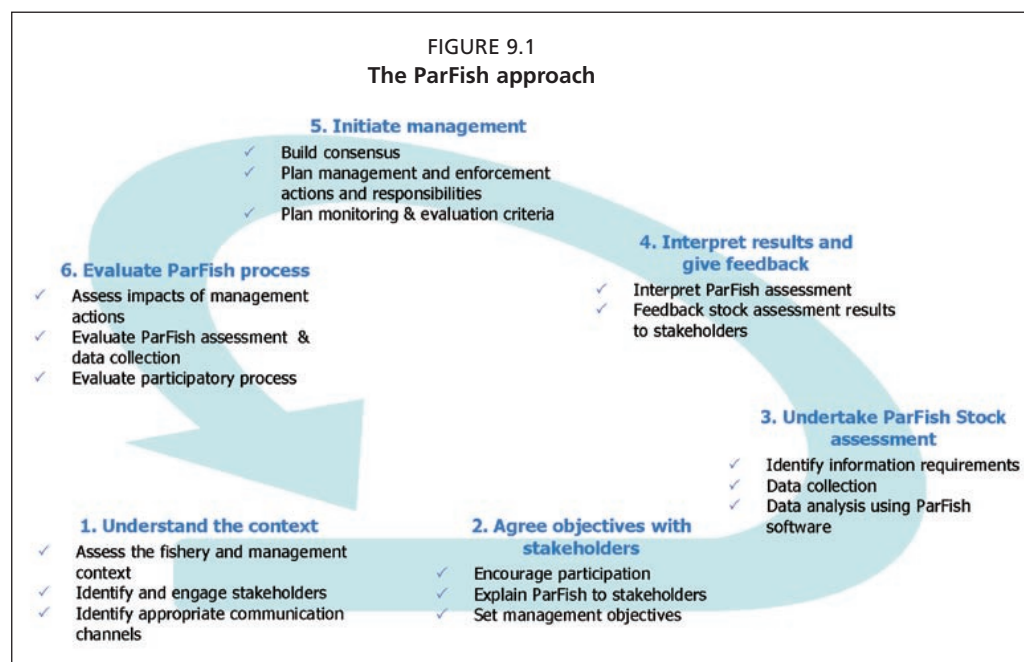


9. ParFish – Participatory Fisheries stock assessment

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.



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.fmmsp.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 scientific 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 controls. 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.

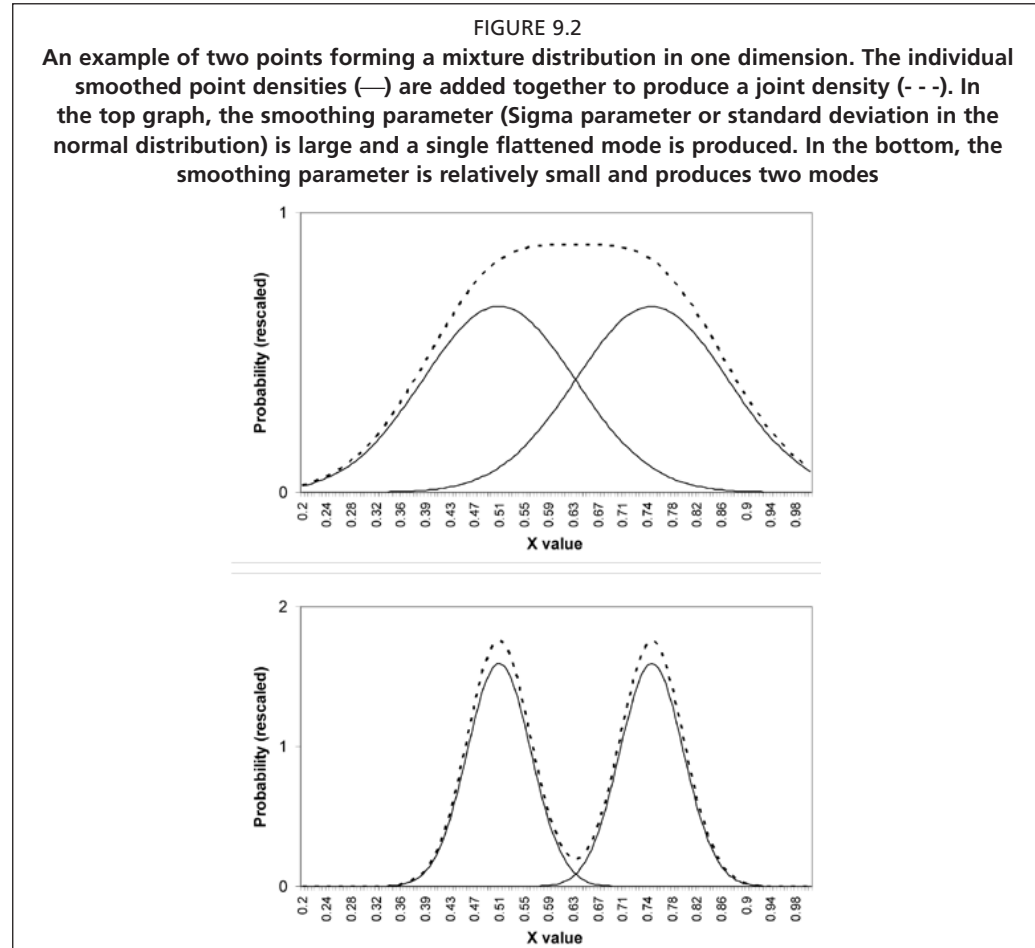
Instead of adding each point to a bin, each point is spread over the real line to smooth the distribution.

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).



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 the 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.

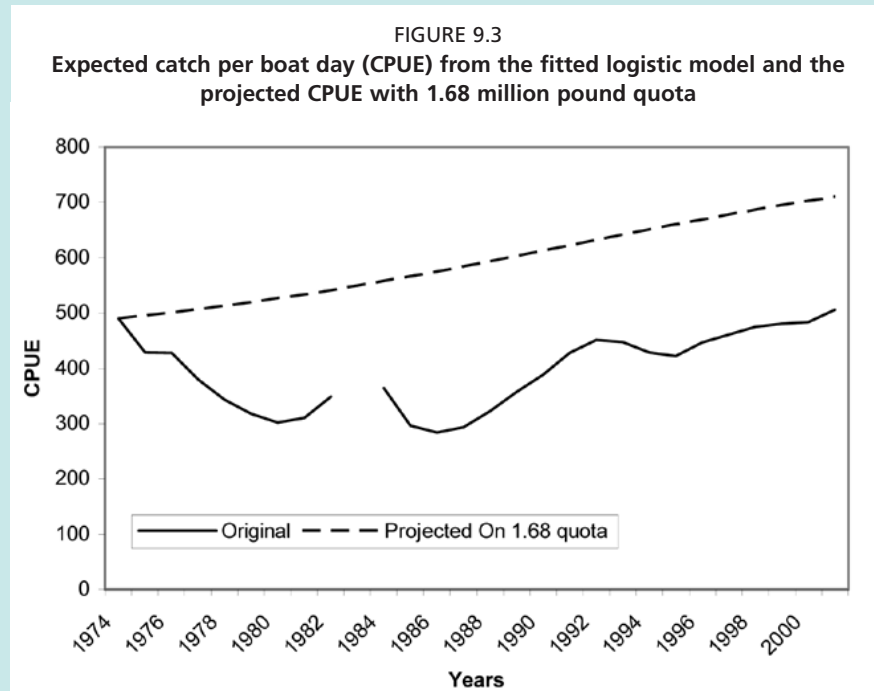
TABLE 9.1
Target and limit controls (landings quota in pounds meat weight) for the Turks and Caicos Islands Conch fishery based on catch-effort and interview data

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.



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.

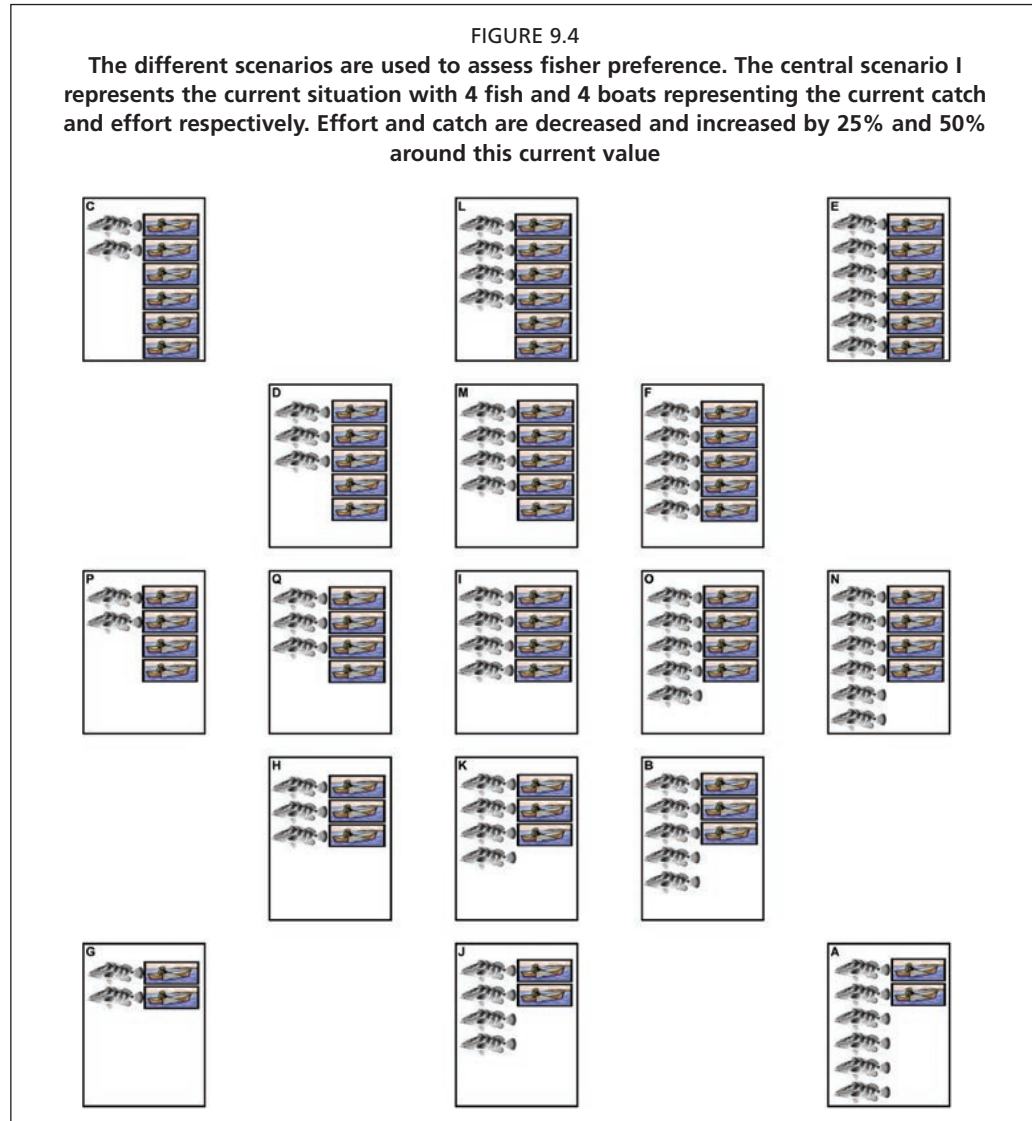
Simplification is achieved by:

- 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).



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.

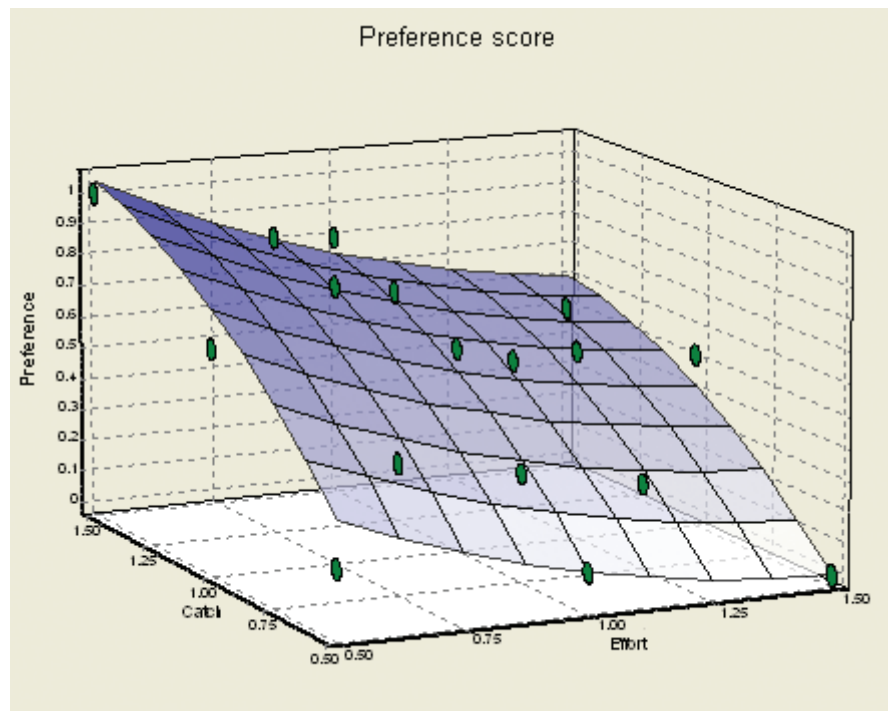
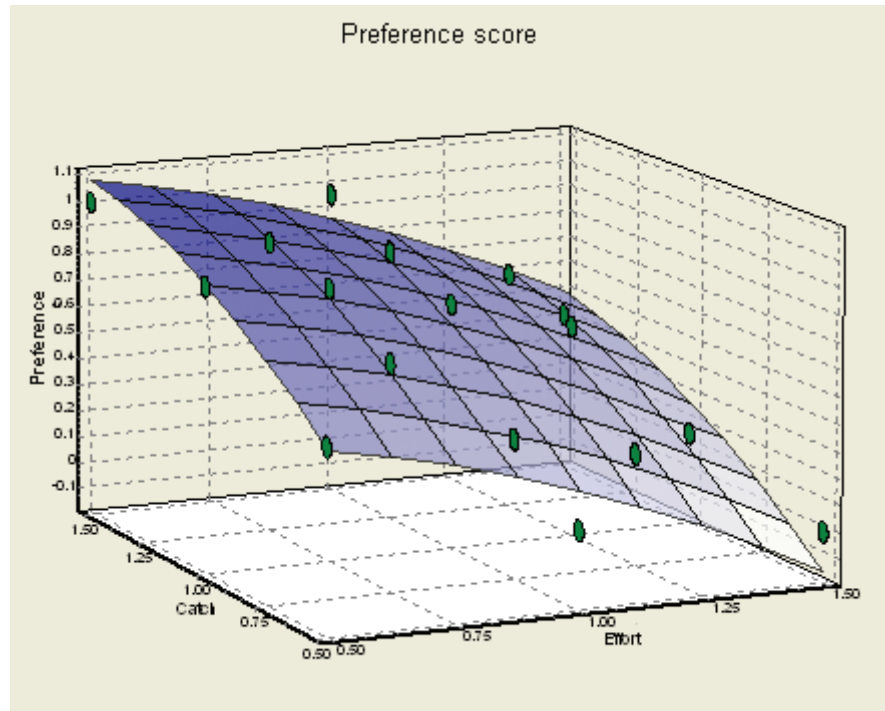
The method works through contrasting catch and effort variables and forces the fisher ranking the scenarios to define an exchange rate between them. Whereas the ranking works well, it was less certain that the scoring was as accurate. Scoring nevertheless gives the fisher the opportunity to draw a distinction 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 Bertalanffy 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.

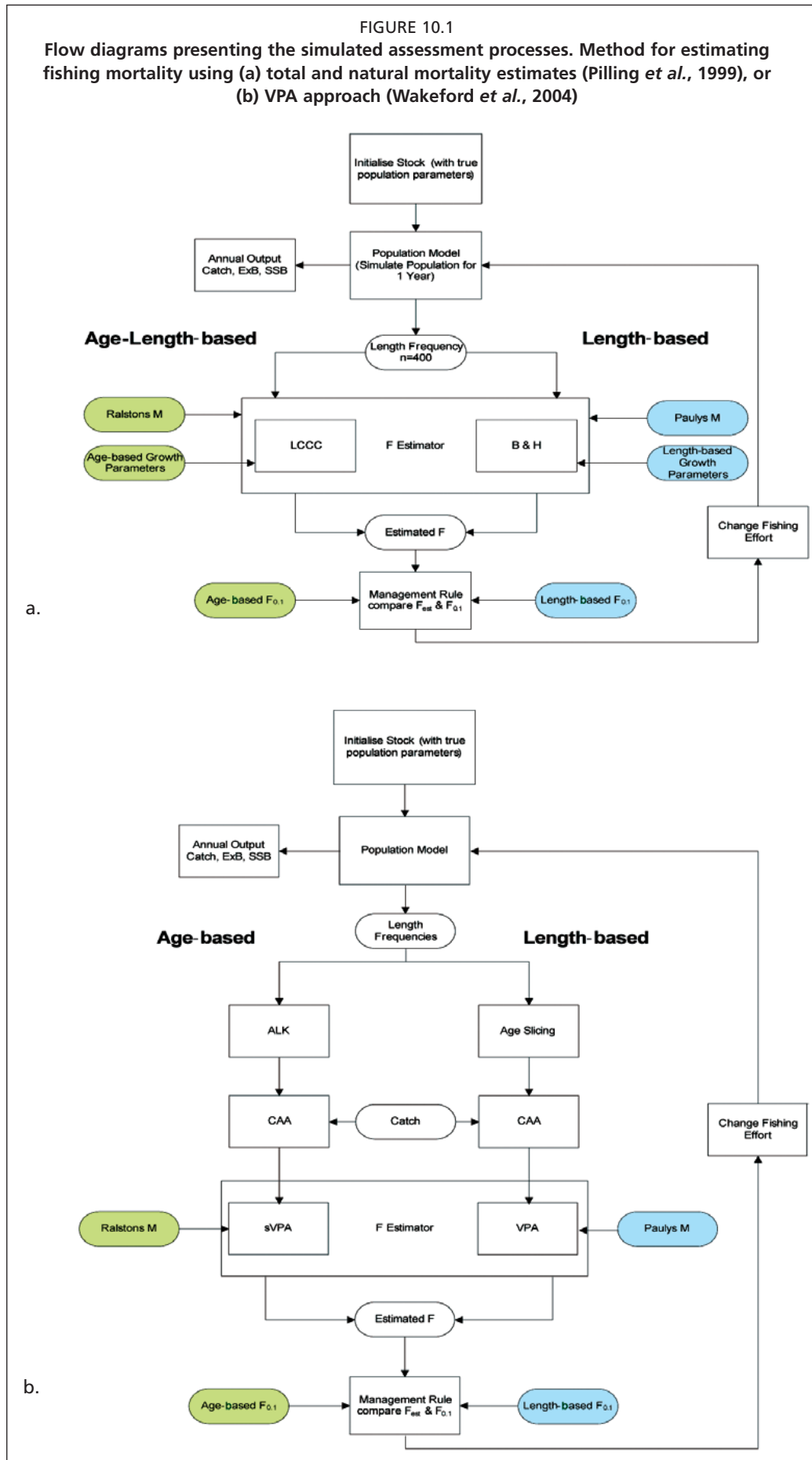
In all cases, uncertainty in management arose since the estimate of $F_{0.1}$ from the yield per recruit curve is strongly affected by the value of natural mortality. In this study, natural mortality was derived through empirical formulae based upon growth parameter estimates. Natural mortality is notoriously 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.

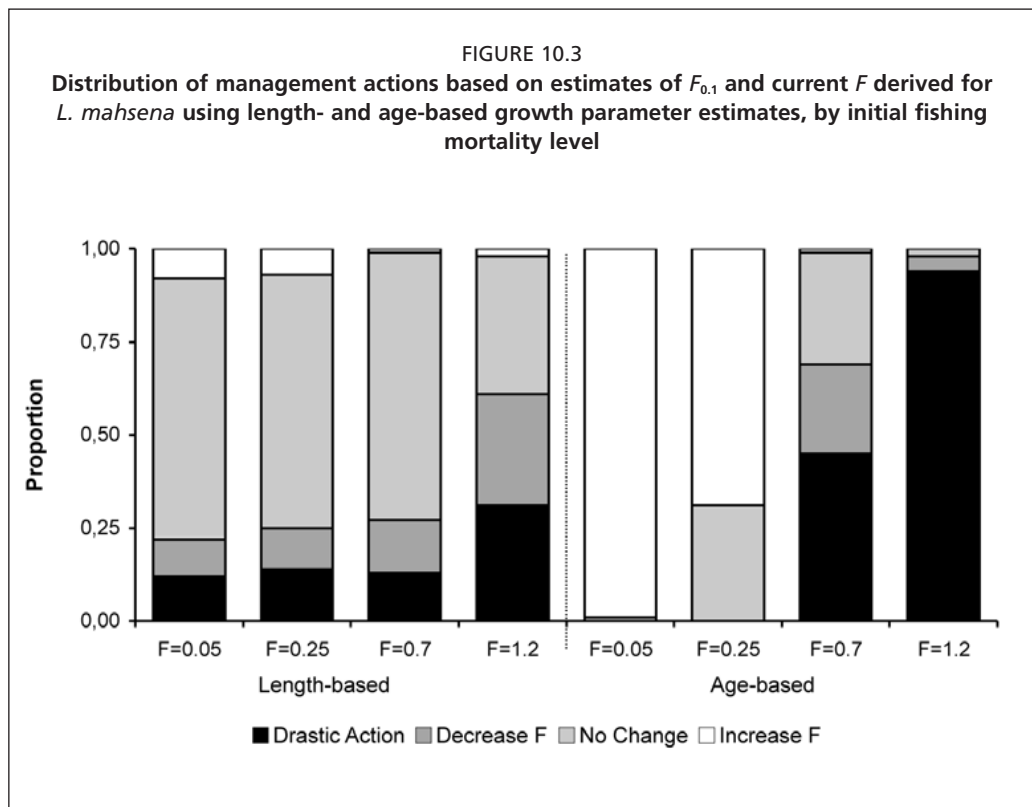
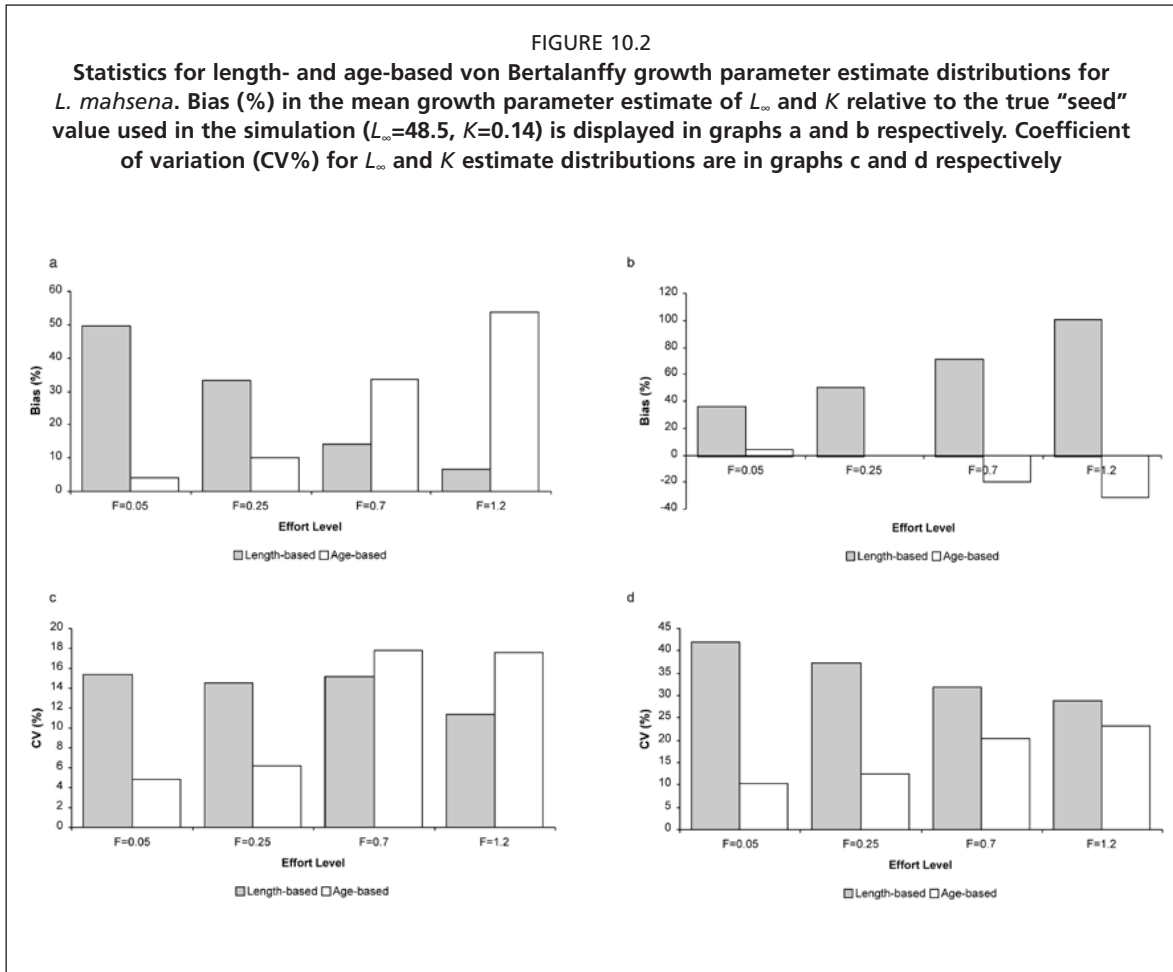
A final issue for the use of age-based methods of assessment is cost. However, cost-benefit analyses detailed in Pilling *et al.* (1999) indicated the higher costs of age-based methods when compared to length-based approaches was offset by additional benefits in terms of management performance (e.g. 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.

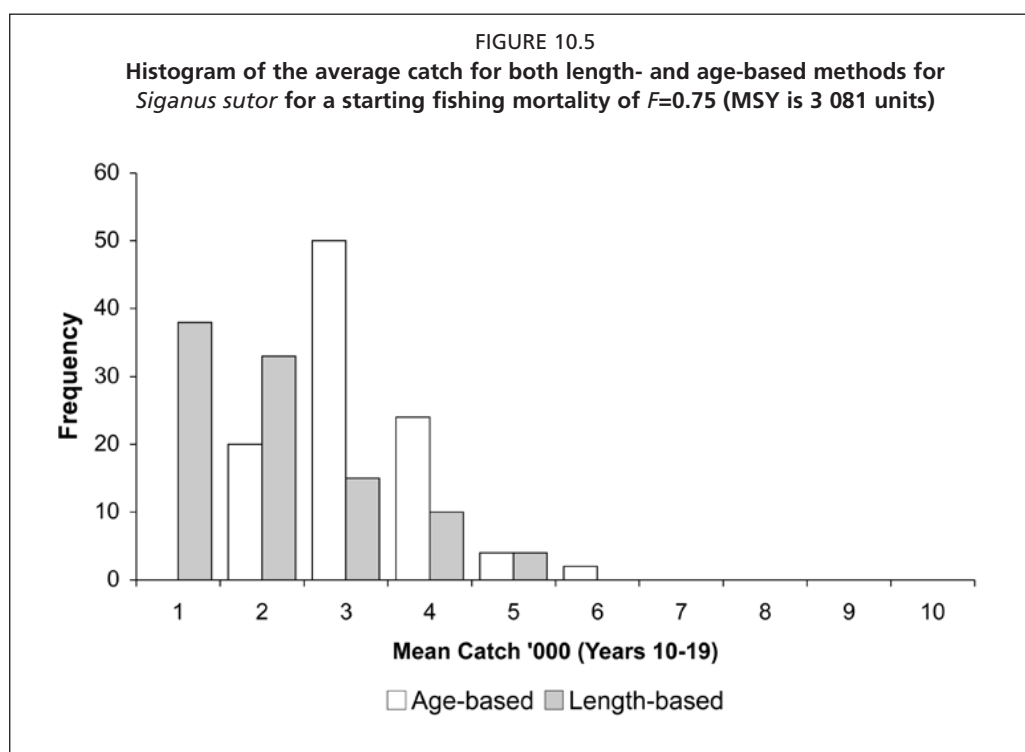
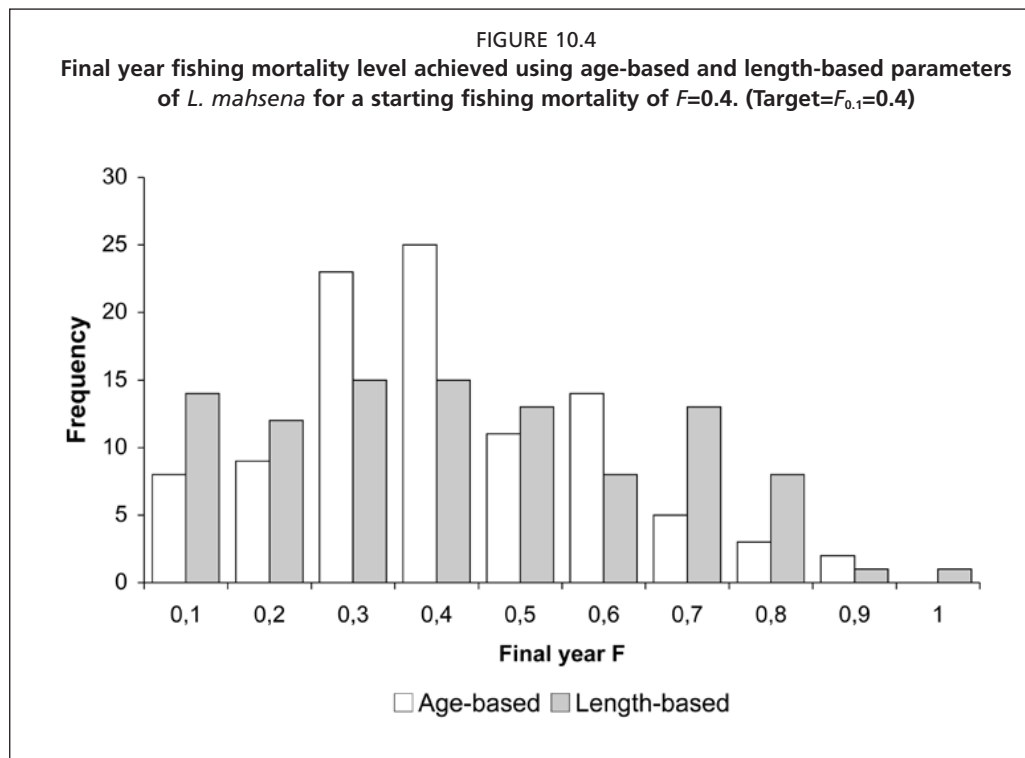
TABLE 10.1

Parameter values used to simulate *L. mahsena* and *S. sutor* populations

Parameter	<i>L. mahsena</i>	<i>S. sutor</i>
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)







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)

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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:

$$Y = 0.5 M B_0 \quad (1)$$

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

$$l(t) = L_\infty (1 - e^{-Kt}) \quad (2)$$

$$w(t) = W_\infty (1 - e^{-Kt})^3 \quad (3)$$

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:

$$Y / ExB_0 = a(L_c) K \quad (4)$$

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.

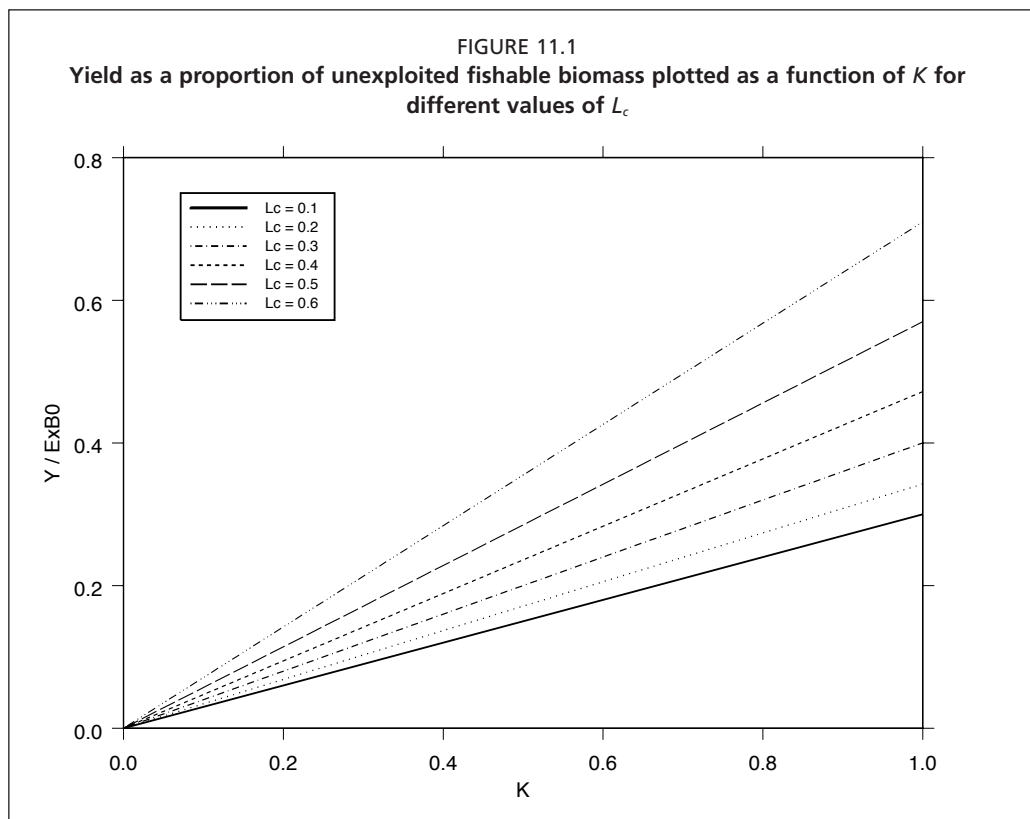


Figure 11.1 indicates that the potential yield increases with both the size at first capture (L_c) and K , as is well known (e.g., Beverton and Holt, 1957). Furthermore, the rate of increase in potential yield with L_c also increases as K increases. However, it is important to remember that situations 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).

$$L_e = \frac{3}{3 + M/K} \quad (5)$$

and from the Beverton-Holt invariants $M/K = 1.5$ and $L_m = 0.67$, it follows that

$$L_e = L_m = 0.67 \quad (6)$$

A simple equation that captures to a good degree of accuracy the relationship illustrated in Figure 11.1 is as follows:

$$Y/ExB_0 = 0.2 K (1 - \ln(0.67 - L_c)) \quad (7)$$

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 than 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 than 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.

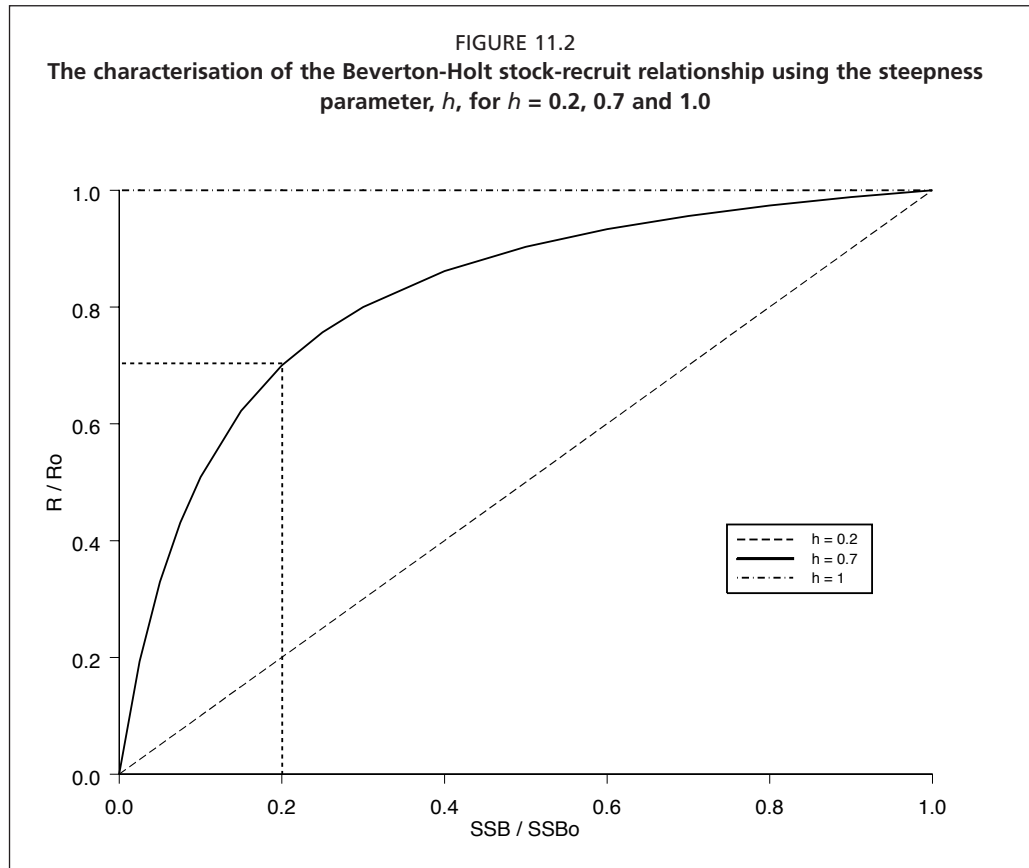
The standard formulation of the Beverton-Holt stock-recruit relationship is

$$R = \frac{\alpha B}{1 + \beta B} \quad (8)$$

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 (b) 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 b approaches 1, the Beverton-Holt relationship approaches a form in which recruitment is constant; when b is 0.2, recruitment is linearly related to SSB . The great advantage of this formulation is that b is a dimensionless parameter characterising the shape of the relationship and it is unaffected by the actual size of the stock.



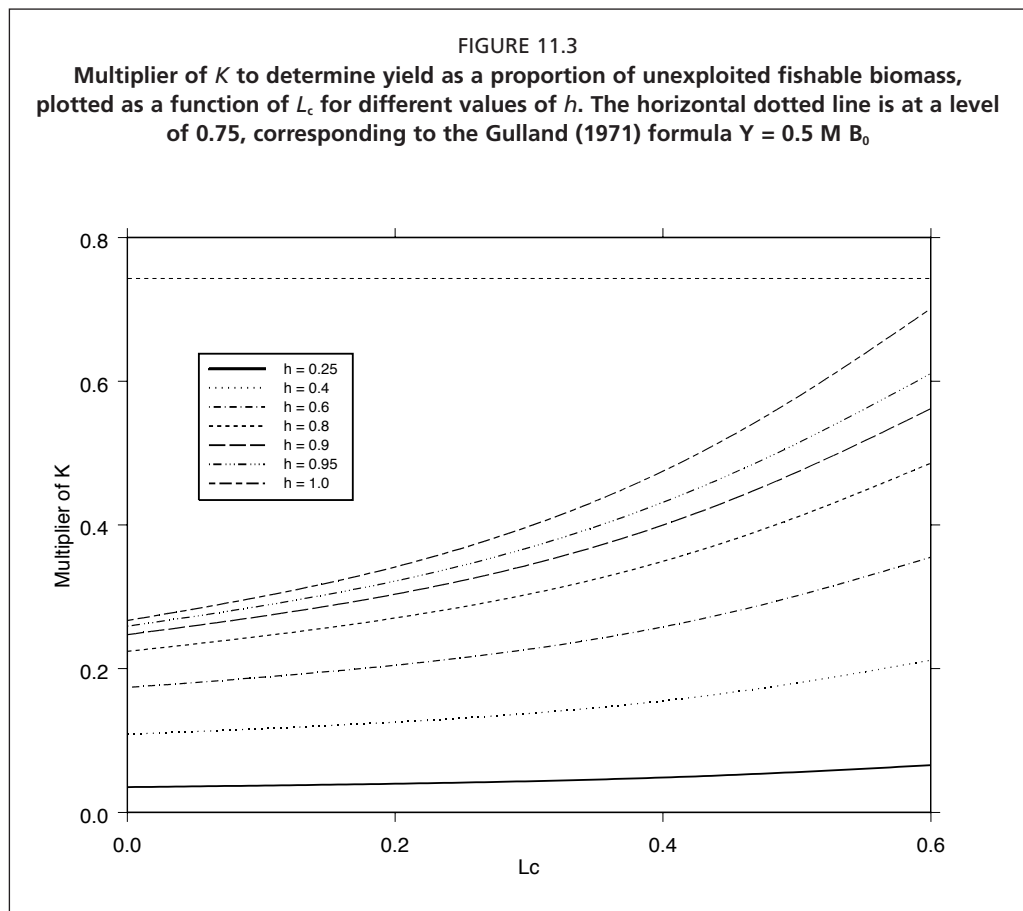
One further parameter needed for this analysis is the value of L_m . This, it will be recalled, is the third Beverton-Holt invariant, so that $L_m = 0.67$.

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:

$$Y / ExB_0 = a(L_c, b) K \quad (9)$$

where $a(L_c, b)$ 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 b .

The results are summarized in Figure 11.3.

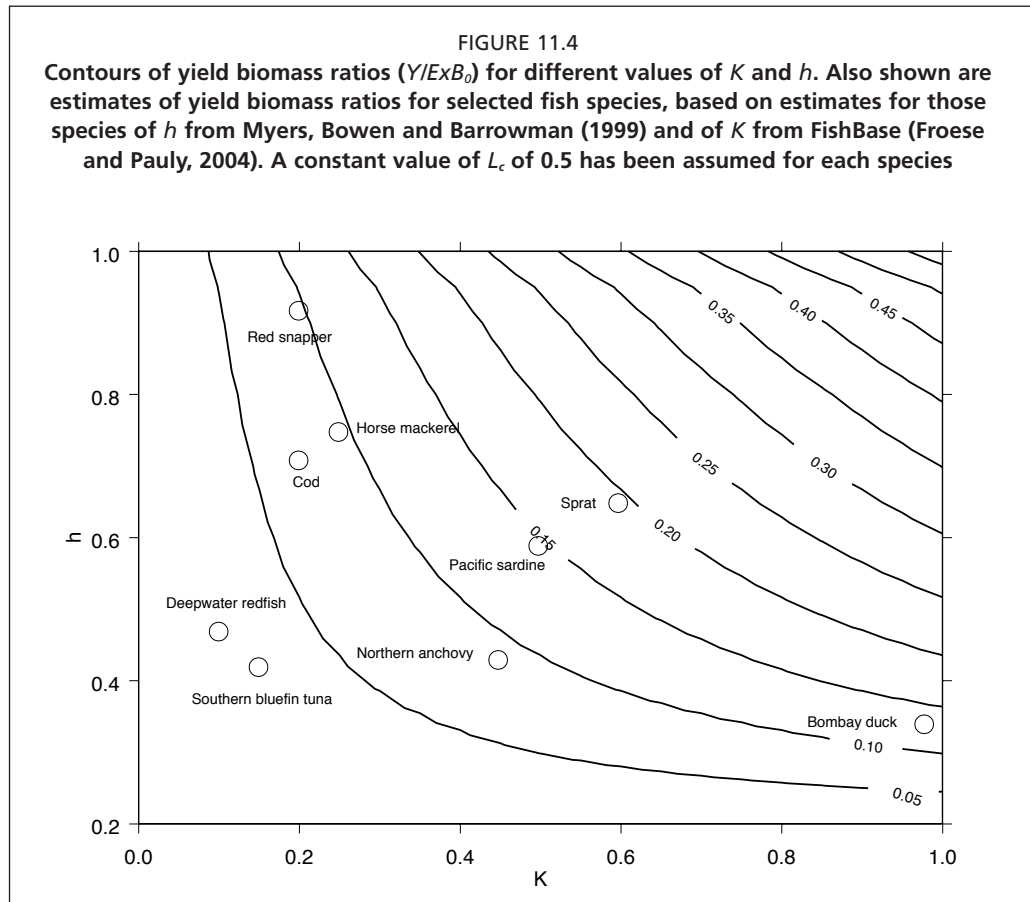


As expected, the multiplier of K increases with increased length at first capture and with an increasing degree of density dependence, with constant recruitment being the limiting case as the steepness parameter b approaches 1.

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 b 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 b (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 b . In particular, Myers, Bowen and Barrowman (1999) summarize estimates of b 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.



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} .

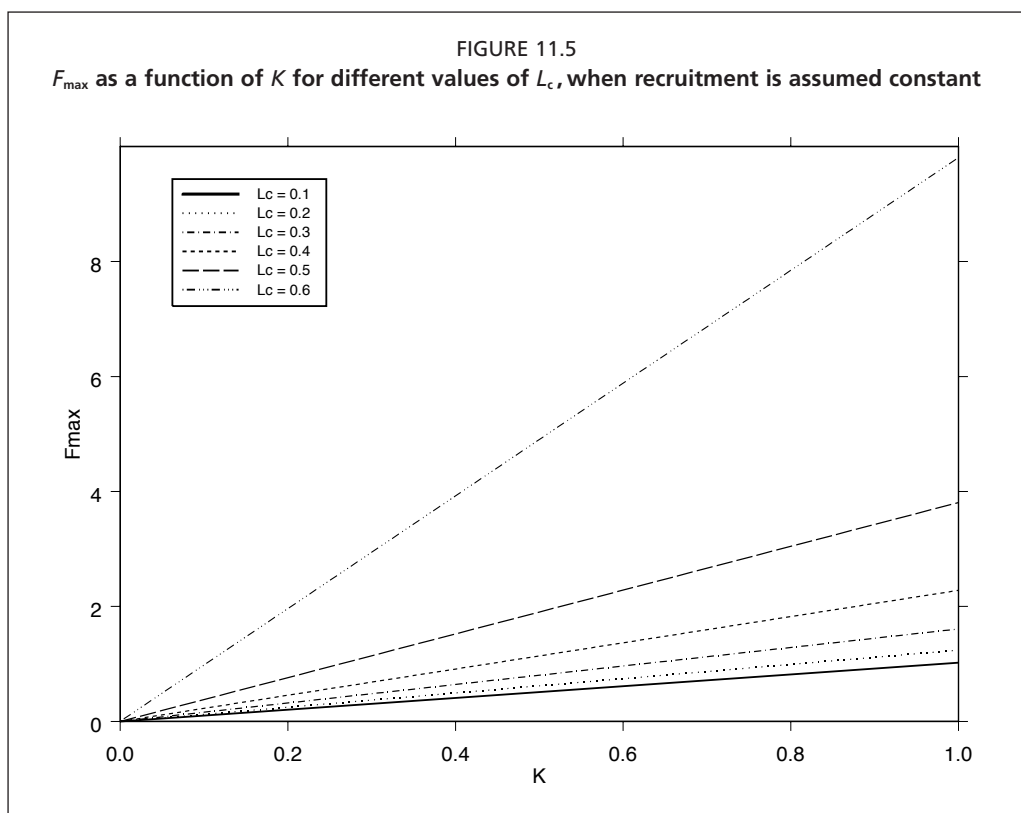
Both Beverton and Holt (1957) and Gulland (1971) observed that in many situations, F_{max} was related to and often close to the level of the annual instantaneous natural mortality rate, M . Other authors have also made similar observations, but to our knowledge no studies have been carried out to elucidate 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:

$$F_{max} = a(L_c) K \quad (3.1)$$

where the coefficient $a(L_c)$ varies with the length at first capture. The results are illustrated in Figure 11.5.



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 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:

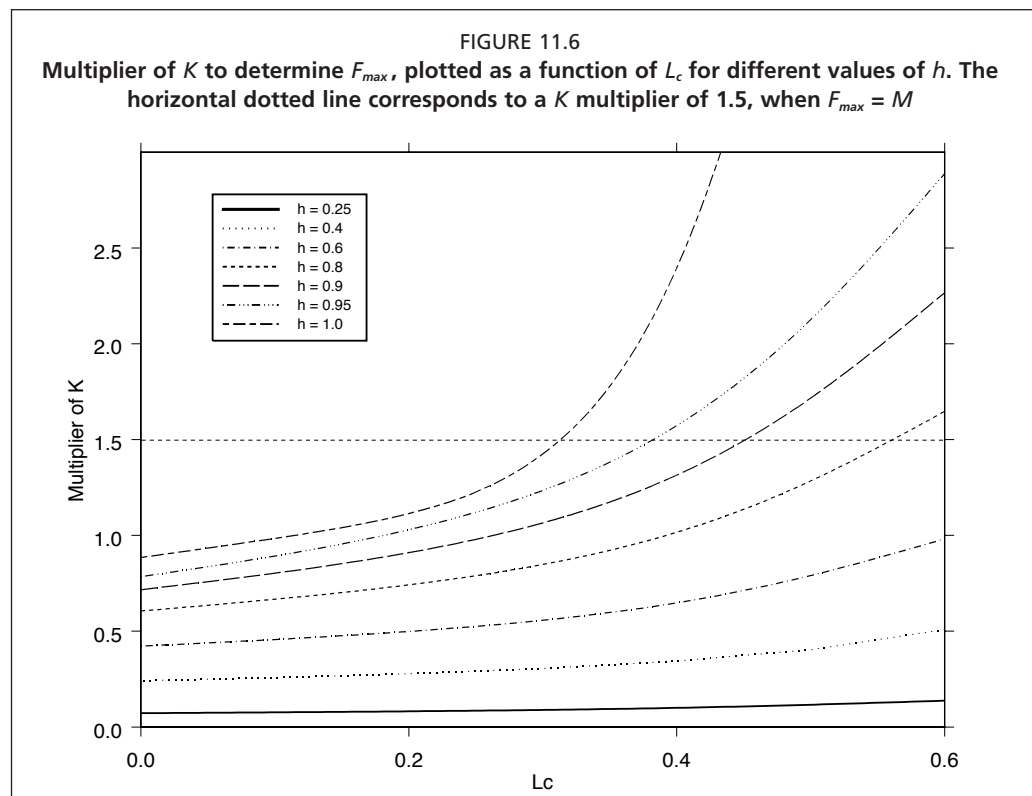
$$F_{max} = \frac{0.6K}{0.67 - L_c} \quad (3.2)$$

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

$$F_{max} = a(L_c, b) K \quad (3.3)$$

where $a(L_c, b)$ is a constant depending on the values of L_c and the degree of density dependence b . The results in terms of values of the multiplier of K are summarized in Figure 11.6.

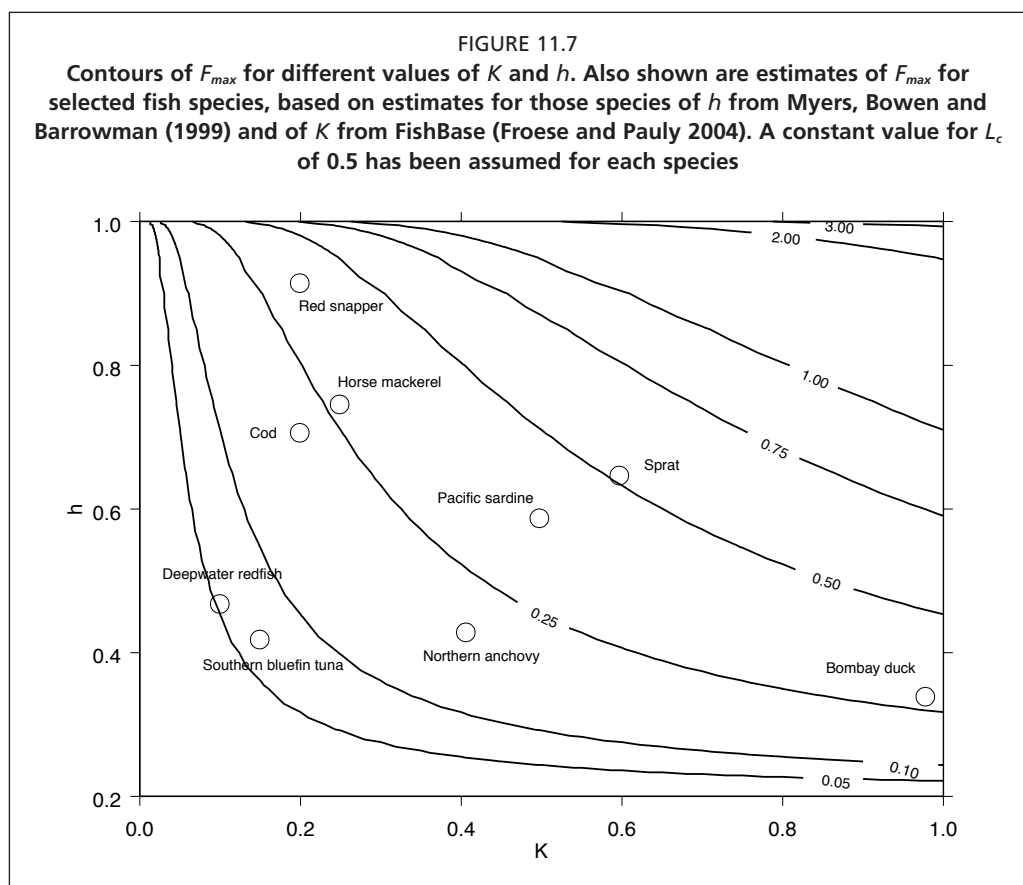


The results shown in Figure 11.6 indicate the very strong influence that the steepness b has on F_{max} . In practice, b is a relatively difficult parameter to estimate reliably, requiring at least a substantial time series of stock and recruitment data corresponding to a wide range of spawning stock 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.



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

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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 homogeneously 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	<ul style="list-style-type: none"> - Key species plus guilds of others (essential) - All fishing grounds and potential fishing areas 	<ul style="list-style-type: none"> - Key species (essential) 	<ul style="list-style-type: none"> - Key species only if resources available, (not essential)
To estimate	<ul style="list-style-type: none"> - catch, - effort, - biomass-prodn models - catchability 	<ul style="list-style-type: none"> - L_c - growth K, L_{∞} - mortality (M & current F) - Apply guidelines 	<ul style="list-style-type: none"> - (L_m) - (growth from hard parts) - (length-weight relationship) - (Location and time of spawning)
Must monitor	<ul style="list-style-type: none"> - Technical interactions - Depth - Gear - vessel power - fishing practices - Location specific 	<ul style="list-style-type: none"> - gear size (hooks); - location specific data essential- must relate to heavily fished locations 	
Strategies for data collection	<ul style="list-style-type: none"> - 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 	<ul style="list-style-type: none"> - Prioritize - Targeted sampling strategy (concentrate on heavily fished locations if cost is limiting) - Increase sample size from lightly fished locations where possible 	<ul style="list-style-type: none"> - 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

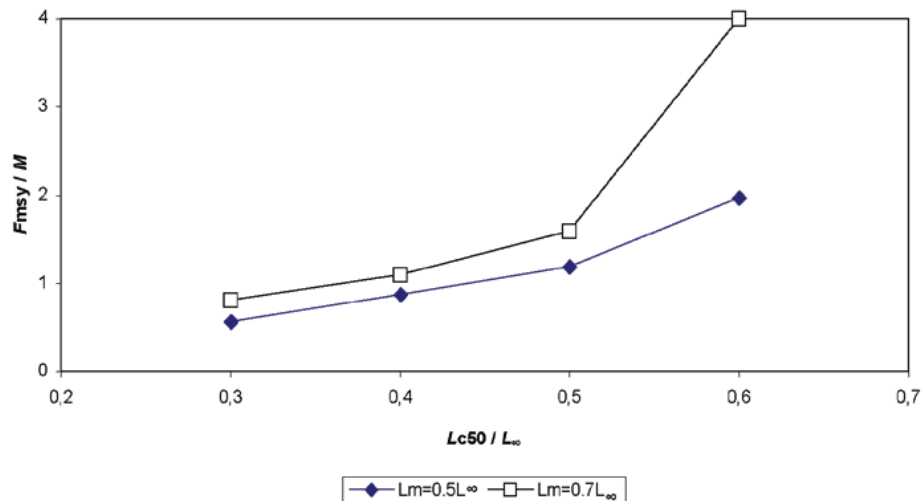
TABLE 12.2

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_∞ ($L_c = L_{c50} / L_\infty$ calculated for Length at maturity equal to $0.5L_\infty$ and $0.7L_\infty$ (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., Johnnies, 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 Johnnies, 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_0 . The stock assessment procedure applied then took draws from this pdf for B_0 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_0 , 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_0 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_0 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_0 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_0 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_0 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_0 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 parameters.* 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 pdfs were constructed individually for each parameter. Priors were applied for the long-term average value for unexploited biomass, B_0 , 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_0 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 Johnnies	Commercial-Swept-area
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_0 .* 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; Kincaid, 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_0 , stock biomass in 2000 (B_{2000}), and B_{2000}/B_0 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.

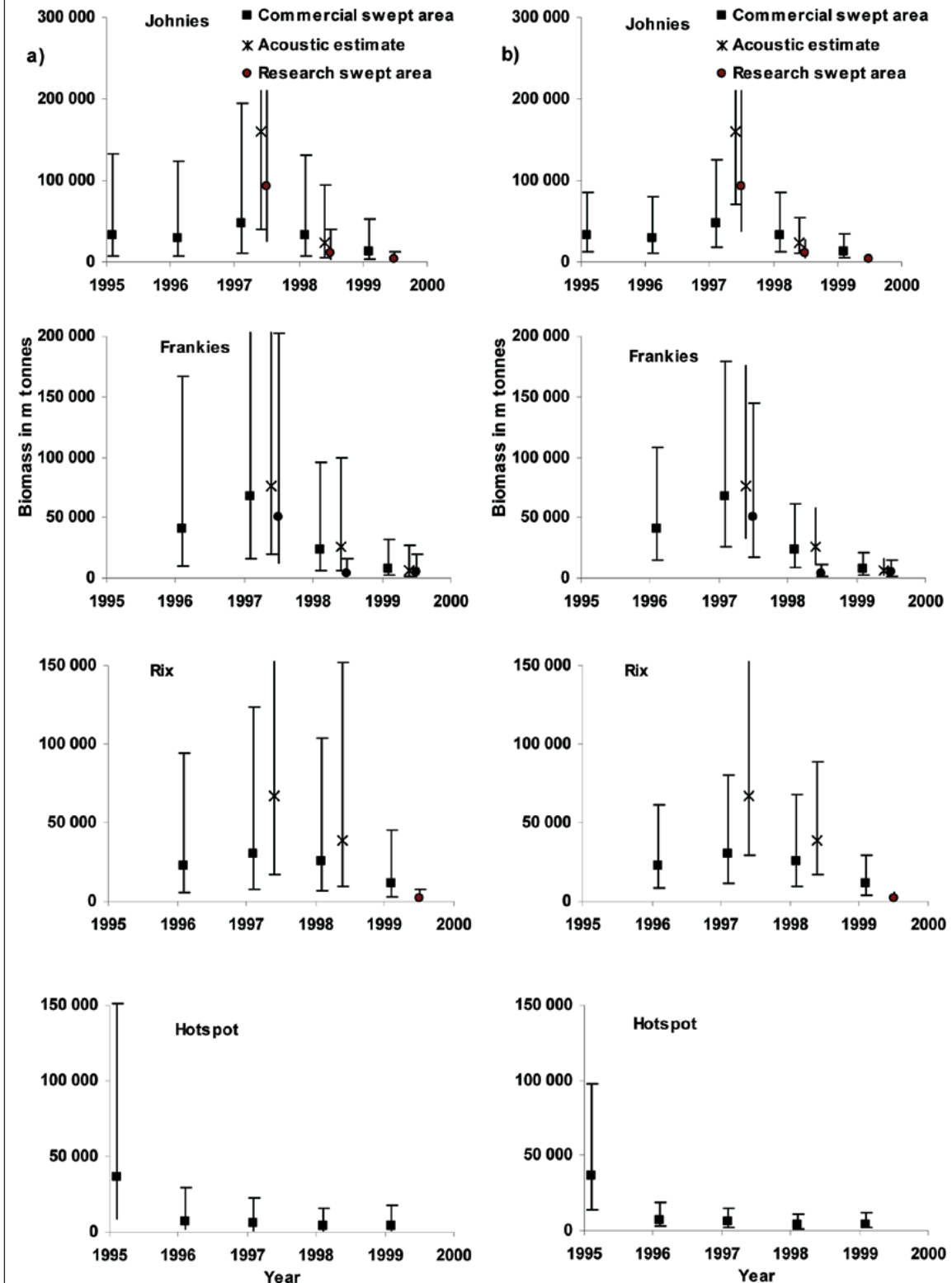
When structural uncertainty was accounted for, the only model that encompassed the rescaled indices within its posterior 95 percent probability intervals for stock biomass on all of the four fishing grounds was the mass emigration / mortality model (Figure 13.3). This model also suggested that current biomass on each of the four fishing grounds was very low.

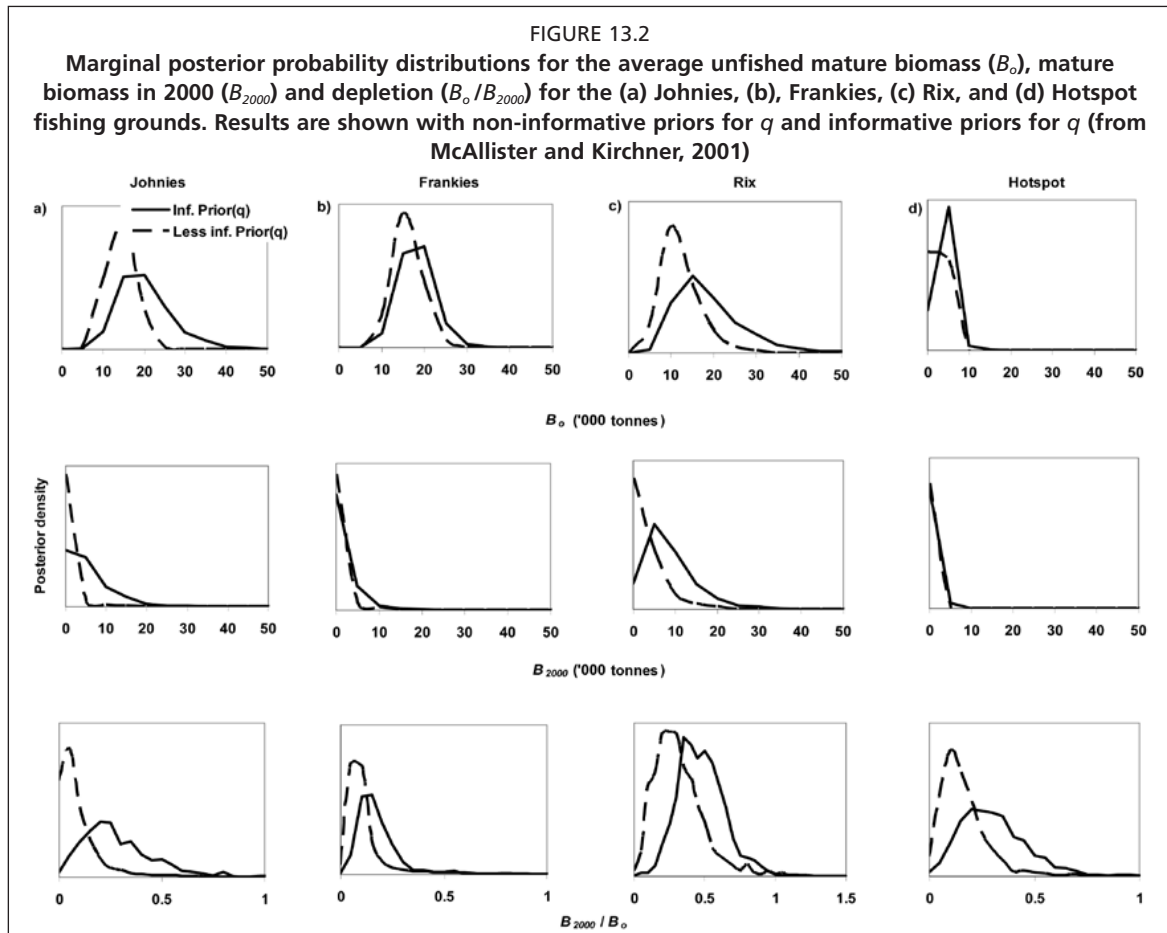
The use of decision analysis results in decision making

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 Johnnies, 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)





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_0 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_0 , 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.

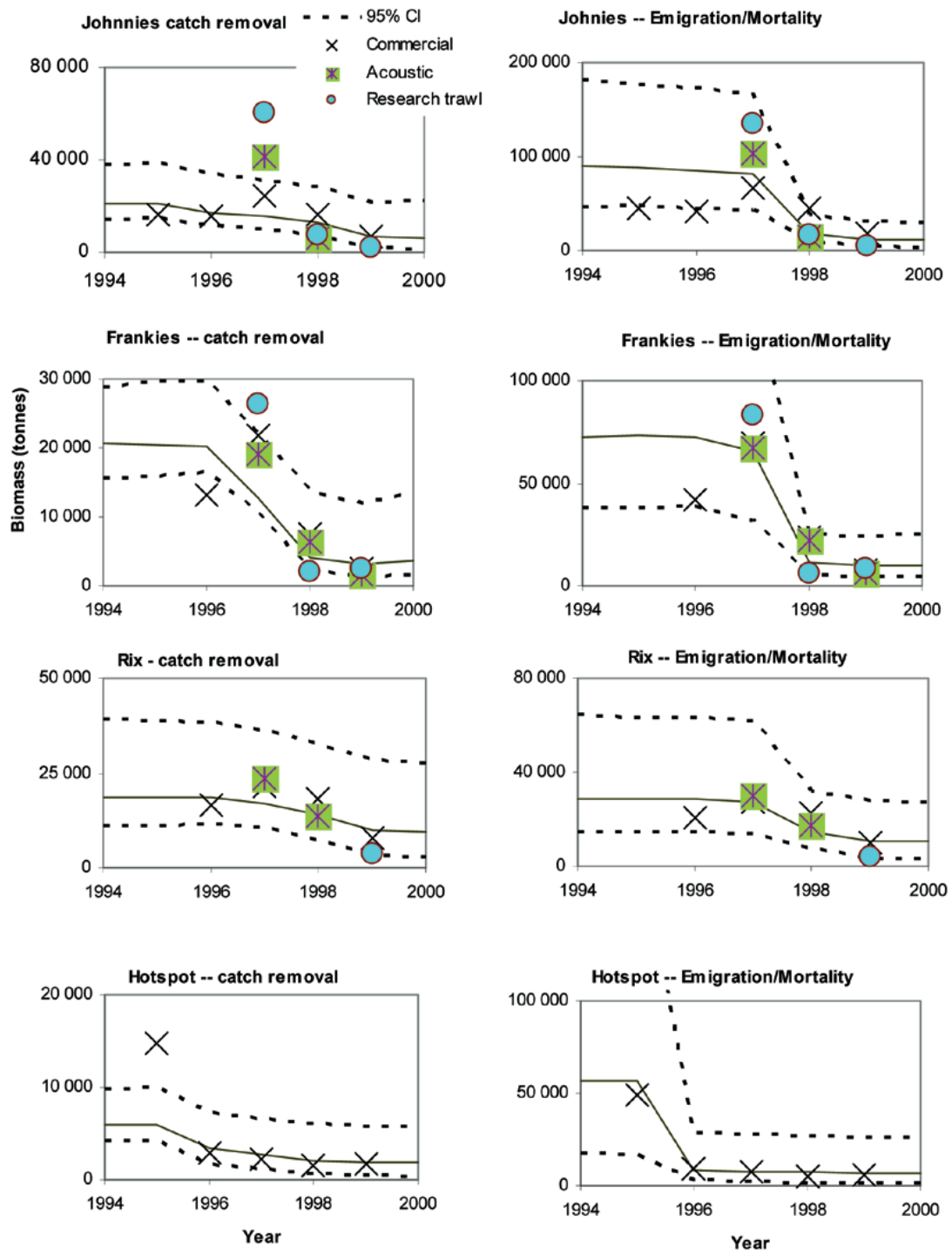
In the 2000 assessment, the declines had continued on the grounds remaining open. Only much smaller TACs, e.g., 1 500 tonnes combined across grounds, had less than a 50 percent chance of causing further decline on all of the fishing grounds. The cabinet followed this advice but made the provision that the TAC could be increased if orange roughly 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) Johnnies, (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%

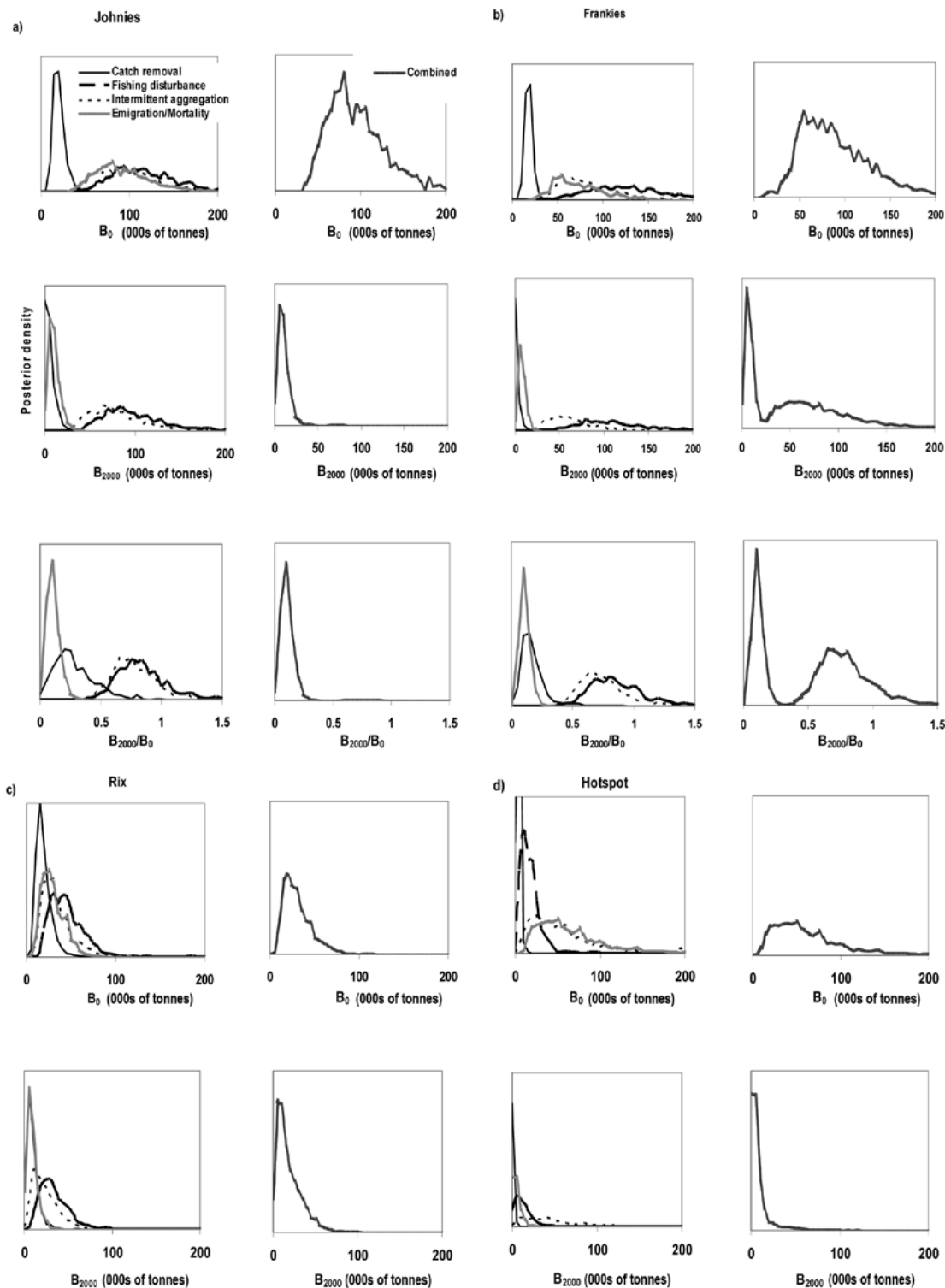
The estimates of risk from each of the structural alternatives could be presented in a single decision table (Hilborn, Pikitch and Francis, 1993; McAllister and Kirkwood, 1998b). For the sake of illustration, results are shown only for the Rix fishing ground (Table 13.5). This shows the four structural 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_0 . 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_0 < 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_0 . 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_0), mature biomass in 2000 (B_{2000}) and depletion (B_0/B_{2000}) for the (a) Johnnies, (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 led 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_0 . 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

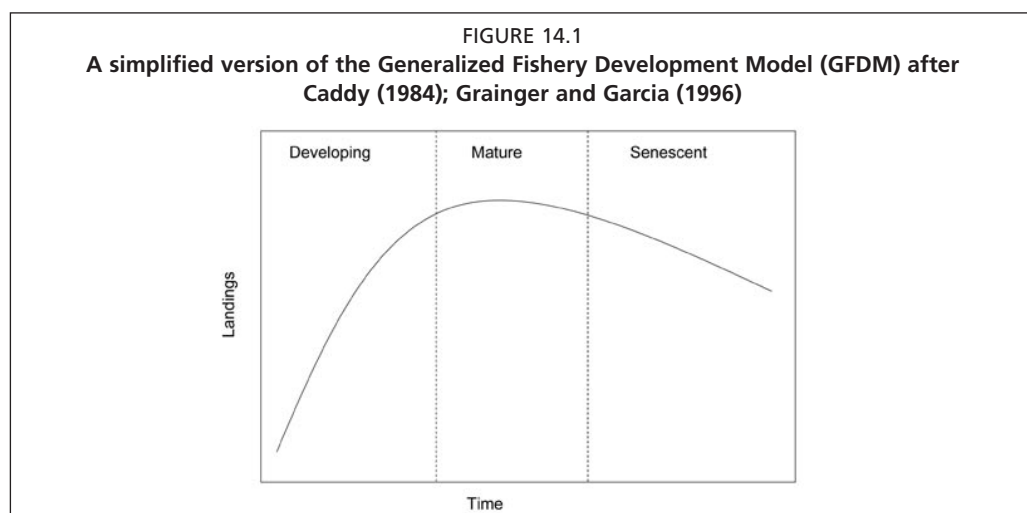
This section describes a number of approaches adopted or developed under FMSP projects for constructing empirical models to support fisheries management and development planning and evaluation. Unlike the *explanatory* or *process* types of models described in many of the previous sections, the models 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).



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:

$$r = (C_{t+1} - C_t) / C_t \quad (1)$$

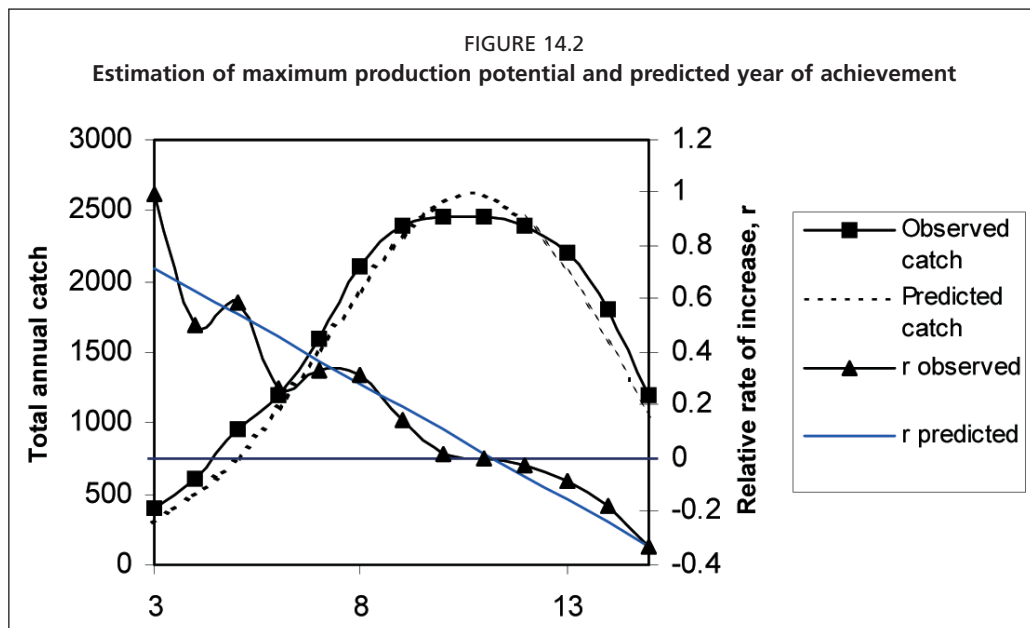
where $t = 1$ year.

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 ($t_{\max \text{ prod}} = -a/b$) 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):

$$r = (C_{t+1} - C_t) / C_t = bt + a \quad (2)$$

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:

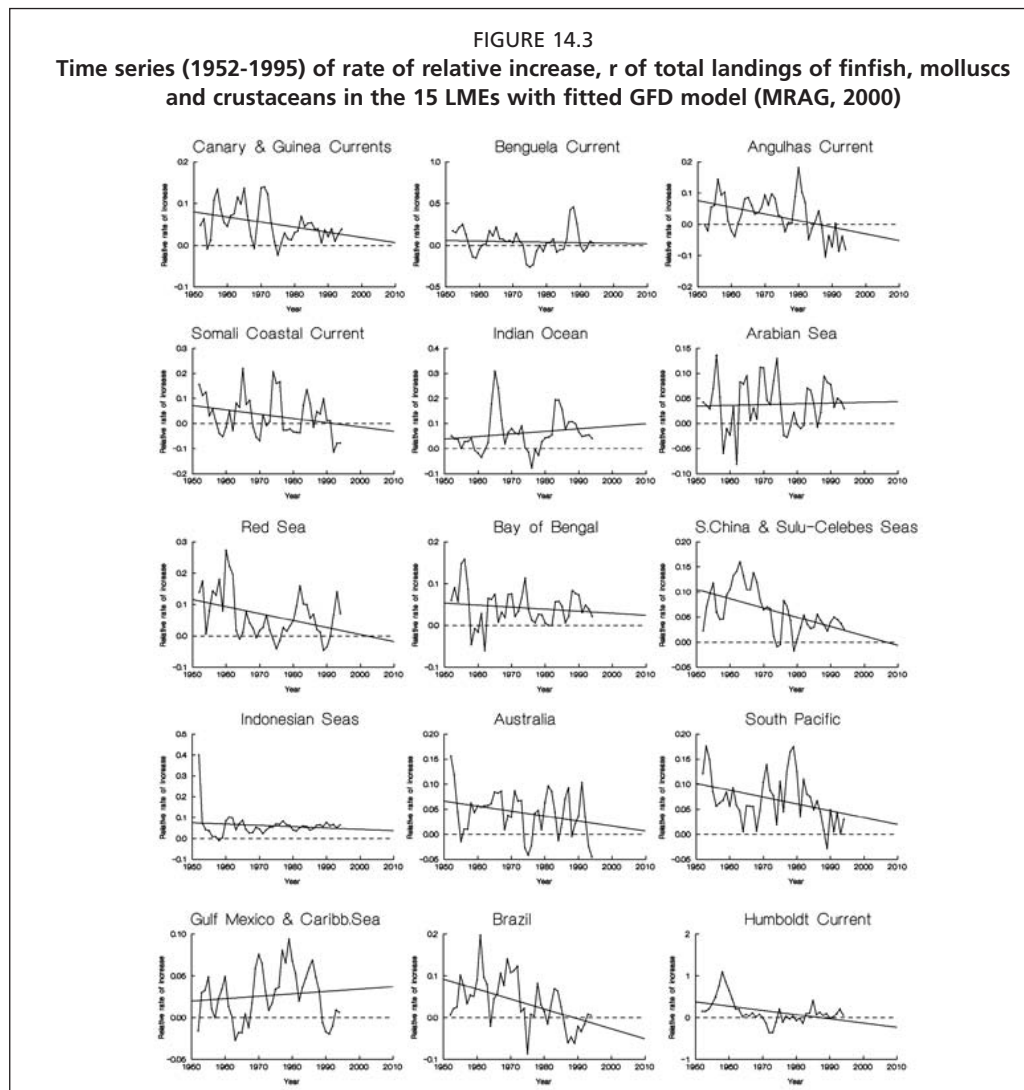
$$C_{t+1} = C_t (bt + a + 1) \quad (3)$$



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.



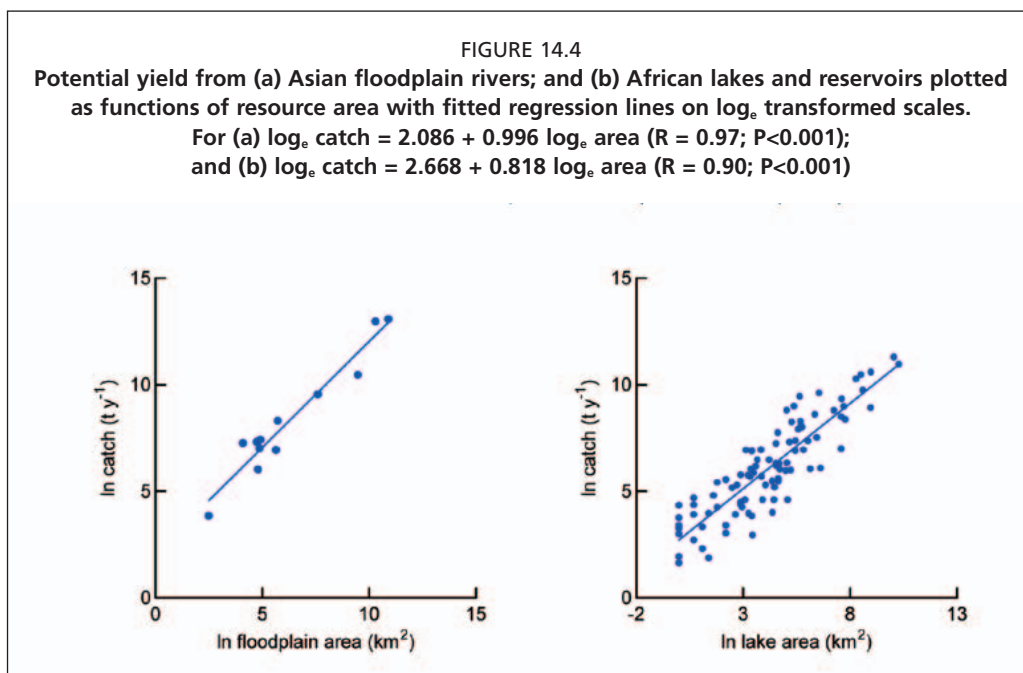
14.2 EMPIRICAL MULTISPECIES YIELD MODELS

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).



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 be 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).

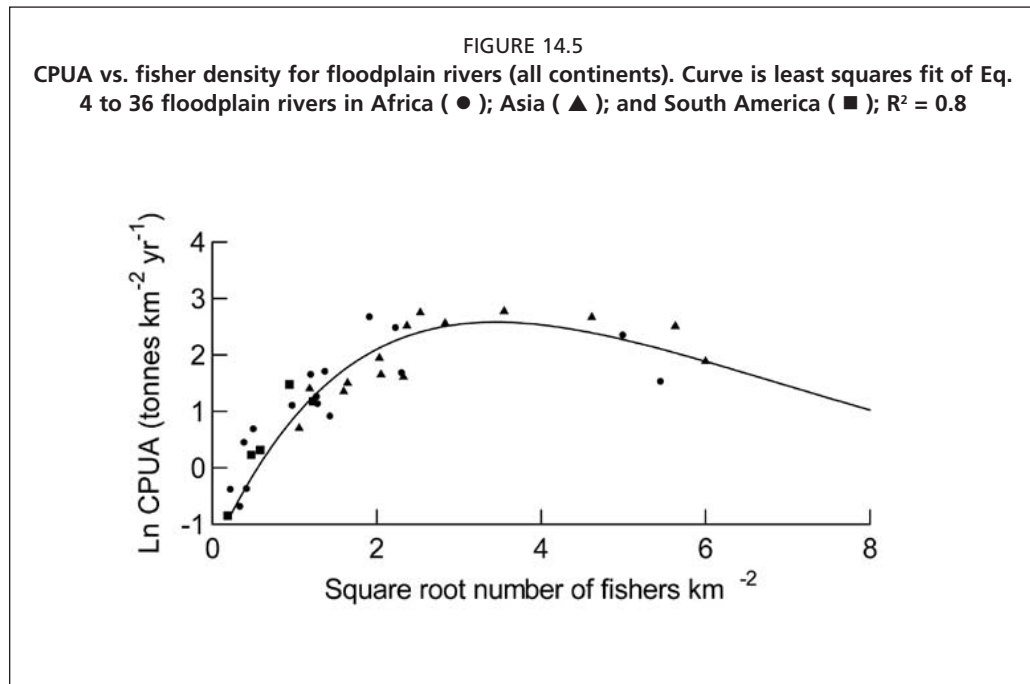
$$\ln(\text{Yield} + 1) = i^{0.5} \exp(a + bi^{0.5}) + c \quad (4)$$

in which i = fishing intensity and a , b and c are fitted constants.

Floodplain rivers

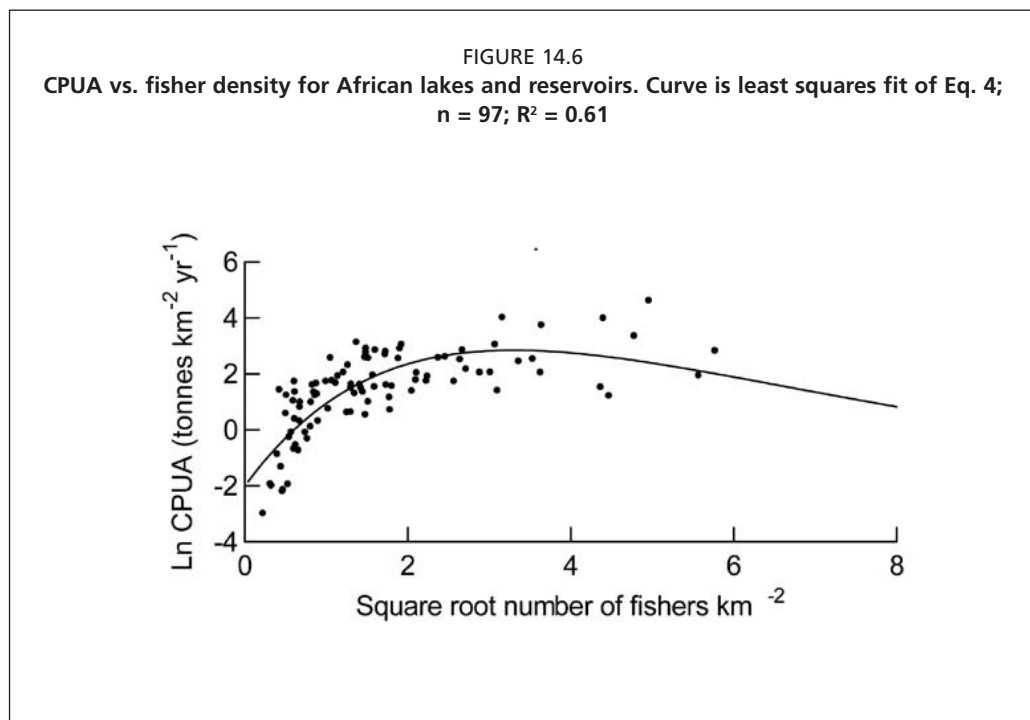
Based upon a combined data set for floodplain-rivers from all major continents examined,²³ the fit of Equation 4 is remarkably good (Figure 14.5). Fishing intensity explained 80 percent of the variation in CPUA (corrected $R^2 = 0.80$). The model predicts a maximum yield (MY) of 13.2 tonnes $\text{km}^{-2} \text{yr}^{-1}$ (95 percent CI [1.9, 225]) or 132 $\text{kg ha}^{-1} \text{yr}^{-1}$ at a fisher density, i_{MY} of approximately 12 fishers km^{-2} (95 percent CI [8.8, 17]).

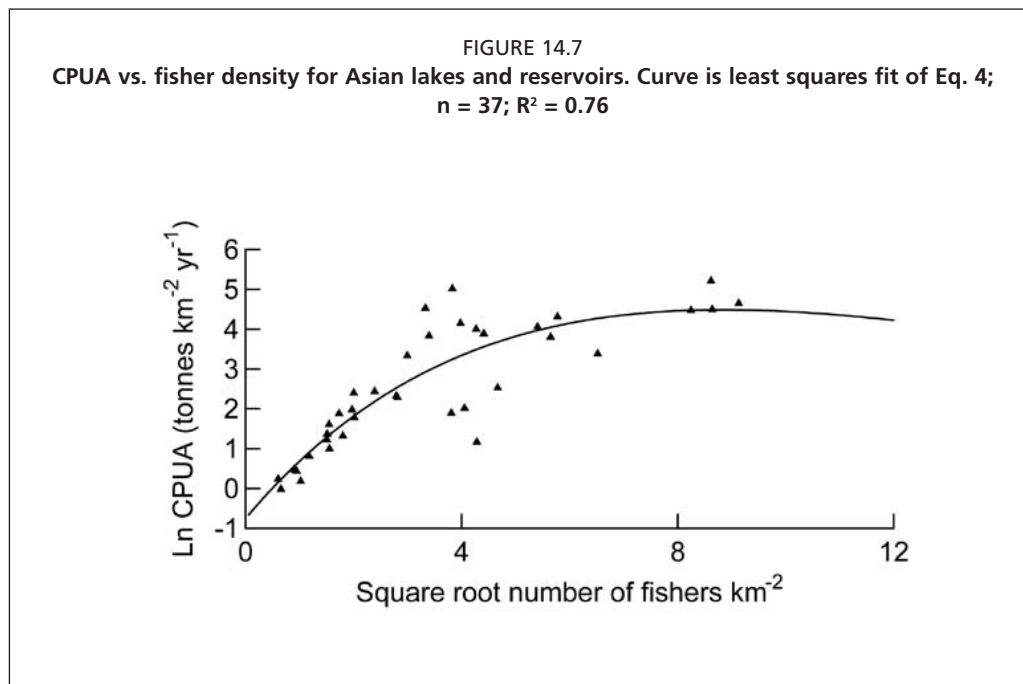
²³ Separately fitting the data for floodplain-rivers from Africa and Asia resulted in very similar curves whose coefficients could not be distinguished at $P = 0.05$. Insufficient data were available to test for differences between South American floodplain-rivers and those of other continents.



Lakes and reservoirs

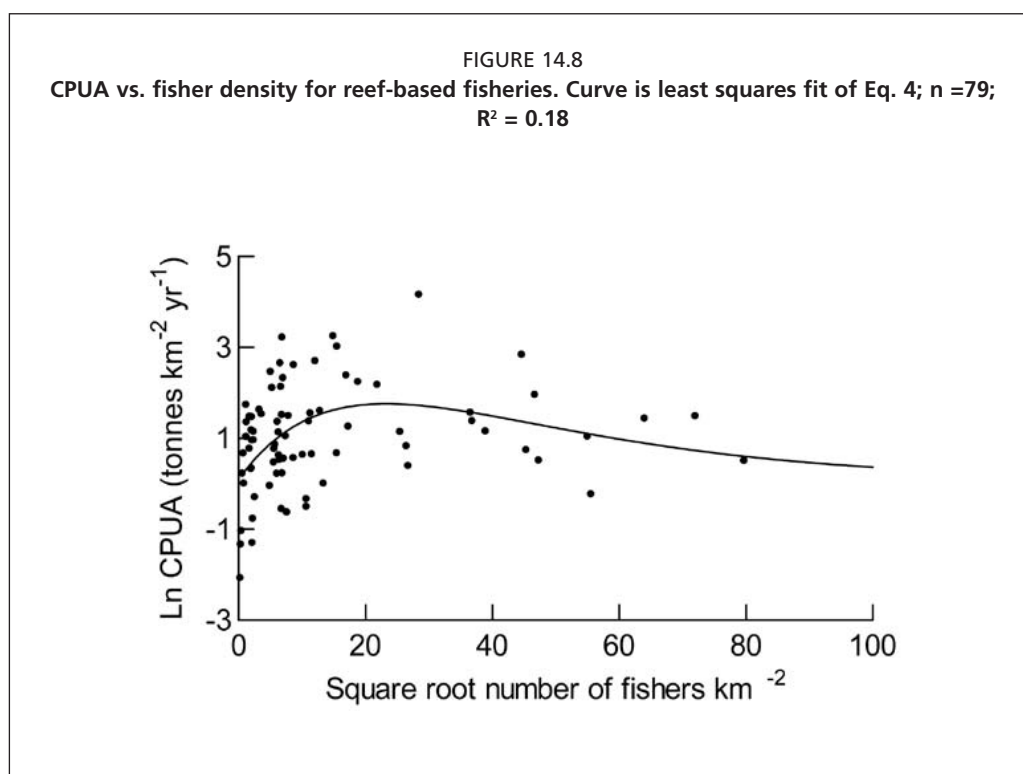
The parameters of Equation 4 were found to be significantly different for African and Asian lakes and reservoirs. The resulting curves (Figure 14.6 and Figure 14.7) imply that much higher yields (MY=880 kg ha⁻¹ y⁻¹) are achieved in Asian compared to African lakes (MY=172 kg ha⁻¹ y⁻¹) and they appear to be able to sustain much higher levels of fishing effort ($i_{MY}=78.3$ fishers km²) and ($i_{MY}=10.9$ fishers km²) 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.





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 $\text{km}^{-2} \text{yr}^{-1}$ (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 (iii) variation in the habitat covered by the term “reef”.



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 km² and 98 kg ha⁻¹ y⁻¹ compared to 10.9 fishers per km² 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)
External Decision-Making Arrangements	Sanctions for non compliance	Sanctions for non-compliance	0;1	No (0); yes (1)
	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)
Exogenous Factors	Effective coordinating body	Nested structure of co-management arrangements	0;1	Absent (0); Present (1)
	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.

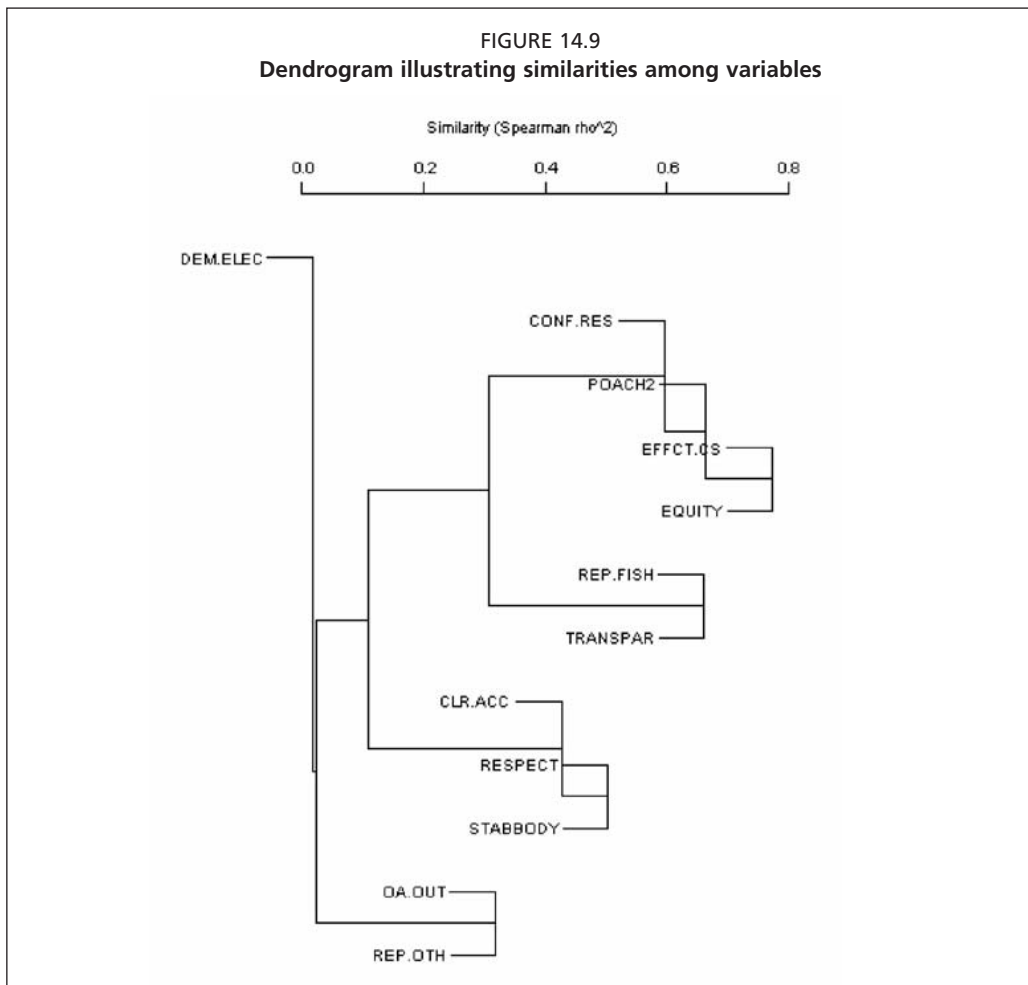
Dimension Reduction

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.

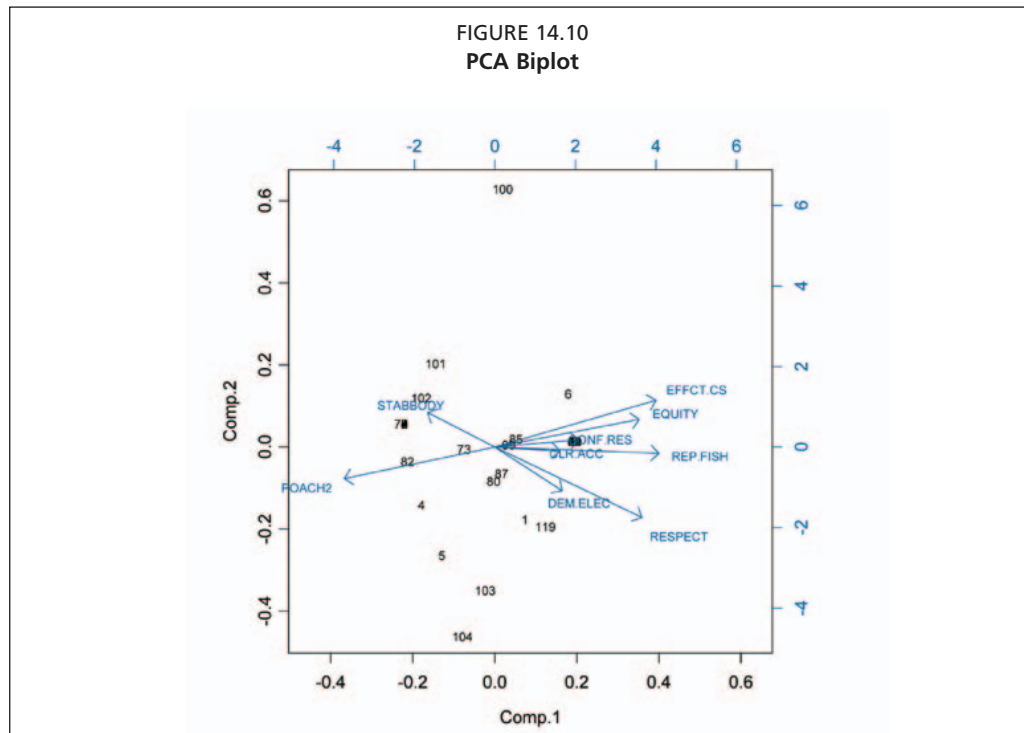
To illustrate the method, we present the results of analyses undertaken by project R7834 for one set of explanatory variables selected from the Decision-Making Arrangements group of variables. An outcome variable EQUITY (distributional equity among community members) was included with a view to having a prior look at how

it might depend on the attributes in this group. The dendrogram below summarizes the results.



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.



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 Approach²⁵

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:

$$y_{ijk} = \mu + \beta_1 x_{1i} + \beta_2 x_{2i} + r_{ij} + s_{ik} + \varepsilon_{ijk}, \quad i = 1, 2, \dots, n; \quad j = 1, 2, 3; \quad k = 1, 2, 3, 4$$

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 km² - 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; R²=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.

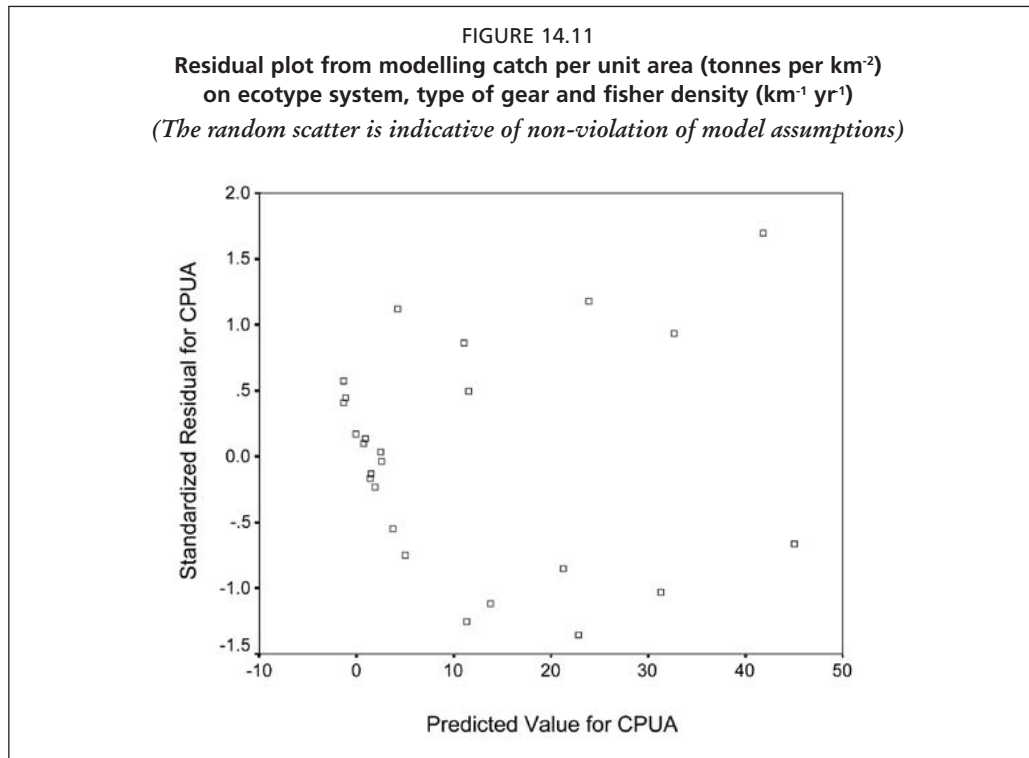
Each of the models in Table 14.3 were subjected to a residual analysis before they were regarded as being acceptable. We provide in Figure 14.11, an illustration of a residual plot for the second model shown in Table 14.3, i.e. the one where explanatory variables entering the model are ecosystem type, 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/m ² /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/m ² /year) (with ecotype and fisher density)	Low	0	7
		Medium	5.6	7
		High	20.8	4
2	GEARTYPE2, i.e. Type of gear (with ecotype and fisher density)	Gillnets	0	10
		Hook & Line or Speargun	-2.5	9
		Nets	16.4	3
		Traps or other	-0.91	3
3	HARM_GR, i.e. Destructive fishing practices? (with ecotype and fisher density)	No	19.8	11
		Yes	0	9
4	BAN_DRIV, i.e. Ban on fish drives (with ecotype)	No	0	19
		Yes	23.6	5
5	SIZE, i.e. landing size restrictions, and NUMB_RES, i.e. number of reserves, according to SIZE.	No	0	19
		Yes	15.5	3
		"Slope" for size=No "Slope" for size=Yes	-0.57 -2.90	-
6	MANG_TYP, i.e. Type of management and OA_COMM, i.e. if open or restricted access. (with ecotype and fisher density)	Govt.	0	6
		Co_mgt	15.4	5
		Self/Trad.	12.4	15
		Open Restricted	0 6.4	11 15
7	LOC_BODY, i.e. Local decision making body and OA_COMM, i.e. if open or restricted access. (with ecotype and fisher density)	Absent	0	6
		Present	15.0	20
		Open Restricted	0 6.4	11 15



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) models²⁶

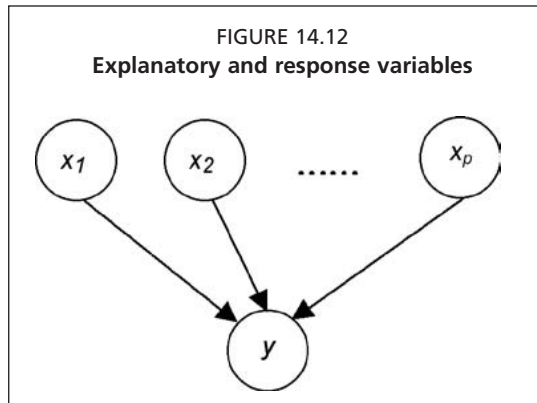
Bayesian Network (BN) models (Jensen, 2001; Cowell *et al.*, 1999; Pearl, 2000) are not statistical models in the usual sense, but rather, probabilistic expert systems that are specifically designed to model complex patterns of causality in the presence of stochastic uncertainty. A BN can be a powerful 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

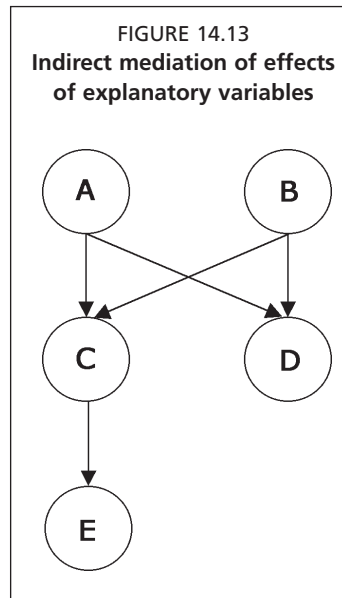
Perhaps the most familiar and general class of statistical models comprises those that seek to account for variation in a response variable y (which may be multivariate) in terms of a set of explanatory variables. This class includes all regression and generalized linear models. The relationships between the variables can be represented graphically as in Figure 14.12, an example of a graphical model.



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 14.5
CPT for Node C

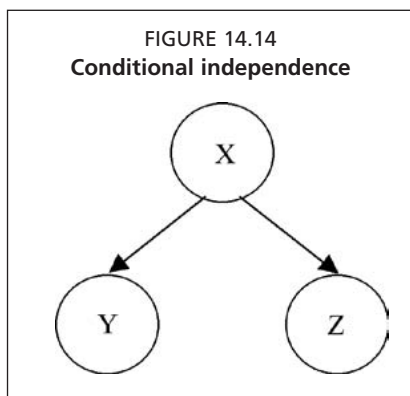
		C		Total
		F	T	
F	F	p_{000}	p_{001}	1
F	T	p_{010}	p_{011}	1
T	F	p_{100}	p_{101}	1
T	T	p_{110}	p_{111}	1

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.



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.

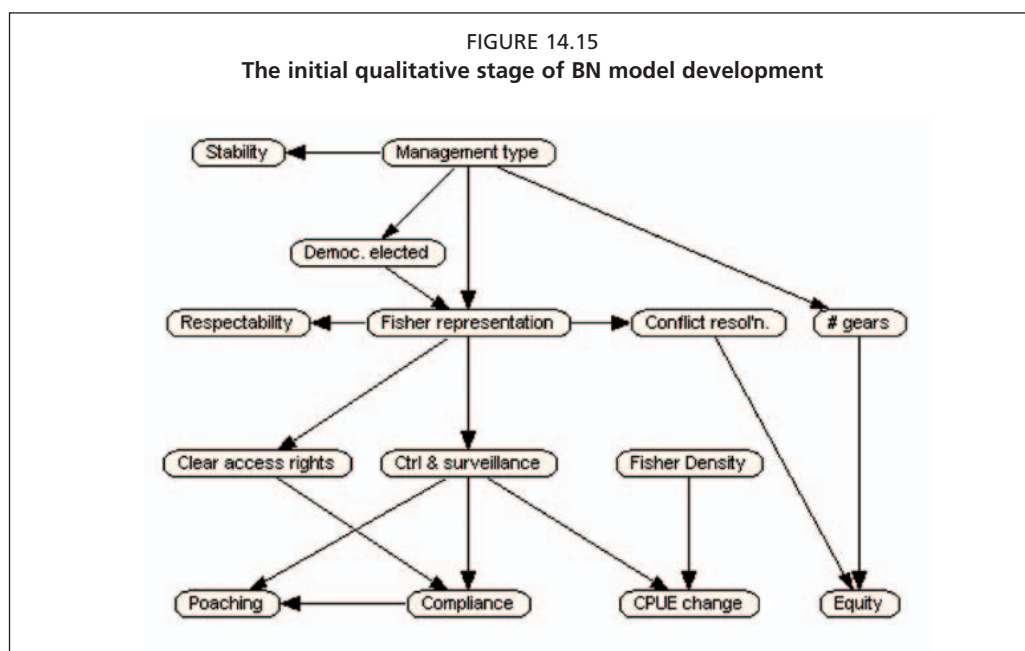


TABLE 14.6
Results of logistic regression analyses

Child node	Parent nodes	Deviance	d.f.	Signif., <i>P</i>
<i>Equity</i>	<i>Conflict resolution</i>	10.11	1	0.001
	<i># gears</i>	4.98	1	0.026
<i>CPUE chg.</i>	<i>Fisher density</i>	7.13	1	0.008
	<i>Ctrl & surveillance</i>	6.29	1	0.012
<i>Compliance</i>	<i>Clear access rights</i>	19.10	1	<0.0001
	<i>Ctrl & surveillance</i>	13.08	1	0.0003
<i>Poaching</i>	<i>Compliance</i>	20.13	1	<0.0001
	<i>Ctrl & surveillance</i>	3.90	1	0.048
<i>Ctrl & surveillance</i>	<i>Fisher representation</i>	41.87	1	<0.0001
<i>Clear access rights</i>	<i>Fisher representation</i>	18.10	1	<0.0001
<i>Fisher representation</i>	<i>Management type</i>	12.67	2	0.002
	<i>Democ. elected</i>	20.89	1	<0.0001
<i>Conflict resolution</i>	<i>Fisher representation</i>	43.05	1	<0.0001
<i># gears</i>	<i>Management type</i>	17.58	2	0.0002
<i>Democ. elected</i>	<i>Management type</i>	30.87	2	<0.0001
<i>Respectability</i>	<i>Fisher representation</i>	12.47	1	0.0004
<i>Stability</i>	<i>Management type</i>	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

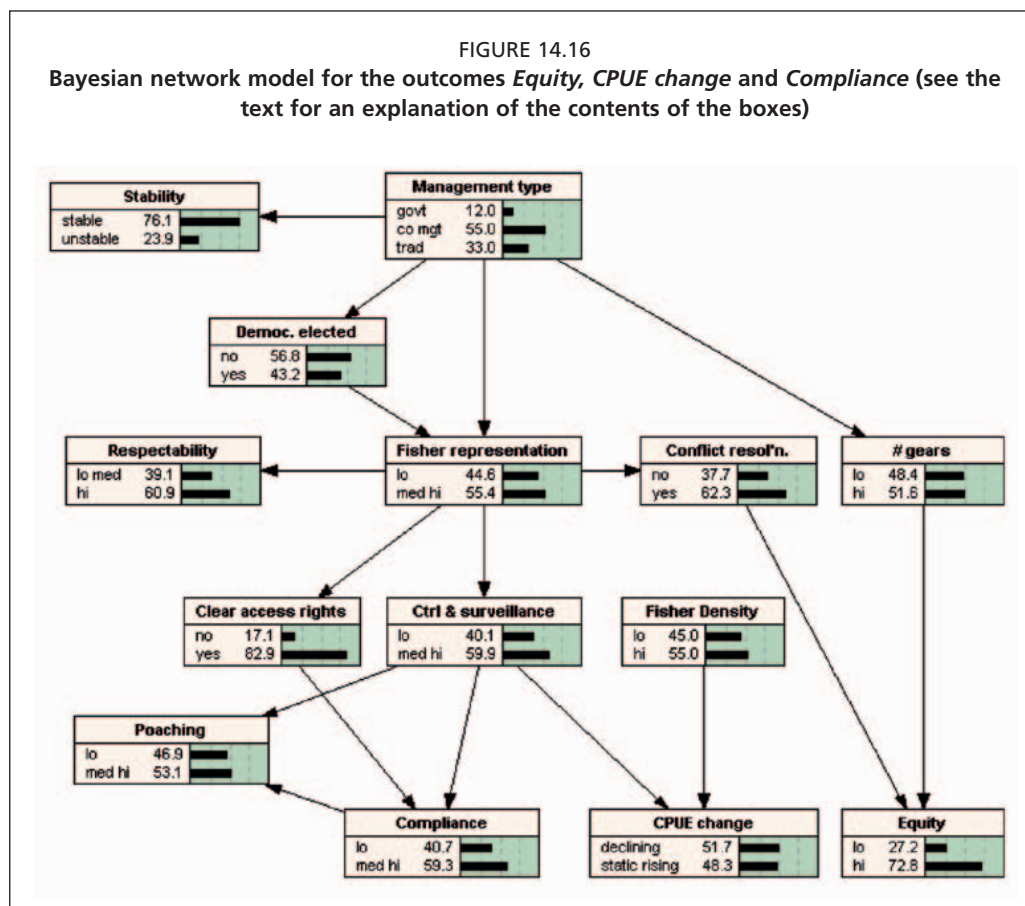
Fisher rep.	Conflict resolution	
	No	Yes
Low	0.77	0.23
Med/high	0.06	0.94

TABLE 14.8
Conditional probabilities for Fisher representation

Mg't. type	Dem. Elec.	Fisher representation	
		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

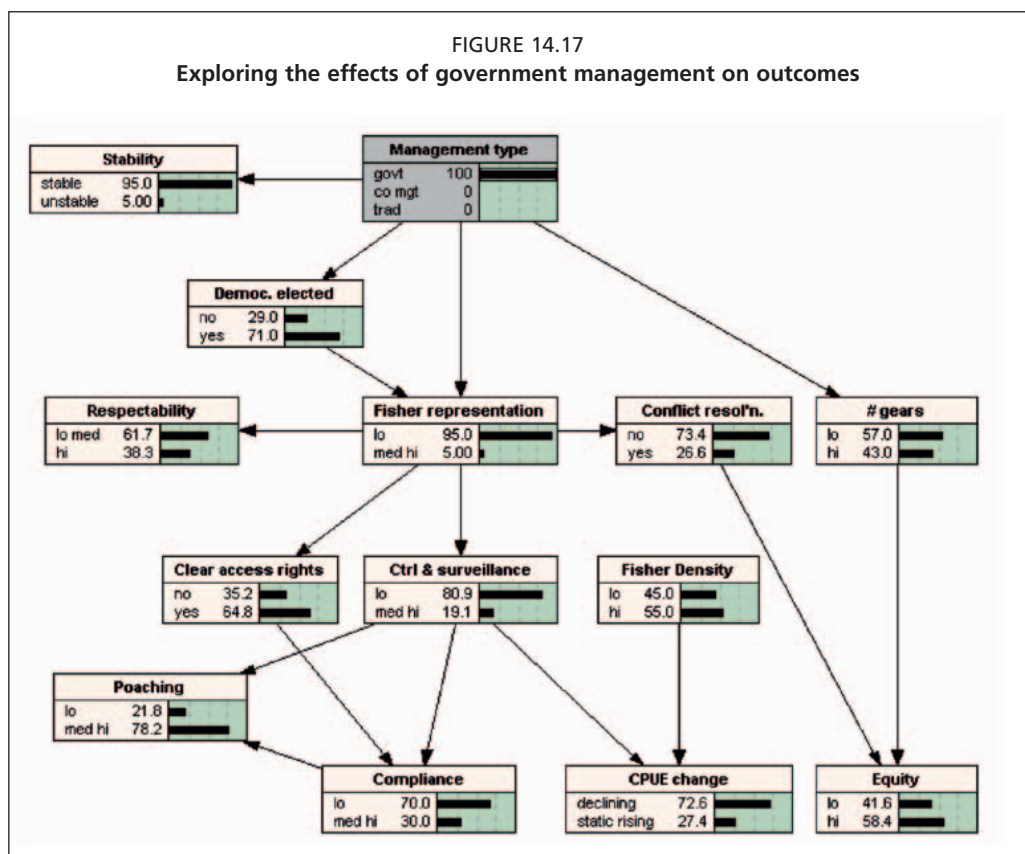
The representation of the model (output from the Netica software) in Figure 14.16 shows each node with probability bars (on a percentage scale). The initial values of these probabilities are the overall average “posterior” probabilities of the states of the nodes, as estimated from the data. The exceptions 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.



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

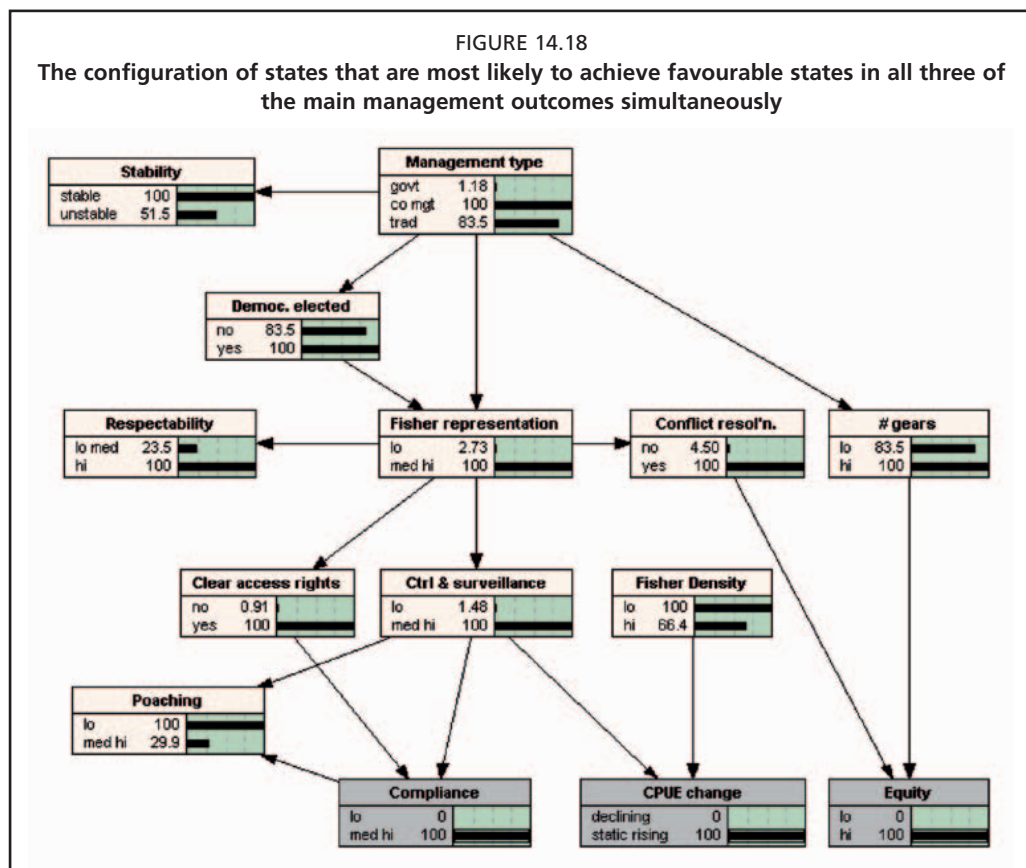
Outcome	Overall	Management type		
		Gov't.	Co-mg't.	Trad.
Equity (high)	73%	58%	80%	67%
CPUE change (static/rising)	48%	27%	50%	53%
Compliance (med/high)	59%	30%	62%	66%

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	Overall	Management type		
		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.



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: $Y = a + bx$, 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
In catch vs ln FPA	Asia	2.086	0.996	0.083	13	4.31	0.531	0.97	<0.001	MRAG (1993) /R5030
In catch vs ln length	Asia	-14.88	3.234	0.585	5	8.06	0.680	0.96	0.01	MRAG (1993) /R5030
In 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
In catch vs ln Area	Africa	2.668	0.818	0.042	94	4.34	1.131	0.90	<0.001	Halls (1999)
In catch vs ln Area (NS)	Africa	2.761	0.786	-	88	-	-	0.90	<0.001	MRAG (1995) /R6178
In catch vs ln Area (NS)	Asia	2.895	0.856	-	39	-	-	0.76	<0.001	MRAG (1995) /R6178
In catch vs ln Area (S)	Asia	4.545	0.552	-	25	-	-	0.76	<0.001	MRAG (1995) /R6178
In 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
In catch vs ln Area (NS)	Africa	2.274	0.876	-	45	-	-	0.91	<0.001	MRAG (1995) /R6178
In catch vs ln Area (S)	Asia	3.048	0.413	-	54	-	-	0.50	<0.001	MRAG (1995) /R6178
In catch vs ln Area (NS)	Asia	2.278	0.823	-	57	-	-	0.70	<0.001	MRAG (1995) /R6178
In 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
In catch vs ln Area	Africa	2.583	0.953	-	31	-	-	0.73	<0.001	MRAG (1995) /R6178
In catch vs ln Area	Asia	2.016	0.871	-	4	-	-	0.99	0.002	MRAG (1995) /R6178
In catch vs ln Area	S. America	1.626	0.920	-	32	-	-	0.72	<0.001	MRAG (1995) /R6178
In 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 (km²); length – river length (km); DBA, drainage basin area (km²); Area – lake or lagoon surface area (km²); Rainfall – Mean annual rainfall (mm y⁻¹); Total P – total surface phosphorus concentration (μg l⁻¹); Total N – total surface nitrogen concentration (μg l⁻¹); surface Chla – chlorophyll a concentration in the surface waters (μg l⁻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:

$$s\{\hat{Y}_{new}\} = \sqrt{s^2_{Y.X} \left(1 + \frac{1}{n}\right) + \frac{(X_i - \bar{X})^2}{(S_b)^2}}$$

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)

Variable Group	Explanatory Variable	Outcome Variables												
		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									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	
External Decision-Making Arrangements (Group V)	Formal performance monitoring by community?	1	1	1					Y		Y	Y		
	Sanctions for non compliance	1	1	1					1		Y	Y	Y	
	Enabling legislation for co-management	1	1	1					1	Y	Y	12	Y	
Exogenous Factors (Group VI)	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 recommended 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 recommended 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 Section 14.3 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.

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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