifespans and mortality rates of fish in nature and the relationship to growth and other physiological characteristics *Ciba Foundation Colloquium on Ageing* 5: 142-177.

Beverton, R.J.H. & Holt, S. J. 1964. Tables of yield functions for fishery assessment. *FAO Fish. Tech. Pap*. 38: 49 pp.

Bjordal, A. 2002. Chapter 2. The use of technical measures in responsible fisheries: regulation of fishing gear. Pp 21-47 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper.* No. 424. Rome, FAO. 231 pp.

Borrini-Feyerabend, G., Farvar, M.T., Nguinguiri, J.C. & Ndangang, V.A. 2000. *Co-management of natural resources: organising negotiating and learning-by-doing.* GTZ and IUCN, Kasparek Verlag, Germany.

Boyer, D., Kirchner, C., McAllister, M., Staby, A., & Staalesen, B. 2001. "The orange roughy fishery of Namibia: Lessons to be learned about managing a developing fishery" (Proc. Symposium 2000: A decade of Namibian Fisheries Science to be published in the *South African Journal of Marine Science*) 23: 205-222.

Branch, T.A. 1998. *Assessment and adaptive management of orange roughy off southern Africa*. M.Sc. thesis. Department of Mathematics and Applied Sciences, University of Capetown.

Branch, T.A., Kirkwood, G.P., Nicholson, S.A. & Zara, S.J. 2001. Yield version 1.0. MRAG Ltd, London, UK.

Bromley, D.W. 1991. *Environment and Economy: Property Rights and Public Policy*. Oxford: Blackwell Publishers.

Butterworth, D. S., Punt, A. E. & Smith, A. D. M. 1996. On plausible hypotheses and their weightings, with implications for selection between variants of the Revised Management Procedure. *Rep. Int. Whaling Comm*. 46: 481–491.

Caddy, J.F. 1984. An alternative to equilibrium theory for management of fisheries. FAO Fisheries Report No. 289, Supplement 2, Rome.

Caddy, J.F. 1996. Checklist for fisheries resource management issues seen from the perspective of the FAO Code of Conduct for Responsible Fisheries. *FAO Fisheries Circular*. 917. Rome FAO. 22 pp.

Caddy, J.F. 1998. A short review of precautionary reference points and some proposals for their use in data-poor situations. *FAO Fish. Tech. Pap*. 379. Rome, FAO. 30 pp.

Caddy, J.F. & Bazigos, G.P. 1985. Practical guidelines for statistical monitoring of fisheries in manpower limited situations. *FAO Fish. Tech. Pap*. 257. 86 pp.

Caddy, J.F. & Mahon, R. 1995. Reference points for fisheries management. *FAO Fish. Tech. Pap*. 347. Rome, FAO. 83 pp.

Cadima, E.L. 2003. Fish stock assessment manual. *FAO Fish. Tech. Pap*. 393. Rome, FAO. 161 pp.

Charles, A.T. 2002. Chapter 6. Use rights and responsible fisheries: limiting access and harvesting through rights-based management. Pp 131-158 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fish. Tech. Pap.* No. 424. Rome, FAO. 231 pp.

Charnov, E.L. 1993 Life history invariants *Oxford University Press, New York*.

Charnov, E.L. & Berrigan, D. 1990. Dimensionless numbers and life history evolution: age of maturity versus the adult lifespan *Evol. Ecol.* 4: 273-275.

Christensen, V., Walters, C. & Pauly, D. 2004. Ecopath with Ecosim: A user's guide. Fisheries Centre Research Reports, Volume 12 (4), University of British Columbia, Vancouver. 154 p. (available online at www.ecopath.org and www.fisheries.ubc.ca)

Clark, M. 1996. Biomass estimation of orange roughy: a summary and evaluation of techniques for measuring stock size of a deep-water fish species in New Zealand. *J. Fish Biol.* A **49**: 114-131.

Clark, M., Tracey, D., Stevens, D. & Coburn, R. 1999. *Age and growth of orange roughy from Namibian waters*. Unpublished report held in Ministry of Fisheries and Marine Resources Library, Swakopmund. 11 pp.

Clark, W. 1991. Groundfish exploitation rates based on life history parameters. survival *Can. J. Fish. Aquat. Sci* 48:734-750.

Cochrane, K.L. 2002a. A fishery manager's guidebook. Management measures and their application. *FAO Fisheries Technical Paper*. No. 424. Rome, FAO. 231 pp.

Cochrane, K.L. 2002b. Chapter 1. Fisheries management. Pp1-20 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper*. No. 424. Rome, FAO. 231 pp.

Cochrane, K.L. 2002c. Chapter 5. The use of scientific information in the design of management strategies. Pp 95-130 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper*. No. 424. Rome, FAO. 231 pp.

Collie, J.S. & Walters, C.J. 1991. Adaptive management of spatially replicated groundfish populations. *Can. J. Fish. Aquat. Sci.* 48: 1273-1284.

Cornwall A. & Jewkes, R. 1995. What is participatory research? *Social Science and Medicine* 41 (12): 1667-1676.

Cowell, R.G., Dawid, A.P., Lauritzen S.L., & Spiegelhalter D.J. 1999. *Probabilistic Expert Systems*. New York: Springer-Verlag Inc.

Dalen, J., Kvinge, B., Johannesen, J., Boyer, D., Staalesen, B., Staby, A., Kirchner, C., Clark, M. & Hampton, I. 1998. *Cruise report "Dr. Fridtjof Nansen". Surveys of the fish resources of Namibia. Orange Roughy survey (1 July – 25 July 1998).* Cruise Report No 4/98, Part 1. (unpublished).

Dalzell, P. 1996. Catch rates, selectivity and yields of reef fishing. *In* N.V.C. Polunin & C.M. Roberts eds. *Reef Fisheries*, pp. 161-192. London, Chapman and Hall.

Dalzell, P. and Adams, T. 1997. Sustainability of Pacific Reef Fisheries. *In* H.A. Lessios & I.E. Macintyre eds. *Proceedings of the 8th Internal Coral Reef Symposium, Panama, June 24-29 1996*, Volume 2. pp. 2027-2032, Balboa, Panama Smithsonian Tropical Research Institute.

Dayton, P.K., Thrush, S. & Coleman, F.C. 2002. *Ecological Effects of Fishing in Marine Ecosystems of the United States*. Pew Oceans Commission, Arlington, Virginia.

de Fontaubert, C. & Lutchman, I. with Downes, D. & Deere, C. 2003. *Achieving Sustainable Fisheries: Implementing the New International Legal Regime*. IUCN. Gland, Switzerland and Cambridge, UK. X + 162 pp.

De La Mare, W.K. 1998. Tidier fisheries management requires a new MOP (management oriented paradigm). *Reviews in Fish Biology and Fisheries*. 8. 349-356.

De Oliveira, J.A.A. & Butterworth, D.S. 2004. Developing and refining a joint management procedure for the multispecies South African pelagic fishery. *ICES J. Mar. Sci.* 61: 1432–1442.

De Young, B., Peterman, R.M., Dobell, A.R., Pinkerton, E., Breton, Y., Charles, A.T., Fogarty, M.J., Munro, G.R. & Taggart, C. 1999. Canadian marine fisheries in a changing and uncertain world. *Canadian Special Publication of Fisheries and Aquatic Sciences* No. 129.

Deriso, R.B. 1980. Harvesting strategies and parameter estimation for an age-structured model. *Can. J. Fish. Aquat. Sci.* 37: 268-282.

DFID. 1999. *Sustainable Livelihoods guidance sheets*. London, Department for International Development.

Die, D. 2002. Chapter 9. Design and implementation of management plans. Pp. 205-220 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper*. No. 424. Rome, FAO. 231 pp.

Dietz, T., Dolšak, N., Ostrom, E. & Stern, P.C. 2002. The drama of the commons. In: E. Ostrom, T. Dietz, N., Dolšak, N., P.C. Stern, S. Stonich and E.U. Weber (Eds) *The drama of the commons*. National Academy Press.

Diggle P.J., Liang, Kung-Yee & Zeger, S.L. 1994 *Analysis of Longitudinal Data*. Oxford University Press.

Dooley, J., Jenness, J. & Aguilar-Manjarrez, J. 2003. The African Water Resource Database. *In Proceedings of the 21st International Cartographic Conference and 12th General Assembly of the International Cartographic Association, Durban, South Africa, 10-16 August 2003*. pp 2154-2165.

Dooley, J., Jenness, J., Aguilar-Manjarrez, J. & Riva, C. 2005. African Water Resource Database (AWRD). GIS based tools for aquatic resource management. CIFA Technical Paper. No. 33. Rome, FAO, 2005.

Eyben, R. & Ladbury, S. 1995. Popular participation in aid-assisted project: why more theory than practice? Pp 192-200 in: N. Nelson and S. Wright (Eds) Power and participatory development. Intermediate technology, London.

FAO. 1995a. *Code of Conduct for Responsible Fisheries*. Rome, FAO. 41 pp.

FAO. 1995b. Precautionary approach to fisheries. Part 1: Guidelines on the precautionary approach to capture fisheries and species introductions. *FAO Fish. Tech. Pap*. 350/1. Rome, FAO. 52 pp.

FAO. 1996. Precautionary approach to capture fisheries and species introductions. *FAO Tech. Guidelines for Responsible Fisheries* No. 2. Rome, FAO. 54 pp. (Same as FAO 1995b above).

FAO. 1997. Fisheries management. *FAO Technical Guidelines for Responsible Fisheries* No. 4. Rome, FAO. 82 pp.

FAO. 1998. Guidelines for the routine collection of capture fishery data. Prepared at the FAO/DANIDA Expert Consultation. Bangkok, Thailand, 18-30 May 1998. *FAO Fish. Tech. Pap.* 382. Rome, FAO. 113 pp.

FAO. 1999. Indicators for sustainable development of marine capture fisheries. *FAO Technical Guidelines for Responsible Fisheries*. No. 8. Rome, FAO. 1999. 68 pp.

FAO. 2003. The ecosystem approach to marine capture fisheries. *FAO Technical Guidelines for Responsible Fisheries.* No. 4(Suppl. 2). 112 pp.

Fournier, D.A., Hampton, J. & Sibert, J.R. 1998. MULTIFAN-CL: a length-based, age-structured model for fisheries stock assessment, with application to South Pacific albacore, *Thunnus alalunga*. *Can. J. Fish. Aquat. Sci.* 55: 2105-2116. (http://www.multifan-cl.org/)

Fowler, A.J. 1995. Annulus formation in otoliths of coral reef fish - a review. Pp. 45-63 *In* D.H. Secor, J.M. Dean and S.E. Campana (Eds.), *Recent Developments in Fish Otolith Research*. Vol. 19. The Bella W Baruch Library in Marine Sciences.

Francis, R.I.C.C. 1992. Use of risk analysis to assess fishery management strategies: a case study using Orange Roughy (*Hoplostethus atlanticus*) on the Chatham Rise, New Zealand. *Can. J. Fish. Aquat. Sci*. 49: 922-930.

Francis, R.I.C.C., Robertson, D.A., Clark, M.R., & Coburn, R.P. 1992. *Assessment of the QMA 3B orange roughy fishery for the 1992/93 season*. N.Z. Fisheries Assessment Research Document 92/4.

Froese, R. & Binohlan, C. 2000. Empirical relationships to estimate asymptotic length, length at first maturity and length at maximum yield per recruit in fishes, with a simple method to evaluate length frequency data. *J. Fish Biol.* 56: 758-773.

Froese, R. & Pauly, D. (eds) 2004. *FishBase*. World Wide Web electronic publication. www.fishbase.org, version (06/2004).

Gabriel, W.L. & Mace, P. M. 1999. *A review of biological reference points in the context of the precautionary approach*. In V.R. Restrepo (Editor), Proceedings of the Fifth National NMFS Stock assessment Workshop: Providing Scientific Advice to Implement the Precautionary Approach Under the Magnusson-Stevens Fishery Conservation and Management Act, p. 34-45. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-F/SPO-40.

Garaway, C.J. & Arthur, R.I. 2002. Adaptive learning - Lessons from Southern Lao PDR. FMSP Project R7335: *Adaptive Learning Approaches to Fisheries Enhancement*. RDC, Lao PDR and MRAG Ltd. 31 pp. (http://www.fmsp.org.uk/)

Garaway, C.J. & Arthur, R.I. 2004. Adaptive learning: a practical framework for the implementation of adaptive co-management. Lessons from selected experiences in South and Southeast Asia. MRAG Ltd. 44 pp.

Garaway, C.J., Lorenzen, K., & Chamsingh, B. 2001. *Developing fisheries enhancements in small waterbodies: lessons from Lao PDR and Northeast Thailand*. In: S.S. De Silva (ed.) Reservoir and culture-based fisheries: biology and management. Proceedings of an international workshop held in Bangkok, Thailand, 15-18 February 2000. ACIAR, Canberra.

Garcia, S.M. 2000. *The precautionary approach to fisheries: progress review and main issues: 1995-2000*. Paper presented at the conference on "Current fisheries issues and the Food and Agriculture Organization (FAO) of the United Nations". Centre for Ocean Law and Policy, University of Virginia School of Law / Rome, Italy, 16-17 March 2000.

Garcia S.M. & De Leiva Moreno, I. 2000. Proposal for a synoptic presentation of state of stock and management advice in a precautionary indicators framework perspective. *Report of the CWP Inter-sessional WG on Precautionary Approach Terminology*, 14-16 February 2000, Copenhagen, Denmark: 49-53. (http://www.ices.dk/reports/acfm/2000/cwp/cwp00.pdf)

Garcia, S.M. & Grainger, R.J.R. 2005. Gloom and doom? The future of marine capture fisheries. *Proc. R. Soc. Lond. B. Biological Sciences.* Special Issue 360.

Garcia, S.M., Zerbi, A., Aliaume, C., Do Chi, T. & Lasserre, G. 2003. The ecosystem approach to fisheries. Issues, terminology, principles, institutional foundations, implementation and outlook. *FAO Fish. Tech. Pap*. 443. Rome, FAO. 71 pp.

Gayanilo, F.C. Jr. & Pauly, D. (eds.), 1997. The FAO-ICLARM Stock Assessment Tools (FiSAT) Reference Manual. *FAO Computerized Information Series (Fisheries).* No. 8. Rome, FAO, 262 pp.

Gayanilo, F.C., Jr., Sparre P. & Pauly, D. 1995. The FAO-ICLARM Stock Assessment Tools (FiSAT) User's guide. *FAO Computerized Information Series (Fisheries)* - No.8. Rome, FAO. 126 pp.

Gelfand, A.E. & Smith, A.F.M. 1990. Sampling-based approaches to calculating marginal densities. *J. Am. Stat. Assoc*. 85: 398-409.

Gelman, A., Carlin, J., Stern, H. & Rubin. D. 1995. *Bayesian data analysis*. Chapman and Hall, London. 552 p.

Goodman D., Mangel, M., Parkes G.B., Quinn, T., Restrepo, V., Smith, T. & Stokes, K., with assistance from Thompson G. 2002. *Scientific Review of the Harvest Strategy Currently Used in the BSAI and GOA Groundfish Fishery Management Plans (Draft Report).* MRAG Americas Inc.

Gower, J.C. & Hand, D.J. 1996. *Biplots*. London, Chapman and Hall.

Grainger, R.J.R. & Garcia, S.M. 1996. Chronicles of marine fishery landings (1950-1994): Trend analysis and fisheries potential. *FAO Fisheries Technical Paper*. 359. Rome, FAO. 51 pp.

Greboval, D. (ed.) 1999. Managing fishing capacity: selected papers on underlying concepts and issues. *FAO Fish. Tech. Pap*. 386. Rome, FAO. 206 pp.

Grimes, C. B. 1987. *Reproductive biology of the Lutjanidae : A review*. In Polovina, J. J. & Ralston, S. (eds.) *Tropical snappers and Groupers: Biology and Fisheries Management*. Westview Press. Boulder and London. pp. 239-294.

Grumbine, R.E. 1994. What is ecosystem management? *Conservation Biology* 8: 27–38.

Gulland, J.A. 1971. *The fish resources of the ocean.* Fishing News Books, West Byfleet, Surrey.

Gulland, J.A. 1983. *Fish Stock Assessment. A manual of basic methods*. John Wiley & Sons. 384 pp.

Gulland, J.A. & Rosenberg, A.A. 1992. Review of length-based approaches to assessing fish stocks. *FAO Fish. Tech. Pap*. 323. Rome, FAO. 100 pp.

Haddon, M. 2001. *Modelling and quantitative methods in fisheries.* Chapman & Hall / CRC. 406 pp.

Hall, S. 2002. Chapter 3. The use of technical measures in responsible fisheries: area and time restrictions. Pp 49-74 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fisheries Technical Paper*. No. 424. Rome, FAO. 231 pp.

Halls, A.S. 1999. *Spatial models for the evaluation and management of Inland Fisheries*. Final Report prepared for the Food and Agriculture Organization of the United Nations (FIR 1998 Plansys 232200120).

Halls, A.S. 2005. *The Use of Sluice Gates for Stock Enhancement and Diversification of Livelihoods: Fisheries Assessment*. R8210 Final Technical Report, London, MRAG Ltd.

Halls, A.S., Abeyasekera, S., Burn, R.W. & Welcomme, R., L. unpubl. (submitted 2003 to *Fisheries Research*). The relationship between multi-species catch and effort: among fishery comparisons.

Halls, A.S., Burn, R.W. & Abeyasekera, S. 2002. *Interdisciplinary Analysis for Adaptive Co-Management.* Project R7834: Final Technical Report. London, MRAG Ltd. 125 pp.

Halls, A.S., Kirkwood, G.P. & Payne, A.I. 2001. A dynamic pool model for floodplain-river fisheries. *Ecohydrology and Hydrobiology* , 1 (3): 323-339.

Halls, A.S., Lewins, R. & Jones, J.C. 2001. Information Systems for the Co-Management of Artisanal Fisheries. Final Technical Report to the UK Department for International Development, MRAG Ltd, London, January 2001, Volume I 230pp, Volume II 170 pp. (http://www.fmsp.org.uk/)

Halls, A.S. & Welcomme, R.L. 2004. Dynamics of river fish populations in response to hydrological conditions: A simulation study. *River Research and Applications*. 20: 985-1000.

Hampton, J. & Majkowski, J. 1987. A simulation model for generating catch length frequency data. *In* D. Pauly and G.R. Morgan (Eds.), *Length-based Methods in Fisheries Research*. ICLARM Conference Proceedings 13. International Centre for Living Aquatic Resources Management, Manila, Philippines and Kuwait Institute for Scientific Research, Safat, Kuwait, 468 pp.

Hanna, S. 2003. The economics of co-management. In: D.C. Wilson, J. Raajaer Nielsen and P. Degnbol. *The fisheries co-management experience: accomplishments, challenges and prospects.* Kluwer, Netherlands.

Hara, M. 2004. Beach village committees as a vehicle for community participation: Lake Malombe/Upper Shire River Participatory Programme In: C. Fabricius, E. Koch, H. Magombe and S. Turner (ed). *Rights, resources and rural development: community-based natural resource management in southern Africa*. Earthscan, London.

Hara, M. & Raakjaer Nielsen, J. 2003. Experiences with fisheries co-management in Africa. In: D.C. Wilson, J. Raajaer Nielsen and P. Degnbol. *The fisheries co-management experience: accomplishments, challenges and prospects.* Kluwer, Netherlands.

Heincke, F. 1913. Investigations on the plaice. General report 1. The plaice fishery and protective measures. Preliminary brief summary of the most important points of the report. *Rapp. Pv Reun. Cons. int. Explor. Mer* 16: 1-67.

Hilborn, R. 2002. The dark side of reference points. *Bull. Marine Science*. 70(2): 403-408.

Hilborn, R. 2003. The state of the art in stock assessment: where we are and where we are going. *Sci. Mar.*, 67 (Suppl. 1): 15-20.

Hilborn, R. & Liermann, M. 1998. Standing on the shoulders of giants: learning from experience in fisheries. *Reviews in Fish Biology and Fisheries*. 8. 273-283.

Hilborn, R. Pikitch, E.K., & Francis, R.C. 1993. Current trends in including risks and uncertainty in stock assessment and harvest decisions. *Can. J. Fish. Aquat. Sci*. 50: 874-880.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., Orensanz, J., Parma, A., Rice, J., Bell, J., Cochrane, K.L., Garcia, S., Hall, S.J., Kirkwood, G.P.,

Sainsbury, K., Stefansson, G., and Walters, C. 2004. When Can Marine Reserves Areas Improve Fisheries Management? *Ocean and Coastal Management*. 47: 197-205.

Hilborn, R. & Walters, C.J. 1992. *Quantitative Fisheries Stock assessment. Choice, dynamics and uncertainty.* Kluwer Academic Publishers. 570 pp.

Hoenig, J. M. & Hanumara, R.C. 1982. A statistical study of a seasonal growth model for fishes. University of Rhode Island, Department of Computer Science, Technical Report, Narragansett.

Hoggarth, D.D. 1999. *Selection Criteria and Co-management Guidelines for River Fishery Harvest Reserves*. FMSP Project R7043. MRAG Ltd. 25 pp. (http://www.fmsp.org.uk/)

Hoggarth, D.D., Cowan, V.J., Halls, A.S., Aeron-Thomas, M., McGregor, A.J., Welcomme, R.L., Garaway C. & Payne, A.I. 1999. Management Guidelines for Asian Floodplain River Fisheries. Part 1. A Spatial, Hierarchical and Integrated Strategy for Adaptive Co Management. *FAO Fish. Tech. Pap*. 384/1. 63 pp. (Also Part 2. Summary of DFID Research. 117 pp.) (See http://www.fao.org/DOCREP/006/X1357E/X1357E00.HTM)

Hoggarth, D.D. & Kirkwood, G.P. 1996. Technical interactions in tropical floodplain fisheries of south and south-east Asia. Pages 280-292 in Cowx, I.G. (Ed), *Stock Assessment in Inland Fisheries.* Fishing News Books.

ICES Advisory Committee on Fisheries Management (ACFM) 2000. *Report of the CWP Intersessional Meeting Working Group on Precautionary Approach Terminology and CWP Sub-group on Publication of Integrated Catch Statistics for the Atlantic*. ICES Headquarters 10–16 February 2000. ICES CM 2000/ACFM:17.

IIED. 2001. *Stakeholder Power Tools for working on policies and institutions: #3. The Four Rs.* (http://www.livelihoods.org/info/tools/PTsum.html).

Insightful Corp. 2002. S-PLUS 6.1 Software. Seattle WA, USA.

Isaac, V. J. 1990. The accuracy of some length-based methods for fish population studies. *ICLARM Tech. Rep.* 27, 81 pp.

Jennings, S., Marshall, S.S. & Polunin, N.V. C. 1995. *Seychelles Marine Protected Areas: Comparative structure and status of reef fish communities.* Biol. Conservation 75: 201-209.

Jensen, A.L. 1996. Beverton and Holt life history invariants result from optimal trade-off of reproduction and survival *Can. J. Fish. Aquat. Sci* 53: 820-822.

Jensen, F.V. 2001. *Bayesian Networks and Decision Graphs.* New York: Springer-Verlag Inc.

Jentoft, S. 2003. Co-management – the way forward. In: D.C. Wilson, J. Raajaer Nielsen and P. Degnbol. *The fisheries co-management experience: accomplishments, challenges and prospects*. Kluwer, Netherlands.

Kass, R. E. & Raftery, A. E. 1995. Bayes factors. *J. Am. Stat. Assoc*. 90: 773–795.

Keeney R.L. & Raiffa, H. 1993. *Decisions with Multiple Objectives. Preferences and Value Tradeoffs*. Cambridge University Press, Cambridge, UK.

Kell, L.T., Pilling, G.M., Kirkwood, G., Pastoors, M., Abaunza, P., Aps, R., Biseau, A., Korsbrekke, K., Kunzlik, P., Laurec, A., Mesnil, B., Needle, C., Roel, B. and Ulrich, C. 2005. An evaluation of the implicit management procedure for some ICES roundfish stocks. *ICES J. Mar. Sci.* 62, 750-759.

Kell, L.T., Pilling, G.M., & O'Brien, C.M. 2005. The implications of climate change for the management of North Sea cod (*Gadus morhua*). *ICES J. Mar. Sci.* 62(7): 1483-1491

Kinas, P. G. 1996. Bayesian fishery stock assessment and decision making using adaptive importance sampling. *Can. J. Fish. Aquat. Sci.* 53: 414-423.

Kirchner, C.H. & McAllister, M. K. 2001. A non-stationary post-stratification method to compute swept area estimates of biomass of Namibian orange roughy stocks from commercial catch rate data. *Fish. Res.* 56: 69-88 (2001).

Kirkwood, G.P. 1997. The Revised Management Procedure of the International Whaling Commission. pp. 91-99 In: *Global trends: fisheries management*. (E.K. Pikitch, D.D. Huppert and M.P. Sissenwine, eds.). Amer. Fish. Soc. Symp. 20: 91-99.

Kirkwood, G.P., Beddington, J.R. & Rossouw, J.A. 1994. Harvesting species of different lifespans. Pp. 199-227 *In*: P.J. Edwards, R. May and N.R. Webb (Ed). *Large-Scale Ecology and Conservation Biology*. Blackwell Scientific Publications.

Kirkwood, G.P. & Smith, A.D.M. 1996. Assessing the precautionary nature of fishery management strategies, *Precautionary approach to fisheries, Part 2: Scientific Papers* 350/2: 141–158.

Langi, S. 1990. The applicability of ELEFAN for use in analysing 3 species of deep-sea snappers (*Etelis corruscans*, *Pristipomoides flavipinnis* and *P. filamentosus*, Family Lutjanidae). *Fishbyte.* 8(1): 21-25.

Lassen, H. & Medley, P. 2001. Virtual population analysis. A practical manual for stock assessment. *FAO Fisheries Technical Paper*. 400. Rome, FAO. 129 pp. (Includes a CD Rom containing additional examples and exercises.)

Lauritzen, S.L. & Spiegelhalter, D.J. 1998. Local computations with probabilities on graphical structures and their application to expert systems (with discussion). *J. Roy. Stat. Soc. B.* 50: 157-224.

Leaman, B.M. & Stanley, R.D. 1993. Experimental management programs for two rockfish stocks off British Columbia, Canada. Pp. 403-418 *In*: S.J. Smith, J.J. Hunt and D. Rivard (Ed.) Risk evaluation and biological reference points for fisheries management. *Can. Spec. Publ. Fish. Aquat. Sci*. 120.

Liermann, M. & Hilborn, R. 1997. A heirarchic Bayesian meta-analysis. *Can. J. Fish. Aquat. Sci.* 9: 1976-1984.

Lorenzen, K. 1995. Population dynamics and management of culture-based fisheries. *Fisheries Management and Ecology*. 2: 61-73.

Lorenzen, K. & Enberg, K. 2002. Density-dependent growth as a key mechanism in the regulation of fish populations: evidence from among-population comparisons. *Proc. R. Soc. Lond.* B 269: 49-54.

Lorenzen, K., Juntana, J., Bundit, J. and Tourongruang, D. 1998. Assessing culture fisheries practices in small waterbodies: a study of village fisheries in north-east Thailand. *Aquaculture Research* 29: 211-224.

Ludwig, D., Hilborn, R., & Walters, C. 1993. Uncertainty, resource exploitation and conservation: lessons from history. *Science*. 260. Pp. 17, 36.

Mace, P.M. 1994. Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. *Can. J. Fish. Aquat. Sci.* 51: 110-122.

Mace, P.M. & Doonan, I.J. 1988. A generalized bioeconomic simulation model. N. Z. Fish. Assess. Res. Doc. No 88/4.

Mace, P.M. & Gabriel, W. 1999. *Evolution, scope and current applications of the precautionary approach in fisheries*. In: Restrepo, V. (editor). Proceedings of the 5th National Stock Assessment Workshop, National Marine Fisheries Service, Office of Science and Technology, 1315 East-West Highway, Silver Spring, MD 20910.

Mace, P.M. & Sissenwine, M.P. 1993. How much spawning per recruit is enough? In: Smith, S.J., Hunt, J.J. and Rivard, D. (eds.) Risk evaluation and biological reference points for fisheries management. *Can. Spec. Publ. Fish. Aquat. Sci.* 120.

Mahon, R. 1997. Does fisheries science serve the needs of managers of small stocks in developing countries? *Can. J. Fish. Aquat. Sci*. 54: 2207-2213.

Majkowski, J., Hampton, J., Jones, R., Laurec, A. & Rosenberg, A.A. 1987. Sensitivity of length-based methods for stock assessment: report of working group 3. *In*: D. Pauly & G.R. Morgan (Eds.), *Length-Based Methods in Fisheries Research*. ICLARM Conference Proceedings 13. International Centre for Living Aquatic Resources Management, Manila, Philippines and Kuwait Institute for Scientific Research, Safat, Kuwait, pp. 363-372.

Mangel, M. 1996. Life history invariants, age at maturity and the ferox trout. *Evol. Ecol*. 10: 249-263.

Manooch, C.S. 1987. Age and growth of snappers and groupers. *In* J.J. Polovina & S. Ralston (Eds.), *Tropical Snappers and Groupers: Biology and Fisheries Management.* Westview Press Inc., Boulder, p329-363.

Marcot, B.G., Holthausen, R.S., Raphael, M.G., Rowland, M. & Wisdom, M. 2001. Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *For. Ecol. and Manage.*, 153(1-3): 29-42.

McAllister, M.K., Babcock, E.A., Pikitch, E.K. & Prager, M.H. 1999. Application of a non-equilibrium generalized production model to South and North Atlantic Swordfish: combining Bayesian and demographic methods for parameter estimation. International Commission for the Conservation of Atlantic Tunas, Madrid. Document SCRS/99/85.

McAllister, M.K., Hill, S.L., Agnew D.A., Kirkwood, G.P. & Beddington, J.R. 2004. A Bayesian hierarchical formulation of the De Lury stock assessment model for abundance estimation of Falkland Islands's squid (*Loligo gahi*). *Canadian J. Fish. Aquat. Sci.* 61: 1048-1059.

McAllister, M.K. & Ianelli, J.N. 1997. Bayesian stock assessment using catch-age data and the Sampling/ Importance Resampling Algorithm. *Can. J. Fish. & Aquat. Sci.* 54: 284-300.

McAllister, M.K. & Kirchner, C.H. 2001. Development of Bayesian stock assessment methods for Namibian Orange Roughy *Hoplostethus atlanticus*. Pp. 241-264 *In*: Payne, A.I.L., Pillar, S.C. & Crawford, R.J.M. (Eds). *A decade of Namibian fisheries science*. S. Afr. J. mar. Sci. 23.

McAllister, M.K. & Kirchner, C.H. 2002. Accounting for structural uncertainty to facilitate precautionary fishery management: illustration with Namibian orange roughy. In "Targets, Thresholds, and the Burden of Proof in Fisheries Management" Mangel, M. Ed. *Bull. Mar. Sci.,* 70(2). 499-540.

McAllister, M.K. & Kirkwood, G.P. 1998a. Bayesian stock assessment: a review and example application using the logistic model. *ICES J. Mar. Sci*. 55, (1998), 1031-1060.

McAllister, M.K. & Kirkwood, G.P. 1998b. Using Bayesian decision analysis to help achieve a precautionary approach for managing developing fisheries. *Can. J. Fish. Aquat. Sci*. 55:2642-2661.

McAllister, M.K. & Peterman, R.M. 1992. Experimental design in the management of fisheries: a review. *North American Journal of Fisheries Management*. 12: 1-18.

McAllister, M.K., Peterman, R.M. & Gillis, D.M. 1992. Statistical evaluation of a largescale fishing experiment designed to test for a genetic effect of size-selective fishing on British Columbia pink salmon (Oncorhynchus gorbuscha). *Canadian J. Fish. Aquat. Sci.* 49: 1294-1304.

McAllister, M.K. & Pikitch, E.K. 1997. A Bayesian approach to choosing a design for surveying fisheries resources: application to the eastern Bering Sea trawl survey. *Can. J. Fish. & Aquat. Sci*. 54: 301-311.

McAllister, M.K. & Pikitch, E.K. 2004. *Why are Bayesian Methods Useful for the Stock Assessment of Sharks? In Sharks of the Open Ocean*. Blackwell Publishers (in press).

McAllister, M.K., Pikitch, E.K. & Babcock, E.A. 2001. Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding. *Can. J. Fish. Aquat. Sci.* 58(9): 1871-1890.

McAllister, M.K., Pikitch, E.K., Punt, A.E., & Hilborn, R. 1994. A Bayesian approach to stock assessment and harvest decisions using the sampling/importance resampling algorithm. *Can. J. Fish. Aquat. Sci.* 51: 2673-2687.

McAllister, M.K., Starr, P.J., Restrepo, V.R. & Kirkwood, G.P. 1999. Formulating quantitative methods to evaluate fishery-management systems: what fishery processes should be modelled and what trade-offs should be made. *ICES J. Mar. Sci.* 56: 900–916.

McCullagh, P. & Nelder, J.A. 1989. *Generalized linear models. Second Edition*. Chapman and Hall, New York.

McLain, R.J. & Lee, R.G. 1996. Adaptive management: promises and pitfalls. *Environmental Management* 20 (4): 437-448.

Medley, P.A.H. & Ninnes, C.H. 1997. A recruitment index and population model for spiny lobster (*Panulirus argus*) using catch and effort data. *Canadian Journal of Fisheries and Aquatic Sciences* 54: 1414-1421.

Medley, P.A.H. & Ninnes, C.H. 1999. A stock assessment for conch (*Strombus gigas* L.) fishery in the Turks and Caicos Islands. *Bulletin of Marine Science* 64(3): 399-406.

Mees, C.C., Pilling, G.M., & Barry, C.J. 1999. *Commercial fishing activity in the British Indian Ocean Territory (Chagos Archipelago) inshore fishery*. In Eds, Sheppard C.R. & Seaward M.R.D. 1999. *Ecology of the Chagos Archipelago*. Linnean Society Occasional Publications 2, pp327-346. The Linnean Society of London.

Mees, C.C. & Rousseau, J. 1996. *Management of multi-species tropical fisheries. Final Report to ODA*. FMSP Project R5484. MRAG Ltd. 193 pp.

Mees, C.C. & Rousseau, J.A. 1997. *The potential yield of the lutjanid fish Pristipomoides filamentosus from the Mahé Plateau, Seychelles: managing with uncertainty*. Fisheries Research 33: 73-87.

Meinzen-Dick, R. & Di Gregorio, M. (eds). 2004. *Collective action and property rights for sustainable development*. CGIAR.

Meinzen-Dick, R. & Knox, A. 1991. Collective action, property rights, and devolution of natural resource management: a conceptual framework. Pp. 41-73 *In*: Meinzen-Dick, A. Knox and M. Di Gregorio, *Collective action, property rights and devolution of natural resource management*. CGIAR. 295 pp.

Melack, J.M. 1976. Primary production and fish yields in tropical lakes. *Trans. Am. Fish. Soc.* 105: 575-580.

Michielsens, C. & McAllister, M.K.. 2004. "A Bayesian hierarchical meta-analysis of stock-recruitment functions for Atlantic salmon: quantifying structural and parameter uncertainties. *Can. J. Fish. Aquat. Sci.* (accepted for June 2004) 61.

Middendorp, A.J., Hasan, M.R. & Apu, N.A. 1996. Community fisheries management in freshwater lakes in Bangladesh. *NAGA The ICLARM Quarterly*, April-June 1996, pp. 4-6.

Mitchell, B. 1997. *Resource and environmental management*. Longman, Harlow, Essex.

MRAG. 1993. *Synthesis of Simple Predictive Models for Tropical River Fisheries*. Fisheries Management Science Programme, Overseas Development Administration, July 1993. London, MRAG Ltd

MRAG. 1995. *A synthesis of Simple Empirical Models to Predict Fish Yields in Tropical lakes and Reservoirs* (R6178). Final Technical Report to the Overseas Development Administration of the UK, October 1995. London, MRAG Ltd.

MRAG. 2000. *Strategic Review of Tropical Fisheries Management*. Project R7040. Final Technical Report, London, MRAG Ltd

MRAG. Americas Inc. 2000. *Understanding SPR and its Use in U.S. Fishery Management - White Paper*. Prepared for Centre for Marine Conservation.

Myers, R.A. 2001. Stock and recruitment: Generalizations about maximum reproductive rate, density dependence and variability. *ICES J. Mar. Science*. 58: 937-951.

Myers, R.A. & Barrowman, N.J. 1994. Is fish recruitment related to spawner abundance? ICES CM 1994/G:37. (republished 1996 in *Fish. Bull.* 94: 707-724)

Myers, R.A., Barrowman, N.J., Hutchings J.A. & Rosenberg, A.A. 1995. Population dynamics of exploited fish stocks at low population levels. *Science* 269: 1106-1108.

Myers, R.A., Bowen, K.G. & Barrowman, N.J. 1999. The maximum reproductive rate of fish at low population sizes. *Can. J. Fish. Aquat. Sci*. 56: 2404-2419.

Myers, R.A., Bridson, J. & Barrowman, N.J. 1995. Summary of worldwide spawner and recruitment data. *Can. Tech. Rep. Fish. Aquat. Sci.* 2024.

Myers, R.A. & Mertz, G. 1998. The limits of exploitation: a precautionary approach. *Ecol. Appl*. 8: 165-169.

Myers, R.A., Rosenberg, A.A., Mace, P.M., Barrowman, N.J. & Restrepo, V.R. 1994. In search of thresholds for recruitment overfishing. *ICES J. Mar. Sci.* 51: 191-205.

Norsys Software Corp. 1998. *Netica*. (available at www.norsys.com/netica)

O'Hagan, A. 1998. Eliciting expert beliefs in substantial practical applications. *The Statisticican* 47(1): 21-35.

Oakerson, R.J. 1992. Analyzing the Commons: A Framework. *In* D. W. Bromley ed. *Making the Commons Work. Theory Practice and Policy*, pp. 41-62. San Francisco, California, Institute for Contemporary Studies.

Olsson, P., Folke, C. & Berkes, F. 2004. Adaptive comanagement for building resilience in social-ecological systems. Environmental Management 34(1): 75-90.

Ostrom, E. 1990. *Governing the commons: evolution of institutions for collective action*. Cambridge University Press, Cambridge.

Parkes, G.B. 2000. Precautionary Fisheries Management: The CCAMLR Approach. Marine Policy 24: 83-91.

Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. *J. Cons. CIEM.* 39(2): 175-192.

Pauly, D. 1987. A review of the ELEFAN system for analysis of length-frequency data in fish and aquatic vertebrates. Pages 7-34 in Pauly, D. and Morgan, G. R. (Eds) *Length-based methods in fisheries research*. ICLARM Conference Proceedings 13. ICLARM, Manila, Philippines and KISR, Safat, Kuwait. 468 pp.

Pauly, D., Christensen, V., Dalsgaard, J., Froese, R., & Torres, F., Jr. 1998. Fishing down marine food webs. *Science* (Washington, D.C.). 279: 860–863.

Pauly, D., Christensen, V., Guénette, S., Pitcher, T.J., Sumaila, U.R., Walters, C.J., Watson, R. & Zeller, D. 2002. Towards sustainability in world fisheries. *Nature*. 418/8 August 2002: 689-695.

Pauly, D. & David, N. 1981. A BASIC program for the objective extraction of growth parameters from length frequency data. *Meeresforschung/Reports on Marine Research.* 28: 205-211.

Pauly, D., Soriano-Bartz, M., Moreau, J. & Jarre, A. 1992. A new model accounting for seasonal cessation of growth in fishes. *Aust. J. Mar. Freshwat. Res*. 43:1151-1156.

Pearl, J. 2000. *Causality*. Cambridge, Cambridge University Press.

Pido, M.D., Pomeroy, R.S., Carlos, M.B. & Garces, L.R. 1996. *A handbook for rapid appraisal of fisheries management systems*. ICLARM Education Series 16. 85 pp.

Pikitch, E.K. 2002. *The Scientific Case for Precautionary Management: Current Fishery Problems Traced to Improper Use of Science*. Pp 59-63 *In*: Managing Marine Fisheries in the United States: Proceedings of the Pew Oceans Commission Workshop on Marine Fishery Management, Seattle, Washington, 18–19 July 2001. Pew Oceans Commission, Arlington, Virginia.

Pilling, G.M., Grandcourt, E.M. & Kirkwood, G.P. 2003. The utility of otolith weight as a method for ageing the emperor *Lethrinus mahsena* and other tropical species. *Fisheries Research* 60: 493-506.

Pilling, G.M. & Halls, A.S. 2003. Age- or length-based methods of growth estimation. What drives the Choice? *NAGA* 26(2): 4-7.

Pilling, G.M., Kirkwood, G.P. & Walker, S.G. 2002. An improved method for estimating individual growth variability in fish, and the correlation between von Bertalanffy growth parameters. *Canadian Journal of Fisheries and Aquatic Sciences* 59(3): 424-432.

Pilling, G.M. & Mees, C.C. 2001. *Implementing management guidelines arising from project R6465 – an assessment of utility.* Final Technical Report. FMSP Project R7521. 100 pp. MRAG Ltd, London. (http://www.fmsp.org.uk/)

Pilling, G.M., Mees, C.C., Barry, C., Kirkwood, G.P., Nicholson, S., & Branch, T. 1999. *Growth parameter estimates and the effect of fishing on size-composition and growth of snappers and emperors: implications for management*. Final Technical Report. FMSP Project R6465. 373 pp. MRAG Ltd, London. (http://www.fmsp.org.uk/)

Pilling, G.M., Millner, R.S., Easey, M.W., Mees, C.C., Rathacharen, S. and Azemia, R. 2000. Validation of annual growth rings in the otoliths of the lethrinid *Lethrinus mahsena* and the lutjanid *Aprion virescens* from sites in the tropical Indian Ocean, with notes on the nature of growth rings in *Pristipomoides filamentosus*. *Fishery Bulletin* 98(3): 600-611.

Pinkerton, E. 2002. Chapter 7. Partnerships in management. Pp 159-173 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fish. Tech. Pap.* No. 424. Rome, FAO. 231 pp.

Pinkerton, E. 2003. Toward specificity in complexity: understanding co-management from a social science perspective. In: D.C. Wilson, J. Raajaer Nielsen and P. Degnbol. *The fisheries co-management experience: accomplishments, challenges and prospects.* Kluwer, Netherlands.

Polovina, J.J. 1987. *Assessment and management of deepwater bottom fishes in Hawaii and the Marianas.* In : Polovina, J.J. & Ralston, S., eds. *Tropical Snappers and Groupers : Biology and fisheries management*. Westview Press, Boulder and London, pp. 375 - 404.

Polovina, J.J. 1992. *Modeling fish stocks: applicability, problems and requirements for multi-species and multigear fisheries in the tropics*. In : Papers presented at the sixth session of the standing committee on resources research and development. Colombo, Sri Lanka, 18-21 May 1990. *FAO Fish Rep* No 463 Suppl. Rome 1992, pp. 28-54.

Pomeroy, R.S. 2003. The government as a partner in co-management. In: D.C. Wilson, J. Raajaer Nielsen and P. Degnbol. *The fisheries co-management experience: accomplishments, challenges and prospects*. Kluwer, Netherlands.

Pomeroy, R.S. & Berkes, F. 1997. "Two to Tango: the Role of Government in Fisheries Co-Management", *Marine Policy*, Vol. 21 (5): 465-480.

Pomeroy, R.S., Katon, B.M. & Harkes, I. 2001. Conditions affecting the success of fisheries co-management: lessons from Asia. *Marine Policy* 25: 197-208.

Pomeroy, R.S., Pollnac, R.B., Katon B.M. & Predo, C. D. 1997. Evaluating Factors Contributing to the Success of Community-Based Coastal Resource Management: the Central Visayas Regional Project-1, Philippines. *Ocean and Coastal Management.* 36(1-3): 24.

Pomeroy, R.S. & Williams, M. J. 1994. *Fisheries Co-management and Small-scale Fisheries: A policy brief.* International Centre for Living Aquatic Resource Management, Manilla, 15pp.

Pope, J.G. 1988. Collecting fisheries assessment data. Pp 63-82 *in* Gulland, J.A. (Ed.), *Fish Population Dynamics (Second Edition).* John Wiley & Sons.

Pope, J.G. 2002. Chapter 4. Input and output controls: the practice of fishing effort and catch management in responsible fisheries. Pp. 75-94 *in*: Cochrane, K.L. (ed). *A fishery manager's guidebook. Management measures and their application. FAO Fish. Tech. Pap*. No. 424. Rome, FAO. 231 pp.

Powell, D. G. 1979. Estimation of mortality and growth parameters from the length-frequency data in the catch. *Rapp. P.-V. Reun. CIEM* 175: 167-169.

Powers, J.E. & Restrepo, V.R. 1998. An examination of operational procedures in management of marine fish stocks. *In* Abstracts of papers presented at the ICES Symposium on Uncertainty in the Evaluation and Implementation of Fisheries Management Systems, Cape Town, South Africa. 16-19 November 1998.

Prager, M. H. 1994. A suite of extensions to a nonequilibrium surplus-production model. *Fishery Bulletin (U.S.)* 92: 374-389.

Press, S.J. 1989. *Bayesian Statistics: Principles, models and applications*. Wiley Series in Probability and Mathematics, John Wiley and Sons, New York.

Punt, A.E. 1993. *The implications of some multiple stock hypotheses for Chatham Rise Orange Roughy.* N.Z. Fisheries Assessment Research Document 93/16.

Punt, A.E. & Hilborn, R. 1996. BIODYN - Biomass dynamic models. User's manual. *FAO Computerized Information Series (Fisheries)* - No.10. Rome, FAO. 62 pp.

Punt, A.E. & Hilborn, R. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. *Reviews in Fish Biology and Fisheries*. 7: 35-63.

Punt, A.E. & Hilborn, R. 2001. BAYES-SA: Bayesian stock assessment methods in fisheries. User's manual. *FAO Computerized Information Series (Fisheries).* No. 12. Rome, FAO. 56 pp.

Punt, A.E. & Smith, A.D.M. 1999. Harvest strategy evaluation for the eastern stock of gemfish (*Rexea solardi*). *ICES J. Mar. Sci*. 56: 860-875.

Quinn, T.J., II & Deriso, R.B. 1999. *Quantitative Fish Dynamics*. Oxford University Press, Oxford. 542 pp.

Raakjaer Nielsen, J., Degnbol, P., Viswanathan, K., Ahmed, M., Hara, M., Abdullah, N.M.R. 2004. Fisheries co-management-an institutional innovation? Lessons from South East Asia and Southern Africa. *Marine Policy* 28: 151-160.

Raftery, A. E., Givens, G.H., & J.E. Zeh 1995. Inference from a deterministic population dynamics model for bowhead whales. *J. Am. Stat. Assoc*. 90: 402-416.

Ralston, S. 1982. *Influence of Hook size in the Hawaiian deep-sea handline fishery*. *Can. J. Fish Aquat. Sci*., 39 : 1297-1302.

Ralston, S. 1987. Mortality rates of snappers and groupers. *In* J.J. Polovina & S. Ralston (Eds.), *Tropical Snappers and Groupers: Biology and Fisheries Management*. Westview Press, Boulder and London, pp. 375-404.

Ralston, S. 1990. Size selection of snappers (Lutjanidae) by hook and line gear. *Can. J. Fish. Aquat. Sci.* 47:696-700.

Ralston, S. & Polovina, J.J. 1982. A multispecies analysis of the commercial deep-sea hand-line fishery in Hawaii. *Fish. Bull.*, 80: 435-448.

Restrepo, V. R., G. G. Thompson, P. M. Mace, W. L. Gabriel, L. L. Low, A. D. MacCall, R. D. Methot, J. E. Powers, B. L. Taylor, P. R. Wade, and J. F. Witzig. 1998. "Technical Guidance on the Use of Precautionary Approaches to Implementing National Standard 1 of the Magnusson-Stevens Fishery Conservation and Management Act." NOAA Technical Memorandum NMFS-F/SPO-31.

Ricker, W.E. 1954. Stock and recruitment *J. Fish. Res. Bd. Can.* 30: 1965-1976.

Roff, D.A. 1984. The evolution of life history parameters in teleosts *Can. J. Fish. Aquat. Sci.* 41: 989-1000.

Rosenberg, A.A. 1998. Controlling Marine Fisheries 50 Years from Now. *J. Northw. Atl. Fish. Sci.*, Vol. 23: 95–103.

Rosenberg, A.A. 2002. The precautionary approach in application from a manager's perspective. *Bulletin of Marine Science*. 2002; 70((2)): 577-588.

Rosenberg, A.A. & Beddington, J.R. 1988. Length-based methods of fish stock assessment. Pp. 83-104 *in* Gulland, J.A. (Ed.), *Fish Population Dynamics (Second Edition).* John Wiley & Sons. 422 pp.

Rosenberg, A.A., Beddington, J. R., & Basson, M. 1986. The growth and longevity of krill during the first decade of pelagic whaling. *Nature*, 324: 152-154.

Rosenberg, A.A., Fogarty, M.J., Sissenwine, M.P., Beddington, J.R. & Shepherd, J.G. 1993. Achieving sustainable use of renewable resources. *Science* 262: 828-829.

Rosenberg, A.A., Kirkwood, G.P., Crombie, J.A. & Beddington, J.R. 1990. The assessment of stocks of annual squid species. *Fisheries Research* 8: 335-350.

Rosenberg, A.A. & Restrepo, V.R. 1995. Uncertainty and risk evaluation in stock assessment advice for U.S. marine fisheries. *Can. J. Fish. Aquat. Sci.* 51: 2715-2720.

Royal Society, 2003. *Environmental effects of marine fisheries*. Policy Document 18/03 (http://www.royalsoc.ac.uk/policy)

Rubin, D.B. 1988. Using the SIR algorithm to simulate posterior distributions. *In* Bayesian Statistics 3: Proceedings of the Third Valencia International Meeting, June 1-5, 1987. Pp. 385-402. Ed. By J.M. Bernardo, M.H. Degroot, D.V. Lindley, and A.M. Smith. Clarendon Press, Oxford. 805 pp.

Ryder, R.A., Kerr, S.R., Loftus, K.H. & Regier, H.A. 1974. The morphoedphic index, a fish yield estimator – review and evaluation. *J. Fish. Res. Bd. Can.* 31: 663-688.

Sainsbury, K.J. 1988. The ecological basis of multispecies fisheries, and management of a demersal fishery in tropical Australia. In J.A. Gulland (ed.) *Fish population dynamics (second edition*). John Wiley and Sons Ltd. 422 pp.

Salm, R.V., Clarke, J. & Siirila, E. 2000. *Marine and Coastal Protected Areas: A guide for planners and managers*. IUCN. Washington DC. xxi + 371 pp.

Santojanni, A., Arneri, E., Barry, C., Belardinelli, A., Cingolani, N., Giannetti, G., and Kirkwood, G. 2004. Trends of anchovy (*Engraulis encrasicolus*, L.) biomass in the northern and central Adriatic Sea. *Scientia Marina* 67: 327 – 340.

Schlager E. & Ostrom, E. 1992. Property rights regimes and natural resources: a conceptual analysis. *Land Economics* 68 (3): 249-262

Sen, S. & Raakjaer Nielsen, J. 1996. Fisheries co-management: a comparative analysis. *Marine Policy* 20 (5): 405-418.

Serchuk, F.M., Rivard, D., Casey, J. & Mayo, R.K. 1999. *A Conceptual Framework for the Implementation of the Precautionary Approach to Fisheries Management Within the Northwest Atlantic Fisheries Organization (NAFO). In* V. R. Restrepo (Editor), Proceedings of the Fifth National NMFS Stock Assessment Workshop: Providing Scientific Advice to Implement the Precautionary Approach Under the Magnusson-Stevens Fishery Conservation and Management Act, p. 103-119. U.S. Dep. Commer., NOAA Tech. Memo. NMFS-F/SPO-40.

Shankar, B., Halls, A.S., & Barr, J. 2004. Rice versus fish revisited: on the integrated management of floodplain resources in Bangladesh. *Natural Resources Forum*, 28: 91-101.

Shepherd, J. G. 1987. A weakly parametric method for the analysis of length composition data. Pages 113-120 in Pauly, D. and Morgan, G. R. (Eds) *Length-based methods in fisheries research*. ICLARM, Manila, Philippines and KISR, Safat, Kuwait. 468 pp.

Shepherd, J.G. 1988. Fish stock assessments and their data requirements. Pp 35-62 *in* Gulland, J.A. (Ed.), *Fish Population Dynamics (Second Edition)*. John Wiley & Sons.

Shotton, R., ed. 2000. Use of Property Rights in Fisheries Management: Proceedings of the FishRights99 Conference, Freemantle, Western Australia, 11–19 November 1999. *FAO Fish. Tech. Pap.* 404/1-2. Rome, FAO.

Silverman, B.W. 1986. *Density Estimation for Statistics and Data Analysis. Mongraphs on Statistics and Applied Probability 26*. Chapman and Hall, London.

Smith, A.D.M. 1993. Risks of over- and under-fishing new resources. *In* Risk evaluation and biological reference points for fisheries management. Edited by by Smith, S.J., Hunt, J.J., & Rivard, D. *Can. Spec. Publ. Fish. Aquat. Sci*. 120: 261-267.

Sparre, P., Ursin, E. & Venema, S.C. 1989. Introduction to tropical fish stock assessment. Part 1. Manual. *FAO Fish. Tech. Pap*. 306.1. Rome, FAO. 337 pp.

Sparre, P. & Venema, S.C. 1998. Introduction to tropical fish stock assessment. Part 1. Manual (Rev. 2). *FAO Fish. Tech. Pap.* 306.1. Rome, FAO. 407 pp.

Sparre, P.J. & Willmann, R. 1992. Software for bio-economic analysis of fisheries. BEAM 4. Analytical bio-economic simulation of space structured multi-species and multi-fleet fisheries. *FAO Computerized Information Series (Fisheries)*, No. 3. Vol. 1: 186 pp. Vol. 2: 46 pp.

SPSS 2001. *SPSS for Windows*. Release 11.0. Illinois, USA, LEAD Technologies, Inc.

Stamatopoulos, C. 2002. Sample based fishery surveys. A technical handbook. *FAO Fish. Tech. Pap*. 425. Rome, FAO. 132 pp.

Staples, D. 1996. Indicators of sustainable fisheries development. In: D.A. Hancock, D.C. Smith, A. Grant and J.P. Beumer (eds.) *Developing and sustaining world fisheries resources: the state of science and management.* Second World Fisheries Congress, Brisbane 1996. CSIRO, Australia.

Viswanathan, K.K., Raakjaer Nielsen, J., Degnbol, P., Ahmed, M., Hara, M. & Abdullah, N.M.R. 2003. *Fisheries co-management policy brief: findings from a worldwide study*. WorldFish Center, Penang.

von Bertalanffy, L. 1938. A quantitative theory of organic growth (Inquiries on growth laws II) *Human Biology* 10: 181-213.

Wakeford, R.C., Pilling, G.M., O'Neill, C.J. & Hine, A. 2004. *Investigations of the implications of different reef fish life history strategies on fisheries management*. Final Technical Report, FMSP Project R7835. MRAG, London. 123 pp.

Walters, C.J. & Hilborn, R. 1978. Ecological optimization and adaptive management. *Annual Reviews in Ecological Systematics* 9: 157-188.

Walters, C.J. & Ludwig, D. 1994. Calculation of Bayes posterior probability distributions for key population parameters: a simplified approach. *Can. J. Fish. Aquat. Sci*. 51: 713-722.

Welcomme, R.L. 1977. Some factors affecting the catch of tropical river fisheries. *In* R.L.Welcomme, ed. *Proceedings of the CIFA Symposium on River and Floodplain Fisheries*, pp. 1-9, Bujumbura, Burundi 21-26 November 1977. Rome, FAO.

Welcomme, R.L. 2001. *Inland fisheries: ecology and management*. Fishing News Books, Blackwell Science Ltd. 358 pp.

West, M. 1993. Approximating posterior distributions with mixtures. *J.R. Statist. Soc*. B. 55: 409-422.

Wetherall, J. A., Polovina, J. J. & Ralston, S. 1987. Estimating growth and mortality in steady-state fish stocks from length-frequency data. Pages 53-74 in Pauly, D. and Morgan, G. R. (Eds) *Length-based methods in fisheries research*. ICLARM Conference Proceedings 13. ICLARM, Manila, Philippines and KISR, Safat, Kuwait. 468 pp.

World Bank. 1999. *Voices from the Village: A Comparative Study of Coastal Management in the Pacific Islands*. Washington, World Bank.

Zar, J.H. 1984. *Biostatistical Analysis*. New Jersey, Prentice Halls. 718 pp.

SOFTWARE INSTALLATION

The CD-ROM included with this publication includes the installation files for the FMSP software packages: LFDA, CEDA, Yield and ParFish. Also included is a graphics server package which is used by the other programmes and should be installed first, before the other software. Double-clicking on the installer files will load the software on to your hard drive, along with the help files, tutorials and example data sets. Once installed, the programmes may be run from the Windows start menu. The software should be compatible with Windows operating systems from Windows 95 onwards.

CEDA

Windows 95, 98, 2000, XP
5MB free disk space (+ 1.6MB for graph server)
64MB RAM
1,024x768 high resolution monitor

Run CEDA3_Installer.exe to install the software

LFDA

Windows 95, 98, 2000, XP
5MB free disk space (+ 1.6MB for graph server)
64MB RAM
1,024x768 high resolution monitor

Run LFDA5_Installer.exe to install the software

YIELD

Windows 95, 98, 2000, XP
9MB free disk sapce (+ 1.6MB for graph server)
64MB RAM
1,024x768 high resolution monitor

Run Yield_Installer.exe to install the software

Graph Server

(this package REQUIRED for CEDA, LFDA, Yield)

Windows 95, 98, 2000, XP
1.6Mb disk space
64Mb RAM
1,024x768 high resolution monitor

Run graphserverinstaller.exe to install the software

ParFish

Windows 2000/XP (has NOT been tested on 95/98 but would probably run on it)
10Mb free disk space
64Mb RAM
1,024x768 high resolution monitor

Run ParFishSetup.exe to install the software

This document provides guidelines for fish stock assessment and fishery management using the software tools and other outputs developed by the United Kingdom's Department for International Development's Fisheries Management Science Programme (FMSP) from 1992 to 2004. It explains some key elements of the precautionary approach to fisheries management and outlines a range of alternative stock assessment approaches that can provide the information needed for such precautionary management. Four FMSP software tools, LFDA (Length Frequency Data Analysis), CEDA (Catch Effort Data Analysis), YIELD and ParFish (Participatory Fisheries Stock Assessment), are described with which intermediary parameters, performance indicators and reference points may be estimated. The document also contains examples of the assessment and management of multispecies fisheries, the use of Bayesian methodologies, the use of empirical modelling approaches for estimating yields and in analysing fishery systems, and the assessment and management of inland fisheries. It also provides a comparison of length- and age-based stock assessment methods. A CD-ROM with the FMSP software packages CEDA, LFDA, YIELD and ParFish is included.

DFID Department for International Development

MRAG

ISBN 92-5-105503-3 ISSN 0429-9345

9 789251 055038

TC/M/A0486E/1/04.06/3000