4 BIOMASS DYNAMIC MODELS

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Biomass dynamic models share most data requirements and assumptions with production models. Unlike production models, however, they do not assume stocks are in equilibrium. They are an attempt to acknowledge the time lags occurring between removals of biomass by fishing and growth in biomass due to the intrinsic productivity of fish stocks. They try to explain changes in an abundance index (normally CPUE) as a function of the removal of biomass by fishing, the biomass in the previous time period and the growth in biomass. The growth in biomass is commonly made a function of the biomass in the previous time period and of a few parameters describing the productivity of the stock. Although originally developed to model annual changes in biomass they can be used to model seasonal patterns too (Die *et al.* in prep). Annual and monthly biomass dynamic models were used during the last two workshops to conduct assessments of shrimp fisheries.

Biomass dynamic models are very simple representations of the dynamics of fish stocks. As a result they make very strong assumptions about the nature of the system being modelled and of the data used to fit them. It is important to remember such assumptions and when possible test them. For a review of such assumptions see Punt and Hilborn (1997).

There are a few simple rules that should be remembered when these models are used. In general, the longer the time series the better the results from fitting biomass dynamic models. The abundance index must also have some sort of trend, or at least time periods with significantly different values of abundance. These changes in the index must also be related to changes in catch (e.g. increasing or stable catches should lead to decreases in the abundance index), otherwise the model will not be able to fit the data. The likelihood of being able to estimate all parameters of the model depends entirely on the information content of the data. The modeller must also be wary when the information content is poor. In such case fitting the model may give an optimum solution that is unfeasible biologically. This is specially the case for the parameter *r*, the biomass growth rate. When fitting these models to short time series with little information content, the best solutions are often those with very high values of r (larger than 1.0). Such solutions should be disregarded unless we know the species is short-lived and highly productive, in which case large *r* values are possible.

The exact range of feasible values of r for marine stocks has not been studied. Haddon (1997) reports for an Australian shrimp fishery a value of r of 0.5 with 95% confidence limits between 0.2 and 0.95. For the South African hake, a fish that lives 10-12 years, Punt and Hilborn (1997) report a value of r of 0.39, with 95% confidence intervals between 0.33 and 0.45. On the basis of theoretical considerations based on life history characteristics Adams (1980) suggested r values of 0.9, 0.6 and 0.3 for stocks with maximum age of 13, 20 and 35 years respectively. Values of r larger than 1.0, however, must be considered with caution even for very short-lived stocks like shrimp.

Model parameters tend to be strongly correlated, especially r and K. Stocks with large r tend to have K values that are small in comparison to the catch extracted. Stocks with low r values tend to have a biomass that is large in comparison to the catch extracted. As a result it is possible to obtain parameter sets that fit the data similarly, but with large differences in terms of stock productivity as measure by r. In such cases we do not advise to choose the best parameter on the basis of a fitting criterion alone (SSQ, Log Likelihood). Both sets of parameters should be used to reach alternative explanations of the status of stocks. Alternatively, on the basis of knowledge on the life history of the fish one may chose to fix the r or the K parameter and let the data determine the value of the other parameter. These models are simple to implement and spreadsheet programs like EXCEL can be easily adapted to fit any type of variation of the original model. During the workshop, we have implemented biomass dynamic models directly in EXCEL, but we also used the BIODYN software developed by Punt and Hilborn (1997).