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, 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).

![A simplified version of the Generalized Fishery Development Model (GFDM) after Caddy (1984); Grainger and Garcia (1996)](image)

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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:

\[
\frac{r}{t} = \frac{(C_{t+1} - C_t)}{C_t}
\]  

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):

\[
r = \frac{(C_{t+1} - C_t)}{C_t} = bt + a
\]  

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:

\[
C_{t+1} = C_t (bt + a + 1)
\]  

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.
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 et 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, transformed scales.

For (a) \( \log_{e} \text{catch} = 2.086 + 0.996 \log_{e} \text{area} \) (\( R = 0.97; P<0.001 \));
and (b) \( \log_{e} \text{catch} = 2.668 + 0.818 \log_{e} \text{area} \) (\( R = 0.90; P<0.001 \)).

**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**

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

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Empirical modelling approaches

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.fmep.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).

\[
\ln(Yield + 1) = \tilde{b}^3 \exp(a + bi^0.5) + c
\]

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,\(^2\) 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, 17]).

\(^2\) 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.
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.
Empirical modelling approaches

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 14.7
CPUA vs. fisher density for Asian lakes and reservoirs. Curve is least squares fit of Eq. 4; n = 37; R$^2$ = 0.76

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 ($i_{opt}$) 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 $i_{opt}$ 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

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

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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

<table>
<thead>
<tr>
<th>Category</th>
<th>Outcome Variables</th>
<th>Indicator</th>
<th>Units</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production/Yield</td>
<td>Annual production per unit area</td>
<td>Catch per unit area (CPUA)</td>
<td>tonnes/km^2 or tonnes/km (specify)</td>
<td></td>
</tr>
<tr>
<td>Sustainability/Biodiversity</td>
<td>Annual production per unit area</td>
<td>CPUA - Trend</td>
<td>0;1;2</td>
<td>Total landings: increasing (0); stable (1); declining (2)</td>
</tr>
<tr>
<td>Sustainability (Resource)</td>
<td>Catch per unit effort (CPUE)</td>
<td>Tonnes/fisher/year</td>
<td></td>
<td>All species combined or specify for each target species.</td>
</tr>
<tr>
<td>Well-Being (Fishers/Households)</td>
<td>Household income from fishing</td>
<td>Household income from fishing</td>
<td>$/year</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Assets eg TV, Bikes, Tin Roofs…etc</td>
<td>Assets eg TV, bikes, tin roofs…etc</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
<tr>
<td></td>
<td>Savings and investments</td>
<td>Savings and investments</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high(2) or state mean value(s)</td>
</tr>
<tr>
<td>Food security</td>
<td>Number of fish meals/week</td>
<td></td>
<td>0;1;2</td>
<td>Declining (0); static (1); rising (2)</td>
</tr>
<tr>
<td><strong>Institutional Performance</strong></td>
<td>Empowerment</td>
<td>Participation in management</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
<tr>
<td></td>
<td>Equity</td>
<td>Distributional among community members</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
<tr>
<td></td>
<td>Compliance with rules and regulations</td>
<td>Compliance with rules and regulations</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
<tr>
<td></td>
<td>Conflicts</td>
<td>Frequency of conflicts</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
</tbody>
</table>

#### (b) Explanatory Variables

<table>
<thead>
<tr>
<th>Category</th>
<th>Explanatory Variables</th>
<th>Indicator</th>
<th>Units</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production potential</td>
<td>Water transparency (Secchi depth)</td>
<td>m</td>
<td></td>
<td>May not be valid indicator in rivers</td>
</tr>
<tr>
<td>Abundance/Biomass</td>
<td>(Total annual catch)/(Numbers of fishers)</td>
<td>Tonnes/fisher</td>
<td></td>
<td>All species combined or specify for each target species.</td>
</tr>
<tr>
<td>Ecosystem Type</td>
<td>Ecosystem Type</td>
<td></td>
<td>0;1;2..n</td>
<td>River (0); fringing floodplain (1); beel (2); lake (3); ...etc</td>
</tr>
<tr>
<td>Waterbody type</td>
<td>Permanence</td>
<td></td>
<td>0;1;2</td>
<td>Seasonal (0); perennial (1); both (2)</td>
</tr>
<tr>
<td>Rule enforcement potential</td>
<td>Area under co-management per fisher</td>
<td>km^2/fisher or km of coastline/fisher (specify)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(b) Explanatory Variables</td>
<td>Environmental health of habitat</td>
<td>Health of critical habitat</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
</tr>
<tr>
<td>---------------------------</td>
<td>---------------------------------</td>
<td>--------------------------</td>
<td>-------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Nutrient recycling</td>
<td>Depth of reserve, lake, fishing area ...etc</td>
<td>m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Habitat descriptors</td>
<td>% Coral cover</td>
<td>%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exploitation intensity</td>
<td>Fisher density</td>
<td>N / km² or km of coastline (specify)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exploitation intensity</td>
<td>Number of villages</td>
<td>N</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exploitation intensity</td>
<td>Number of fishers</td>
<td>N</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exploitation intensity</td>
<td>Mean size of fish caught in Month x, with gear x</td>
<td>cm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stocking density</td>
<td>Stocking density</td>
<td>kg/ha</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Habitat alteration activities</td>
<td>Habitat alteration activities</td>
<td>0 - 5</td>
<td>Destructive (0); none (1); beneficial (5)</td>
<td></td>
</tr>
<tr>
<td>Economic value of resource</td>
<td>Mean unit value of target species</td>
<td>US$/kg</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market facilities/ infrastructure</td>
<td>Transport/infrastructure/ landing sites...etc</td>
<td>0;1;2</td>
<td>Poor (0); medium (1); good (2)</td>
<td></td>
</tr>
<tr>
<td>Cost of marketing (market fees)</td>
<td>Cost of marketing (market fees)</td>
<td>0;1;2;3</td>
<td>None (0); low (1); medium (2); high (3)</td>
<td></td>
</tr>
<tr>
<td>Price control mechanism</td>
<td>Price control mechanism</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Social cohesion</td>
<td>Social cohesion</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
<td></td>
</tr>
<tr>
<td>Dependence on fishery for livelihood</td>
<td>% of household income derived from fishing</td>
<td>%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level of local (ecological) knowledge</td>
<td>Level of local (ecological) knowledge of fishers</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high(2)</td>
<td></td>
</tr>
<tr>
<td>Legitimacy / widely accepted</td>
<td>Legitimacy of local decision-making body</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high(2)</td>
<td></td>
</tr>
<tr>
<td>Membership to decision-making body</td>
<td>Democratically elected?</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Clear access (property) rights</td>
<td>Clear access (property) rights</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Management plan</td>
<td>Present/implemented</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Management measures (operational rules)</td>
<td>Mesh / gear size restrictions</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Management measures (operational rules)</td>
<td>Gear ban(s)</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Management measures (operational rules)</td>
<td>Closed seasons</td>
<td>0;1</td>
<td>No (0); yes (1) if yes specify month(s) closed</td>
<td></td>
</tr>
<tr>
<td>Management measures (operational rules)</td>
<td>Reserve area as a % of total management area</td>
<td>%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Representation in rule making</td>
<td>Representation in rule making (fishers)</td>
<td>0;1;2</td>
<td>Low (0); medium (1); high (2)</td>
<td></td>
</tr>
<tr>
<td>Formal performance monitoring?</td>
<td>Formal performance monitoring by community?</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Sanctions for non compliance</td>
<td>Sanctions for non-compliance</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Enabling legislation for co-management</td>
<td>Enabling legislation for co-management</td>
<td>0;1</td>
<td>No (0); yes (1)</td>
<td></td>
</tr>
<tr>
<td>Local political/institutional support</td>
<td>Local political/institutional support</td>
<td>0;1;2;3</td>
<td>Anti (0); Weak (1); indifferent (2); strong (3)</td>
<td></td>
</tr>
<tr>
<td>Effective coordinating body</td>
<td>Nested structure of co-management arrangements</td>
<td>0;1</td>
<td>Absent (0); Present (1)</td>
<td></td>
</tr>
<tr>
<td>External financial assistance</td>
<td>Expenditure on community</td>
<td>$/year/ fisher</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capacity building support from NGO's</td>
<td>Support for community from NGO's</td>
<td>0;1;2;3</td>
<td>none (0); weak (1); medium (2); strong (3)</td>
<td></td>
</tr>
</tbody>
</table>

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 \texttt{varclus}, which is part of the \texttt{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.

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.
Empirical modelling approaches

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

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:

$$y_{ijk} = \mu + \beta_1 x_1i + \beta_2 x_2i + r_j + s_k + e_{ijk}, \quad i = 1,2,...,n; \quad j = 1,2,3; \quad k = 1,2,3,4$$

In this equation, $\mu$ represents a constant, similar to the intercept in multiple linear regression, while $e_{ijk}$ represents the residual component and reflects the random (or unexplained) variation in $y$ after the effect of $x_1$, $x_2$, $R$ and $S$ have been taken into account. The parameters $\beta_1$, (and $\beta_2$) 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 $r_j$ and $s_k$, 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. $r_3 = 0$ and $s_4 = 0$, 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 $\epsilon$, 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

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>d.f.</th>
<th>Type III MS</th>
<th>F</th>
<th>Sig. Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECOTYPE</td>
<td>4</td>
<td>1526.9</td>
<td>1.81</td>
<td>0.177</td>
</tr>
<tr>
<td>PERMEN</td>
<td>1</td>
<td>338.8</td>
<td>0.40</td>
<td>0.536</td>
</tr>
<tr>
<td>FISHERS1</td>
<td>1</td>
<td>313.4</td>
<td>0.37</td>
<td>0.551</td>
</tr>
<tr>
<td>VILLAGES</td>
<td>1</td>
<td>0.13</td>
<td>0.00</td>
<td>0.990</td>
</tr>
<tr>
<td>Residual</td>
<td>16</td>
<td>845.6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* 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 CPUE

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory variable</th>
<th>Variables in model</th>
<th>Prob. for sig.</th>
<th>Residual d.f.</th>
<th>Residual M.S.</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PRIM. PRO, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>12</td>
<td>36.2</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Primary Production</td>
<td>PRIM. PRO</td>
<td>0.014</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(g/Cm/year), with</td>
<td>FISH_DEN</td>
<td>0.033</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ecotype and fisher</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>GEARTYP2, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>16</td>
<td>33.3</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Type of gear, with</td>
<td>GEARTYP2</td>
<td>0.006</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ecotype and fisher</td>
<td>FISH_DEN</td>
<td>0.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>HARM. GR, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>13</td>
<td>28.1</td>
<td>88%</td>
</tr>
<tr>
<td></td>
<td>Destructive fishing</td>
<td>HARM. GR</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>practices, with</td>
<td>FISH_DEN</td>
<td>0.013</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ecotype and fisher</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>BAN. DRIV, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>18</td>
<td>25.7</td>
<td>89%</td>
</tr>
<tr>
<td></td>
<td>Ban on fish drives,</td>
<td>BAN. DRIV</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>with ecotype.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>SIZE, i.e. landing</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>14</td>
<td>12.1</td>
<td>93%</td>
</tr>
<tr>
<td></td>
<td>size restrictions,</td>
<td>SIZE</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>and NUMB. RES, i.e.</td>
<td>NUMB. RES</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>number of reserves,</td>
<td>SIZE x NUMB. RES</td>
<td>0.013</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>with their</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>interaction, and with</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ecotype</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>MANG. TYP, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>17</td>
<td>32.6</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Type of management</td>
<td>MANG. TYP</td>
<td>0.005</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>and OA_COMM, i.e.</td>
<td>OA_COMM</td>
<td>0.018</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>if open or restricted</td>
<td>FISH_DEN</td>
<td>0.043</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>access, with ecocyte</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>and fisher density.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>LOC. BODY, i.e.</td>
<td>ECOTYPE</td>
<td>0.000</td>
<td>18</td>
<td>30.8</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Local decision making</td>
<td>LOC. BODY</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>body, and OA_COMM,</td>
<td>OA_COMM</td>
<td>0.015</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>i.e. if open or</td>
<td>FISH_DEN</td>
<td>0.011</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>restricted access,</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>with ecotype and</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>fisher density.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE 14.4
Predicted Changes in CPUE from a base level of each significant explanatory variable

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory variable</th>
<th>Variable Levels</th>
<th>Changes from base level</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PRIM. PRO, i.e.</td>
<td>Low</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Primary Production</td>
<td>Medium</td>
<td>5.6</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>(g/Cm/year)</td>
<td>High</td>
<td>20.8</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>(with ecotype and</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>fisher density)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>GEARTYP2, i.e.</td>
<td>Gillnets</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Type of gear</td>
<td>Hook &amp; Line or</td>
<td>–2.5</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>(with ecotype and</td>
<td>Speargun</td>
<td>16.4</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>fisher density)</td>
<td>Traps or other</td>
<td>–0.91</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>HARM. GR, i.e.</td>
<td>No</td>
<td>19.8</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Destructive fishing</td>
<td>Yes</td>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>practices?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(with ecotype and</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>fisher density)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>BAN. DRIV, i.e.</td>
<td>No</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>Ban on fish drives</td>
<td>Yes</td>
<td>23.6</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>(with ecotype)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>SIZE, i.e. landing</td>
<td>No</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>size restrictions,</td>
<td>Yes</td>
<td>15.5</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>and NUMB. RES, i.e.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>number of reserves,</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>according to SIZE.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>MANG. TYP, i.e.</td>
<td>Govt.</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Type of management</td>
<td>Co_mgt</td>
<td>15.4</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>and OA_COMM, i.e.</td>
<td>Self/Trad.</td>
<td>12.4</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>if open or restricted</td>
<td>Open</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>access, (with</td>
<td>Restricted</td>
<td>6.4</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>ecotype and fisher</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>density)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>LOC. BODY, i.e.</td>
<td>Absent</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Local decision making</td>
<td>Present</td>
<td>15.0</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>body and OA_COMM, i.e.</td>
<td>Open</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>if open or restricted</td>
<td>Restricted</td>
<td>6.4</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>access, (with</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ecotype and fisher</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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

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...
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.

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.

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>
<thead>
<tr>
<th></th>
<th>F</th>
<th>T</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>F</td>
<td>F</td>
<td>( p_{00} )</td>
</tr>
<tr>
<td>F</td>
<td>F</td>
<td>T</td>
<td>( p_{10} )</td>
</tr>
<tr>
<td>T</td>
<td>F</td>
<td>F</td>
<td>( p_{00} )</td>
</tr>
<tr>
<td>T</td>
<td>T</td>
<td>F</td>
<td>( p_{10} )</td>
</tr>
</tbody>
</table>

TABLE 14.5
CPT for Node C

![Figure 14.12](image1)

![Figure 14.13](image2)
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](image)

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 these 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.
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.
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”).

### Table 14.7
Conditional probabilities for Conflict resolution

<table>
<thead>
<tr>
<th>Fisher rep.</th>
<th>Conflict resolution</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>No</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.23</td>
</tr>
<tr>
<td>Med/High</td>
<td>No</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.94</td>
</tr>
</tbody>
</table>

### Table 14.8
Conditional probabilities for Fisher representation

<table>
<thead>
<tr>
<th>Mgmt. type</th>
<th>Dem. Elec.</th>
<th>Fisher representation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Med/High</td>
</tr>
<tr>
<td>Gov’t.</td>
<td>No</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.05</td>
</tr>
<tr>
<td>Co-mgmt.</td>
<td>No</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.11</td>
</tr>
<tr>
<td>Trad.</td>
<td>No</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1.00</td>
</tr>
</tbody>
</table>

### 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.
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>
<thead>
<tr>
<th>Outcome</th>
<th>Equity (high)</th>
<th>CPUE change (static/rising)</th>
<th>Compliance (med/high)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management type</td>
<td>Overall</td>
<td>Gov't.</td>
<td>Co-mgmt.</td>
</tr>
<tr>
<td></td>
<td>73%</td>
<td>58%</td>
<td>80%</td>
</tr>
<tr>
<td></td>
<td>48%</td>
<td>27%</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>59%</td>
<td>30%</td>
<td>62%</td>
</tr>
</tbody>
</table>

In the same way we can obtain the posterior probabilities of the subsidiary outcomes (shown in Table 14.10).

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Poaching (low)</th>
<th>Stability (stable)</th>
<th>Respectability (high)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management type</td>
<td>Overall</td>
<td>Gov't.</td>
<td>Co-mgmt.</td>
</tr>
<tr>
<td></td>
<td>47%</td>
<td>22%</td>
<td>49%</td>
</tr>
<tr>
<td></td>
<td>76%</td>
<td>95%</td>
<td>66%</td>
</tr>
<tr>
<td></td>
<td>61%</td>
<td>38%</td>
<td>63%</td>
</tr>
</tbody>
</table>
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](image)

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.
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.