Tools for assessing data-limited fisheries and communicating stock status information

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Submitted by

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I declare that this thesis is my own account of my research and contains as its main content work which has not previously been submitted for a degree at any tertiary education institution.

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Emily Anna Fisher

Dedication

To my late grandpa
Jack E. Fisher
for the many happy memories
catching crabs off the quay
in Wells-next-the-sea
during my summer school holidays
and, of course,
for providing me with such a
great last name!

ABSTRACT

This PhD study was focused on developing and exploring tools for assessing the status of data-limited fish stocks.

A management strategy evaluation (MSE) framework was developed to explore the effectiveness of alternative strategies for managing fish stocks for which sufficient data are available to allow a catch curve-based assessment, but which lack the reliable time series data on catches and/or catch per unit of effort required for developing an integrated age-structured fishery model. Explorations using the operating model of this framework indicated that, particularly for demersal fish species with limited movements and which suffer high levels of post-release mortality, use of temporal closures throughout the full area of a fishery are likely to be more effective for reducing fishing mortality than reducing daily bag limits, imposing more restrictive size limits, or constraining the areas open to fishing. Implications of differences in biological characteristics of fish species, including longevity, annual recruitment variability and post-release mortality, for the effectiveness of different management controls were explored using the operating model.

The effectiveness of the graphical interface employed by the MSE model in communicating stock assessment information to fisheries managers and stakeholders was evaluated in a “scenario testing” study involving university students. Students viewed model outputs for several hypothetical fish stocks with different biological attributes and initial exploitation states. Based on their perception of the true status of each stock, students then “pulled” various alternative “management levers” available in the program. Analyses of data resulting from the study indicated that, provided the design was not overly complex, the interface of the MSE framework was effective for communicating stock assessment information. The results of the study illustrated the potential of this type of approach for evaluating and improving the effectiveness of the ways in which stock assessment information is communicated to fisheries managers and other stakeholders.

During the next project phase, several methods for estimating rates of mortality of fish stocks were developed and explored. Maximum likelihood estimates of total mortality, calculated assuming that the age composition of fully-recruited fish was drawn from a geometric distribution and that annual recruitment was variable, had lower root mean squared error (RMSE) than other estimates obtained using traditional methods of catch curve analysis that did not allow for such variability. This catch curve model, which also provided potentially valuable information on recruitment variability, was then extended to allow for a change in total mortality, as might result from a major change to management. Analyses demonstrated that, despite variability in annual recruitment, it was possible to distinguish such a change in mortality in the age composition data if the mortality change was of sufficient magnitude and adequate time had elapsed since the change in mortality. Bias in the estimates of mortality for the two periods was explored.

Next, a model was developed to provide estimates of mortality for fish species which undertake pronounced unidirectional, size-dependent movements during life, *e.g.* a size-dependent, offshore movement of fish to deeper water, when it is only possible to obtain representative samples of age and size compositions from the different areas and not for the overall population. The model was able to "disentangle" the similar, but slightly different, influences of mortality and movement on size and age data. Following simulation testing, the technique was applied to "real" data for a fish species in Western Australia (*Pseudocaranx georgianus*). The model fills a "void" for existing methods for such fish species, particularly if those species are of insufficient economic value to warrant an expensive, large-scale tagging program.

Areas in which the work presented in this thesis could be expanded are discussed in the light of some likely directions for future fisheries research relating to data-limited fisheries.

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COMMON ABBREVIATIONS

AFMA – Australian Fisheries Management Authority

ANOSIM – Analysis of similarity

BPH – Body proportional hypothesis

CV – Coefficient of variation

FAO – Food and Agricultural Organisation (of the United Nations)

FRDC – Fisheries Research and Development Corporation

MDS – Multi-dimensional scaling

MLE – Maximum-likelihood estimator

MLL – Minimum legal length (for retention)

MSC – Marine Stewardship Council

MSE – Management strategy evaluation

PERMANOVA – Permutational multivariate analysis of variance

PERMDISP – Permutational test of homogeneity of multivariate dispersions

RMSE – Root mean square error

SIMPER – Similarity percentage analysis

TAC – Total allowable catch

TL – Total length

WA – Western Australia

WAFIC – Western Australian Fishing Industry Council

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proof-reading and reference-checking during the final stages of writing this thesis, and in particular to the gorgeous Amanda Buckland for providing me with a place to stay on occasions when I was too tired to drive home after a late night in the office! Thank you to Dr Fiona Valesini (Murdoch University) and Prof Bob Clarke (Plymouth Marine Laboratory, UK) for providing expert statistical advice and help with using PRIMER, and to the Murdoch University students who participated in the scenario testing workshops and allowed me to include the data in my study. Thanks also to Dan French for letting me use the data he collected for silver trevally to test the movement model described in Chapter 5.

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CHAPTER 1

General introduction

1.1 Background

Fisheries for which the available information about exploited fish stocks is inadequate for providing managers with accurate and precise assessments of its state may be referred to as data-limited. These include developing fisheries, as well as fisheries that are already established but for which data are scarce, or of poor quality (Pilling *et al.*, 2008). Recreational fisheries often fit into the latter of these two categories and, as a consequence, their assessment and management can be extremely challenging (Brooks *et al.*, 2010). The large uncertainties associated with the state of many fish stocks that are targeted by the recreational sector are of growing concern to fisheries scientists (Cooke and Cowx, 2004).

As pointed out by Bentley and Stokes (2009), some fisheries may have an abundance of data, yet lack quality information. This is often because the methods used to extract information from the data produce inaccurate or imprecise estimates of parameters. Another issue with fisheries data is that it may lack sufficient contrast to reliably estimate stock assessment parameters (Scandol and Rowling, 2007). For the remainder of the thesis, the term “data-limited fisheries” will thus be used collectively to refer to fisheries for which there is a scarcity of available data and those for which there is a paucity of information.

This introductory chapter provides a general overview of fisheries management and describes some of the issues encountered by scientists when facing large uncertainties about the state of exploited resources, with particular focus on stock assessment and management of data-limited fisheries. It also presents an outline of the overall aims of the research undertaken for this PhD.

1.2 History of fisheries management

For many thousands of years, people have relied on the rich abundance of fish in the world’s oceans as a source of food and income. Because of the enormity of the oceans and the great potential fecundity of fish, this vast resource was long regarded as inexhaustible (Huxley, 1884). Today we know better. From the 1950s onwards, rapid population growth and advances in fishing technology has resulted in many traditional small-scale fisheries being developed into global commercial enterprises (Pauly *et al.*, 2003). The marked increase in fishing effort that followed caused widespread over-exploitation of fish stocks worldwide (Garcia *et al.*, 2005) and even led to some fisheries collapsing (Hutchings, 2000; Jackson *et al.*, 2001).

Despite early efforts to control global fishing pressures (McGoodwin, 1995; Roberts, 2007), it is widely recognised that fisheries management to date has largely failed to protect fish resources from over-exploitation (Pauly *et al.*, 2003; Caddy and Seijo, 2005; Garcia and Grainger, 2005). Various attempts have been made to explain the poor performance of fisheries management in the past (Botsford *et al.*, 1997; Buckworth, 1998). Many have suggested that it stems primarily from the failure to adequately explain and deal with the significant uncertainties inherent in fisheries (*e.g.* Ludwig *et al.*, 1993; Hilborn, 1997).

The main challenge for fisheries scientists and managers is to produce reliable estimates of the exploitation states of fish stocks, and make predictions about the effectiveness of alternative management options for helping ensure that fisheries remain sustainable and productive (Hilborn and Walters, 1992; Haddon, 2001). When considering the many biological and environmental factors that can affect the size and productivity of a fish stock, however, the difficulties associated with these seemingly straightforward tasks soon become very apparent. Like most other natural systems, fish populations are complex and highly stochastic and, as a result, it is virtually impossible to predict their dynamics in detail (Quinn and Deriso, 1999; Haddon, 2001). Over the last few decades, however, there has been a rapid development of new stock assessment approaches that enable scientists to explicitly account for uncertainty in advice to managers (Walters, 1998; Cooke, 1999; Punt and Donovan, 2007).

1.3 Dealing with uncertainty in fisheries

Uncertainties are everywhere in fisheries and their effect on the sustainability of exploited fish stocks has been widely underestimated in the past (Hilborn, 1997). In general, uncertainty reflects the probability that the data available for a fishery, estimates of mortality for a fish stock, or some component of a stock assessment model, may be inaccurate, imprecise or misleading (Harwood and Stokes, 2003). Uncertainty, in turn, creates risk which is the probability that a harmful outcome, such as the collapse of a fish stock, will occur as a consequence of an inadequate understanding of the exploited resource (Lane and Stephenson, 1998). To avoid the situation where fish stocks are being placed at risk of over-exploitation, there has been growing recognition of the need for reliable methods for quantifying and dealing with uncertainty in fisheries (Ludwig *et al.*, 1993; Hilborn, 1997).

Uncertainty has many different sources and the ways by which they have been classified in the literature varies extensively (Francis and Shotton, 1997; Charles, 1998; Harwood and Stokes, 2003). The most important uncertainties to consider for fisheries modelling and management are listed by Francis and Shotton (1997) as:

(1) *process error*, which arises as a consequence of natural variability inherent in fish populations,

(2) *observation error*, which arises from inaccuracies in the techniques used to sample fisheries resources and in the ways data are analysed,

(3) *model structure error*, which arises from a lack of understanding about the dynamics of the fishery being modelled,

(4) *parameter estimation error*, which arises from uncertainty about parameter estimates used in the model and whether they change over time, and

(5) *implementation error*, which arises from poor implementation of management measures and failure to adequately enforce fishing regulations.

The processes that lead to uncertainty in fisheries are relatively well understood and most uncertainties can be reduced through further study and, if resources permit, more extensive data collection (Fogarty *et al.*, 1996). A wide range of statistical methods have been developed for examining and quantifying different uncertainties, the majority of which are concerned with assessing impacts of uncertainties in model parameters and variables such as population abundance and mortality (Punt and Hilborn, 1997; Haddon, 2001). It is becoming increasingly accepted, however, that the best way to account for uncertainties is through the design of management itself (Punt, 2006). As a result, recent efforts in fisheries research have focused, to a large extent, on the development of novel approaches to management that are precautionary, adaptive and robust to uncertainties.

One fisheries management initiative that has received widespread attention in the last few decades is the precautionary approach (Richards and Maguire, 1998), which simply highlights the need for managers to act cautiously in the face of uncertainty (Hilborn, 1997). The underlying philosophy of this approach is to leave sufficient margins for error in the formulation of management strategies, and thereby reduce the risk of over-exploiting fish stocks (Garcia, 1994). It forces managers to account for uncertainty in decision-making by specifying biological reference points to be used as indicators of stock status (Gabriel and Mace, 1999; Caddy, 2002). Such reference points in fisheries management are often expressed either in terms of the rate of fishing mortality of the exploited stock, or the level of biomass of the spawning stock that is able to contribute towards future recruitment to the population (Smith *et al.*, 1993; Wetzel and Punt, 2011). Two commonly used types of biological reference points are the target reference point, at which the level of fishing mortality or spawning stock biomass should be kept to maximise production without jeopardising the sustainability of the resource, and the limit reference point, which should not be breached to avoid placing the stock at risk of collapse (Caddy and Mahon, 1995). Some also consider a threshold reference point that lays between the target and limit reference points and which represents the exploitation level at which actions need to be taken to avoid the limit being reached (Gabriel and Mace, 1999).

Most present day fisheries operate around some type of feedback framework, in which management actions are regularly adjusted to help ensure that the fisheries management objectives can be achieved (Walters and Martell, 2002; Butterworth, 2007). This use of feedback control in fisheries decision-making was first introduced through the development of an approach known as adaptive management, which directly addresses uncertainty and risk by aiming to increase the understanding of the dynamics of a fishery over time (Walters and Hilborn, 1978; Walters, 1986). Adaptive management can be passive, where the response of a system to management is monitored and management actions updated as new information about the fish stock becomes available, or active, where a set of management actions are implemented as experimental treatments in the exploited system and the outcomes of the alternative management actions are determined by analysis of the experimental data (Walters, 1986; Bundy, 1998). Despite being a valuable approach in theory, adaptive management is now commonly considered impractical as it is not only time-consuming and costly, but it also requires the cooperation of those involved in the fishery (Bundy, 1998; Walters and Martell, 2002). As a consequence, some of the more recent efforts in fisheries research have tended to focus on using computer simulation methods to explore the likely effectiveness of alternative management options (Cooke, 1999; Punt, 2003).

1.3.1 Management strategy evaluation

Rapid advances in computer technology during the last few decades have led to the development of a fisheries management approach referred to as management strategy evaluation or MSE (Schnute *et al.*, 2007). MSE involves the use of computer simulation models for evaluating the performance of different strategies for managing exploited fish stocks (*e.g.* Butterworth and Punt, 1999; Cooke, 1999). As stated in a review of MSE for Australian fisheries by Smith *et al.* (1999), the approach involves

(1) clearly specifying the management objectives to be achieved,
(2) turning the management objectives into easily measured, quantitative performance indicators,
(3) specifying alternative strategies for managing the resource,
(4) evaluating the effectiveness of each management strategy against the specified objectives, and
(5) communicating the results of the evaluation to decision-makers in a way that exposes the trade-offs in performance of the different strategies across the various management objectives.

An important feature of MSE is that it attempts to evaluate the effectiveness of all the different aspects of the management strategy, from sampling and monitoring strategies, through to stock assessment, decision-making and implementation of management measures (Kell *et al.*, 2005; Dichmont *et al.*, 2006). The approach is valuable especially because of its emphasis on the need to identify and model key uncertainties in the various components of the evaluation process and determine how these may influence the robustness of each of the strategies for satisfying the specified objectives (*e.g.* Smith *et al.*, 1999; Kell *et al.*, 2007).

MSE is widely recognised as a valuable tool for helping managers and other fisheries stakeholders reach agreement when formulating new fisheries management plans in the face of large uncertainties (Smith, 1993; Schnute *et al.*, 2007) and the approach has been successfully applied to the management of a number of important fisheries throughout the world (*e.g.* Punt *et al.*, 2002; Kell *et al.*, 2005; Ianelli *et al.*, 2011). Because of the inherent complexities of MSE and its high demands of resources, however, both with regards to data requirements and the time and expertise required for model development (Smith *et al.*, 1999), use of the approach to date has mainly been restricted to commercial fisheries with large economic value (*e.g.* Polacheck *et al.*, 1999; Punt *et al.*, 2005; Dichmont *et al.*, 2006).

1.4 Data limitations in recreational fisheries

One type of data-limited fisheries that has received an increasing amount of attention in the last decade is recreational fisheries (Cooke and Cowx, 2004; Arlinghaus *et al.*, 2010a). Contrary to the early view of the recreational sector being of low social and economic value, a relatively recent national survey of recreational fishing in Australia, for example, estimated that 3.36 million residents of an age of five or older had fished at least once in the previous year, which translates into a participation rate of close to 20% (Henry and Lyle, 2003). Moreover, such surveys have demonstrated that the economic value of recreational fisheries can be substantial. In the case of the Australian study, an estimated 511,000 boats, worth a total of $3.3 billion, are being used annually for recreational fishing activities (Henry and Lyle, 2003). The importance of recreational fishing has also been highlighted by research in various other parts of the world, such as in Canada (Post *et al.*, 2002), Germany (Steffens and Winkel, 2002), the UK (Aprahamian *et al.*, 2010) and Scandinavia (Toivonen *et al.*, 2004; Salmi *et al.*, 2008).

As a consequence of a significant recent expansion of the recreational fishing sector in many parts of the world, with a growing number of boats and an increasing ability of fishers to locate fish using new technologies, fishing pressure on many recreationally targeted fish stocks is likely to now be substantial (Post *et al.*, 2002; Coleman *et al.*, 2004; Cooke and Cowx, 2004). Indeed, in a number of countries worldwide, the catches of fish taken by the recreational sector make up a large component of the total annual catches landed (Griffiths and Lamberth, 2002; Coleman *et al.*, 2004; Cooke and Cowx, 2006). Despite the potential impacts that this sector may have on global fish stocks, however, the data available for assessments and management of recreational fisheries are often scarce (Arlinghaus, 2005; Cooke and Cowx, 2006). In contrast to commercial fisheries, for which long time series of fisheries catch and effort data are readily available from fishers' logbooks (Chen *et al.*, 2003), such data for the recreational sector are often limited to estimates obtained from infrequent creel surveys (Brouwer *et al.*, 1997).

Recreational fisheries are often characterised by a large number of participants with widespread access to the resource, making the collection of reliable catch data extremely challenging (Murray-Jones and Steffe, 2000; McPhee *et al.*, 2002). Furthermore, because fishing efficiency may vary considerably among individual fishers, owing to differences in skills and equipment, accurate estimates of recreational fishing effort are difficult to obtain (Rijnsdorp *et al.*, 2006). The lack of data available for recreational fisheries increases the uncertainty associated with stock assessments and, as a consequence, also heightens the risk of making inappropriate management decisions (Murray-Jones and Steffe, 2000).

1.4.1 Assessing and managing data-limited fisheries

The key to successfully managing any fishery is to develop an understanding of the underlying dynamics of the resources being exploited (Hilborn and Walters, 1992; Chen *et al.*, 2003). This can be achieved by fitting mathematical models to fisheries data and estimating parameters that describe the various biological processes that influence the exploited fish stock (Quinn and Deriso, 1999). In order to obtain reliable estimates of such parameters, it is fundamental that the data to which models are fitted are representative of the fish population from which they were sampled (Murphy, 1997; Miranda, 2007). Although most fisheries stock assessment methods assume that each sampled fish represents a random and independent observation from the underlying fish stock (Hilborn and Walters, 1992; Murphy, 1997), this assumption is very difficult to fully satisfy. Because of the large costs associated with the collection of data, in particular when employing fishery-independent sampling methods (Kimura and Somerton, 2006), scientists working with recreational fisheries are often forced to work with data that are far less representative than would be desirable.

Stock assessments for data-limited recreational and smaller commercial fisheries commonly rely on basic information about the biological characteristics of the targeted fish species, and age and length composition data obtained by sampling the catches taken by fishers (*e.g.* Wise *et al.*, 2007; Wayte and Klaer, 2010). Consequently, assessments for these fisheries are mainly focused on the use of relatively simple mortality-based methods, such as catch curve and per-recruit analyses, which have limited data requirements (Dowling *et al.*, 2008; Coulson *et al.*, 2009; Wayte and Klaer, 2010). Despite the importance of such analyses for stock assessments of data-limited fisheries, there are many reasons why they should be used with much caution (Schnute and Haigh, 2007).

Catch curve and per-recruit analyses are based on a number of assumptions, the most significant being that the fish population is in an equilibrium state (Quinn and Deriso, 1999). More specifically, these methods commonly assume that recruitment to the fishery is constant over time and that the mortality rate is equal for all fish of ages greater than that at which they become fully vulnerable to the fishing gear (Hilborn and Walters, 1992). In reality, these assumptions can be extremely difficult to satisfy. For example, the recruitment of many fish species is known to fluctuate substantially between years (Myers, 1991; Hamer and Jenkins, 2004; Ianelli, 2005) and the selectivity of fish is often logistic rather than "knife-edge" (Wayte and Klaer, 2010; Thorson and Prager, 2011). Thus, one of the greatest challenges to the management of data-limited fisheries is to develop assessment methods that are capable of providing reliable estimates of mortality for fish stocks when equilibrium conditions cannot be satisfied.

In contrast to the management of most large-scale commercial fisheries, for which decision-making frameworks are often in place to assist managers with regulating the exploitation of stocks as new information about their states becomes available, management decisions for recreational fisheries have commonly been undertaken in a largely *ad hoc* manner (McPhee *et al.*, 2002). In the face of limited data, management of small-scale fisheries is often based on qualitative, as well as quantitative, stock status information to help account for the large uncertainties associated with the exploitation states of targeted fish stocks (Scandol, 2005). For example, employing what is often referred to as a "weight-of-evidence" approach, advice to managers for such fisheries in Australia commonly constitutes results from catch curve and per-recruit analyses, combined with subjective information regarding levels of risk associated with various identified threats to the fish stocks (Wise *et al.*, 2007; Scandol *et al.*, 2009).

Another key characteristic of recreational fisheries is that the management objectives can differ markedly from those for commercial fisheries. Rather than simply seeking to maximise fishery yields and profits, as in a commercial fishery, the motivations of recreational fishers to go fishing may vary widely. For example, people may fish recreationally for relaxation or as a way to spend time with family and friends, or to participate in competitions for catching (and then possibly releasing) large, trophy-sized fish (Clavert, 2002; Ditton, 2008). Recreational fisheries are also unique in that they are often managed in a different way to commercial fisheries, employing a combination of management controls that range from temporal and spatial closures to bag and boat limits, size restrictions and catch quotas (Bartholomew and Bohnsack, 2005). As a consequence, MSE models that have been developed and successfully applied to many commercial fisheries are often not directly applicable to the recreational sector. To manage the complexity inherent in recreational fisheries, there is a need to develop robust management strategies that not only satisfy the objective of conserving the exploited resource, but also achieve this in a way that is preferred by the fishers themselves (Arlinghaus *et al.*, 2010a).

1.5 Research objectives

In general, the research undertaken for this thesis is focused on the development and testing of methods and strategies for assessing and managing data-limited recreational and small-scale commercial fisheries. The first phase of the study involved the development of a MSE framework, which was employed to address the first two of the following objectives of this PhD research:

(1) To evaluate, using the operating model of the developed MSE framework, the likely effectiveness of a range of management controls common to recreational fisheries for reducing fishing mortality of exploited fish stocks, and explore the

implications of differences in the biological characteristics of fish species for the value of these controls (Chapter 2).

(2) To explore, using a scenario testing approach with groups of university students, the effectiveness of the user interface of the MSE model for communicating stock status information to people with limited technical stock assessment knowledge (Chapter 3).

(3) To test, using simulation, the robustness of different types of catch curve analyses for estimating mortality of fish stocks. Two catch curve models are described; a catch curve which allows for inter-annual variability in recruitment to a fish stock, and a catch curve which allows for a change in mortality of fish as could result from the implementation of more stringent management measures (Chapter 4).

(4) To develop and test a model for estimating mortality of fish species which undertake a pronounced, size-dependent movement from inshore to offshore waters. The model was also fitted to real data for silver trevally *Pseudocaranx georgianus* to provide, for the first time, estimates of mortality for this species in the two main environments in south-western Australia in which it is exploited (Chapter 5).

CHAPTER 2

Evaluating the effectiveness of alternative management controls for recreational fisheries

2.1 Introduction

It is now widely accepted that management strategy evaluation (MSE) constitutes a valuable tool for exploring the implications of uncertainties in fisheries and accounting for these in decision-making (Smith, 1993; Sainsbury *et al.*, 2000). A key characteristic of the MSE modelling framework is that it distinguishes between the true state of a natural system and that perceived through monitoring and assessment (Kell *et al.*, 2005; Dichmont *et al.*, 2006). The true system is represented by an operating model, which simulates the dynamics of the fish stock and its fishery, as well as interactions between them (Butterworth and Punt, 1999; Rademeyer *et al.*, 2007). An operating model needs to be sufficiently complex to capture the key aspects of the simulated system and allow the consequences of different assumptions about the true dynamics of the system to be evaluated (Kell *et al.*, 2007; Ianelli *et al.*, 2011). The latter is especially important in situations where relevant data may be limited or lacking, which is true for many recreational fisheries.

In general, the term management strategy (or harvest strategy) is used to describe, collectively, the different processes that contribute to the management of a fisheries resource (Sainsbury *et al.*, 2000; Dichmont *et al.*, 2006; Smith *et al.*, 2008). A management strategy comprises three main elements:

(1) an observation model which represents the data collected from the fish resource and its associated fishery,

(2) an assessment model which uses the data to assess the state of the resource, and

(3) a decision rule which is used to adjust management given the perceived state of the resource that results from the stock assessment.

The final element of the management strategy also commonly includes an implementation model that simulates the effects of chosen management actions on the fish stock and the fishery (Sainsbury *et al.*, 2000). An outline of a typical MSE framework and its core components is illustrated in Fig. 2.1.

The MSE approach to date has been limited mainly to large-scale, commercial fisheries, which typically have adequate data for the application of sophisticated, integrated stock assessment models (*e.g.* Polacheck *et al.*, 1999; Ianelli *et al.*, 2011). In Australia, for example, the Australian Fisheries Management Authority (AFMA) has applied the approach to manage fisheries for southern bluefin tuna, eastern gemfish, orange roughy, eastern tuna and billfish and southern sharks (Smith *et al.*, 1999). MSE models produced for such fisheries are typically not well suited to the types of data and stock assessment methods used for managing recreational fisheries.

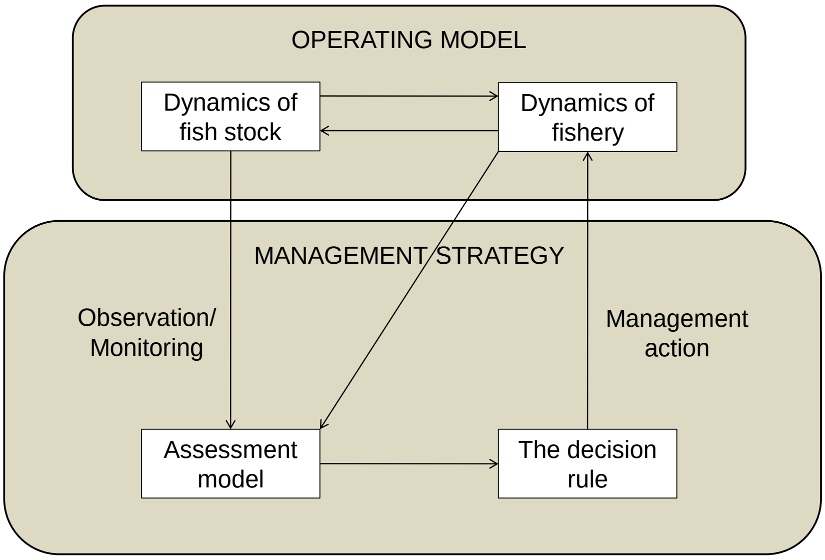


Fig. 2.1. Schematic overview of the traditional MSE model framework and the different components of the operating model and the management strategy. Modified from Kell *et al.* (2005) and Dichmont *et al.* (2006).

The evaluation of management strategies for the recreational sector is challenging because reliable data for such fisheries are difficult and expensive to collect, and management controls often need to be directed towards individual fishers rather than the fishing sector as a whole, *e.g.* using bag limits.

This chapter provides a description of the MSE model that was developed as a part of this PhD and which is relevant to many small-scale fisheries worldwide, for which there is often a paucity of data for use in stock assessments. The model is widely applicable to fish species for which available data are limited to the types of information obtained from a typical biological study (*e.g.* estimates of growth and maturity parameters) and age and length composition data obtained using fishery-dependent and/or fishery-independent sampling methods. While the full MSE framework is described (and was applied to address another objective of this PhD research in Chapter 3), only the synthetic data from the operating model of the MSE was used in the current study. Specifically, the operating model was applied to explore the effectiveness of different management controls common to recreational fisheries (*i.e.* a bag/boat limit, a minimum legal length (MLL) for retention, and temporal and spatial closures) for regulating the exploitation of fish stocks. In particular, simulations were undertaken to evaluate:

(1) The extent to which the effectiveness of the management controls for reducing fishing mortality of a fish stock is influenced by the type of the control and the magnitude of change to the control that is implemented.

(2) The extent to which the effectiveness of each management control for reducing fishing mortality of a fish stock is influenced by the biological characteristics of the species that is being managed. In particular, this will depend on:

    a. the susceptibility of the fish species to high post-release mortality, and
    b. the magnitude of variability in annual recruitment to the fish stock.

2.2 Overview of MSE model

The MSE simulation model is a single-species, single-area, and sex-, length- and age-structured model that can be used to predict the effectiveness of several fisheries management controls. It employs an annual time step, which is assumed to start midway through the main spawning period of the fish species. In accordance with the general MSE framework, the model consists of two core components, namely the operating model and the management strategy. The operating model simulates the population dynamics of the fish stock and estimates the effects of the different management controls on fishing effort and on the catches taken by the fishery. The simulated fish stock is considered to be a single, spatially homogenous entity and it is assumed that fishers are randomly distributed across the area of the fishery. As a singles-species model, it also makes the assumption that no explicit interactions with other species influence the dynamics of the fishery. The model keeps track of the relative numbers of fish in the population by their age, length and sex, and reflects the key biological processes characteristic of the simulated fish stock, such as recruitment, growth and mortality. Although not explored in this study, the operating model also explicitly accounts for the probability of sex change in functionally hermaphroditic fish species, thus making it applicable to protogynous (female to male sex change) and protandrous (male to female sex change) hermaphrodites, as well as to gonochoristic (separate sexes) species.

The operating model simulates the combined effects of a number of input and output management controls on the exploited resource. These include bag and boat limits, a MLL for retention, and spatial and temporal closures. An effort reduction control and a catch quota control were also added to the model, thus making it relevant also to some commercial fisheries. Because output controls such as bag/boat limits and size restrictions may require fishers to release fish after they are captured, the model was designed to account for the possibility that fish can experience post-release mortality from hooking or barotrauma-related injuries, the latter of which may occur when fish are rapidly brought to the surface from depth. The potential that high-grading may be practised by some fishers, and consequently impact on the overall fishing mortality of the stock, is also taken into account.

The management strategy component of the MSE model consists of a sampling model applied to generate sample data for the simulated population, an assessment model that determines the state of the stock (using catch curve and per-recruit analyses), and a decision-making model that simulates how management changes are chosen and implemented. In a traditional MSE, the decision-making component of the management strategy usually consists of a decision rule that specifies how management controls should be modified given the perceived state of the fish stock, relative to a set of specified reference points (Dichmont *et al.*, 2006). Such a specification allows the MSE to be run as a “closed loop” (Walters, 1998), where the decision-making process is internal to the MSE framework. The general application of such a fixed decision rule is based around a feedback loop in which the management of the fishery is automatically adjusted at set intervals over a total, specified projection period. This approach does not recognise, however, that assessments of many small-scale fisheries are often infrequent and undertaken at irregular intervals, and that, particularly in the case of recreational fisheries in Australia, management decisions are typically based on the outcomes of a review process rather than according to a pre-determined decision rule.

The MSE model was designed with the intent to allow users of the program to explore the likely consequences of making different management decisions for a simulated fishery, rather than to evaluate the effectiveness of alternative decision rules over an extensive projection period. Thus, each simulation undertaken by the model begins with an initialisation step to determine the initial state of the exploited fish stock under an existing management regime. The results of this initial assessment are presented to the user of the MSE program (*i.e.* a fishery manager, fisher or other stakeholder) via the graphical interface of the model. This user can then assess, from a range of stock assessment information that is presented to them, the state of the fish stock at this initial stage, after which changes to the existing management can be introduced. Once the specified projection period has elapsed, a second assessment of the state of the stock is undertaken, and the outcomes of the management change can be evaluated.

Although the simulation model contains most of the elements that would be present in any traditional MSE application, it should be noted that the analyses undertaken for this PhD study do not qualify as formal MSE analyses. As stated by Sainsbury *et al.* (2000), a key requirement of an MSE is that the objectives of management need to be clearly specified and that the performance of management strategies for satisfying these objectives can be quantitatively measured using some form of indicator. Such an approach was originally developed for quota-managed fisheries, for which the use of fixed decision rules constitutes a valuable approach for setting annual total allowable catches (TACs). Given the different decision-making processes characteristic of recreational fisheries and the lack of formal management objectives for many low-value fish species, however, the development of these specifications in this simulation model are not likely to be of value for facilitating research and management of such fisheries.

A detailed specification of the mathematical formulations underlying the MSE model is provided in Appendix A and information on how to install and use the model is presented in Appendix B.

2.3 Methods

The MSE model was applied to evaluate the effectiveness of four alternative management controls for regulating the mortality of fish stocks; (i) a bag/boat limit, (ii) a MLL for retention, (iii) a temporal closure, and (iv) a spatial closure. Simulations were undertaken using values of parameters for two fish species that differ markedly in biology, namely the West Australian dhufish *Glaucosoma hebraicum* and tarwhine *Rhabdosargus sarba*. The former of these species attains a maximum length of about 1200 mm and can live for over 40 years (Hesp *et al.*, 2002). In contrast, *R. sarba* reaches a maximum length of only about 400 mm and lives to 11 years of age (Hesp *et al.*, 2004). Whilst *G. hebraicum* exhibits relatively high post-release mortality (St John and Syers, 2005), a species such as *R. sarba* is likely to be less susceptible to injuries associated with catch and release fishing.

The simulations were repeated for two levels of recruitment variability, which were considered to be within the likely range for the two species. This was achieved by setting the value for the standard deviation of the natural logarithms of recruitment deviations to a low level (σ_R = 0.3), or a moderately high level (σ_R = 0.6). For all the simulations undertaken, the initial state of each fish species was specified according to a base case scenario. These represented the two fish species experiencing a high level of fishing pressure but with some existing fishing regulations, including an initial bag/boat limit and a MLL for retention. All model parameters that were used in the simulations of *G. hebraicum* and *R. sarba* are listed in Table 2.1 and 2.2.

The extent to which the four alternative management controls can regulate the exploitation of *G. hebraicum* and *R. sarba* was explored for a range of scenarios representing different specified values for each control (Table 2.3). For each scenario, the dynamics of the fish stock following the change to the management control were simulated over a ten year projection period. At the end of the projection period, the

Table 2.1. Biological and fishery parameters used in simulations for *Glaucosoma hebraicum* and *Rhabdosargus sarba.*

Species parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Reproductive strategy	Gonochoristic	Gonochoristic
Maximum age (years)	41	11
von Bertalanffy growth parameters		
L_∞ female (mm)	929	290
k female (year^{-1})	0.111	0.59
t_0 female (years)	-0.141	0.12
L_∞ male (mm)	1025	290
k male (year^{-1})	0.111	0.59
t_0 male (years)	-0.052	0.12
Standard deviation of L_∞ (both sexes)	20	20
Standard deviation of k (both sexes)	0.02	0.05
Standard deviation of t_0 (both sexes)	0.02	0.05
Standard deviation of length-at-age (both sexes)	5	10
Length-weight parameters		
a	0.0000259715	0.000038822
b	2.9308711000	2.846243544
Sex ratio (proportion female at birth)	0.5	0.5
Maturity		
L_{50} female (mm)	331	177
L_{95} female (mm)	509	192
L_{50} male (mm)	324	170
L_{95} male (mm)	454	196
Recruitment		
Virgin recruitment (thousands of fish)	100	100
Steepness of stock-recruitment curve	0.7	0.7
Recruitment variability, σ_R	0.3/0.6	0.3/0.6
Correlation for one year lag	0.3	0.3
Fecundity parameters		
a	10.432	5.0025
b	0.0841	17.557
Selectivity/vulnerability to capture		
L_{50} female (mm)	456	198
L_{95} female (mm)	661	235
L_{50} male (mm)	456	198
L_{95} male (mm)	661	235
Probability of post-release mortality	0.4	0.05
Probability of fishers complying	0.8	0.9
Probability of being high-graded	0.2	0.2

Table 2.2. Parameters used to explore the effectiveness of different management controls for regulating exploitation of *Glaucosoma hebraicum* and *Rhabdosargus sarba*.

Simulation parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Simulation projection period (years)	10	10
Number of simulation trials (recruitment series)	1	1
Number of trials per recruitment series	100	100
Initial equilibrium fishing mortality (years^{-1})	0.2	0.8
Probability of release due to bag/boat limit	0.01	0.01
Initial mean catch with bag/boat limit (fish per trip)	1	5
Maximum daily catch of fishers (fish per trip)	100	100
Maximum number of fishers per boat	10	10
50% effectiveness of temporal closure	0.3	0.3
95% effectiveness of temporal closure	0.8	0.8
Distribution for the numbers of fishers on boats	Number of fishers	% of boats
	1	10
	2	50
	3	25
	4	10
	5	4
	6	1
	7-10	0
Initial management controls (base case senario)	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Bag/boat limit (fish per trip)	5	20
Minimum legal length, MLL (mm)	500	240
Temporal closure (months of year closed to fishing)	0	0
Spatial closure (% of area closed to fishing)	0	0

Table 2.3. Ranges of specified values for the four alternative fisheries management controls evaluated for *Glaucosoma hebraicum* and *Rhabdosargus sarba* over the ten year projection period for each simulation.

Parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Boat/bag limit (fish per trip)	1-10	4-40
Minimum legal length, MLL (mm)	300-750	200-290
Temporal closure (months per year closed to fishing)	1-12	1-12
Spatial closure (% of fishing area closed to fishing)	10-100	10-100

new true rate of fishing mortality, F (year^{-1}), which was calculated by the operating model for fully-recruited, *i.e.* the largest (and oldest), fish in the stock after allowing for the effect of the different management controls, was retrieved. Note that this value represents the fishing mortality that, if the assumptions of the operating model are true, would have been experienced by these fish, not the estimate of this fishing mortality determined when undertaking a stock assessment based on the simulated data. For scenarios exploring the effectiveness of the MLL and spatial closure controls, the total numbers of fish killed (of all sizes, not just those fully recruited to the fishery) in the final year of the projection period were also determined.

A total of 100 simulations were undertaken for each scenario (*i.e.* for the different specified values of the four management controls, for the two fish species, and the two levels of recruitment variability), with the values for the random number seed used for generating the recruitment series for the projection period being allowed to differ among those simulations. The true values for the final F and number of fish killed reported in the remainder of this chapter represent the median values of these variables at the end of the ten year projection period, as calculated from the 100 simulation runs carried out with different recruitment series.

2.4 Results

2.4.1 Effectiveness of a bag/boat limit control

When recruitment variability for *G. hebraicum* was low and the fishing mortality of the stock at its initial equilibrium state was set to 0.2 year^{-1}, the initial management regulations specified for the base case scenario (bag and boat limit = 5 fish per trip, MLL = 500 mm) had no effect on fishing pressure ($F = 0.20$ year^{-1} after accounting for the initial management controls). Note that, as for all scenarios, the bag limit was set equal to the boat limit, for convenience, these controls are hereafter referred to as just the bag limit.

Reducing the bag limit for *G. hebraicum* from 5 to 4, 3 and 2 fish per trip for the projection period resulted in the median value of *F* (*i.e.* as calculated from the 100 simulations with different recruitment series) declining by only 1.4, 5.5 and 16%, respectively (Fig. 2.2a). Further reducing the bag limit to 1 fish per trip resulted in *F* declining more substantially (by 35%, to 0.13 year^{-1}). Although mortality declined in a similar manner when recruitment variability was high, the values of the final *F* for the fish stock after the projection period were more variable, particularly when the bag limit was 1 or 2 fish per trip. For example, when the bag limit was 2 fish per trip, *F* ranged between 0.15 and 0.19 year^{-1} when recruitment variability was high, compared with 0.16 to 0.17 year^{-1} when recruitment variability was low (Fig. 2.2a).

For *R. sarba*, with recruitment variability specified as low and the value of *F* prior to the projection set to 0.8 year^{-1}, initially setting the bag limit to 20 fish per trip and the MLL to 240 mm had essentially no effect on mortality (F = 0.79 year^{-1} after taking into account the initial management controls). Although reducing the bag limit for *R. sarba* to 16 and 12 fish per trip had only a minor effect on mortality (F = 0.77 and 0.71 year^{-1}, respectively), changing the bag limit to 8 fish per trip yielded values for the final *F* that ranged between 0.30 and 0.70 year^{-1} (lower quartile = 0.42 year^{-1}, upper quartile = 0.55 year^{-1}). As with *G. hebraicum*, increasing the recruitment variability for *R. sarba* led to prediction of *F* at the end of the projection period being more variable, particularly when the bag limit was low (Fig. 2.2b).

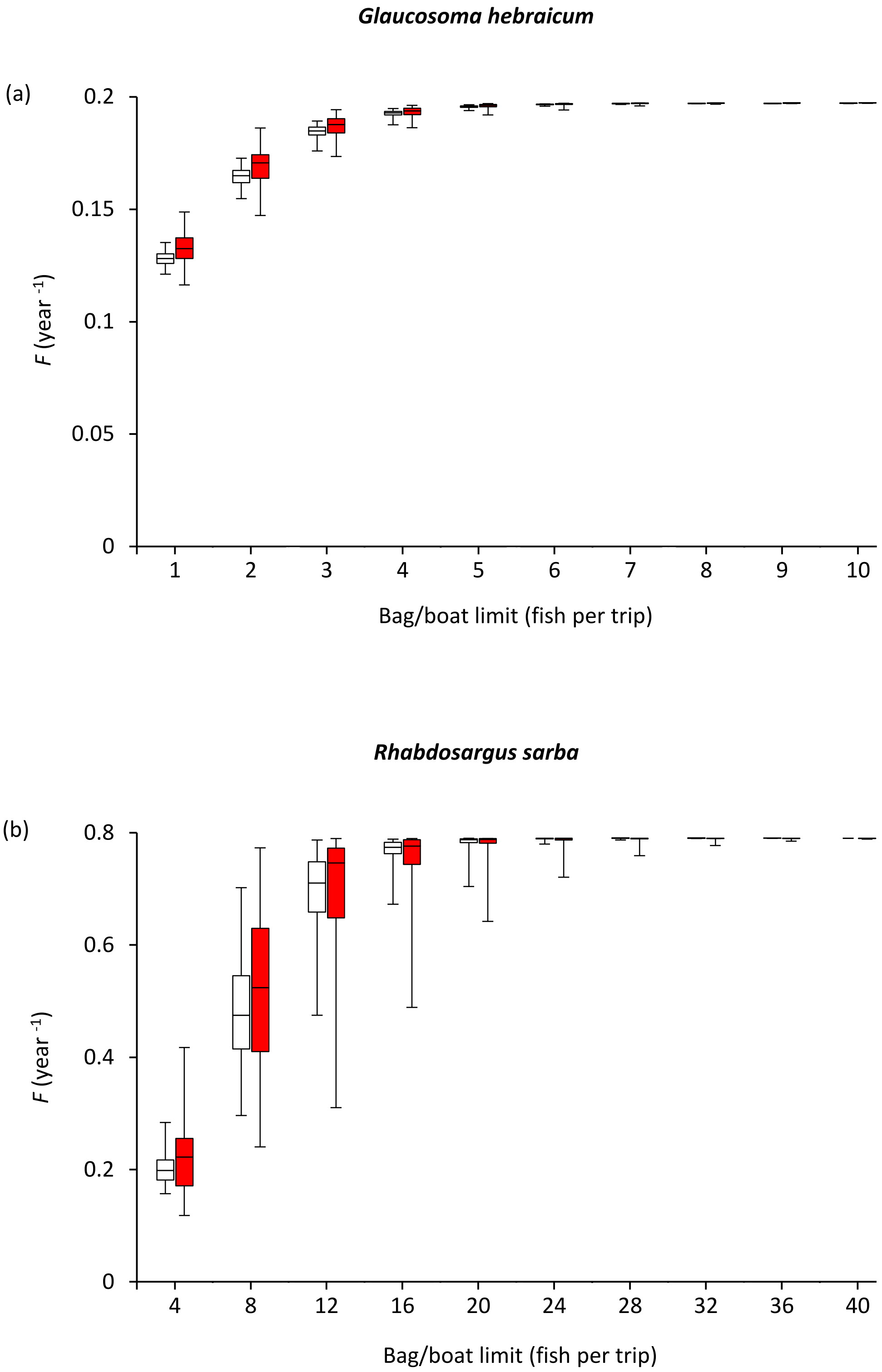


Fig. 2.2. Effect of the bag/boat limit control on fishing mortality (*F*) for fully-recruited (a) *Glaucosoma hebraicum* and (b) *Rhabdosargus sarba*, when recruitment variability is low (σ_R = 0.3; white, left) and moderately high (σ_R = 0.6; red, right). The lower and upper bounds of each box represent the lower and upper quartiles for values of *F*, respectively (from 100 simulations). The line in the middle of each box indicates the median value for *F* and the lower and upper bars show the minimum and maximum values for *F*, respectively.

2.4.2 Effectiveness of a MLL control

Changing the MLL for *G. hebraicum* had essentially no effect on the level of mortality to which fully-recruited fish were exposed (Fig. 2.3a). This result was expected as the MLL affects only the smaller fish in the catch, not the larger (and older) fish. It does, however, impact on the number of fish that are killed. When recruitment variability was low, increasing the MLL from 300 to 750 mm reduced the total number of fish (of all sizes) killed by fishing in the final year of the projection period by only 19%, from 23,600 to 19,200 fish (Fig. 2.3b). Similarly, when recruitment variability was high, the numbers killed declined by only 17% as the MLL was increased from 300 to 750 mm. When recruitment variability was high, the numbers of fish killed varied far more among each set of 100 simulation runs with different recruitment series. For example, the numbers killed when the MLL was set to 350 mm ranged by as much as 12,800 to 42,300 fish, compared with only 18,400 to 30,000 fish when recruitment variability was low (Fig. 2.3b).

As with *G. hebraicum*, changing the MLL for *R. sarba* from the value specified for the stock in its initial state typically had no effect on the fishing mortality for fully-recruited fish. In contrast to the situation with *G. hebraicum*, the minimum values for the distribution of values of F at the end of the projection period were occasionally much lower than the value of F for *R. sarba* when the stock was in its initial state (0.79 year^{-1}), in particular when recruitment variability was high and the MLL was low (Fig. 2.3c). Increasing the MLL for *R. sarba* had a greater effect on the numbers of fish killed than it did for *G. hebraicum* (*cf.* Fig. 2.3b, d). For example, when recruitment variability was set to a low level, increasing the MLL for *R. sarba* from 200 to 290 mm reduced the number of fish killed by as much as 41%, from 33,700 to 19,800 fish.

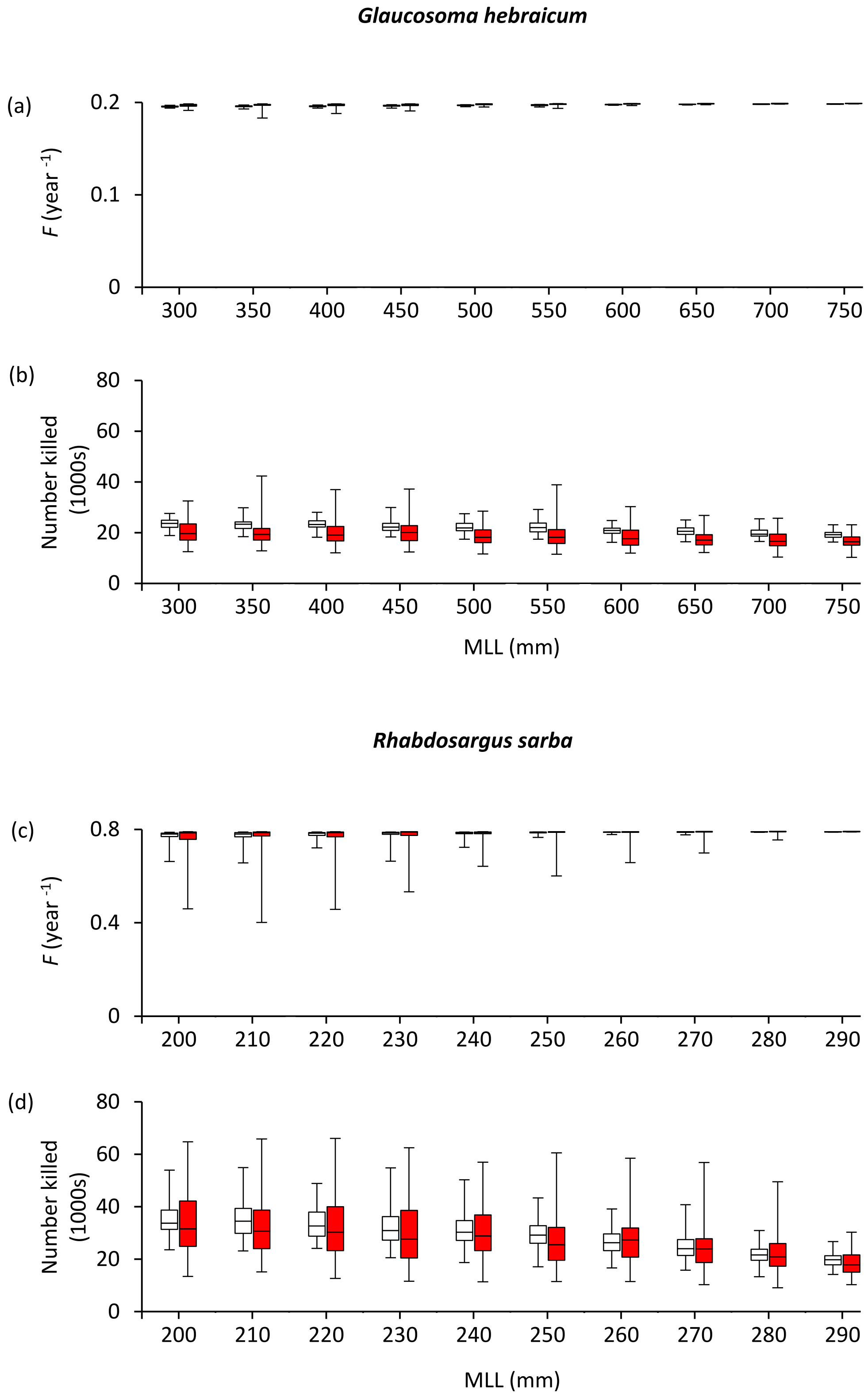


Fig. 2.3. Effect of the minimum legal length (MLL) control on (a, b) the true level of fishing mortality (*F*) for fully-recruited fish and (c, d) the annual number of fish killed for the two fish species, when recruitment variability is low (σ_R = 0.3; white, left) and moderately high (σ_R = 0.6; red, right). The lower and upper bounds of each box represent the lower and upper quartiles for values of *F* (a, c) or numbers of fish killed (b, d), respectively (from 100 simulations). The line in the middle of each box indicates the median value and the lower and upper bars show the minimum and maximum values, respectively.

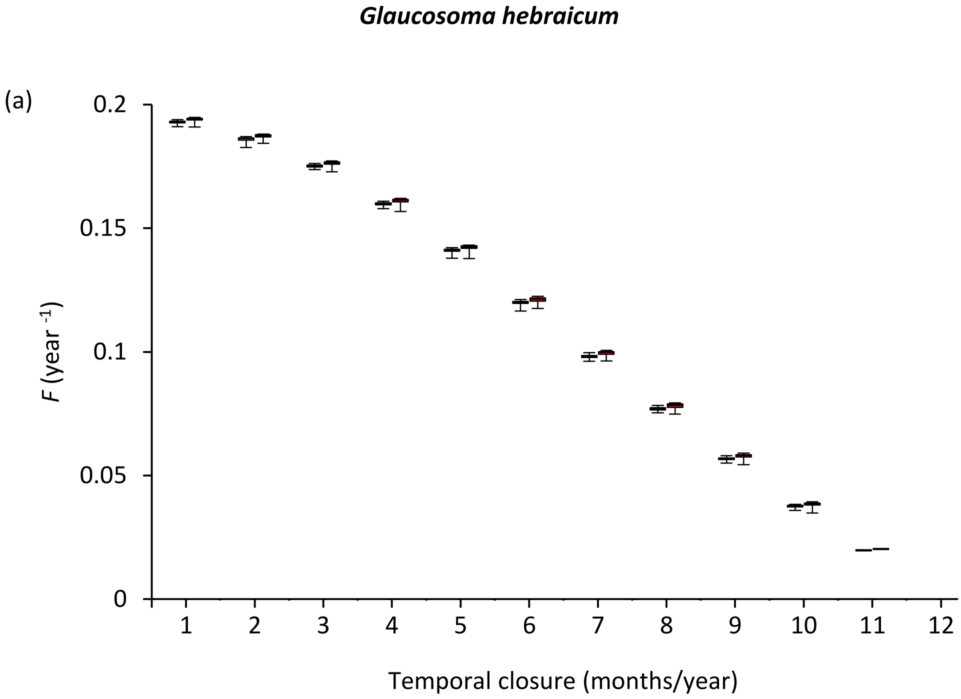
2.4.3 Effectiveness of a temporal closure control

For *G. hebraicum* with low recruitment variability, introducing a two month temporal closure resulted in only a 5% reduction in F for the fish stock, from 0.20 to 0.19 year^{-1} (Fig. 2.4a). Extending the closure to 4 and 6 months resulted in F being reduced more substantially, by 20 and 40% (to 0.16 and 0.12 year^{-1}), respectively. Recruitment variability had essentially no impact on the effectiveness of temporal closures for *G. hebraicum* (Fig. 2.4a).

For *R. sarba*, when recruitment variability was low, introducing temporal closures of 2, 4 and 6 months resulted in the value of F for the fish stock being reduced by 5.6, 19 and 40%, respectively. The reductions for each closure duration were thus of a very similar magnitude for *R. sarba* as for *G. hebraicum* (*cf*. Fig. 2.4a, b). When recruitment variability was high, the minimum values of F for *R. sarba* at the end of the projection period after the introduction of temporal closures were often substantially less than the median values of F (Fig. 2.4b).

2.4.4 Effectiveness of a spatial closure control

Introduction of spatial closures impacted greatly on the mortality of both fish species in the area remaining open to fishing, particularly when the extent of the area closed to fishing was large (Fig. 2.5a, c). For *G. hebraicum* with low recruitment variability, F for fully-recruited fish within the open area increased from 0.20 year^{-1}, when there was no closure, to 0.25, 0.33 and 0.50 year^{-1}, when 20, 40 and 60% of the total area was closed to fishing, respectively. The same trend occured when recruitment variability was high (Fig. 2.5a). The total numbers of *G. hebraicum* killed as a result of fishing (*i.e.* the mortality of fish of all sizes due to individuals being caught and retained, or from injury on release) remained at a similar level (20,600 to



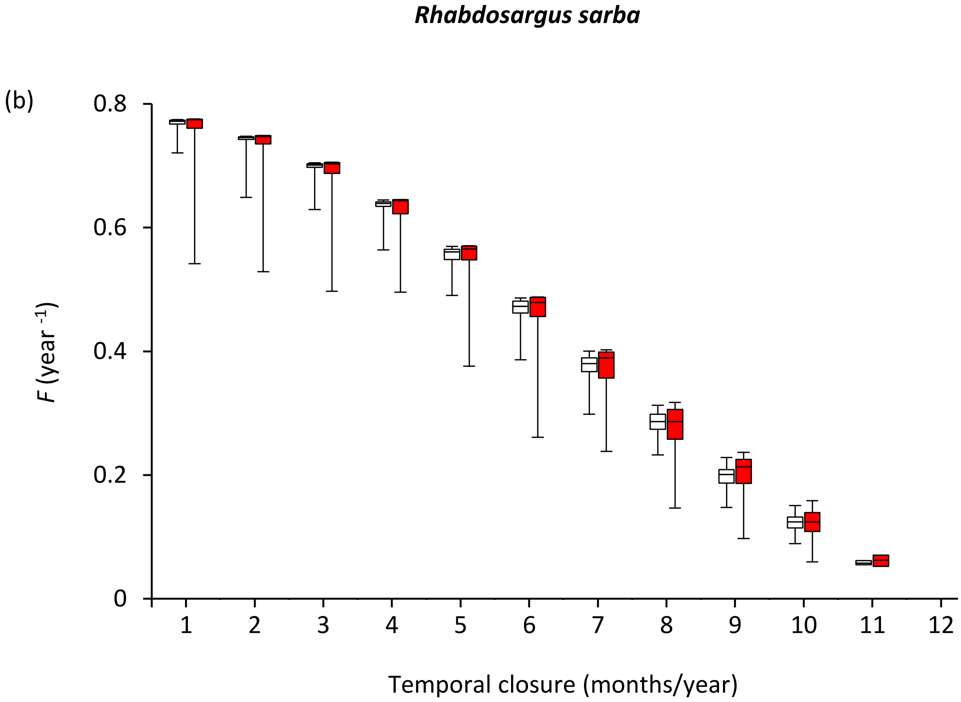
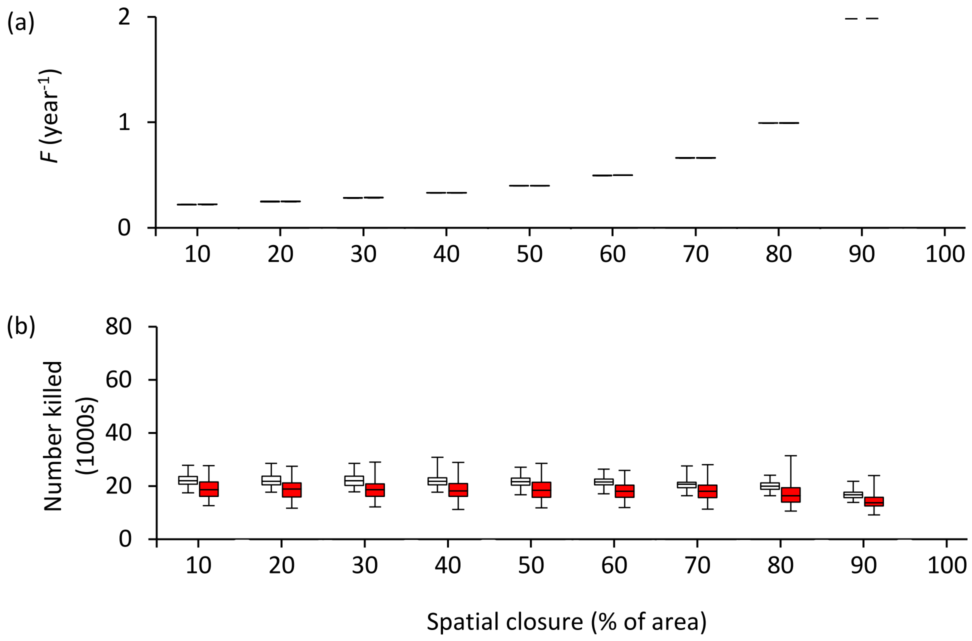


Fig. 2.4. Effect of the temporal closure control on fishing mortality (*F*) for fully-recruited (a) *Glaucosoma hebraicum* and (b) *Rhabdosargus sarba*, when recruitment variability is low (σ_R = 0.3; white, left) and moderately high (σ_R = 0.6; red, right). The lower and upper bounds of each box represent the lower and upper quartiles for values of *F*, respectively (from 100 simulations). The line in the middle of each box indicates the median value for *F* and the lower and upper bars show the minimum and maximum values for *F*, respectively.

Glaucosoma hebraicum



Rhabdosargus sarba

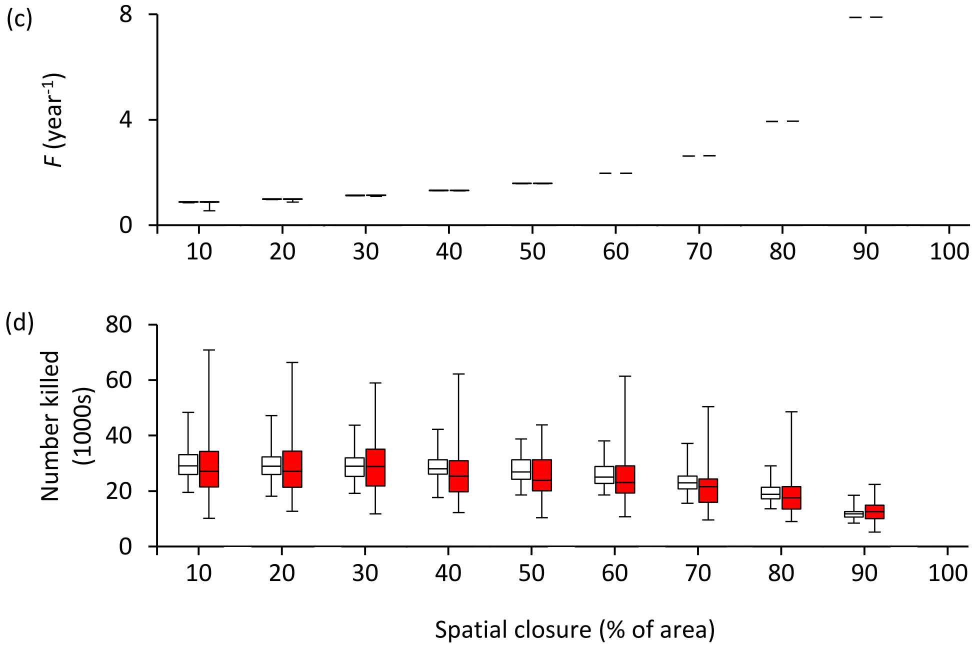


Fig. 2.5. Effect of the spatial closure control on (a, c) the true fishing mortality (*F*) for fish in the area open to fishing and (b, d) the annual number of fish killed for the two fish species, when recruitment variability is low (σ_R = 0.3; white, left) and moderately high (σ_R = 0.6; red, right). The lower and upper bounds of each box represent the lower and upper quartiles for values of *F* (a, c) or numbers of fish killed (b, d), respectively (from 100 simulations). The line in the middle of each box indicates the median value and the lower and upper bars show the minimum and maximum values, respectively.

22,000 fish) when between 10 and 70% of the total area was closed (Fig. 2.5b). The numbers of fish killed declined only slightly to 19,900 and 16,700 fish, respectively, when the closure was extended to 80 and 90% of the total fishing area. When recruitment variability was high, the numbers of *G. hebraicum* killed were consistently slightly less, for example, ranging between 18,000 and 18,800 fish for area closures of 10 to 70% (Fig. 2.5b).

A similar situation occurred with *R. sarba*, with spatial closures exceeding 50% of the total area resulting in large increases in mortality within the area remaining open to fishing (Fig. 2.5c). The total numbers of *R. sarba* killed declined substantially only when most of the area was closed to fishing (Fig. 2.5d). For corresponding levels of closure, the median numbers of fish killed were only slightly affected by different levels of recruitment variability. There was more variability in the numbers of fish killed (for different recruitment series) when recruitment variability was high (Fig. 2.5d).

2.5 Discussion

2.5.1 Effectiveness of a bag/boat limit control

The simulations exploring the effectiveness of bag limits suggested that, if the two fish species were initially heavily exploited at approximately twice their rates of natural mortality, an 80% bag limit reduction (from 5 to 1 fish per trip for *G. hebraicum* and 20 to 4 fish per trip for *R. sarba*) would reduce F far more for *R. sarba*. Although bag limits constitute one of the most commonly used tools for managing recreational fisheries (Radomski *et al.*, 2001), their effectiveness is likely dependent on several factors. The calculations used in the MSE model to determine the effectiveness of the bag and boat limit controls account for variables such as the distribution of the number of fishers on boats, mortality rate, catch rate, level of compliance (*i.e.* probability of fishers high-grading) and post-release mortality rate. Thus, the difference in effectiveness of the bag limit for the two fish species could potentially have been due to one or more of these factors.

As the distribution specified for the number of fishers on boats was kept the same for the two species, this would not have influenced the result. Furthermore, since both fish species were initially exploited at similar levels (relative to their rate of natural mortality), the observed differences in the effectiveness of the control are not likely to be linked to this factor. Although the bag limits specified for *G. hebraicum* (initially 5 fish per trip) and *R. sarba* (initially 20 fish per trip) differed, they were of a similar magnitude relative to the catch rates specified for the two species (1 and 5 fish per trip, respectively). Thus, differences in values specified for the bag limit controls would not have markedly influenced the results. The assumed levels of compliance by fishers when targeting *G. hebraicum* (80%) and *R. sarba* (90%) were also similar, suggesting that high-grading did not strongly affect the result.

In contrast to all of the above factors, the probability of post-release mortality specified for *G. hebraicum* (0.4 year^{-1}) was substantially greater than that specified for *R. sarba* (0.05 year^{-1}). Because of the high post-release mortality of *G. hebraicum*, the ability of a bag limit control to reduce fishing mortality will be negated by the mortality of any fish caught in excess of this allowance and released (St John and Syers, 2005). As shown in this simulation study, the importance of accounting for post-release mortality (and high-grading) when estimating the effectiveness of bag limits as management tools has also been highlighted by Woodward and Griffin (2003). Although the MSE model applied in the current study accounts for a range of factors which can influence the value of bag and boat limit controls, it is important to note, however, that it does not take into account the potential influence of changing fisher behaviours resulting from the introduction of more stringent regulations. Because fishers may respond to a reduced bag limit by fishing more frequently (Woodward and Griffin, 2003), or by being less likely to comply with the new regulations (Wilberg, 2009), the effectiveness of this control may be less than indicated by the results.

An important consideration regarding bag limits is that these controls are likely to have the greatest effect on the most successful fishers (Woodward and Griffin, 2003). Thus, if relatively few fishers take a large proportion of the total catch, imposing more stringent bag and boat limits can represent an attractive option for recreational fisheries managers to reduce the impacts of those fishers, whilst having minimal effect on the fishing experience of the majority of anglers. The finding that *F* for *G. hebraicum* was still relatively high (*i.e.* greater than the rate of natural mortality) after the bag limit had been reduced to only 1 fish per trip, however, does highlight the point made by Cox *et al.* (2002) that, on their own, bag and boat limit controls are unlikely to protect a stock from heavy exploitation.

2.5.2 Effectiveness of a MLL control

The simulations showed that, as expected, changing the MLL for retention of a species does not influence the fishing mortality for fish above the age at full recruitment into the fishery if the length of those fish is beyond the range affected by the MLL. The results of this study suggest that, as was the case with the bag/boat limit control, post-release mortality can have a major impact on the effectiveness of a MLL control. For *G. hebraicum*, which experiences high levels of post-release mortality due to barotrauma and hooking-related injuries associated with capture (St John and Syers, 2005), the simulations indicated that raising the MLL would have little effect on overall mortality. In contrast, for *R. sarba*, which is likely to experience far less post-release mortality, the analysis suggests that increasing the MLL will reduce overall mortality substantially. The conclusion that post-release mortality can greatly influence the effectiveness of a MLL control parallels that of Woodward and Griffin (2003) in a simulation study of the recreational fishery for red snapper *Lutjanus campechanus* in the Gulf of Mexico.

In discussing minimum size restrictions, Kirchner *et al.* (2001) state that their value for regulating exploitation of a fish stock is “questionable” and highlighted the example of the silver kob *Argyrosomus inodorus* stocks in South Africa, which have collapsed despite a MLL being in place since 1940 (citing Griffiths, 1997). MLL restrictions have often been applied with the intention of ensuring that individuals spawn at least once before being harvested (Arlinghaus *et al.*, 2010b), however, this policy is likely to be inadequate for many species. For example, it fails to recognise that, for species with high recruitment variability, spawning by individuals over several years is likely to be important as a bet-hedging strategy for helping to ensure long-term reproductive success despite long periods of unfavourable environmental conditions for larval survival (Leaman and Beamish, 1984). It also does not recognise that egg production increases disproportionately with the size of fish, and that egg quality and larval survival may change with maternal age (Berkeley *et al.*, 2004; Bobko and Berkeley, 2004). For these and other reasons, some fisheries are managed using maximum size limits and slot limits, both of which aim to protect larger and older fish in the population (Arlinghaus *et al.*, 2010b; Matsumura *et al.*, 2011).

In some fisheries, MLL controls have also been used as a means for increasing yields (Matsumura *et al.*, 2011). On the basis of analyses of creel survey data, Paukert *et al.* (2002) and Isermann *et al.* (2007) conclude that a MLL will be more effective for improving yields (and increasing the number of larger and older fish in a population) when individuals grow rapidly and when exploitation is high but natural mortality is low. The effectiveness of an MLL will thus depend on the level of post-release mortality experienced by the fish species, as well as on the proportion of the life span during which fish are protected, the latter which will depend, to some extent, on the pattern of growth of the species during the earlier part of life. The findings of this study support the suggestion made by Apostolaki *et al.* (2006), that introducing changes to the management arrangements for fisheries need to be based on species-specific predictions of the likely effectiveness of such changes.

2.5.3 Effectiveness of a temporal closure control

The simulation results, for both *G. hebraicum* and *R. sarba*, indicate that the effectiveness of a short temporal closure (< 2-3 months) for reducing *F* is limited. Temporal closures are predicted to become increasingly effective (relative to duration) as closure period expands up to about 6 months. The results indicate that, beyond this point, the effectiveness of temporal closures, relative to duration, tends to "level off" and then start to decline. This trend is due largely to assumptions made in the operating model of the MSE about how fishers are likely to respond to temporal closures. The model's calculations take into account that temporal closures will often induce a pulse of fishing effort when the fishery re-opens, as fishers aim to compensate for their losses during the closed period (*e.g.* Guénette *et al.*, 1998; Coleman *et al.*, 2004). The calculations also assume that there is likely to be an upper limit on the amount of fishing activity that fishers will undertake during any period of time (*e.g.* Watson *et al.*, 1993), although, as highlighted by Cox *et al.* (2002), this may be untrue in the long-term for recreational fisheries. As has been pointed out in other studies, understanding the dynamics of fishing fleets and how fishers respond to new regulations is crucial for reliably predicting the effects of management (Sluczanowski, 1984; Branch *et al.*, 2006; Haapasaari *et al.*, 2007).

A range of other factors may be important in influencing the effectiveness of temporal closure controls for different types of fisheries. For example, factors such as market demands (for commercial fishers) and temporal differences in the abundance of target species can all effect behavioural responses of fishers to management changes (Allen and McGlade, 1986; Somers and Wang, 1997; Pradhan and Leung, 2004). The timing of temporal closures is also likely to be important, particularly for recreational fisheries, depending on when people are more likely to go fishing. For multi-species fisheries, a key factor to consider is how fishing effort may be re-allocated towards species that are not affected by the closure (Holland and Sutinen, 1999; Little *et al.*, 2008) or to other, unprotected, fishing grounds (Somers and Wang, 1997). Furthermore, temporal closures may be used for various reasons other than for just reducing fishing mortality. For example, they are often applied as a means to protect spawning aggregations (Cox *et al.*, 2002) or, as in the case with commercial fisheries for short-lived species with highly variable recruitment (*e.g.* prawns), temporal closures may be used to optimise economic profits by limiting catches of smaller animals, *i.e.* preventing growth over-fishing (Watson *et al.*, 1993).

Although outside the scope of this study, the MSE model could be extended to incorporate additional factors that may influence the effectiveness of temporal and other closures. For recreational fisheries, information on seasonal differences in fishing effort for different fisheries, such as from creel survey data, are likely to be of particular importance for improving model predictions of the effects of temporal closures.

2.5.4 Effectiveness of a spatial closure control

For spatial closures, the simulation results for both species suggest that, as the proportion of the total fishery area closed to fishing increases, mortality in the area remaining open to fishing will increase markedly as a consequence of the displacement of fishing effort from the closed area to the area still open to fishing. The simulations also indicated that, for both *G. hebraicum* and *R. sarba*, a spatial closure of even as much as 50% is likely to have very limited impact on overall fishing mortality for the population if the assumptions regarding movement of fishers are correct. This highlights the fact that, when applying area closures, fishing effort in areas remaining open to fishing needs to be controlled using other measures (Jones, 2001; Kaiser, 2005; Greenstreet *et al.*, 2009; Halpern *et al.*, 2010).

Although the simulation results for spatial closures indicate that, at extreme levels of fishing pressure, mortality in the open area will continue to rise exponentially with an increasing proportion of area closed, this may not be true. As pointed out by Smith *et al.* (2010), the increased fishing pressure in the areas remaining open to fishing will lead to depletion of the portion of stock in those areas over time, thereby reducing the incentive for people to continue fishing. Future work on this aspect could focus on relaxing the assumption made by this and many other models (*e.g.* Guénette *et al.*, 1998; Lynch, 2006) that fishing effort and the amount of area closed are directly correlated. Further model development could also focus on alternative assumptions about the spatial distribution of fishing effort and rates of migration of fish between open and closed areas.

In discussing spatial closures, it needs to be pointed out that they may be of value for a variety of purposes other than for managing single target species (see *e.g.* Jones, 2001). As this MSE model is a single-species model, it is not suited for answering broader questions about the effectiveness of this type of control for social and ecosystem objectives. Other types of models, such as agent-based models, are likely to be more appropriate for exploring questions about the consequences of behavioural responses of fishers to fisheries management controls, as well as evaluating the complex interactions between fleet dynamics, fish stocks and management processes (Soulié and Thébaud, 2006; Hesp *et al.*, 2010). In the context of management controls, the operating model of the MSE produced for this study has shown to be valuable for understanding some of the broad implications of applying commonly used controls for conserving target species. The modular nature of the MSE program readily allows extension of the model to incorporate and explore different factors and alternative assumptions about how different management controls are likely to impact on fish stocks and fishers.

2.5.5 Influence of variable recruitment on the effectiveness of management controls

The simulations undertaken by this study indicated that, on average, annual recruitment variability has limited impact on the effectiveness of each of the four management controls for reducing exploitation of fish species. Simulations clearly demonstrated, however, that the outcomes of changes to the management controls are less predictable when recruitment varies substantially among years than when the variability is low. This was particularly apparent with the shorter-lived *R. sarba*, for which the mortality of the stock at the end of the simulation projection period often ranged widely around the median value. The finding that recruitment variability increases the uncertainty of model predictions has also been reported by other simulation studies (*e.g.* Ianelli, 2005). It is clear that, when managing fish species that experience high levels of recruitment variability, it will be important to account for this uncertainty in the expected outcome of the controls that are imposed by applying management measures that are sufficiently precautionary to avoid placing stocks at risk of over-exploitation.

2.5.6 Conclusion

In conclusion, the simulations undertaken to evaluate the effectiveness of the four different management controls indicate that some were more effective than others for reducing fishing mortality, and that the value of these controls will vary for different species. For demersal fish species with limited movements and which suffer high levels of post-release mortality, temporal closures throughout the full area of a fishery are likely to be more effective for reducing fishing mortality than reducing daily bag limits, imposing more restrictive size limits, or constraining the areas open to fishing. There was greater variability in the effectiveness of the different management controls as the level of recruitment variability of the fish species increased.

While the results of simulation studies like this one can be of considerable benefit for helping inform fisheries managers and decision-makers about the likely consequences of alternative management actions for exploited fish stocks, some fisheries modellers argue that the findings generated by simulation models may be most efficiently communicated by the models themselves, *i.e.* through “computer gaming” exercises (*e.g.* Walters, 1986; Scandol, 2000). When developing models for this purpose, however, it is essential that the design of the user interface is tailored specifically for communicating information to the intended audience. Following recommendations by Scandol (2000) for developing visual models, the next chapter of this thesis (Chapter 3) is focused on exploring the effectiveness of the user interface of the MSE program for conveying stock assessment information and how differences in the complexity of the interface can influence interpretation and decision-making by users of the model.

CHAPTER 3

Exploring the use of a fisheries simulation model for communicating stock assessment information

3.1 Introduction

Fisheries management revolves around making choices (Hilborn and Walters, 1992). In theory, this involves managers making decisions about which of a range of alternative management arrangements for a resource is most likely to best achieve a set of specified management objectives (Punt and Hilborn, 1997; Lackey, 1998). To help ensure that appropriate choices are made, it is fundamental that decisions are based on the best information available about the current state of the resource being managed (Hilborn, 2003). Traditionally, such information is represented by the results of scientific stock assessments, and is provided to decision-makers in the form of fisheries management advice (Haddon, 2007; Punt, 2008).

Fisheries stock assessments typically require large amounts of data for analyses (Hilborn and Liermann, 1998). To optimise use of available data, which for many fisheries come in a variety of forms, fisheries scientists often apply a variety of statistical approaches in their analyses (Hilborn and Liermann, 1998; McAllister *et al.*, 2001). As a consequence, stock assessments produce a wide range of complex outputs and results, each of which may be dependent on a variety of different assumptions. A major concern is that this complex, uncertain and sometimes conflicting stock status information, when presented to decision-makers, is commonly used in an *ad hoc* manner which can lead to poor management outcomes (Walters and Maguire, 1996).

Recognition of the limitations of traditional stock assessment approaches for dealing with uncertainties in fisheries led to the development of management strategy evaluation (MSE; *e.g.* Smith *et al.*, 1999). This simulation approach is used to predict the likely effectiveness of alternative management strategies before they are implemented and thereby improve the likelihood of achieving desired management objectives (Sainsbury *et al.*, 2000; Haddon, 2007; Kell *et al.*, 2007). MSE has also been recognised for its value as a vehicle for involving not only scientists and managers, but also other fishery stakeholders in the management process (Smith *et al.*, 1999; McDonald *et al.*, 2008). Indeed, the adoption of such a collaborative and participatory management approach has been argued by many as an important step forward for improving decision-making in fisheries (de la Mare, 1998; Kaplan and McCay, 2004; Johnson and van Densen, 2007).

One issue that may be acting to limit the application of MSE to fisheries throughout the world is that, because of its complexity, stakeholders with non-science backgrounds may struggle to fully understand the implications of MSE model outputs (Rochet and Rice, 2009). This issue was highlighted when implementing MSE for the Australian Fisheries Management Authority (AFMA) partnership approach, with managers sometimes being reluctant to accept MSE as playing a major role in management because of its inherent technical complexity (Smith *et al.*, 1999). The challenge is thus to develop robust MSE tools that can effectively convey complex stock assessment information to people who may range broadly in background and technical expertise. If such tools can be developed, this could help bridge the communication gap between science and management.

Although, ideally, management advice should be based on the results of many carefully designed simulations, there is great benefit to be gained from developing computer programs that allow stakeholders to “pull the management levers” and thereby act as the decision-makers themselves (Hilborn and Walters, 1992; Butterworth *et al.*, 1997). Simulation gaming has been used widely as a tool for natural resource management, particularly as a means for communicating information to managers (Scandol, 2000), promoting discussion among stakeholders and for facilitating problem-solving (Barreteau *et al.*, 2007). Simulation models can be excellent for providing simplified and easily understood representations of naturally complex systems and, consequently, such models have also proven useful for teaching and training purposes (Ryan, 2000; Martin *et al.*, 2007).

The first aim of this study was to design an effective and user-friendly interface for a MSE simulation model to be used for a range of purposes, including fisheries research, education and helping facilitate stakeholder involvement in fisheries decision-making. The MSE model was developed for data-limited fisheries for which sufficient biological data are available to enable mortality-based assessments and predictions of stock status (see Chapter 2), *i.e.* the approach being used for many finfish species in Western Australia (Wise *et al.*, 2007). The next aim was to explore, by undertaking scenario testing workshops with university students, the effectiveness of the user interface of MSE model for conveying stock assessment information to people with limited prior understanding of fisheries assessments and management. These computer workshops involved participants taking on the role of fisheries managers and using the MSE model to make management decisions for a range of different simulated fishery scenarios, based on stock assessment information presented to them via the user interface. The following hypotheses were explored in this study:

(1) When conveying stock status information to participants via the user interface of the MSE model, presenting them with an additional information screen, which contains a risk summary of the extent to which certain characteristics of a fish species can make it more vulnerable to over-fishing, will improve their ability to make appropriate management decisions.

(2) The user interface of the MSE model can effectively communicate stock assessment information to the participants and thus help them select appropriate management measures for the various fishery scenarios. That is, their decisions will be influenced by:

    a. the fish species being “managed”,
    b. the initial exploitation state of the fish species, and
    c. the level of variability in recruitment to the fish stock.

(3) Modifying the user interface of the MSE model to include more comprehensive information about uncertainties associated with certain stock status indicators, and to enhance the information screen containing the risk assessment summary, will help workshop participants make more informed management decisions.

3.2 Methods

3.2.1 Overview of scenario testing workshops

The study involved the running of three computer workshops in which participants were asked to use the MSE model (see Chapter 2, Appendix A and B) and undertake a number of different fishery scenarios, for which they acted as the managers. The first two workshops, held in 2009, were attended by a total of 23 science students at Murdoch University in Western Australia (nine undergraduate students in the first workshop and 14 postgraduate students in the second). The third workshop, prior to which the user interface of the MSE model had been substantially modified to allow the final hypothesis of the study to be explored, was held in 2010 and was attended by 13 students.

At the start of each workshop, participants were randomly assigned to individual computers on which the MSE software had been installed. Prior to the commencement of the scenario testing exercise, the students were provided a brief presentation about fisheries stock assessments and MSE, which also outlined the objectives of the exercise. The scenario testing workshops involved the participants viewing information presented via the user interface of the MSE model, assessing the exploitation states of several simulated fish stocks, and then deciding how to best manage those fisheries by selecting from various alternative management controls available in the model. These included bag limits, minimum legal lengths (MLLs) for retention, temporal closures and spatial closures. Once management decisions had been made (by changing none, some or all of the controls), simulations were undertaken to project the state of the fish stock, given its initial exploitation state and management regime, and thereby provide feedback to participants about the success of their management choices. Such feedback included values of certain stock status indicators at the beginning and end of the simulation projection period and a score calculated according to how well their management had worked, which was based on how close the fish stock in its final state was to some often-used target reference points.

All participants repeated this procedure 12 times, with the fishery scenario differing on each occasion. Prior to initiating the scenario testing experiment, students were asked to repeatedly undertake a fixed preliminary scenario trial to familiarise themselves with the model, including its various indicators of stock status, and the effects of applying changes to the different management controls. Participants were instructed to take as much time as they needed on these preliminary runs (typically 30 minutes) before commencing the 12 scenarios. Although each workshop was scheduled to run for three hours, none of the students required more than two hours to complete all scenarios. Thus, time did not constrain the participants when viewing stock assessment information and making decisions.

3.2.2 Design of user interface for scenario testing

The different screens presented by the user interface of the MSE model (see Appendix B) provided participants with a wide range of information, including details about the biological characteristics of the simulated fish species, parameters describing various aspects of the simulation procedures and the values of the initial management controls specified for the fish stock, as well as information about the initial state of the simulated stock. The stock status information presented to participants included age and length composition data from a specified sample of fish, estimates of mortality, yield per recruit and spawning potential ratio (in terms of both spawning stock biomass per recruit and eggs per recruit), plots displaying results of catch curve and per-recruit analyses, and a risk assessment summary. The screen presenting the risk summary included information about several potential hazards to the fish species, related to its spawning behaviour, larval dispersal, distribution and movements of adults, susceptibility to environmental change or habitat degradation and degree to which the species is targeted by fishers. These risk criteria are similar to those considered by Wise *et al.* (2007) for assessing demersal finfish species in Western Australia.

Several features were built into the MSE model to make it sufficiently robust and user-friendly to be applied in workshop situations. When the program is set to “scenario testing mode”, users are denied the ability to change values for model input parameters, and the range of alternative values that can be selected for each management control is limited to within a feasible range. Access to the various procedures and information screens that comprised the user interface of the MSE model was also tightly controlled. To ensure that the procedures undertaken in each scenario were completed in the correct order, the buttons within the interface that were set to activate a particular procedure, or to navigate to the next screen, were only made visible to the user at appropriate steps. The interface of the model was also designed to ensure that users viewed all of the screens containing assessment information for the fish stock in its initial state before they could make any changes to the management controls and initiate the procedures for undertaking simulations for the projection period. Furthermore, help buttons have been added next to each of the various boxes containing the input and output parameters to explain their meaning and relevance to the MSE procedure.

3.2.3 Experimental design

The first of the three hypotheses of this study, *i.e.* that providing participants with additional risk assessment information would influence their decision-making, was explored using two alternative versions of the MSE model (hereafter referred to as Model A and B). These were installed on computers located at opposite sides of the classroom and differed only in the amount of stock status information presented to users via the interface. Half of the workshop participants, those using Model A, were provided with the additional risk assessment summary screen, whilst this was hidden for participants using Model B.

Each participant completed a total of 12 simulation scenarios, the order of which was randomised to ensure that students did not work together (as the order was different on each computer). The randomisation also helped to ensure that, overall, potential effects of learning associated with continued use of the model on results for a particular scenario were minimised. To explore the second hypothesis of the scenario testing study, three different factors were considered in the experimental design. Each fishery scenario represented (i) one of two fish species simulated using the operating model, (ii) one of three initial levels of fishing mortality of the fish stock, and (iii) one of two levels of variability in annual recruitment to the stock.

Details of the different scenarios undertaken by participants are presented in Table 3.1.

The two fish species selected for the workshops, the West Australian dhufish *Glaucosoma hebraicum* and tarwhine *Rhabdosargus sarba*, differ markedly in their biological characteristics. For example, the much larger-growing *G. hebraicum* can attain a maximum age of 41 years (Hesp *et al.*, 2002) whilst the smaller and shorter-lived *R. sarba* reaches a maximum age of only 11 years (Hesp *et al.*, 2004). Values of the biological and fishery parameters used for simulating the two species are listed in Tables 3.2 and 3.3.

Values for fishing mortality specified to represent scenarios of low, moderate and high levels of initial exploitation for each species differed slightly between the workshops undertaken in 2009 and 2010, but were essentially of a similar magnitude (Table 3.1). It is worth noting, however, that scenarios of recruitment variability differed more substantially among the workshops held in the different years (Table 3.1). For the workshops undertaken in 2009, scenarios of no recruitment variability and low recruitment variability were explored by specifying the standard deviation of the natural logarithms of recruitment deviations, σ_R, to 0 and 0.3, respectively. The decision to initially avoid scenarios with higher recruitment variability was based on feedback obtained during a preliminary workshop (prior to those undertaken for this study) with fisheries scientists and managers, which suggested that such scenarios may confuse users of the program. For example, this could occur if participants sometimes were presented with counter-intuitive stock assessment outputs resulting from the unpredictable impacts of annual recruitment fluctuations. The potential that higher levels of recruitment variability may influence decision-making by participants was tested in the most recent workshop held in 2010, for which σ_R was specified as either low (0.3) or moderately high (0.6).

Table 3.1. Factorial design applied to the scenario testing study, describing the 12 simulation scenarios undertaken by participants of the workshops held in 2009 and 2010.

Scenario number	Fish species	Level of fishing mortality ($year^{-1}$)		Recruitment variability (σ_R)	
	2009/2010	2009	2010	2009	2010
1	*Glaucosoma hebraicum*	0.02	0.05	0	0.3
2	*Glaucosoma hebraicum*	0.02	0.05	0.3	0.6
3	*Glaucosoma hebraicum*	0.08	0.1	0	0.3
4	*Glaucosoma hebraicum*	0.08	0.1	0.3	0.6
5	*Glaucosoma hebraicum*	0.16	0.15	0	0.3
6	*Glaucosoma hebraicum*	0.16	0.15	0.3	0.6
7	*Rhabdosargus sarba*	0.15	0.2	0	0.3
8	*Rhabdosargus sarba*	0.15	0.2	0.3	0.6
9	*Rhabdosargus sarba*	0.35	0.4	0	0.3
10	*Rhabdosargus sarba*	0.35	0.4	0.3	0.6
11	*Rhabdosargus sarba*	0.55	0.6	0	0.3
12	*Rhabdosargus sarba*	0.55	0.6	0.3	0.6

To explore the final hypothesis of the study, *i.e.* that providing participants with information about the uncertainty associated with some of the stock status indicators and more sophisticated risk assessment information will improve their management decisions, a number of the information screens of the user interface were modified prior to the 2010 scenario testing workshop (*cf.* Figs. 3.1 and 3.2). The changes made to the screens included presenting measures of the uncertainty associated with estimates of mortality, yield per recruit and spawning potential ratios for the simulated fish species, as well as enhancing the risk summary screen to more closely resemble a formal risk assessment methodology (*e.g.* Department of Fisheries, Western Australia, 2005; Fletcher, 2005).

In each workshop, the management decisions made by participants for the different scenarios were logged by the MSE model and saved as text files on their computers for analysis.

Table 3.2. Biological and fishery parameters applied to simulations for the two fish species considered in the scenario testing study.

Species parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Reproductive strategy	Gonochoristic	Gonochoristic
Maximum age (years)	41	11
von Bertalanffy growth parameters		
L_∞ female (mm)	929	290
k female (year^{-1})	0.111	0.59
t_0 female (years)	-0.141	0.12
L_∞ male (mm)	1025	290
k male (year^{-1})	0.111	0.59
t_0 male (years)	-0.052	0.12
Standard deviation of L_∞ (both sexes)	20	20
Standard deviation of k (both sexes)	0.02	0.05
Standard deviation of t_0 (both sexes)	0.02	0.05
Standard deviation of lengths at age (both sexes)	5	10
Length-weight parameters		
a	0.0000259715	0.000038822
b	2.9308711000	2.846243544
Sex ratio (proportion female at birth)	0.5	0.5
Maturity		
L_{50} female (mm)	331	177
L_{95} female (mm)	509	192
L_{50} male (mm)	324	170
L_{95} male (mm)	454	196
Recruitment		
Virgin recruitment (thousands of fish)	100	100
Steepness of stock-recruitment curve	0.7	0.7
Recruitment variability, σ_R	*	*
Correlation for one year lag	0.3	0.3
Fecundity parameters		
a	10.432	5.0025
b	0.0841	17.557
Selectivity/vulnerability to capture		
L_{50} female (mm)	456	198
L_{95} female (mm)	661	235
L_{50} male (mm)	456	198
L_{95} male (mm)	661	235
Probability of post-release mortality	0.4	0.05
Probability of fishers complying	0.8	0.9
Probability of being high-graded	0.2	0.2

* dependent on scenario number, see Table 3.1.

Table 3.3. MSE simulation parameters and initial management parameters applied to simulations for the two fish species considered in the scenario testing study.

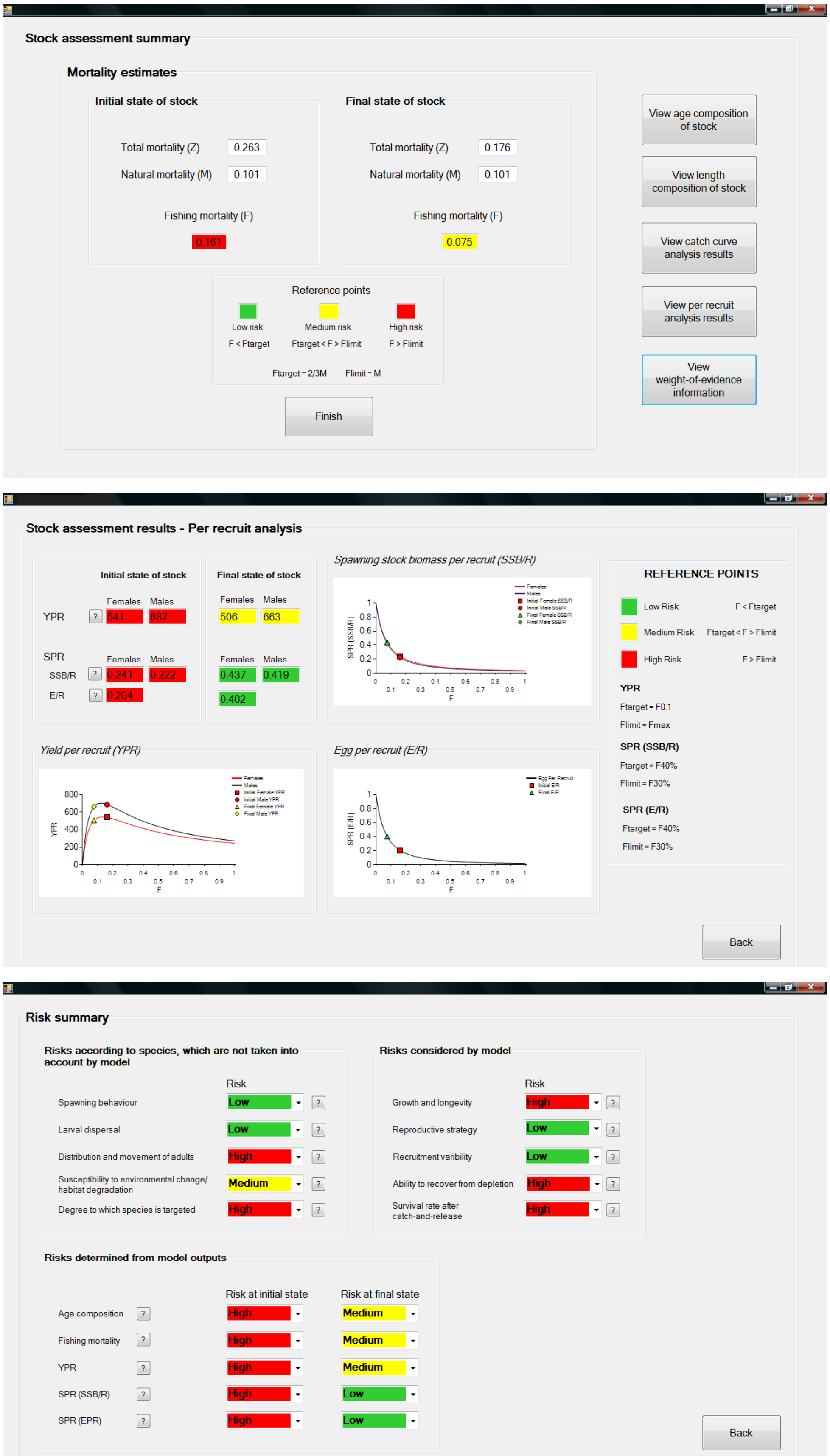
Simulation parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Simulation projection period (years)	20	10
Number of simulation trials (recruitment series)	1	1
Number of trials per recruitment series	1	1
Sample size (number of fish)	1000	1000
Interval for length classes (mm)	50	20
Initial equilibrium fishing mortality (years^{-1})	*	*
Catch curve analysis	Linear**	Linear**
F-based reference points		
F_{target} (proportion of *M*)	0.667	0.667
F_{limit} (proportion of *M*)	1	1
SPR $(SSB/R)_{\text{target}}$	0.4	0.4
SPR $(SSB/R)_{\text{limit}}$	0.3	0.3
SPR $(E/R)_{\text{target}}$	0.4	0.4
SPR $(E/R)_{\text{limit}}$	0.3	0.3
Probability of release due to bag/boat limit	0.01	0.01
Initial mean catch with bag/boat limit (fish per trip)	1	5
Maximum daily catch of fishers (fish per trip)	100	100
Maximum number of fishers per boat	10	10
50% effectiveness of temporal closure	0.3	0.3
95% effectiveness of temporal closure	0.8	0.8

Distribution for the numbers of fishers on boats	Number of fishers	% of boats
	1	10
	2	50
	3	25
	4	10
	5	4
	6	1
	7-10	0

Management parameters	*Glaucosoma hebraicum*	*Rhabdosargus sarba*
Bag limit (fish per trip)	4	8
Minimum legal length, MLL (mm)	500	230
Temporal closure (months of year closed to fishing)	0	0
Spatial closure (% of area closed to fishing)	0	0

* dependent on scenario number, see Table 3.1.

** linear, regression-based catch curve analysis (*e.g.* Ricker, 1975).



Stock assessment summary

Mortality estimates

Initial state of stock		Final state of stock	
Total mortality (Z)	0.263	Total mortality (Z)	0.176
Natural mortality (M)	0.101	Natural mortality (M)	0.101
Fishing mortality (F)	0.161	Fishing mortality (F)	0.075

Reference points

🟩	🟨	🟥
Low risk	Medium risk	High risk
F < Ftarget	Ftarget < F > Flimit	F > Flimit

Ftarget = 2/3M Flimit = M

Stock assessment results - Per recruit analysis

		Initial state of stock		Final state of stock	
		Females	Males	Females	Males
YPR	?	541	687	506	663
SPR		Females	Males	Females	Males
SSB/R	?	0.241	0.222	0.437	0.419
E/R	?	0.204		0.402	

REFERENCE POINTS

🟩	Low Risk	F < Ftarget
🟨	Medium Risk	Ftarget < F > Flimit
🟥	High Risk	F > Flimit

YPR

Ftarget = F0.1

Flimit = Fmax

SPR (SSB/R)

Ftarget = F40%

Flimit = F30%

SPR (E/R)

Ftarget = F40%

Flimit = F30%

Risk summary

Risks according to species, which are not taken into account by model

	Risk	
Spawning behaviour	Low	?
Larval dispersal	Low	?
Distribution and movement of adults	High	?
Susceptibility to environmental change/ habitat degradation	Medium	?
Degree to which species is targeted	High	?

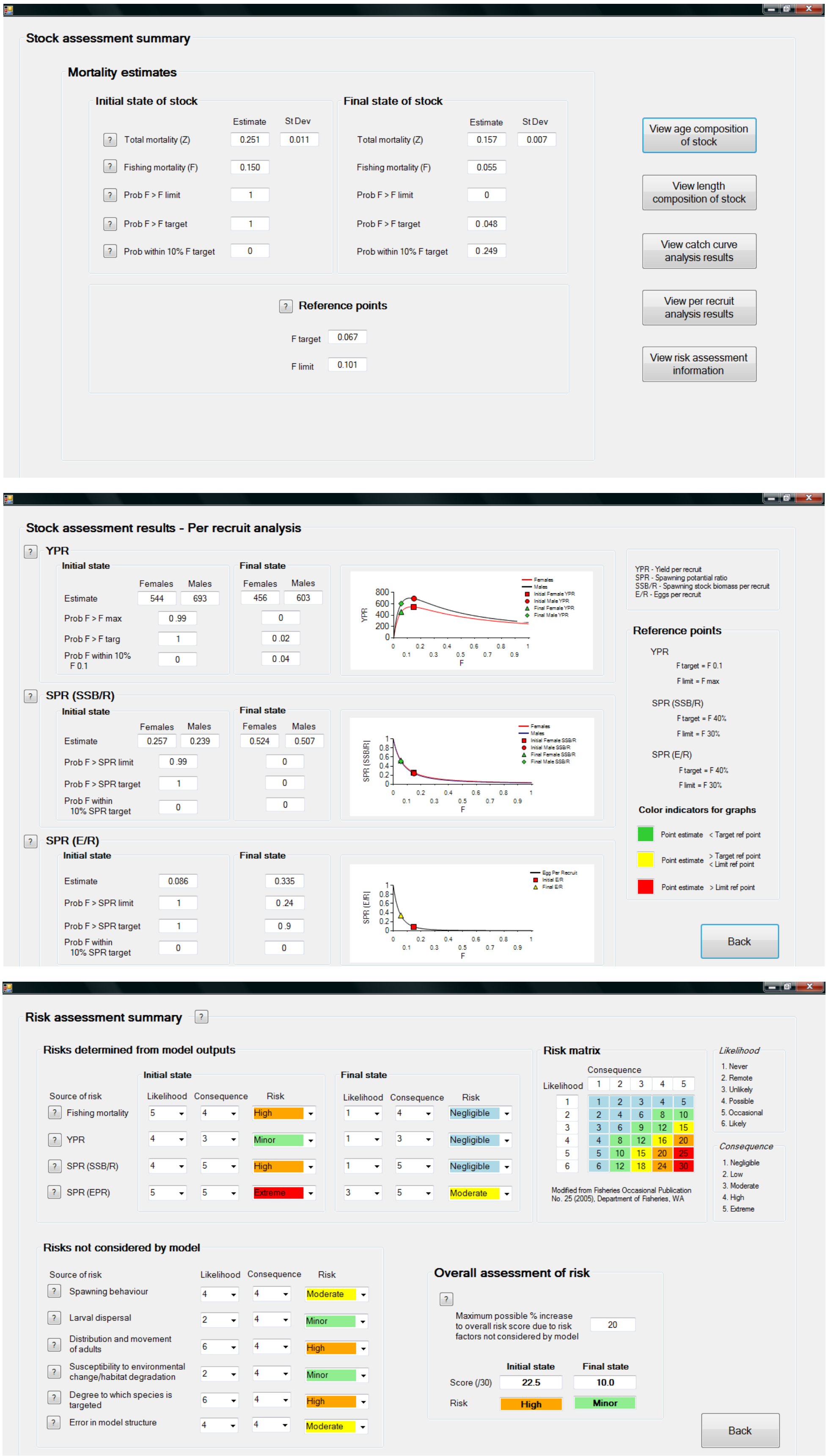
Risks considered by model

	Risk	
Growth and longevity	High	?
Reproductive strategy	Low	?
Recruitment varibility	Low	?
Ability to recover from depletion	High	?
Survival rate after catch-and-release	High	?

Risks determined from model outputs

		Risk at initial state	Risk at final state
Age composition	?	High	Medium
Fishing mortality	?	High	Medium
YPR	?	High	Medium
SPR (SSB/R)	?	High	Low
SPR (EPR)	?	High	Low

Fig. 3.1. Three of the stock status information screens that were presented to participants of the scenario testing workshops held in 2009, in their original, pre-modified format.



Stock assessment summary

Mortality estimates

Initial state of stock

	Estimate	St Dev
? Total mortality (Z)	0.251	0.011
? Fishing mortality (F)	0.150	
? Prob F > F limit	1	
? Prob F > F target	1	
? Prob within 10% F target	0	

Final state of stock

	Estimate	St Dev
Total mortality (Z)	0.157	0.007
Fishing mortality (F)	0.055	
Prob F > F limit	0	
Prob F > F target	0.048	
Prob within 10% F target	0.249	

? Reference points

F target 0.067

F limit 0.101

Stock assessment results - Per recruit analysis

? YPR

	Initial state Females	Initial state Males	Final state Females	Final state Males
Estimate	544	693	456	603
Prob F > F max	0.99		0	
Prob F > F targ	1		0.02	
Prob F within 10% F 0.1	0		0.04	

? SPR (SSB/R)

	Initial state Females	Initial state Males	Final state Females	Final state Males
Estimate	0.257	0.239	0.524	0.507
Prob F > SPR limit	0.99		0	
Prob F > SPR target	1		0	
Prob F within 10% SPR target	0		0	

? SPR (E/R)

	Initial state	Final state
Estimate	0.086	0.335
Prob F > SPR limit	1	0.24
Prob F > SPR target	1	0.9
Prob F within 10% SPR target	0	0

YPR - Yield per recruit
SPR - Spawning potantial ratio
SSB/R - Spawning stock biomass per recruit
E/R - Eggs per recruit

Reference points

YPR
F target = F 0.1
F limit = F max

SPR (SSB/R)
F target = F 40%
F limit = F 30%

SPR (E/R)
F target = F 40%
F limit = F 30%

Color indicators for graphs

🟩 Point estimate < Target ref point
🟨 Point estimate > Target ref point < Limit ref point
🟥 Point estimate > Limit ref point

Risk assessment summary ?

Risks determined from model outputs

Source of risk	Initial state Likelihood	Initial state Consequence	Initial state Risk	Final state Likelihood	Final state Consequence	Final state Risk
? Fishing mortality	5	4	High	1	4	Negligible
? YPR	4	3	Minor	1	3	Negligible
? SPR (SSB/R)	4	5	High	1	5	Negligible
? SPR (EPR)	5	5	Extreme	3	5	Moderate

Risk matrix

Likelihood \ Consequence	1	2	3	4	5
1	1	2	3	4	5
2	2	4	6	8	10
3	3	6	9	12	15
4	4	8	12	16	20
5	5	10	15	20	25
6	6	12	18	24	30

Modified from Fisheries Occasional Publication No. 25 (2005), Department of Fisheries, WA

Likelihood
1. Never
2. Remote
3. Unlikely
4. Possible
5. Occasional
6. Likely

Consequence
1. Negligible
2. Low
3. Moderate
4. High
5. Extreme

Risks not considered by model

Source of risk	Likelihood	Consequence	Risk
? Spawning behaviour	4	4	Moderate
? Larval dispersal	2	4	Minor
? Distribution and movement of adults	6	4	High
? Susceptibility to environmental change/habitat degradation	2	4	Minor
? Degree to which species is targeted	6	4	High
? Error in model structure	4	4	Moderate

Overall assessment of risk

?

Maximum possible % increase to overall risk score due to risk factors not considered by model: 20

	Initial state	Final state
Score (/30)	22.5	10.0
Risk	High	Minor

Fig. 3.2. Three of the stock status information screens that were presented to participants of the scenario testing workshop held in 2010, after modifications were made to their original format.

3.2.4 Statistical analyses of data

Because of the modifications made to the user interface of the MSE model prior to the 2010 scenario testing workshop, the data collected from the 2009 workshops were analysed seperately from the data obtained in 2010. Non-parametric multivariate analyses of these data sets were undertaken using the PRIMER v.6 software package (Clarke and Gorley, 2006) with the PERMANOVA+ add-on module (Anderson *et al.*, 2008) to explore the first two hypotheses of the study. More specifically, analyses of the 2009 and 2010 data tested the null hypothesis of no significant differences between the suite of management decisions made by workshop participants (i) using the two alternative versions of the model (Model A and B) and (ii) undertaking the 12 scenarios.

For each of the data sets obtained from the 2009 and 2010 workshops, the following procedures were undertaken. The management decisions recorded for each participant in each of the 12 scenarios (*i.e.* where each such "sample" comprised the values selected for the four management controls) were subjected to normalisation to overcome differences in the units of measurements of the different variables of interest. A resemblance matrix, constructed between all pairs of samples and using Euclidean distance as the resemblance coefficient, was calculated from the normalised data and displayed using non-metric multi-dimensional scaling (nMDS) ordination. To obtain an overview of the main effects on the management decisions made by participants of the two key factors considered in the analysis (model version and scenario), and to detect any interaction between these, the above-mentioned Euclidean distance matrix, was subjected to permutational multivariate analysis of variance (PERMANOVA; Anderson, 2001; McArdle and Anderson, 2001). For the 2009 data only, included in this preliminary PERMANOVA was also the additional factor of group (*i.e.* undergraduate *vs.* postgraduate students) to explore whether the data obtained from the two workshops undertaken with these two different groups of participating students could be pooled for subsequent analyses.

Following the preliminary analysis, a second PERMANOVA was undertaken for each annual data set to determine, in more detail, the influence on decision-making of the three factors considered within the scenarios undertaken by participants (fish species, initial level of exploitation, and level of recruitment variability of the simulated fish stock). Any potential interactions between these scenario factors were also assessed. All factors in the above analyses were considered to be fixed, and the null hypothesis of no significant differences among the various factor groupings was rejected if $p \leq 0.05$. The components of variation attributed to each factor considered in the PERMANOVA tests were used to determine their relative importance for explaining the overall variation in the data (Anderson *et al.*, 2008).

When PERMANOVA detected significant differences among either of the main effects, analysis of similarities tests (ANOSIM; Clarke and Green, 1988) were then used to examine those differences in more detail. Two-way crossed ANOSIM tests were applied when significant interactions between factors were detected, whereas one-way ANOSIM tests were used when no interactions were detected. For each ANOSIM test, the null hypothesis that there were no significant differences in the suite of management decisions among factor groupings was rejected when $p \leq 0.05$. The relative extent of any significant differences was assessed using the R-statistic, *i.e.* values close to zero indicate little difference between groups, while those close to +1 indicate large differences between groups (Clarke and Green, 1988).

When ANOSIM pair-wise comparisons detected a significant difference between management decisions, similarity percentage analysis (SIMPER; Clarke, 1993) was used to determine which of the management controls (the bag limit, MLL, temporal closure or spatial closure) contributed most consistently to the observed effects, *i.e.* those which had relatively high dissimilarity to standard deviation ratios. Furthermore, permutational tests of multivariate dispersions (PERMDISP; Anderson, 2006) were undertaken to identify any differences in the extent of dispersion within groups of samples representing the various levels of those factors for which significant differences had been detected. The null hypothesis of no difference in dispersion within different groups was rejected if the value of $p \leq 0.05$.

3.3 Results

3.3.1 Model with a simpler user interface

The preliminary PERMANOVA of the 2009 workshop data demonstrated that there was no significant difference between the management decisions (*i.e.* the set of values chosen for the four management controls) made by the undergraduate and postgraduate student groups ($p > 0.05$, Pseudo F = 2.575) or between participants using the two alternative versions of the MSE model, *i.e.* those with and without the additional risk assessment summary screen ($p > 0.05$, Pseudo F = 0.231). This preliminary PERMANOVA did, however, detect a significant difference between the management choices made for the 12 different scenarios ($p = 0.001$, Pseudo F = 32.48). The PERMANOVA detected no significant interactions between any of the three factors considered in this preliminary analysis (all values of $p > 0.05$). As no significant difference was detected between the management decisions made by undergraduate and postgraduate students, the data obtained from these two participant groups were pooled for all the subsequent analyses.

The second PERMANOVA demonstrated significant differences between the management choices made for the two fish species ($p = 0.001$, Table 3.4) and for the different initial levels of exploitation for the simulated stock ($p = 0.001$, Table 3.4). No difference was detected between management decisions made for scenarios with

Table 3.4. Results of PERMANOVA of the 2009 workshop data for management decisions made by participants for the different scenarios undertaken, including mean squares (MS), pseudo F-ratios, significance levels (*p*) and components of variation (COV). df = degrees of freedom. Significant results are highlighted in bold.

Factors	df	MS	Pseudo F	*p*	COV
Main effects					
Species (S)	1	**362.5**	**218.4**	**0.001**	**2.615**
Level of exploitation (F)	2	**132.7**	**79.93**	**0.001**	**1.424**
Recruitment variability (R)	1	3.436	2.070	0.103	0.013
Two-way interactions					
S × F	2	**10.62**	**6.397**	**0.001**	**0.195**
S × R	1	0.961	0.579	0.602	-0.010
F × R	2	3.097	1.866	0.086	0.031
Three-way interaction					
S × F × R	2	1.039	0.626	0.687	-2.698
Residual	264	1.660			1.660

different levels of recruitment variability ($p > 0.05$, Table 3.4). PERMANOVA demonstrated a significant interaction between species and level of exploitation ($p = 0.001$; Table 3.4). The relatively low components of variation for that interaction term, however, indicates that it accounted for far less of the total variability in the data set than did differences in species and level of exploitation (Table 3.4).

The nMDS plots provided good two-dimensional representations of the similarities and dissimilarities between the different factor groupings. All stress values were 0.09, indicating ordinations with minimal distortion of data in order to fit the required dimensions (Clarke and Warwick, 2001). As was also confirmed by the preliminary PERMANOVA, there was no separation of the management decisions made by participants using the different model versions (Fig. 3.3). When management decisions were separated according to the different factors considered for the fishery scenarios, however, nMDS plots showed distinct clustering of data points for the different fish species, and for the different levels of initial exploitation of the fish stock (Fig. 3.4a, b). In contrast, when scenarios were separated according to the different levels of recruitment variability specified for the fish stocks, there was no tendency for data points to cluster (Fig. 3.4c). Two-way crossed ANOSIM tests showed that, when comparing management decisions made for the fishery scenarios, significant differences were detected for the two fish species (*p* = 0.001, R = 0.766), and for the different levels of exploitation (*p* = 0.001, R = 0.367). Pair-wise comparisons of management choices made by participants for scenarios of the three different exploitation levels were all significant (*p* = 0.001), with values of R ranging from 0.241 (when comparing scenarios for low and moderate levels of exploitation) to 0.574 (when comparing scenarios for low and high levels of exploitation).

For the two significant factors, *i.e.* fish species and initial level of exploitation, two-way crossed SIMPER analysis employing these factors showed that the MLL control made the most consistent contribution to the average dissimilarity between decisions made for the two fish species, followed by that for the bag limit control. When scenarios for low initial exploitation were compared to those with

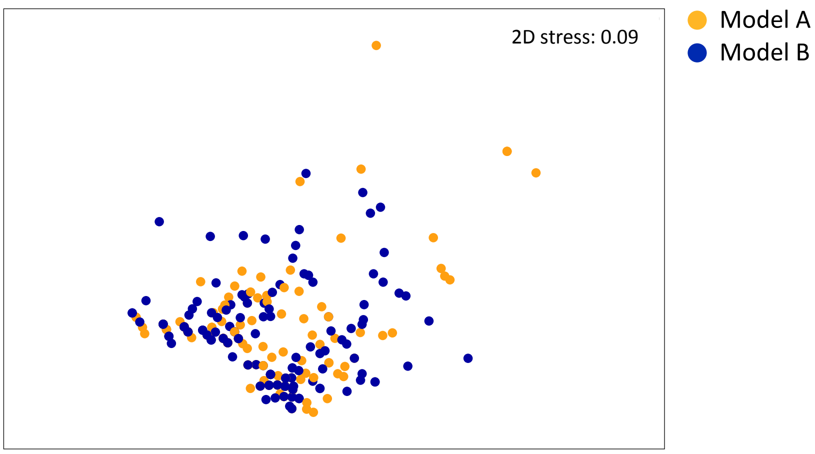
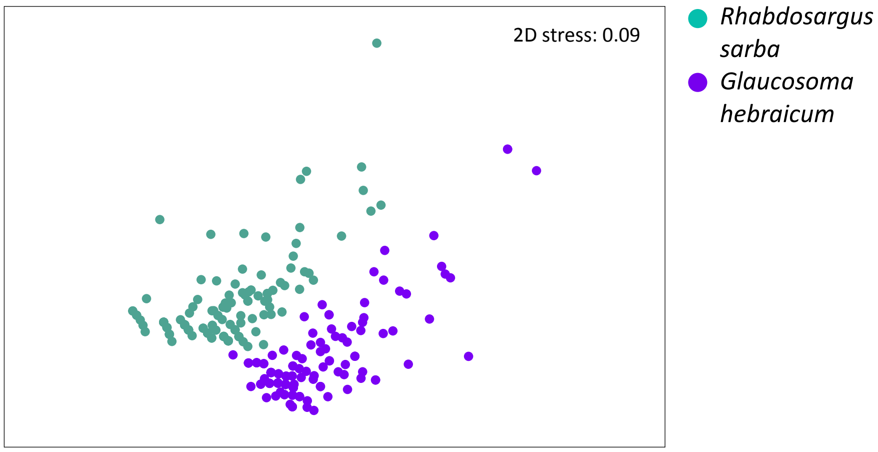
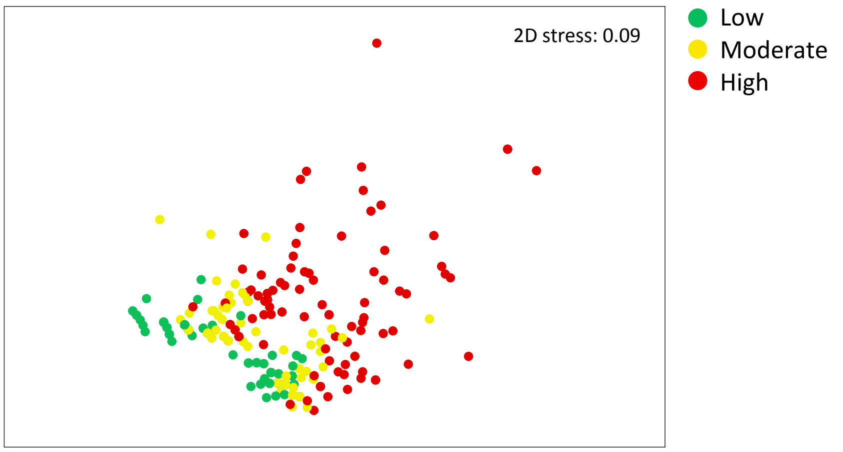


Fig. 3.3. nMDS ordination plot of management decisions made by users of the two alternative versions of the MSE model in the 2009 workshops, with Model A presenting the additional risk assessment summary screen and Model B displaying outputs from the model only.

(a) Fish species



(b) Level of exploitation



(c) Recruitment variability

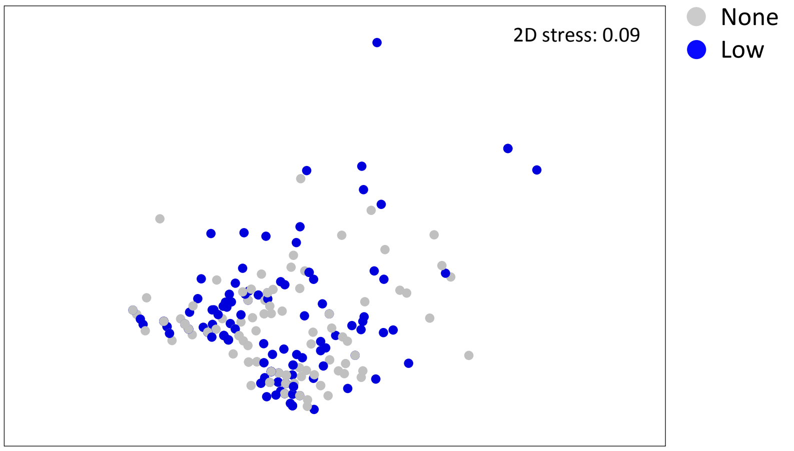


Fig. 3.4. nMDS ordination plots of management decisions made by participants for the different scenarios in the 2009 workshops, when separated by (a) fish species, (b) level of exploitation, and (c) recruitment variability.

moderate and high exploitation, SIMPER showed that the control consistently most responsible for the observed differences in management decisions was again the bag limit. For the comparison of scenarios of moderate and high levels of exploitation, SIMPER showed that the four management controls made similar contributions to the observed differences in management decisions.

PERMDISP showed that the levels of dispersion among management decisions made by participants undertaking scenarios for the two fish species were similar ($p > 0.05$, t = 0.309). This was also the case when comparing decisions made for scenarios of low and moderate initial levels of exploitation ($p > 0.05$, t = 0.330). In contrast, decisions were found to be significantly more varied for scenarios of heavily exploited fish stocks compared with lightly exploited stocks ($p = 0.001$, t = 6.40) and moderately exploited stocks ($p = 0.001$, t = 5.90), as also shown by the nMDS plot (Fig. 3.3b).

3.3.2 Model with a more complex user interface

As was also demonstrated for the 2009 workshop data, the preliminary PERMANOVA of data from the 2010 workshop showed that there was no significant difference between management decisions made by participants using the two versions of the MSE model, *i.e.* with and without the risk assessment summary screen ($p > 0.05$, Pseudo F = 2.65). PERMANOVA did demonstrate, however, a significant difference between decisions made for the various scenarios undertaken by participants ($p = 0.001$, Pseudo F = 13.38). When samples were grouped by the three factors considered in the different scenarios, PERMANOVA once again detected significant differences between the management decisions made for the two fish species ($p = 0.001$, Table 3.5) and for the different initial levels of fishing mortality for the simulated stock ($p = 0.001$, Table 3.5), but showed no difference between

Table 3.5. Results of PERMANOVA of the 2010 workshop data for management decisions made by participants for the different scenarios undertaken, including mean squares (MS), pseudo F-ratios, significance levels (*p*) and components of variation (COV). df = degrees of freedom. Significant results are highlighted in bold.

Factors	df	MS	Pseudo F	*p*	COV
Main effects					
Species (S)	1	**219.6**	**100.7**	**0.001**	**2.787**
Level of exploitation (F)	2	**32.16**	**14.74**	**0.001**	**0.576**
Recruitment variability (R)	1	0.578	0.265	0.854	-0.002
Two-way interactions					
S × F	2	5.905	2.707	0.059	0.143
S × R	1	6.034	2.766	0.052	-0.010
F × R	2	0.724	0.332	0.890	-0.006
Three-way interaction					
S × F × R	2	1.078	0.494	0.771	-0.008
Residual	144	2.340			2.181

scenarios with different levels of recruitment variability ($p > 0.05$, Table 3.5). PERMANOVA detected no significant interactions between the different factors (all p-values > 0.05; Table 3.5).

nMDS plots showed that, despite the modifications made to the user interface of the MSE model, the management decisions made by participants in the 2010 workshop, to some extent, resembled those made in the 2009 workshops (*cf.* Figs. 3.3-3.6). As was also demonstrated by the preliminary PERMANOVA of the 2010 data, even if substantial changes had been made to the risk summary screen to improve the way in which the risk information was communicated to model users, the ordination plot demonstrated that management decisions made by participants using Model A and Model B still overlapped (Fig. 3.5). When scenarios were grouped by the two fish species, the data points in the nMDS plot once again formed two distinct clusters (Fig. 3.5a) and one-way ANOSIM confirmed that there was a significant difference in the management decisions made for *G. hebraicum* and *R. sarba* ($p = 0.001$, R = 0.633).

In contrast to the relatively clear clustering of the 2009 data observed when these were separated according to the initial level of exploitation of the fish stock, the decisions made by the participants in the 2010 workshop for these scenarios overlapped far more (Fig. 3.6b). Although one-way ANOSIM tests demonstrated a significant difference between management decisions made for scenarios of different levels of exploitation ($p = 0.001$, R = 0.118), the low R-statistic indicated that the level of separation was not as great as that observed with the 2009 data. Pair-wise comparisons showed that the difference in management decisions was greatest between scenarios of low and high initial exploitation levels ($p = 0.001$, R = 0.234), and least significant between scenarios of low and moderate exploitation ($p = 0.047$, R = 0.029). Similar to the 2009 results, no separation was observed between management decisions when grouped by level of recruitment variability (Fig. 3.6c), despite the changes made to the scenarios prior to the 2010 scenario testing workshop to include a higher level of recruitment variability (*i.e.* $\sigma_R = 0.6$).

Results from SIMPER analysis of the 2010 workshop data were largely consistent with those reported from the 2009 data, with the values for the MLL and

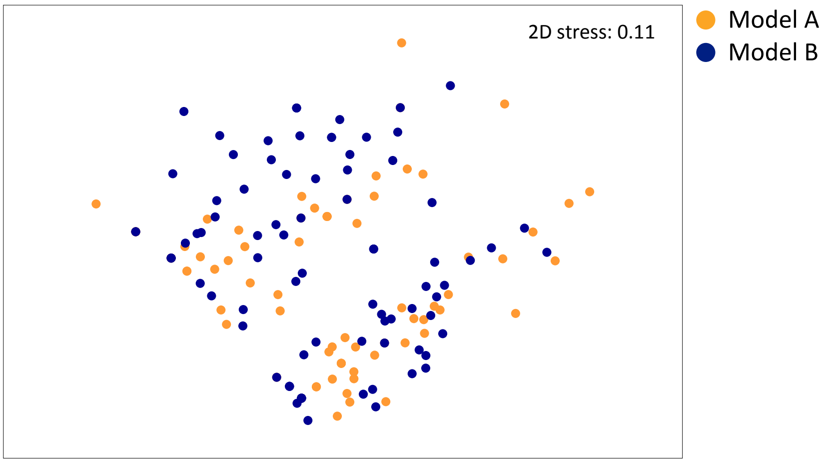
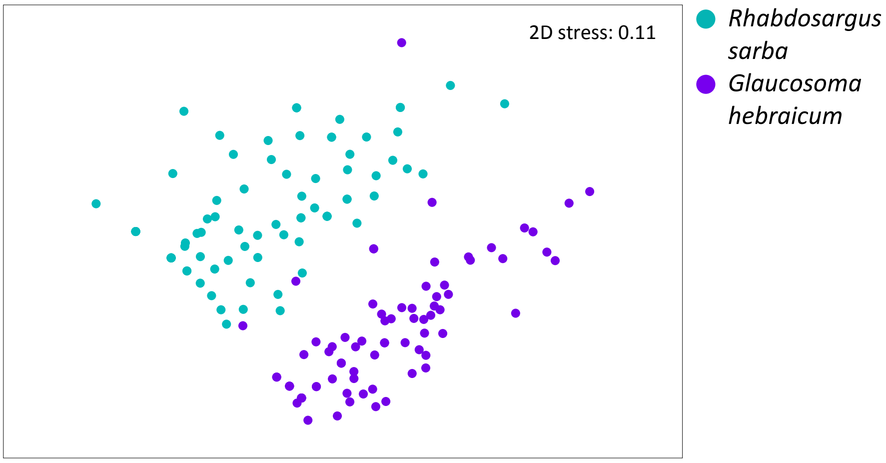
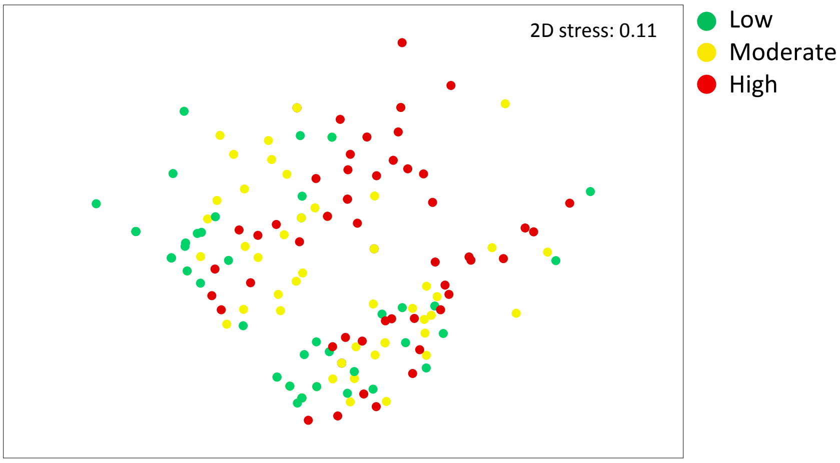


Fig. 3.5. nMDS ordination plot of management decisions made by users of the two alternative versions of the MSE model in the 2010 workshop, with Model A presenting the additional risk assessment summary screen and Model B displaying outputs from the model only.

(a) Fish species



(b) Level of exploitation



(c) Recruitment variability

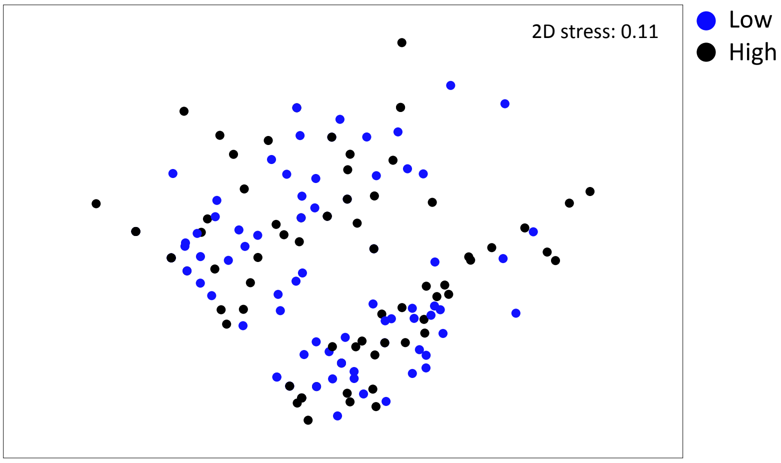


Fig. 3.6. nMDS ordination plots of management decisions made by participants for the different scenarios in the 2010 workshop, when separated by (a) fish species, (b) level of exploitation, and (c) recruitment variability.

the bag limit controls typically making the most consistent contributions to the average dissimilarity between decisions made for the two fish species and for the different levels of exploitation. PERMDISP tests showed that, unlike the greater dispersion of management decisions made by the 2009 workshop participants when the initial level of exploitation was high, no differences in the dispersion of 2010 data were evident among scenarios ($p > 0.05$ for all pair-wise scenario comparisons, including those between the two fish species and different initial levels of exploitation).

3.4 Discussion

3.4.1 Effectiveness of the model for communicating stock status information

The results of this study showed that the management decisions made by the participants exhibited a strong tendency to vary between scenarios. In particular, users of the MSE model made different decisions when faced with the scenarios for the two fish species and with those for different initial levels of exploitation. It is also concluded that, to a large extent, participants made logical decisions, indicating that the user interface was effective for communicating stock assessment information to the workshop participants. For example, as clearly showed by the data collected from the 2009 scenario testing workshops, the values selected for the management controls were typically more variable when the stock was in a heavily exploited state compared to when exploitation was low. Given that the workshop participants received only limited training in how to use the model before undertaking the scenario testing exercise, and that they had limited prior knowledge of fisheries stock assessment, these findings suggest that the model has potential for communicating stock status information to people with different backgrounds.

Focus is next turned to exploring which factors are likely to be important in developing software for conveying stock assessment information and how the design of the scenario testing experiment and user interface may have influenced the management decisions made by the workshop participants.

3.4.2 Important model design features for developing effective communication tools

As pointed out by Mathevet *et al.* (2007), when designing a computer simulation model for communicating information to stakeholders, it is important to find an appropriate balance between simplification and realism. For complex systems, simplification is often required to facilitate stakeholder understanding of the various processes that influence the dynamics of the system. Realism is equally important to the process as it allows stakeholders to project their newly acquired understanding back into reality (Mathevet *et al.*, 2007).

To make the MSE model relevant for research as well as to be used in workshop situations as a communication and education tool, the program can be run in two different "modes" or "levels" depending on the purpose of its use (see Appendix B), which is an approach that has also been described by Scandol (1999; 2000). To simplify use of the MSE model for stakeholder and educational workshops, various features have been added to the user interface. A number of these features restrict certain user "freedoms" when exploring the model. For example, users were disallowed access to change input data such as values of the biological parameters for the fish species, the initial management measures to which stocks were subjected prior to simulations, and parameters specifying other aspects of the simulations. The route by which participants could navigate through the user interface was also restricted to a single pathway, thereby ensuring that they activated each of the various model procedures in the correct order and that all of the available stock assessment information was displayed. Limiting the values that users could select for the different management controls to within feasible ranges was necessary to prevent the model from crashing, however, it is important to note that this may have inhibited the ability of participants to learn about the effects extreme management measures.

Analysis of the data collected from the scenario testing workshop held in 2010, for which the user interface had been modified to include estimates of uncertainty for some of the stock status indicators, and more sophisticated risk assessment information, demonstrated that participants more often made “poorer” management decisions. In comparison to the 2009 workshops, and as indicated by the nMDS plots (*cf.* Figs. 3.4b and 3.6b), participants appeared to more often implement stringent management measures when the stock was lightly exploited and *vice versa*. Thus, in contrast to the hypothesis that the more comprehensive stock assessment information presented by the modified user interface would help model users to obtain a better overall understanding of the underlying status of the fish stocks being assessed, some participants appear to have become confused by that information. The contrasting results between the workshops undertaken in 2009 (with the simpler user interface) and 2010 thus provides an indication of the level of complexity, in user interface design, that is likely to be more optimal for effectively conveying stock status information to people with limited stock assessment experience. It might also be worth noting that results from another scenario testing workshop undertaken with students in 2011 (data not shown), for which participants were once again using the MSE model with the more complex user interface, were very similar to those obtained in 2010, providing further support for this conclusion.

Where possible for this study, and particularly for the 2009 scenario testing workshops, “traffic light” colour indicators were employed in the user interface to draw the attention of participants to key stock assessment results and help communicate the significance of these for the conservation status of the fish stock. The use of reference point-based traffic light indicators was originally proposed by Caddy (1998; 1999) as an approach when designing stock assessment models to assist fisheries managers in developing countries with relatively limited expertise in population modelling (see also Caddy, 2002). As MSE is inherently complex, visual aids such as the use of colour when presenting information, is likely to be particularly important for helping stakeholders without technical or scientific backgrounds interpret the risk implications of different stock assessment results. In the context of using traffic light colours, the more complex user interface design applied in the 2010 workshop (incorporating uncertainty for stock status indicators and more sophisticated risk assessment information) did not readily allow for consistent application of traffic light colours as for the simpler user interface applied in the 2009 workshops. This may thus help explain the more varied management decisions made by participants in the 2010 (and 2011) workshop.

Another feature that may have been important for facilitating an understanding of the relevance of the various model parameters and outputs is the way in which “help information” is presented to users of the MSE model. In contrast to most other software, help buttons are distributed throughout the various screens of the interface, adjacent to each parameter of interest. This thereby eliminated the need for users having access to a program menu to check whether help was available by scrolling through a list, or entering in a “search term” to find the relevant information.

3.4.3 Potential factors influencing decisions of participants

Although the results of the scenario testing experiment suggest that the model was effective in communicating stock assessment information, questions are raised as to the extent to which various factors may have influenced the decisions of the participants. For example, our efforts to simplify use of the software by fixing the route by which users can navigate through the interface meant that stock assessment information was always accessed in a particular order, which potentially could have influenced the decisions made. For example, it is possible that the negligible effect on management decisions of the additional interface screen with risk summary information screen presented by Model A may have been due, at least in part, to the fact that this screen was always presented to users last, at which point they may have already made up their minds based on the information that had been provided to them previously.

A second potentially important factor influencing decisions was that the initial management arrangements displayed to participants prior to each simulation differed for the two fish species (*e.g.* the MLL of 500 mm for *G. hebraicum* was greater than that of 230 mm for *R. sarba).* Although the different starting points for management of the two species undoubtedly influenced the decisions made by participants, it would not have made sense to specify the same starting values for the MLL for the two species given that they attain very different maximum lengths. The alternative of not specifying any values for initial management controls would also not have been realistic because most fish species are already subject to some particular management regime.

A third factor that would have influenced the decisions of the participants was the objective specified for the scenario testing exercise, *i.e.* for the stock to be in a “healthy” state whilst supporting a productive fishery, as indicated by various reference points. Participants were continually reminded of this objective through the display of traffic light colour indicators for most of the stock assessment outputs. The program further highlighted this objective by providing participants with a score at the end of each scenario, calculated according to the final state of the exploited stock relative to fishing mortality-based reference points. For example, if exploitation was well below the specified target reference point for fishing mortality, participants were advised that the fishery was not productive, whereas if exploitation exceeded the limit reference point, feedback was provided that the stock was over-fished. As pointed out by Bertsche *et al.* (1996), an important element of computer simulation exercises is the need for participants to feel challenged, so that at the end of each simulation they will not want to stop, but rather to continue testing the consequences of different actions and improve on their performance. Thus, although the feedback provided to participants may have influenced their decisions, this element is important for capturing and maintaining interest. Future work aimed at exploring the various factors that most influence decision-making of model users could focus on further scenario testing experiments in which certain factors discussed in this section of the discussion are manipulated.

3.4.4 Implications of scenario testing results for fisheries management and MSE

The scenario testing experiment indicated that, of the four available management controls (bag limit, MLL, temporal closure and spatial closure), workshop participants most consistently made changes to existing bag limits and MLL. It also suggested that, when participants perceived the stock to be heavily fished, they tended to apply a wider range of management controls. Given that the workshop participants had limited prior experience in fisheries management and, being university students, may have had views regarding conservation that differ from people within the fishing industry and the broader community, to what extent might their decisions reflect the types of decisions that would be made in a real life situation when managing a fishery?

As an example, taking the recent experience in Western Australia of the recreational fishery for demersal finfish in the West Coast Bioregion, management initially consisted of bag and boat limits as well as MLLs for the retention of species. As exploitation of these stocks became increasingly heavy, however, existing bag and boat limits were tightened and a temporal closure and other measures, such as the compulsory use of release weights, were introduced (Department of Fisheries, Western Australia, 2012). Although the decisions made by participants in the workshop resembled, to some extent, the pattern experienced by this particular fishery, the factors that influence management decisions in real life are complex and involve consideration of multiple and often conflicting objectives (*e.g.* Hilborn and Walters, 1992). Thus, in addition to the extent to which management changes may be needed, other factors such as the extent to which different stakeholders accept, or are opposed to, each of the different types of controls, will inevitably influence the types of management choices made by decision-makers. The increasing influence of environmentalist groups on government policy is another factor affecting fisheries decision-making (Gray *et al.*, 1999; Todd and Ritchie, 2000).

The tendency, in the 2009 workshops, for variability in management decisions among participants to increase as the initial stock state worsened is likely to reflect an increased difficulty for participants to comprehend the likely effects of management changes when a broader range of controls are used. Indeed, feedback from students who participated in the workshops indicated that they preferred to use controls that they thought they best understood and only tended to use the other (closure) controls when they considered that the situation demanded further action. It would appear likely that, to a certain extent, such decision-making behaviours do translate to real life situations. Logically, as management arrangements become increasingly complex, the risk of unexpected consequences as a result of increased difficulty in being able to accurately predict their effects, will also increase (Healey and Hennessey, 1998; Cochrane, 1999). This point emphasises one of the great values of simulation in fisheries management, that is, to explore the effectiveness of alternative combinations of management controls and learn from mistakes in a risk-free, simulated environment (Bertsche *et al.*, 1996).

3.4.5 Value of scenario testing for facilitating stakeholder discussion and education

Some of the greatest challenges to successful fisheries management include the typically conflicting values and objectives of different fishery stakeholders (Hilborn and Walters, 1992), and the lack of effective communication between these groups (de la Mare, 1998; Peterman, 2004). In regard to the latter point, MSE could provide a valuable tool for facilitating increased stakeholder participation in fisheries decision-making (Smith *et al.*, 1999). This stems from the fact that simulation modelling has shown to be particularly valuable for problem-solving in situations that involve many people or organisations whose actions need to be coordinated (Bertsche *et al.*, 1996). In particular, it is recognised that by providing a vehicle for engaging industry in decision-making, MSE may also play an important role in facilitating greater stakeholder understanding and trust in the fisheries management process.

The MSE approach is likely to be valuable to fisheries co-management initiatives, where government administrators act more as arbiters among interests within the general public than as decision-makers in the public interest (Beierle and Cayford, 2002). Indeed, it has been widely accepted that inclusion of stakeholders in fisheries decision-making can lead to better management outcomes by increasing the efficiency of enforcing regulations through a higher level of compliance (Jentoft and McCay, 1995; Mikalsen and Jentoft, 2001). Given the potential of MSE for facilitating more informed fisheries decision-making, it is a concern that its use is being limited by the fact that stakeholders and managers with non-science or non-technical backgrounds often struggle with its complexity (Smith *et al.*, 1999; Rochet and Rice, 2009). Indications from our scenario testing results, however, show that, if well designed, MSE programs can be effective for conveying stock assessment outputs to an audience with widely varying backgrounds.

3.4.6 Conclusion

The findings of the study suggest that the approach taken to develop the MSE model, with the intent purpose of testing its effectiveness for communicating relatively complex stock status information to people with little or no experience in stock assessment, is of value when developing software for stakeholder use. It is also concluded that, although it is possible to maintain a level of model sophistication and complexity needed for robust analyses, modification of various aspects of the program interface when applying the model to workshop situations allows users to more easily use the software and interpret the results in a manner more intuitive to non-scientists.

Although it is clear that fisheries simulation models such as the one described in this study can constitute valuable communication and education tools to help facilitate a participatory fisheries management approach, it is essential that the stock assessment information being conveyed to users is reliable. For example, if the estimates of stock status indicators produced by the model are biased, users may unknowingly be basing their management decisions on false perceptions about the true state of the simulated fish stock. Due to the data limitations characteristic of many recreational and small-scale commercial fisheries, stock assessment scientists often rely on simplified assessment methods such as catch curve analysis for estimating mortality of fish species. Despite the popularity of catch curves for assessing data-poor fisheries, these methods are typically based on strong assumptions about the exploited fish stock that are extremely difficult to satisfy (Ricker, 1975; Dunn *et al.*, 2002). The next chapter (Chapter 4) is focused on exploring, using simulation, the robustness of several different catch curve models for producing reliable estimates of mortality. Specifically, the study describes two catch curve methods which were developed to allow some of the assumptions associated with conventional mortality estimators to be relaxed.

CHAPTER 4

To what extent can mortality estimates produced by catch curve analysis be improved by accounting for variable recruitment and changes in mortality?

4.1 Introduction

Stock assessments for fisheries which lack extended time series of catch and effort data typically employ catch-at-age analyses of age composition data derived from samples of fish (Jensen, 1985; Wayte and Klaer, 2010). The key focus of such analyses is to estimate the instantaneous rate of total mortality, Z, for an exploited fish stock (Smith, 1990; Schnute and Haigh, 2007). One of the simplest and most popular methods for estimating Z from age composition data is catch curve analysis. Although catch curves continue to be used extensively in fisheries assessments (*e.g.* Grandcourt *et al.*, 2008; Smith *et al.*, 2008; Griffiths, 2010), a situation which is largely due to the limited data requirements of these methods, they are also frequently criticised because of the strong assumptions required about the data to which the curves are fitted (Deriso *et al.*, 1985; Hilborn and Walters, 1992). Although it is widely recognised that some of these assumptions are difficult to fully satisfy, for data-poor fisheries, alternative methods for estimating mortality from age samples are very limited.

Several catch curve methods have been described in the scientific literature. Two of the most popular include the mortality estimator described by Chapman and Robson (1960) and the conventional, regression-based catch curve, which is fitted to the logarithms of number of sampled fish of different ages above the age at which fish are fully recruited into the fishery (Ricker, 1975). Common to both of these approaches is the assumption that the fish population is in a steady state, *i.e.* that annual recruitment and mortality are constant with respect to time and age of fish

(Chapman and Robson, 1960; Ricker, 1975; Jensen, 1984). Chapman and Robson (1960) recognised that, even when these assumptions are satisfied, the estimate of Z produced by the equation that they developed will be biased. Furthermore, results of simulation studies have indicated that departures from steady-state conditions will result in increased bias in mortality estimates (*e.g.* Jensen, 1985; Dunn *et al.*, 2002). These findings are particularly concerning as catch curves often appear to underestimate the true mortality of fish stocks, which could potentially have serious implications for the sustainability of fisheries if those biased mortality estimates are the basis for management decisions. For example, a recent study, using the MSE model described in Chapter 2, indicated that linear catch curve analysis can substantially underestimate mortality for shorter-lived fish species, but less so for longer-lived species (Fisher *et al.*, 2011). This negative bias of the estimates of Z produced by the regression-based catch curve has also been highlighted by Murphy (1997) and Dunn *et al.* (2002) for scenarios in which annual recruitment was assumed to be constant.

The Chapman and Robson (1960) method produces unbiased estimates of survival S $(= \exp(-Z))$ and, under steady-state conditions, it has also been found to produce more accurate estimates of Z than the regression-based catch curve (Murphy, 1997; Dunn *et al.*, 2002). In situations when recruitment to the fish stock is allowed to vary among years, however, the Chapman and Robson (1960) estimator has also been found to introduce additional negative bias into mortality estimates, albeit less bias than evident in the regression-based estimates (Dunn *et al.*, 2002). Scientists have attempted to deal with the assumption of constant recruitment when estimating Z in various ways. It has been suggested, for example, that sample data collected over multiple consecutive years may be pooled to smooth out peaks and troughs in the age compositions (Seber, 1973; Ricker, 1975). Others have explicitly accounted for recruitment variability by applying catch curve approaches that deal with individual year classes of fish (Deriso *et al.*, 1985).

It is important to recognise that the steady-state assumptions of conventional catch curve approaches can also be violated for other reasons, such as when, for heavily exploited stocks, more stringent management measures are introduced to reduce fishing pressure. Catch curve analyses typically rely on the mortality of fully-recruited fish being constant over age and time (Ricker, 1975). It thus becomes challenging when catch curve analysis is being used as the primary assessment method for data-limited fisheries to assess how well a fish stock is responding to a relatively recent management change. Indeed, an evaluation of whether the management change has succeeded in shifting mortality to the intended level is typically required well before the age composition has stabilised to its new steady state, as required by conventional catch curve methods. In this situation, an age-based catch curve method that is able to provide robust estimates of Z only a short time period after the change would be very beneficial to scientists and managers.

This study examines the performance of two catch curve approaches that allow the assumptions of constant recruitment and mortality to be relaxed. The ability of each approach for producing reliable estimates of mortality, when fitted to simulated data for a hypothetical fish species, was explored for various scenarios of different specified values of Z and different levels of recruitment variability. The following hypotheses were explored:

(1) For a fish species in which annual recruitment to the stock varies substantially among years, a catch curve model that allows for such variability in recruitment to be estimated from age composition data will produce estimates of Z that have

a lower root mean square error (RMSE) than a catch curve model which assumes constant annual recruitment.

(2) For fisheries in which management measures have recently been introduced to reduce the fishing pressure on a fish stock, *i.e.* at a known point in time, a catch curve model which accounts for a change in mortality at that time will provide a significantly better fit to age composition data than one which does not account for that change in mortality. The power to obtain such a statistically significant improvement in fit will depend upon the following factors:
    a. the sample size of the age composition data to which models are fitted,
    b. the number of years that have elapsed since the implementation of the management change,
    c. the "old" value of Z prior to the management change,
    d. the percentage by which Z is reduced as a result of the change, and
    e. the level of annual recruitment variability that the fish stock experiences.

(3) The catch curve model that allows for a change in mortality in response to management change will produce estimates of the "new" and "old" Z that have a lower RMSE when recruitment variability is accounted for in the estimation process than mortality estimates obtained from a model with similar structure that assumes that annual recruitment is constant.

4.2 Methods

4.2.1 Estimators of Z assuming constant recruitment and mortality

Assuming that recruitment of fish to the first fully-recruited age class is constant and that the instantaneous rate of total mortality, Z, is age-independent and constant for all ages after the age of full recruitment, the expected number of survivors per recruit, N_a, may be calculated as

$$N_a = \exp[-Za] \tag{4.1}$$

where a is the age relative to the age at full recruitment, *i.e.* $a = 0$ years represents the age at full recruitment. If it is assumed that the instantaneous rate of natural mortality, M, is constant, it follows that, as $Z = M + F$, the instantaneous rate of fishing mortality, F, must also be constant. The expected catch of age a fish per recruit, C_a may therefore be determined as

$$C_a = \frac{F}{Z}(1 - \exp[-Z])\, N_a. \tag{4.2}$$

The sum of catches per recruit over all ages from $a = 0$ to infinity is F/Z. Thus, the expected proportion of fish of age a in the catch, $\hat{p}_a$, is

$$\hat{p}_a = (1 - \exp[-Z])\, N_a. \tag{4.3}$$

$\hat{p}_a$ is assumed to have the form of a geometric distribution, where, as expected, the sum from age $a = 0$ to infinity is equal to one. The expected proportion of fish in a random sample from the catches taken during the year is the expected proportion of fish of age a in the catch. Note that, if the sample is truncated at age A, where A is treated as a plus-group, then the expected proportion of fish at age A is

$$\hat{p}_A = \exp[-ZA]. \tag{4.4}$$

To derive a minimum variance, unbiased estimator of the annual rate of survival, S, for a fish stock, Chapman and Robson (1960) and Robson and Chapman (1961) employ the fact that the proportion of fish at age follows the geometric distribution. That is,

$$S = \frac{\bar{a}}{1 + \bar{a} - {}^{1}\!/_{n}} \tag{4.5}$$

where $\bar{a}$ is the mean age above the age at full recruitment and n is the sample size of fish at and above this age. These authors advise, however, that no unbiased estimator of the instantaneous rate of total mortality is available, but that a nearly unbiased estimate is given by

$$\hat{Z} = \ln\left[\frac{1 + \bar{a} - {}^{1}\!/_{n}}{\bar{a}}\right] - \left[\frac{(n-1)(n-2)}{n(n\bar{a}+1)(n+n\bar{a}-1)}\right]. \tag{4.6}$$

The Chapman and Robson estimator of Z that is typically used as the "Chapman-Robson estimate" (*e.g.* Dunn *et al.*, 2002) is

$$\hat{Z} = \ln\left[\frac{1 + \bar{a} - {}^{1}\!/_{n}}{\bar{a}}\right] \tag{4.7}$$

noting that, as Dunn *et al.* (2002) advise, this differs from the maximum likelihood estimate for Z by the inclusion of the term $1/n$, and that

$$\mathrm{Bias}(\hat{Z}) \approx \frac{(1 - \exp[-Z])^2}{n \exp[-Z]} \approx \mathrm{Var}(\hat{Z}). \tag{4.8}$$

Rather than estimating Z using the mean age, as was proposed by Chapman and Robson (1960), a maximum likelihood estimate of Z may be obtained by fitting the above model to a representative random sample of the age composition by maximising the multinomial log-likelihood, λ_{age}, where

$$\lambda_{\text{age}} = \upsilon \sum_{a} p_a \ln \hat{p}_a \tag{4.9}$$

and where υ is the sample size, p_a is the observed proportion at age a, and $\hat{p}_a$ is the estimated proportion at age. Following Dunn *et al.* (2002), in the simulations that follow, appropriate values for υ (depending on the value of Z) were selected so that the mean coefficient of variation (standard deviation/mean) of p_a corresponds to a particular target value, $\mathrm{CV_s}$. That is,

$$\upsilon = \frac{\sum_a \sqrt{p_a(1 - p_a)}}{\mathrm{CV_s}}. \tag{4.10}$$

Based on the analyses presented by Chapman and Robson (1960), the resulting maximum likelihood estimate of Z that is obtained (from Equation 4.9) will be biased, where the magnitude of the bias will depend on the variance of the estimate of Z. This bias will be assessed later in this chapter.

4.2.2 Accounting for recruitment variability

Let us now turn to the model that was used in this study to explore the effect of recruitment variability on the estimate of Z, and how this variability might be taken into account to improve the estimate. For this model, it is assumed that the expected value of recruitment of all year classes to the age at full recruitment, $\bar{R}$, is constant, and that annual recruitments for ages 0 to $A - 1$ are randomly drawn from a log-normal distribution, where the standard deviation of the natural logarithms of the recruitment deviations is σ_R. In this study, the age class immediately following the greatest observed age was employed as age A. That is, if we use the notation R_a to refer to the recruitment (to the age at full recruitment) of the year class, which is currently of relative age a, then we assume that

$$R_a = \begin{cases} \bar{R} \exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right] & \text{for } 0 \le a < A \\ \bar{R} & \text{for } a \ge A \end{cases} \tag{4.11}$$

where $\varepsilon_a \sim N(0, \sigma_R^2)$ and ε_a is termed the "recruitment deviation" for age a (Maunder and Starr, 2001; Maunder and Deriso, 2003).

If Z is constant, the number of fish of age a, where $0 \le a \le A$ and A is a plus-group (*i.e.* contains all fish of age A or greater) in the population, N_a, is calculated as

$$N_a = \begin{cases} R_a \exp[-Za] & \text{for } 0 \le a < A \\ \bar{R} \dfrac{\exp[-ZA]}{(1-\exp[-Z])} & \text{for } a = A \end{cases} \tag{4.12}$$

The expected proportion of fish at age a in a random sample is then

$$\hat{p}_a = \frac{N_a}{\sum_{a=0}^{A} N_a}. \tag{4.13}$$

Specifically, $\hat{p}_a$ is thus calculated as

$$\hat{p}_a = \begin{cases} \dfrac{\exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right]\exp[-Za]}{\sum_{a=0}^{A-1} \exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right]\exp[-Za] + \frac{\exp[-ZA]}{(1-\exp[-Z])}} & \text{for } 0 \le a < A \\ \dfrac{\frac{\exp[-ZA]}{(1-\exp[-Z])}}{\sum_{a=0}^{A-1} \exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right]\exp[-Za] + \frac{\exp[-ZA]}{(1-\exp[-Z])}} & \text{for } a = A. \end{cases} \tag{4.14}$$

The process of drawing a random sample and undertaking a catch curve analysis using the above model may be simulated as follows. If values of Z, σ_R and ε_a (for $0 \leq a < A$) are specified, then random samples may be drawn from the expected proportions at age and models fitted to produce estimates of Z (and of ε_a). In practice, a value of maximum age very much greater than the expected value of A was used when generating the simulated age composition, and the value of A that was used in the subsequent catch curve analysis was determined from examination of the resulting age composition. When fitting stock assessment models which estimate similar recruitment deviations, it is typical to assume a prior probability distribution for these deviations. In a number of assessments (*e.g.* Smith and Punt, 1998; Maunder and Deriso, 2003), it has been assumed when fitting the fishery model that $\varepsilon_a \sim N(0, \sigma_R^2)$, where σ_R has a value of 0.6, based on meta-analyses for teleosts reported by Beddington and Cooke (1983) and Myers (1991). The same prior probability distribution was used in this study when fitting the catch curve model and estimating recruitment deviations. That is, when generating the simulated age composition sample, it was assumed that $\varepsilon_a \sim N(0, \sigma_R^2)$, where σ_R was set to the specified value for the scenario that was being investigated, and when fitting the catch curve model that allowed for recruitment variability, it was assumed that $\varepsilon_a \sim N(0, \sigma_R^2)$, where σ_R = 0.6.

When fitting the recruitment deviations, a forward-selection algorithm was adopted by successively adding the recruitment deviation for that age class that contributed the greatest improvement to model fit while still improving that fit significantly, and repeating until no improvement in log-likelihood was gained by including recruitment deviations for the remaining age classes. According to Smith and Punt (1998), the contribution to the log-likelihood that is associated with the recruitment deviations, denoted by λ_R, may be calculated as

$$\lambda_R = \frac{1}{2\sigma_R^2}\sum_a \varepsilon_a^2. \tag{4.15}$$

The overall log-likelihood for both the age composition and recruitment deviations is

$$\lambda = \lambda_{\text{age}} + \lambda_R. \tag{4.16}$$

4.2.3 *Accounting for a change in mortality*

If a representative random sample is drawn from a fish stock that experiences constant annual recruitment, R, and was originally subjected to a constant total mortality of Z_{old} and, subsequently, for a period of T years, has experienced a constant total mortality of Z_{new}, then the expected number of fish of age a (relative to the age at full recruitment) is n_a, where

$$n_a = \begin{cases} kR\exp[-Z_{\text{new}}a] & \text{for } a < T \\ kR\exp[-Z_{\text{new}}T - Z_{\text{old}}(a-T)] & \text{for } a \geq T \end{cases} \tag{4.17}$$

where k is a constant of proportionality relating sample size to population size. If the sample is truncated at age A, where A is treated as a plus-group, then the expected number of fish at age A is

$$n_A = \frac{kR\exp[-Z_{\text{new}}T - Z_{\text{old}}(A-T)]}{1-\exp(Z_{\text{old}})}. \tag{4.18}$$

The sum, s, of the numbers at age may be calculated as

$$s = kR\frac{1 - \exp[-Z_{\text{new}}T]}{1 - \exp[-Z_{\text{new}}]} + kR\frac{\exp[-Z_{\text{new}}T]}{1 - \exp[Z_{\text{old}}]}. \tag{4.19}$$

The expected proportion of fish of age a in the sample may be calculated as

$$\hat{p}_a = \frac{n_a}{s} \tag{4.20}$$

noting that kR is a common factor in both the numerator and denominator and thus may be ignored when calculating proportions at age. The maximum likelihood estimates of Z_{old} and Z_{new} may be obtained by maximising the value of λ_{age} in Equation 4.9.

If annual recruitment, R_a, varies for ages $0 \leq a < A$ and is constant for older ages, as described in Equation 4.11, then

$$n_a = \begin{cases} k\bar{R}\exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right]\exp[-Z_{\text{new}}a] & \text{for } a < T \\ k\bar{R}\exp\left[\varepsilon_a - \frac{\sigma_R^2}{2}\right]\exp[-Z_{\text{new}}T - Z_{\text{old}}(a - T)] & \text{for } T \leq a < A \\ \frac{k\bar{R}\exp[-Z_{\text{new}}T - Z_{\text{old}}(A - T)]}{1 - \exp[Z_{\text{old}}]} & \text{for } a = A. \end{cases} \tag{4.21}$$

Noting that $k\bar{R}$ is common to each expression, the expected proportions at age $\hat{p}_a$ may be calculated by setting $k\bar{R} = 1$, and calculating the relative number at age using the above equation, then dividing the relative number at age by the sum of the relative numbers at age from ages 0 to A. The same forward selection algorithm as described earlier may then be used to obtain maximum likelihood estimates of Z_{old} and Z_{new} and those recruitment deviations ε_a for age classes that significantly improve the log-likelihood.

4.2.4 Hypothesis testing: accounting for recruitment variability

To test the first hypothesis of this study (*i.e.* that by accounting for variability in recruitment and allowing recruitment deviations to be estimated, the RMSE of the estimates of Z can be reduced from that RMSE obtained by using a model that assumes recruitment to be constant), 1000 data sets were simulated for a hypothetical fish species and estimates of Z were calculated using (i) the Chapman-Robson estimator (Equation 4.7), (ii) the catch curve model that estimates proportions at age based on the assumption of constant annual recruitment (*i.e.* Equations 4.3, 4.4 and 4.9), and (iii) the catch curve model that estimates proportions at age based on the assumption of variable annual recruitment and employing a forward selection algorithm to determine which of the recruitment deviations are to be included in the final model structure (Equations 4.9 and 4.11). The 1000 simulated data sets to which each of the three models were fitted were generated for a number of different values of Z (0.2, 0.5 and 0.8 year^{-1}) and for differing levels of recruitment variability (σ_R = 0 and 0.7). Assuming a CV_s (*i.e.* sampling error) of 0.2, the sample size υ that corresponds to such a level of variability was determined for each of the three Z values and using Equations 4.3 and 4.4 to calculate the expected proportions at age (see Equation 4.10). The same sample sizes were used when simulating the age compositions for the scenarios where annual recruitment was assumed to vary. That is, when Z was specified as 0.2, 0.5 and 0.8 year^{-1}, the values of υ used for those scenarios were 466, 166 and 91 fish, respectively.

The estimates of Z obtained from fitting the three catch curve models to the 1000 data sets generated for each scenario were compared with the specified true value of Z to obtain an estimate of the bias of the estimate resulting from the individual trial, *i.e.* $\hat{Z} - Z$. These 1000 values were then used to determine, for each of the scenarios, the average bias and RMSE for the estimates of Z, which were calculated as

$$\mathrm{Bias}(\hat{Z}) = \frac{1}{n_{rep}} \sum (\hat{Z} - Z) \tag{4.22}$$

$$\mathrm{RMSE}(\hat{Z}) = \sqrt{\mathrm{Var}(\hat{Z}) + [\mathrm{Bias}(\hat{Z})]^2}. \tag{4.23}$$

RMSE is the typical indicator that is used to assess the performance of two models, *i.e.* their ability to produce a reliable estimate of a parameter, where it is concluded that the model with the lower RMSE provides the better estimator (*e.g.* Dunn *et al.*, 2002). To allow comparisons of calculated values for the bias and RMSE across different scenarios of specified true Z, the relative percentage bias and RMSE (%Bias and %RMSE) were determined as

$$\%\mathrm{Bias} = \mathrm{Bias}(\hat{Z}) \, \frac{100}{Z} \tag{4.24}$$

$$\%\mathrm{RMSE} = \mathrm{RMSE}(\hat{Z}) \, \frac{100}{Z}. \tag{4.25}$$

4.2.5 Hypothesis testing: accounting for a change in mortality

For the second part of the study, simulations were carried out to explore the effectiveness of the catch curve model that accounts for a recent change in mortality of a fish stock at a known point in time. A simulation study was undertaken to test the hypothesis that this new catch curve model produces a better fit than a model that assumes constant mortality, when applied to age composition data from a fishery that has undergone such a change in mortality, and that this improvement in fit is statistically significant. That is, this study intended to assess whether it is possible, given the variability present in age composition data, to detect the change in mortality. For each of 1000 simulation trials, an age composition sample of a specified size was randomly drawn from the proportions at age that would be expected for a fish stock that has recently undergone a reduction in Z. The two models were then fitted to these data to obtain maximum likelihood estimates of their parameter(s).

The scenarios that were explored comprised two different values of Z prior to the management change (0.5 and 0.8 year^{-1}), two different magnitudes of change (25% and 50% reductions in the specified values of Z_{old}), and the same two levels of recruitment variability that were considered above (σ_R = 0 and 0.7). For each such scenario, and for each of two specified levels of sampling error (CV_s = 0.1 and 0.2), 1000 data sets were generated by assuming that the sample had been collected 3, 4, 5 and 6 years after the change in mortality to explore the impact of this on the effectiveness of the models for reliably estimating Z_{new} and Z_{old}. The fits of the two models to age composition data were compared assuming that recruitment was constant. It was considered inappropriate to compare models that assumed variable recruitment as, when using the forward selection algorithm to estimate recruitment deviations, the number of these deviations making a significant improvement in model fit was likely to vary with the age composition data used in each simulation trial. Consequently, the number of parameters fitted by the models would vary between models and among simulation trials. Likelihood-ratio tests (Kimura and Somerton, 2006) were used to determine, for each of the corresponding values of the log-likelihoods obtained by fitting the two models to the 1000 data sets generated for the different scenarios, whether allowing for the change in mortality resulted in a significant improvement in the fit. For each scenario, the percentage of the 1000 trials in which a significant improvement in the log-likelihood was observed by employing the estimator that accounted for the mortality change was then calculated.

To test the final hypothesis of the study, the model fits of the above-mentioned catch curve model to the different data sets were also repeated when accounting for variability in recruitment, *i.e.* by allowing the annual recruitment deviations to be estimated in addition to Z_{new} and Z_{old}. The mortality estimates obtained from these model fits were compared by calculating, as previously described, the %RMSE and %Bias for each scenario and assessing whether also estimating the annual recruitment deviations led to a reduced bias in estimates of Z_{new} and Z_{old} than when assuming that annual recruitment is constant.

4.3 Results

4.3.1 Accounting for recruitment variability

For scenarios in which recruitment was kept constant (σ_R = 0), fitting the three different catch curve models that assume constant mortality, *i.e.* the Chapman-Robson (1960) estimator and two different maximum likelihood estimators (one which assumes constant annual recruitment and one which allows for variability in recruitment among years, hereafter referred to as MLE and MLER, respectively) to simulated age composition data yielded estimates of Z with very similar %RMSE (Table 4.1). In contrast, for scenarios in which recruitment was variable (σ_R = 0.7), MLER typically provided a better fit to age composition data (Fig. 4.1), and produced estimates of mortality that, for all values of Z used to generate the simulated data, had a lower value of %RMSE than the other two catch curve models (Table 4.1). Values of %RMSE for Z estimates produced by all three models for variable recruitment scenarios were generally higher than for scenarios of constant annual recruitment.

Table 4.1. %RMSE and %Bias of mortality estimates produced by three catch curve methods (the Chapman-Robson estimator and two different maximum likelihood estimators (MLE); one which assumes constant recruitment and one which accounts for recruitment variability), for different specified values of total mortality (Z; year^{-1}) and recruitment variability (*i.e.* different specified values for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). A CV$_s$ (sampling error) of 0.2 was specified for all scenarios. Comparative values of %RMSE obtained by Dunn *et al.* (2002) using the Chapman-Robson estimator are presented in parentheses.

		%RMSE			%Bias		
Z	σ_R	CR[a]	MLE[b]	MLER[c]	CR[a]	MLE[b]	MLER[c]
0.2	0	5 (6)	5	5	-0.2	0	0.2
	0.7	19 (18)	19	14	-0.3	-0.1	-2.8
0.5	0	7 (9)	8	8	0.1	0.3	0.7
	0.7	28 (28)	28	21	-0.9	-0.5	-0.2
0.8	0	11 (13)	11	12	0.2	1.0	1.2
	0.7	35 (35)	35	30	1.8	2.5	3.7

[a] Chapman-Robson estimator.

[b] Maximum likelihood estimator that assumes constant annual recruitment and mortality.

[c] Maximum likelihood estimator that accounts for recruitment variability but assumes constant mortality.

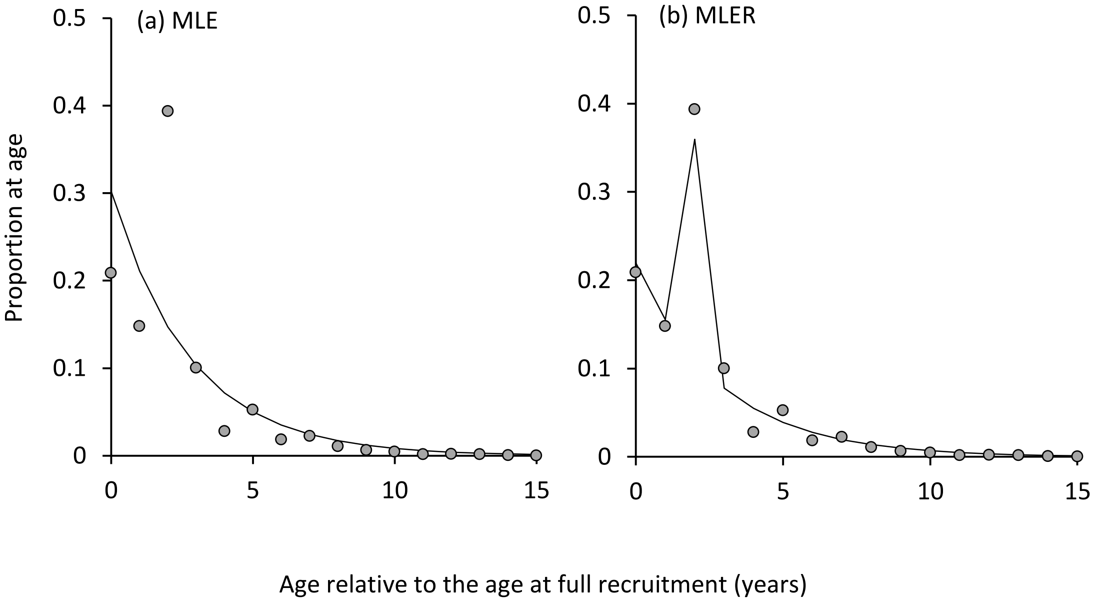


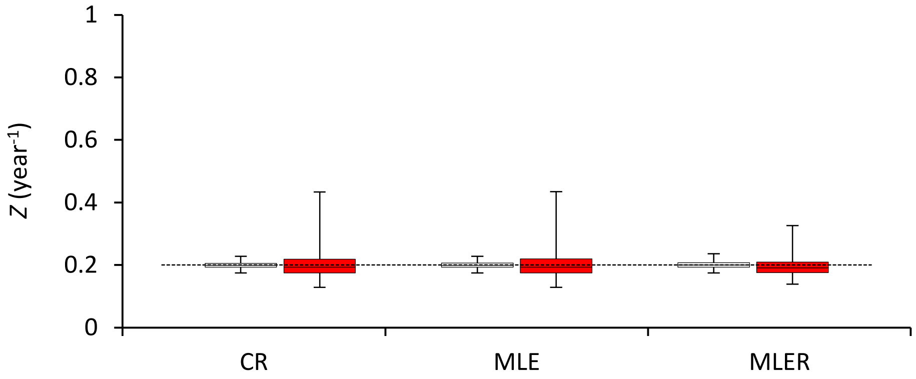
Fig. 4.1. Fits of the two maximum likelihood estimators (both which assume constant mortality) to identical simulated age composition data, where (a) MLE assumes constant annual recruitment, and (b) MLER accounts for recruitment variability. The age composition data were generated by specifying a value for total mortality of 0.5 year^{-1}, and assuming that annual recruitment is variable (*i.e.* the standard deviation of the natural logarithms of annual recruitment deviations, σ_R, was set to 0.7).

For example, when Z was 0.2 year^{-1}, the %RMSE calculated from mortality estimates produced by the Chapman-Robson estimator and MLER increased from 5 to 19, and 5 to 14, respectively, as recruitment to the simulated stock was allowed to vary (Table 4.1). For all three catch curve models, the %RMSEs of Z estimates were found to increase as the specified value for Z was increased from 0.2 to 0.5 and 0.8 year^{-1}.

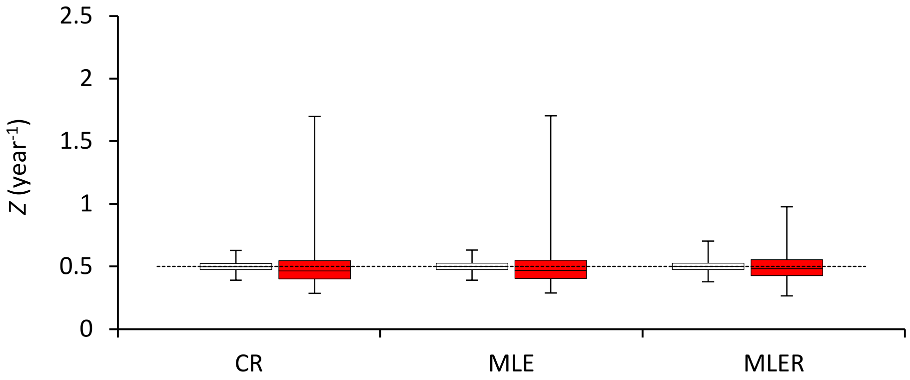
Values of %Bias calculated for mortality estimates produced by the three different catch curve models were always relatively small, ranging from -2.8 to 3.7% (Table 4.1). Across all three catch curve models, and regardless of the level of recruitment variability, the %Bias values were typically greatest for the highest specified value of Z (0.8 year^{-1}; Table 4.1). The values of %Bias for mortality estimates produced by MLER were often slightly greater in magnitude than those produced by the models that assume constant annual recruitment (Table 4.1).

Presenting the estimates of Z produced by the three catch curve models as box-and-whisker plots showed that the variance around the median Z estimates typically became greater as variability in recruitment increased (Fig 4.2). Although the majority of estimates obtained from the 1000 fits for variable recruitment scenarios were relatively close to the specified true values for Z, all models produced a few estimates of Z that were substantially larger than these values (Fig. 4.2). For scenarios with the lowest specified values of Z (0.2 and 0.5 year^{-1}), MLER produced less variable estimates of mortality than the models which assumed constant recruitment (Fig. 4.2). This pattern was not observed for the scenario with the highest specified value of Z (0.8 year^{-1}), for which the estimates produced by the three estimators were similar, regardless of the level of recruitment variability (Fig. 4.2).

(a) $Z = 0.2$ year^{-1}



(b) $Z = 0.5$ year^{-1}



(c) $Z = 0.8$ year^{-1}

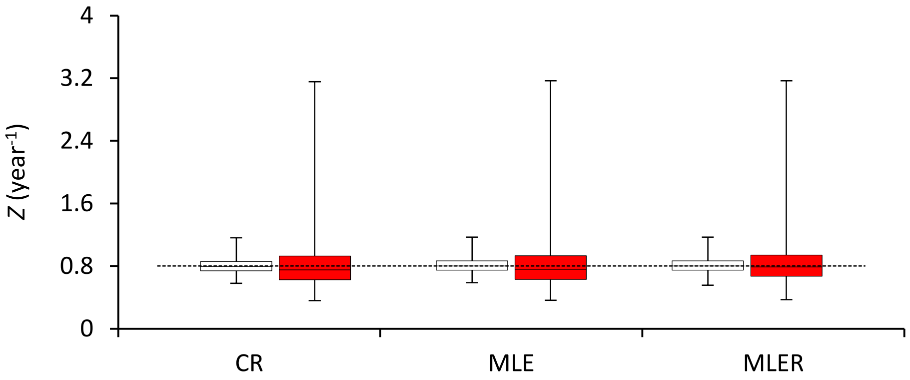


Fig. 4.2. Estimates of total mortality (Z) produced by the Chapman-Robson (CR) estimator and two maximum likelihood estimators; one which assumes constant recruitment (MLE) and the other which accounts for recruitment variability (MLER), when the specified value of Z used when generating sample data was (a) 0.2, (b) 0.5, or (c) 0.8 year^{-1}, and the standard deviation of the natural logarithms of annual recruitment deviations, σ_R, was 0 (white, left) or 0.7 (red, right). CV$_s$ was specified as 0.2. For each scenario, the line inside the box shows the median value, the bottom and top of the box show the 25th and 75th percentiles, and the lower and upper bars show the minimum and maximum values produced when a model was fitted to 1000 simulated data sets. The true values for Z are represented as the dashed lines.

4.3.2 Accounting for a change in mortality

Simulations in which catch curve models were fitted to age composition data generated on the basis that there had been a recent reduction in mortality demonstrated that accounting for such a change can result in significant improvements in model fit (Table 4.2). The probability of observing a significant improvement in the model fit by accounting for a change in mortality when estimating Z was found to be influenced by several factors. For example, as the value specified for $\mathrm{CV_s}$ (sampling error) was increased from 0.1 to 0.2, *i.e.* leading to a reduction in sample size, the percentage of occasions when the catch curve model that accounts for a mortality change provided a better fit to the data was consistently less across all scenarios for different levels of true mortality and recruitment variability (*cf.* Tables 4.2 and 4.3). For both levels of specified sampling error, the percentage of occasions when accounting for the mortality change resulted in an improved fit to the data was often highest when only three years that had elapsed since the change, and typically decreased as time continued to pass (Tables 4.2 and 4.3).

Although the percentage of occasions when accounting for a mortality change improved the fit to age composition data only differed slightly between scenarios of moderate and high levels of true Z_{old}, the magnitude of the reduction in mortality had a greater impact on model fit (Tables 4.2 and 4.3). Simulation outputs showed that, for both specified values of Z_{old}, reducing this mortality by 25% yielded a lesser percentage of improved fits by accounting for the mortality change than for scenarios in which mortality was reduced by 50% (Tables 4.2 and 4.3). For example, when recruitment was assumed to be constant and the values for Z_{old} and $\mathrm{CV_s}$ were specified as 0.8 year^{-1} and 0.1, respectively, the percentage of occasions for which the model accounting for a mortality change provided a better fit to data, when assessed

3, 4, 5 and 6 years after that change, were always much lower (28, 24, 16 and 13%, respectively) when the mortality was quartered compared with when mortality was halved (92, 92, 88 and 80%, respectively) (Table 4.2).

Table 4.2. Percentage of occasions when the catch curve model accounting for a change in mortality provided a significantly better fit to age composition data than the model that assumes constant mortality, when these data were generated for a fish stock that had experienced a lower mortality in recent years. Data sets were generated for scenarios in which 3, 4, 5 or 6 years had elapsed since mortality has been reduced, for two levels of total mortality prior to the management change (Z_{old}; year^{-1}), different reductions in Z_{old}, and two levels of recruitment variability (*i.e.* different specified values for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). CV$_s$ was specified as 0.1.

			% of fits improved			
Z_{old}	Z_{new}	σ_R	3 years	4 years	5 years	6 years
0.5	0.375	0	50	54	53	46
		0.7	80	78	72	73
0.5	0.25	0	99	100	100	100
		0.7	84	84	84	81
0.8	0.6	0	28	24	16	13
		0.7	73	69	62	54
0.8	0.4	0	92	92	88	80
		0.7	81	77	76	71

Table 4.3. Percentage of occasions when the catch curve model accounting for a change in mortality provided a significantly better fit to age composition data than the model that assumes constant mortality, when these data were generated for a fish stock that had experienced a lower mortality in recent years. Data sets were generated for scenarios in which 3, 4, 5 or 6 years had elapsed since mortality has been reduced, for two levels of total mortality prior to the management change (Z_{old}; year^{-1}), different reductions in Z_{old}, and two levels of recruitment variability (*i.e.* different specified values for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). CV$_s$ was specified as 0.2.

			% of fits improved			
Z_{old}	Z_{new}	σ_R	3 years	4 years	5 years	6 years
0.5	0.375	0	16	20	15	14
		0.7	63	63	57	49
0.5	0.25	0	56	62	66	69
		0.7	67	68	70	66
0.8	0.6	0	12	10	7	3
		0.7	52	42	35	56
0.8	0.4	0	39	37	34	29
		0.7	57	56	54	45

Although the model accounting for a mortality change provided a better fit to the data than the constant mortality model more often when annual recruitment was variable (σ_R = 0.7), on a few occasions the opposite trend was observed (Tables 4.2 and 4.3). Simulations showed that, when the change in mortality was small (25% reduction of Z_{old}), the percentage of occasions when accounting for this change resulted in an improved fit to the data was always higher for scenarios of variable recruitment than when recruitment was assumed to be constant (Tables 4.2 and 4.3). In contrast, when the reduction in mortality was more substantial (50% reduction of Z_{old}), the percentage of occasions when accounting for the mortality change led to a better fit to the data was less influenced by the level of recruitment variability (Tables 4.2 and 4.3).

The influence of some of the above factors on the ability of the two catch curve methods to produce reliable estimates of the mortality after a change, *i.e.* Z_{new}, is further illustrated in Fig 4.3. Simulations undertaken for the scenario in which Z_{old} was specified as 0.5 year^{-1} and recruitment was assumed to be constant (σ_R = 0) yielded median values of Z_{new} estimates produced by the model that accounts for a change in mortality that were substantially closer to the true new value of mortality (0.375 and 0.25 year^{-1}, following a 25 and 50% reduction in Z_{old}, respectively), compared with estimates of Z produced by the model that assumes constant mortality (Fig. 4.3). The accuracy of mortality estimates three years after the implementation of the management change was found to be greater when the magnitude of the change was less (*cf.* Fig. 4.3a, b and c, d). Although the variance around the median values of mortality estimates produced by the simpler model was less than that for estimates produced by the model that accounts for a change in mortality, as the number of years that had elapsed since the management change increased from 3 to 6 years, the reduction in the variance of estimates produced by the latter model was substantial (Fig. 4.3). Simulations further demonstrated that the variance around the median values of mortality estimates produced by both catch curve models was much greater when a high value of CV_S was specified for simulating data, *i.e.* the sample size was small (*cf.* Fig. 4.3a, c and b, d).

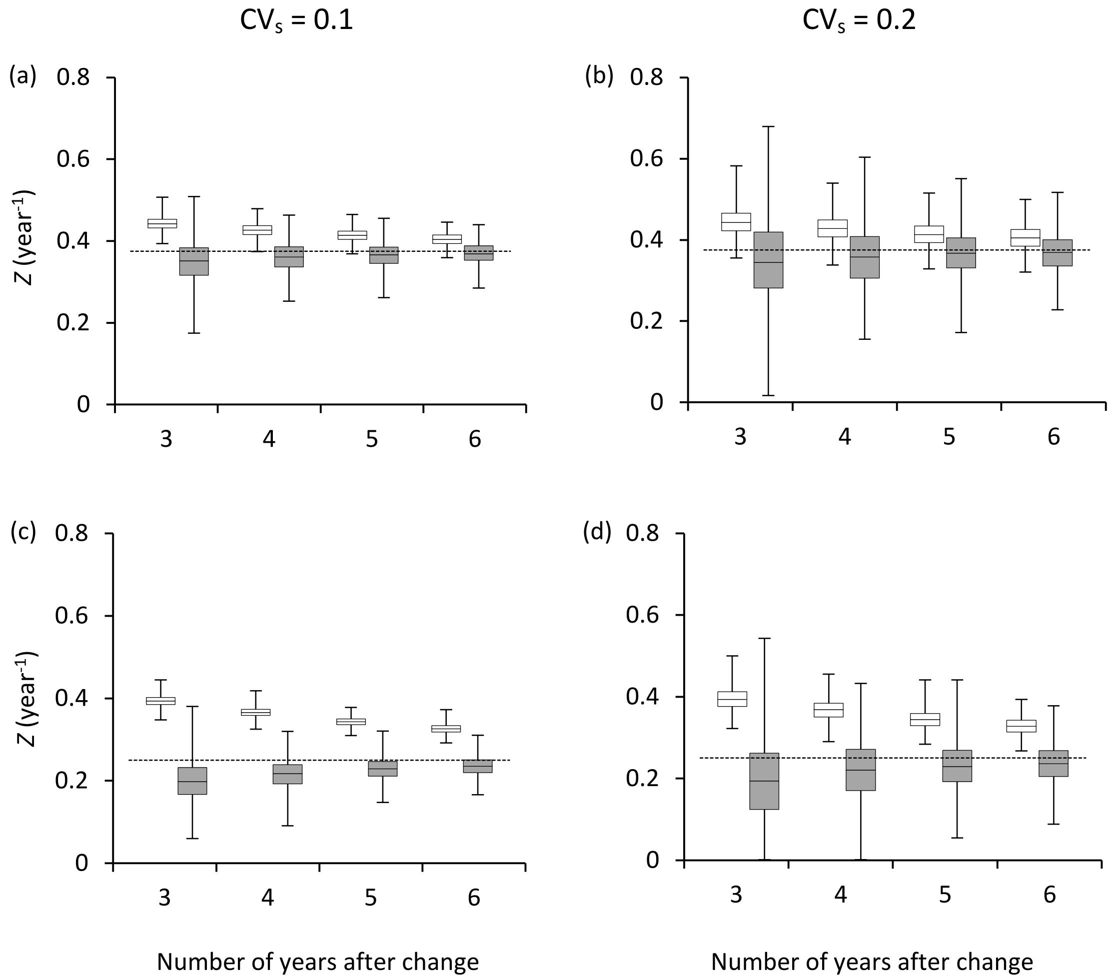


Fig. 4.3. Estimates of total mortality (Z) produced by a maximum likelihood estimator assuming constant mortality (white, left) and another accounting for a change in mortality (grey, right), when fitted to data generated on the basis of a recent (a, b) 25% and (c, d) 50% reduction in mortality (from 0.5 year^{-1}). Model fits were repeated for two specified values of CV_s (sampling error). For each scenario, the line inside the box shows the median value, the bottom and top of the box show the 25th and 75th percentiles, and the lower and upper bars show the minimum and maximum values produced when a model was fitted to 1000 simulated data sets. The true values for Z after the change are represented as the dashed lines.

4.3.3 Accounting for recruitment variability and a change in mortality

Simulations demonstrated that, for scenarios in which recruitment varied among years and there had been a change in mortality at a known point in time, allowing the annual recruitment deviations to be estimated in a catch curve model which also accounts for a mortality change does not markedly improve the %RMSE of estimates of Z_{new} (Tables 4.4 and 4.5). The %RMSE values of Z_{new} estimates ranged widely from 7 to 48 when recruitment was assumed constant (σ_R = 0), and between 19 and 131 when recruitment was variable (σ_R = 0.7). The highest values of %RMSE calculated for estimates of Z_{new} were obtained for scenarios of variable recruitment and when the minimum of 3 years had elapsed since the mortality change (Tables 4.4 and 4.5). As the time since the change in mortality increased, there was a strong tendency for the %RMSE of Z_{new} estimates to decrease (Tables 4.4 and 4.5).

As with %RMSE, simulations showed that accounting for recruitment variability as well as a change in management resulted in no clear improvement in the %Bias of Z_{new} estimates produced by the catch curve model (Tables 4.4 and 4.5). In contrast to the observed pattern of reduced %RMSE with decreasing level of recruitment variability and increasing number of years since the change in mortality, %Bias showed no clear trends between the different scenarios considered in the study (Tables 4.4 and 4.5). Values of %Bias for estimates of Z_{new} ranged from -25.3 to 0.8 for scenarios in which recruitment was constant, and from -14.0 to 24.9 for scenarios in which recruitment was allowed to vary.

For scenarios which assumed that recruitment varied among years, accounting for this variability in the catch curve model generally resulted in a minor reduction in %RMSE for Z_{old}, however, on some occasions, the opposite occurred (Tables 4.6 and 4.7). Values of %RMSE for estimates of Z_{old} were generally lower than those

Table 4.4. %RMSE and %Bias of estimates of Z_{new} produced by two different maximum likelihood estimators that both account for a change in mortality, and one which also accounts for recruitment variability. Each model was fitted to data sets generated on the basis that 3, 4, 5 or 6 years had elapsed following a mortality change, for different specified values of Z_{old}, percentage reductions in Z_{old}, and levels of recruitment variability (*i.e.* different value for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). The specified CV for sampling error was kept constant as 0.1.

			%RMSE								%Bias							
			3 years		4 years		5 years		6 years		3 years		4 years		5 years		6 years	
Z_{old}	Z_{new}	σ_R	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]
0.5	0.375	0	14	17	10	13	8	9	7	8	-6.6	-7.0	-3.7	-4.2	-2.4	-2.5	-1.3	-1.6
		0.7	93	98	70	71	54	56	47	46	-5.0	14.7	-12.5	-4.3	-8.8	-5.3	-6.7	-5.8
0.5	0.25	0	28	38	19	25	14	17	11	13	-20.4	-25.3	-13.3	-16.0	-8.3	-8.7	-5.9	-6.2
		0.7	125	131	92	94	76	76	62	63	2.7	24.9	-8.7	2.1	-11.6	-2.8	-10.2	-8.6
0.8	0.6	0	11	13	9	9	8	8	7	8	-3.3	-3.5	-1.2	-1.5	-0.6	-0.8	-0.5	-0.6
		0.7	75	72	58	54	44	40	37	33	-2.7	3.4	-5.4	-4.0	-5.0	-6.1	-3.9	-4.3
0.8	0.4	0	21	26	14	18	11	13	9	10	-12.7	-13.6	-7.4	-7.9	-4.0	-4.2	-2.6	-2.8
		0.7	96	94	70	69	57	56	19	19	-9.6	-1.1	-14.0	-11.3	-8.5	-11.0	-7.0	-9.7

[a] Maximum likelihood estimator that accounts for a change in mortality.

[b] Maximum likelihood estimator that accounts for a change in mortality and recruitment variability.

Table 4.5. %RMSE and %Bias of estimates of Z_{new} produced by two different maximum likelihood estimators that both account for a change in mortality, and one which also accounts for recruitment variability. Each model was fitted to data sets generated on the basis that 3, 4, 5 or 6 years had elapsed following a mortality change, for different specified values of Z_{old}, percentage reductions in Z_{old}, and levels of recruitment variability (*i.e.* different value for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). The specified CV for sampling error was kept constant as 0.2.

			%RMSE								%Bias							
			3 years		4 years		5 years		6 years		3 years		4 years		5 years		6 years	
Z_{old}	Z_{new}	σ_R	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]
0.5	0.375	0	29	30	20	22	15	16	13	14	-7.4	-7.7	-4.4	-4.7	-1.8	-2.0	-1.5	-2.0
		0.7	91	96	77	73	58	57	47	46	-8.2	5.1	-9.4	-0.2	-7.5	-3.6	-6.9	-5.9
0.5	0.25	0	45	48	31	34	24	26	19	21	-22.5	-22.4	-12.2	-12.8	-8.4	-8.4	-5.7	-5.6
		0.7	117	128	92	91	75	73	64	65	0.1	19.3	-9.7	-1.1	-13.9	-9.0	-10.2	-9.5
0.8	0.6	0	24	24	18	19	15	16	14	14	-3.5	-3.4	-1.6	-1.5	-0.6	-0.4	0.6	0.8
		0.7	73	72	58	57	48	45	40	38	-11.1	-8.0	-4.3	-3.8	-3.2	-2.9	-1.0	2.1
0.8	0.4	0	36	38	25	27	20	21	18	19	-12.7	-13.1	-7.1	-7.5	-4.5	-4.8	-2.7	-2.8
		0.7	90	91	74	73	59	58	49	48	-9.5	-2.2	-11.6	-11.1	-11.2	-10.3	-6.0	-6.6

[a] Maximum likelihood estimator that accounts for a change in mortality.

[b] Maximum likelihood estimator that accounts for a change in mortality and recruitment variability.

Table 4.6. %RMSE and %Bias of estimates of Z_{old} produced by two different maximum likelihood estimators that both account for a change in mortality, and one which also accounts for recruitment variability. Each model was fitted to data sets generated on the basis that 3, 4, 5 or 6 years had elapsed following a mortality change, for different specified values of Z_{old}, percentage reductions in Z_{old}, and levels of recruitment variability (*i.e.* different value for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). The specified CV for sampling error was kept constant as 0.1.

			%RMSE								%Bias							
			3 years		4 years		5 years		6 years		3 years		4 years		5 years		6 years	
Z_{old}	Z_{new}	σ_R	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]
0.5	0.375	0	6	7	7	7	8	9	10	10	-4.5	-3.4	-5.0	-4.1	-4.9	-4.1	-5.4	-4.7
		0.7	24	17	26	18	25	20	29	23	-4.4	-5.0	-2.9	-5.2	-1.1	-5.3	0.5	-3.7
0.5	0.25	0	9	8	9	9	11	10	11	11	-9.8	-7.0	-10.4	-8.6	-11.5	-10.0	-11.3	-9.9
		0.7	22	16	22	18	24	18	25	20	-12.8	-9.0	-10.9	-8.8	-9.1	-9.5	-9.4	-9.0
0.8	0.6	0	11	11	13	14	17	17	26	27	-8.8	-7.6	-8.3	-7.4	-6.3	-5.3	-1.9	-1.6
		0.7	30	24	35	30	41	34	48	39	-9.7	-7.1	-3.4	-4.1	2.7	-2.6	5.7	-2.3
0.8	0.4	0	15	14	16	15	18	17	19	19	-17.7	-14.8	-18.6	-16.6	-19.1	-17.5	-17.9	-16.6
		0.7	27	21	28	23	29	26	33	28	-17.9	-12.7	-13.8	-11.5	-13.9	-13.9	-10.4	-11.4

[a] Maximum likelihood estimator that accounts for a change in mortality.

[b] Maximum likelihood estimator that accounts for a change in mortality and recruitment variability.

Table 4.7. %RMSE and %Bias of estimates of Z_{old} produced by two different maximum likelihood estimators that both account for a change in mortality, and one which also accounts for recruitment variability. Each model was fitted to data sets generated on the basis that 3, 4, 5 or 6 years had elapsed following a mortality change, for different specified values of Z_{old}, percentage reductions in Z_{old}, and levels of recruitment variability (*i.e.* different value for the standard deviation of the natural logarithms of annual recruitment deviations, σ_R). The specified CV for sampling error was kept constant as 0.1.

			%RMSE								%Bias							
			3 years		4 years		5 years		6 years		3 years		4 years		5 years		6 years	
Z_{old}	Z_{new}	σ_R	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]	MLE[a]	MLER[b]
0.5	0.375	0	12	12	14	15	16	16	21	21	-3.2	-2.4	-2.1	-1.3	-4.2	-3.6	-1.6	-0.8
		0.7	26	22	30	26	35	31	37	32	-4.2	-5.7	0.2	-4.3	3.0	-2.6	3.8	-3.5
0.5	0.25	0	11	11	13	13	14	15	16	16	-8.4	-7.2	-8.8	-7.8	-9.3	-8.4	-8.0	-7.3
		0.7	23	21	25	23	26	23	28	25	-11.8	-10.6	-10.0	-10.5	-6.9	-9.7	-5.2	-9.7
0.8	0.6	0	21	21	31	31	40	40	38	38	-5.1	-4.7	0.4	0.6	6.7	6.5	0.1	0.2
		0.7	38	35	47	46	51	47	50	45	-0.9	-3.3	6.4	3.1	9.8	3.5	6.5	-0.2
0.8	0.4	0	19	19	21	22	25	25	33	33	-16.0	-14.6	-14.4	-13.5	-11.4	-10.7	-6.2	-6.1
		0.7	31	29	34	33	43	39	42	39	-15.5	-14.0	-12.5	-12.4	-3.6	-8.2	-3.8	-8.2

[a] Maximum likelihood estimator that accounts for a change in mortality.

[b] Maximum likelihood estimator that accounts for a change in mortality and recruitment variability.

calculated for estimates of Z_{new} (*cf.* Tables 4.4 and 4.5 with 4.6 and 4.7). For example, the %RMSE calculated for estimates of Z_{old} ranged from 6 to 40 when recruitment was constant and from 16 to 51 when recruitment was variable. Although, as was also observed for Z_{new}, the %RMSE for Z_{old} estimates were typically larger variable recruitment scenarios, in contrast that observed for Z_{new}, %RMSE tended to increase slightly as the number of years that elapsed since the mortality change increased (Tables 4.6 and 4.7).

Simulations showed that allowing for recruitment variability when fitting the catch curve model accounting for a change in mortality did not markedly influence the %Bias for estimates of Z_{old} (Tables 4.6 and 4.7). As was also the case for the %Bias calculated for estimates of Z_{new}, the various factors considered in the different scenarios had little impact on the %Bias for Z_{old} (Tables 4.6 and 4.7). Values of %Bias for estimates of Z_{old}, for scenarios of constant and variable recruitment, ranged from -19.1 to 6.7, and from -17.9 to 9.8, respectively.

4.4 Discussion

This simulation study has demonstrated that the robustness of catch curve models for providing reliable estimates of mortality can often be enhanced by relaxing some of the strong assumptions on which many conventional catch curve methods typically rely. Simulations showed that, in situations when the assumptions of constant recruitment and constant mortality of fish stocks over time cannot be fully satisfied, the two MLE catch curve models described in this study can, in a number of circumstances, produce more robust estimates of mortality than methods that do not allow for departures from these assumptions. As such, these methods constitute potentially valuable alternatives to the equilibrium-based methods that are still widely used by scientists around the world for assessing the states of fish species from catch-at-age data. The circumstances in which the new approaches are most likely to provide more reliable mortality estimates than such conventional catch curve methods are discussed below.

4.4.1 Accounting for recruitment variability in catch curve analysis

The simulations undertaken in this study have demonstrated that, when annual recruitment to a fish stock is variable, a catch curve model that accounts for such variability, by allowing the annual recruitment deviations to be estimated, will typically produce more reliable estimates of mortality than a model assuming constant recruitment. As many fish species are known to exhibit substantial variation in annual recruitment (*e.g.* Myers *et al.*, 1990; Punt *et al.*, 2001; Ianelli, 2005), this finding thus has broad implications for fisheries stock assessments which employ catch curve analysis. Other modifications to conventional catch curve models that allow the assumption of constant recruitment to be relaxed include those described by Deriso *et al.* (1985) and Schnute and Haigh (2007), where the latter authors also explore how the estimate of mortality and its distribution depends on the choice of model.

Although comparisons of mortality estimates produced by the catch curve models showed that accounting for recruitment variability clearly reduced the %RMSE for scenarios which assumed variable recruitment, the estimates were still biased. Even if the magnitude of this bias was typically small (< 4%), simulations demonstrated that the level of bias increased with increasing values of Z. This result is consistent with the findings of Murphy (1997) and Dunn *et al.* (2002), who also reported that the performance of mortality estimators generally degrades as Z increases. As was also suggested by Dunn *et al.* (2002), in the absence of a method that can provide completely unbiased estimates of mortality, it would seem most appropriate to use the one that is most robust, *i.e.* which produces mortality estimates with the lowest %RMSE. Simulations undertaken for this study have clearly indicated that, for fish species which exhibit variable annual recruitment, a catch curve model that accounts for this variability is likely to provide the most robust estimates of mortality.

An added advantage of using a catch curve model that accounts for variable annual recruitment such as the one described in this study is that, in addition to providing an estimate of Z, it also produces quantitative estimates of the relative recruitment strengths for the different year classes in the age composition sample. An ability to quantify recruitment variability, and make inferences regarding the strengths of individual year classes of fish, can be useful to help inform management decisions for fish stocks (Catalano *et al.*, 2009). That is, estimates of annual recruitment deviations can be used in correlation and regression analyses to improve our understanding of how different abiotic and biotic factors influence the recruitment of fish species (Maceina, 1997; 2004; Abesamis and Russ, 2010). Another noteworthy result of this study is that the catch curve model which accounts for recruitment variability essentially performed equally well (very similar %RMSE values) in situations when zero recruitment variability was specified for simulating the data (a completely atypical case for wild fish stocks). Thus, the model is likely to be valuable for quantifying, for any fish stock, the level of variability in annual recruitment when this information is not otherwise available.

4.4.2 Accounting for a mortality change in catch curve analysis

Simulations employing the catch curve model that accounts for a change in mortality at a known point in time showed that, for situations when mortality was reduced fairly substantially, the model was able to detect this change and thereby provide more robust mortality estimates for a fish stock than a catch curve model assuming constant mortality. Although the results of this study suggest that the new model could often detect a change in mortality if fitted to data collected in only three subsequent years, the results were very imprecise. The variance of mortality estimates did decrease substantially, however, after about 5-6 years had elapsed following the mortality change. This indicates that, when assessing a stock using this catch curve approach, scientists advising managers about the success of a recent management change are likely to need to wait for at least five years before the method is likely to yield a reliable estimate of the new mortality.

The catch curve model developed in this study to allow for a recent change in mortality apparently constitutes the first method attempting to estimate such a mortality change from a set of age composition data for a fish species. A focus towards developing approaches able to detect a recent change in mortality is likely to represent an important step forward in the development of age-based methods for assessing data-limited fisheries, particularly as many targeted fish stocks are currently experiencing substantial changes in management regulations to combat excessive fishing pressures (Allen and Pine, 2000; McPhee *et al.*, 2002). Although a similar method for detecting a change in mortality of fish stocks was described by Gedamke and Hoenig (2006), that method uses data on the mean lengths of fish in samples, rather than age composition data. The ability of that approach to detect an increase in the mortality of fish was demonstrated using length frequency data for goosefish *Lophius americanus* (Gedamke and Hoenig, 2006), however, as was recognised by these authors, the approach relies on an added assumption of constant growth for individual fish over time, which is one that can be difficult to satisfy for many fish species (*e.g.* Brander, 2000; Hernández-Miranda and Ojeda, 2006). Similarly, a number of other authors have questioned the robustness of length-based catch curve methods, in general, due to their dependency on reliable estimates of growth (Pauly *et al.*, 1995; Sparre and Venema, 1998).

Although not considered in this study, other workers have explored the effect of variation in annual mortality on the estimates of mortality that are derived from catch-curve analysis. Thus, for example, Dunn *et al.* (2002) explored the effect of variable annual mortality on the estimates of mortality produced using the Chapman and Robson (1960) method and various other regression-based methods. In another relatively recent study, Griffith (2008) explored the use of a random effects model, within a Bayesian catch-curve framework, to represent inter-annual variation in mortality for multiple years of data for lake trout from Lake Superior in North America and concluded that this form of model represents an important advance in catch curve development.

The demonstration of the current study, that the robustness of the catch curve model that accounts for a mortality change is affected by several variables, highlights the value of simulation studies such as this one to scientists for better understanding the potential impacts of such factors on mortality estimation. For example, the marked decrease in the variance of mortality estimates produced by the model when the effective sample size was increased strongly suggests that, as previously reported by Murphy (1997) and Dunn *et al.* (2002), sample size is a key factor that should be carefully considered when applying catch curve analysis to real data. Indeed, the value of methods developed for determining the effective sample size required by fisheries models to yield sufficiently robust estimates of model parameters has been widely recognised in the literature (McAllister and Ianelli, 1997; Deriso *et al.*, 2007; Hulson *et al.*, 2012).

The findings of this study indicated that, when fitting the catch curve model which accounts for a change in the mortality of a fish stock experiencing variable recruitment, no significant improvement in the bias of mortality estimates was gained from allowing the annual recruitment deviations to be estimated. This highlights that the information content of the age composition data was insufficient to allow estimation of recruitment deviations using this catch curve model. It has been suggested that, as the complexity of fisheries models increases to include a greater number of parameters in their analysis, the robustness of model predictions often become more and more uncertain (Cochrane, 1999). Consequently, in data-limited situations, it may be favourable to use simpler models with fewer parameters.

In discussing the results obtained from the simulations undertaken for this study, it must be pointed out that these are based on explorations for a single (hypothetical) fish species with certain specified life history traits. In this context, it is relevant that preliminary explorations of the effectiveness of several other catch curve approaches (see Fisher *et al.*, 2011) showed that, in addition to the level of recruitment variability experienced by a fish species, longevity is an important factor which can also influence the robustness of catch curve analysis in different ways. For example, although that study showed that the conventional regression-based catch curve model tended to perform better when fitted to data simulated for a long-lived fish species (*Glaucosoma hebraicum*, maximum age = 41 years), the more complex relative abundance analysis, which accounts for recruitment variability (Deriso *et al.*, 1985) produced more reliable estimates of mortality when fitted to data simulated for a shorter-lived species (*Rhabdosargus sarba*, maximum age = 11 years) (Fisher *et al.*, 2011). An exploration of the potential effect of longevity on the performance of the catch curve models described in this study would thus be recommended for future research. In addition, an exploration of the relative effectiveness of alternative catch curve approaches that account for recruitment variability, *e.g.* relative abundance analysis (Deriso *et al.*, 1985), Poisson regression methods (Chuwen *et al.*, 2011) and the one developed in this study, is also likely to be useful.

4.4.3 Conclusion

Simulations have demonstrated that, by accounting for recruitment variability in the catch curve model developed in this study, the reliability of mortality estimates was improved when the (simulated) stock exhibited substantial recruitment variability. Findings of the simulations also indicated that the catch curve model developed to account for a recent mortality change typically provided a better fit to age composition data than a catch curve model assuming constant mortality, demonstrating that it was possible to produce estimates of the total mortality of a fish stock before and after the change. The study further indicated that, for this latter catch curve model to be able to provide reliable estimates of the new mortality for a fish stock, about five years would need to elapse following the change in mortality.

This chapter has focused on exploring the effectiveness of methods for addressing issues associated with two key steady-state assumptions of catch curve analysis. In this regard, it is important to recognise that catch curve analyses also rely on a number of other assumptions, including that the sample data represent random observations from the overall exploited fish population (*e.g.* Murphy, 1997). For various reasons, this is often not the case in reality. Chapter 5 describes a new method for assessing, using age and length data, the mortality of fish species that undertakes a pronounced size-dependent, unidirectional movement from inshore to offshore waters and for which it is difficult to obtain a representative, random sample from the overall population.

CHAPTER 5

A method for assessing stock status of fish species that undertake size-dependent, offshore movements

5.1 Introduction

Most fisheries stock assessments are based around the simplifying assumption that fish stocks constitute homogenous collections of individuals that are evenly distributed across the area of the fishery and have equal probabilities of being caught by fishers (Hilborn and Walters, 1992). In reality, however, this is rarely the case. For example, many fish species have patchy distributions, with individuals being highly concentrated in particular habitats (Anderson and Millar, 2004; Morton and Gladstone, 2011). Other fish species are known to undertake pronounced movements between different regions at certain stages of their lives (Lenormand *et al.*, 2004; Kimirei *et al.*, 2011), or at particular times of the year, such as during the spawning season (Sheaves *et al.*, 1999; Östergren *et al.*, 2011). Thus, depending on the extent to which fish sample data used in assessment models fail to constitute a random sample from the overall fish population, stock status indicators derived from these models may be heavily biased. This, in turn, can lead to highly uncertain or incorrect management advice (Hilborn and Walters, 1992; Welch *et al.*, 2010).

A common characteristic of many fish species is that they occupy estuaries and/or shallow, coastal waters as juveniles or young adults and move into deeper, more offshore waters as they become larger and older (Hyndes *et al.*, 1998; Platell *et al.*, 2007). Such species present a challenge for fisheries stock assessment scientists, particularly when the offshore movement is strongly size-dependent. This is because differences in sampling methods, catchability and abundance of fish among the different regions can all impact on the randomness of sample data (Morales-Nin and

Ralston, 1990; Walters, 2003; Hesp *et al.*, 2004). As biases in sample data arising from size-dependent differences in spatial distributions of fish in a population are difficult to quantify, the potential impacts of such biases have rarely been considered in stock assessments in the past (Chen *et al.*, 1997; 1998).

For a number of large-scale commercial fisheries, spatially-explicit stock assessment methods are now becoming increasingly applied to deal with non-random spatial distributions of fish (*e.g.* Hampton and Fournier, 2001; Gardner *et al.*, 2003; Aires-da-Silva *et al.,* 2009). These types of assessment models typically employ data derived from tagging studies, as well as historic time series of catch and effort data collected from throughout the area of the fishery (Punt *et al.*, 2000). In data-limited situations, which are common to many small-scale fisheries around the world, scientists are forced to rely on assessment methods with more modest data requirements, such as employing catch curve analysis for estimating mortality rates (Dowling *et al.*, 2008; Wayte and Klaer, 2010). For species that undertake pronounced movements, however, the results of such analyses are likely to be biased unless they account for the confounding influences of mortality and movement on the sample data (McGarvey *et al.*, 2010). Regardless of the amount of data available, this latter task can be challenging.

As a consequence of the difficulty in obtaining non-biased estimates of mortality for fish species that undertake movements from inshore to offshore waters, reliable stock assessment information for these species is often lacking. One such example is the silver trevally *Pseudocaranx georgianus* (formerly considered as *P. dentex*), which is found in coastal marine waters off the southern half of Australia, from the lower coast of Western Australia to New South Wales in the east, and off northern New Zealand (Smith-Vaniz and Jelks, 2006). A biological study of this species on the lower west coast of Australia, where *P. georgianus* is commonly caught by recreational fishers (Department of Fisheries, Western Australia, 2011a), indicated that it undertakes a pronounced offshore movement associated with an increase in the age and size of fish (Farmer *et al.*, 2005). Such a movement is further supported by data for the closely related *P. dentex* in the central North Atlantic (Afonso *et al.*, 2008) and in Japan (Masuda and Tsukamoto, 1999), which appear to suggest that this species also undertakes a movement to offshore waters.

To better understand offshore movements undertaken by fish species such as *P. georgianus,* comparisons of age and length data for fish collected in inshore and offshore waters will be important for determining whether these movements are more closely related to the age or size of fish. If the offshore movement is largely size-related, one would expect that, at any given age, the mean lengths of fish sampled in offshore waters would be greater than the mean lengths of inshore fish at that age. In situations when this can be confirmed, it is important to recognise that the size-dependency of movements can have a profound influence on the ability to estimate reliably the pattern of growth of a fish species (Hesp *et al.*, 2004). Although most growth models used in fishery applications, including the von Bertalanffy growth model, describe the average growth of fish in a population, in more recent years there has been an increased focus towards developing methods that account for variability in growth among individual fish (*e.g.* Pilling *et al.*, 2002; Schirripa, 2002). An understanding of growth variability is also important to stock assessments because it allows more realistic individual-based simulations of fish populations to be undertaken (Martínez-Garmendia, 1998; Challier *et al.*, 2006).

The overall objective of this study was to develop a method for assessing the stock status of fish species which undertake a pronounced size-dependent movement to offshore waters. The first aim was to determine whether the age and length compositions of *P. georgianus* are consistent with this species exhibiting an offshore movement that is more strongly associated with size than age of individuals. The second aim was to describe the pattern of growth of *P. georgianus* using a method that can account for variability in growth among individual fish. The third aim was to develop a model which, when fitted to simulated length-at-age data for a species that undertakes a size-dependent, offshore movement, could be shown to reliably estimate both this movement and the levels of fishing mortality in inshore and offshore waters. Sensitivity analyses were undertaken to explore the robustness of the model for producing reliable estimates of the model parameters, given different specified scenarios relating to the size-dependent vulnerability of fish to fishing gear and the movement characteristics of the fish species. The fourth aim was to fit the model to observed length-at-age data for *P. georgianus* to estimate the rates of fishing mortality of this species in inshore (< 60 m deep) and offshore (≥ 60 m deep) waters in an area of south-western Australia where it is exploited by recreational fishers (~ 31-32°S). The final aim of the study was to develop a simple, modified per-recruit analysis for taking into account size-dependent movements of fish from inshore to offshore waters. This per-recruit analysis was used to explore the implications, for *P. georgianus,* of different levels of fishing mortality in the inshore and offshore waters for the overall yield and spawning biomass per recruit of the population.

5.2 Methods

5.2.1 Exploration of age and length data

Length-at-age data for *P. georgianus* caught between 2001 and 2004 were available from a previous biological study of this species in south-western Australia (Farmer *et al.*, 2005). The data used for this current study (n = 354) consisted of fish sampled by rod and line fishing in inshore (< 60 m deep) and offshore (≥ 60 m deep) coastal marine waters between Mandurah (32°32’S) and Lancelin (31°01’S). The majority of these samples had been donated to researchers by recreational fishers, although some additional research sampling was also undertaken to increase the sample size of fish for lengths that were not well represented in catches taken by recreational fishers. For example, *P. georgianus* in offshore waters were targeted over artificial reefs (sunken barges) in waters of ~ 110 m depth where these fish are known to form localised aggregations between the months of September and December (Farmer *et al.*, 2005). It has been assumed in this study that the selectivity of the fishing gear used by recreational fishers and researchers to catch fish in inshore waters was equivalent to that of the fishing gear employed to catch the offshore fish, and that the inshore and offshore samples of fish are representative of the fish in these two regions.

As described by Farmer *et al.* (2005), the total length (TL) of each sampled fish was measured to the nearest 1 mm and the ages of individuals at their times of capture were determined from the number of opaque zones visible on sectioned otoliths using standard fish ageing procedures, assuming a common birth date of *P. georgianus* of October 1. Marginal increment analysis was employed to validate that the opaque zones on the otoliths of this species are formed annually (Farmer *et al.*, 2005).

To determine whether the offshore movement of *P. georgianus* is more strongly related to the age or size of fish, the mean lengths at each age of fish were calculated from the inshore and offshore data and compared for those ages that are represented in both regions.

5.2.2 Estimation of individual growth of fish

From each of the random samples of *P. georgianus* collected from inshore and offshore waters, the lengths at each age of a randomly selected sub-sample of 29 fish, which collectively covered essentially the full size range of this species, were estimated using otolith back-calculation methods. A key assumption of such back-calculation methods is that there is a direct (linear or non-linear) relationship between somatic growth of the fish and the growth of their otoliths (or other calcified structures used for ageing) (Campana, 1990; Francis, 1990; Francis *et al.*, 1993). For this study, back-calculation was based on the widely-used approach referred to by Francis (1990) as the body proportional hypothesis (BPH). Following the BPH, the relationship between the TL of individual *P. georgianus* at their times of capture, L_c (mm), and their otolith radius, R_c (mm), was described by the power function:

$$L_c = a\, {R_c}^b \tag{5.1}$$

where a and b are parameters that determine the form of the relationship.

Back-calculated lengths at ages, L_i, for the 58 sub-sampled *P. georgianus* were derived by using measurements (to the nearest 0.01 mm and along the same axis of the otolith as the radius measurements were taken, near the sulcus) of the distances from the primordium of each otolith to the outer edge of each successive opaque zone, R_i. As described by Francis (1990), the estimated length (mm) of each fish corresponding to its age when opaque zone i was fully formed was then calculated from the BPH as

$$L_i = L_c\, (R_i/R_c)^{\,b} \tag{5.2}$$

where b is the constant obtained from the non-linear regression of L_c on R_c.

Estimates of the growth of individual *P. georgianus* were obtained by fitting a non-linear random effects model, similar to that described by Pilling *et al.* (2002), to the otolith back-calculated lengths at ages. The model fitted to the back-calculated data, *i.e.* the estimated lengths L_{ix} for $x = 1, 2\ldots, n$ fish, at ages a_{ix} when opaque zones $i = 0, 1\ldots, I_x$ were formed, was

$$L_{ix} = L_{\infty x}\,(1 - \mathrm{e}^{\,-k_x(a_{ix}-t_{0x})}) + \varepsilon_{ix} \tag{5.3}$$

where $L_{\infty x}$, k_x and t_{0x} are the von Bertalanffy growth parameters for the x^{th} fish and ε_{ix} are assumed to be independent, normally distributed error terms with a mean of zero and a common variance σ_ε^2, *i.e.* $\varepsilon_{ix} \sim N(0, \sigma_\varepsilon^2)$. In contrast to the random effects model described by Pilling *et al.* (2002), which assumes that the individual growth parameters are sampled independently from a trivariate normal probability distribution, the model fitted in this study to the back-calculated data for *P. georgianus* assumes that $L_{\infty x}$ (mm) and k_x (year^{-1}) have a bivariate normal distribution with a mean μ and covariance Σ. That is,

$$\begin{pmatrix} L_{\infty x} \\ k_x \end{pmatrix} \sim \mathrm{N}_2(\mu, \Sigma) \qquad \text{for } x = 1, 2\ldots, n. \tag{5.4}$$

where the prior probability distributions for t_{0x} (years) was assumed to be normal with a mean of zero and a specified precision ($= 1/$ variance) of 0.001. Note that the above simplification of the growth model described by Pilling *et al.* (2002) was made with the intent of reducing the complexity of the model that was subsequently developed to estimate mortality of fish that undertake a size-dependent, offshore movement.

As with the method described by Pilling *et al.* (2002; see also Helser and Lai, 2004), the random effects model was fitted using a Bayesian approach with prior probability distributions for the estimated parameters (μ, Σ and σ_ε^2), which were specified to be as uninformative as possible (Smith and Wakefield, 1994). The model was fitted to the back-calculated lengths at ages for *P. georgianus* using Markov Chain Monte Carlo (MCMC) simulation methods in the WinBUGS software (Bayesian inference using Gibbs sampling, version 1.4.3; Spiegelhalter *et al.*, 2003). Estimates of the von Bertalanffy growth parameters, the correlation between L_∞ and k, and standard deviations for each parameter were estimated from the results of 10,000,000 iterations from each of two Markov chains, after discarding the first 50,000 iterations and thinning the remaining 9,950,000 samples at a rate of 1 in 4,000. Note that diagnostic plots in WinBUGS indicated that, by following this procedure, convergence between the two chains was likely to have been achieved.

5.2.3 Description of the offshore movement model

The model developed in this study to account for the size-dependent movement of fish between inshore and offshore regions classifies individual fish into a number of age classes j $(1 < j < J)$, where the upper bound of the maximum (integer) age class J corresponds to the integer age $A + 1$, and where A is the maximum age for the species (specified as 18 years for *P. georgianus*). Recruitment to the population is considered as the number of fish of age zero, *i.e.* the individuals that recruit to the first age class $(j = 1)$. All age classes have a common age class interval of 0.05 years, which also corresponds to the age step Δa used in this model. The use of a small step size facilitated the “discretization” of lengths at age for successive age classes, *i.e.* justifying the use of an assumption that the length of each fish remained constant during the age step with relatively small length increments between age steps, noting the trade-off that exists between the size of the age step and the computational demand when subsequently fitting the model. The lower bound of the j^{th} age class is denoted by a_j, where $a_j = 0.05(j-1)$ years, and the upper bound of the age class interval is $0.05j$ years. No separation was made between females and males.

The age and length distributions of fish in each region were assumed to be determined by the size-dependent movement of individuals from inshore to offshore waters, the mortality experienced by the fish in each region, and by the variability in growth exhibited by the fish in the population. For this calculation, the bivariate normal distribution of values for L_∞ and k calculated using the parameters estimated when fitting the random effects model (see section 5.2.1) was divided into a bivariate grid of discrete class intervals for each of these two parameters, *i.e.* the range for each parameter was "discretized". The distribution for L_∞ was divided into n_{L_∞} classes $(1 \le \omega \le n_{L_\infty})$, where the mid-point of the ω^{th} class and the lower and upper bounds of that class were determined, respectively, as

$$L_\infty^\omega = \{\omega - (\lfloor n_{L_\infty}/2 \rfloor + 1)\}\left[\frac{R\sigma_{L_\infty}}{n_{L_\infty} - 1}\right] \tag{5.5}$$

$$L_\infty^{\omega-} = L_\infty^\omega - \left[\frac{R\sigma_{L_\infty}}{2(n_{L_\infty} - 1)}\right] \tag{5.6}$$

$$L_\infty^{\omega+} = L_\infty^\omega + \left[\frac{R\sigma_{L_\infty}}{2(n_{L_\infty} - 1)}\right]. \tag{5.7}$$

σ_{L_∞} is the standard deviation for the asymptotic length, and the multiplier R, which was used to specify the range of values of asymptotic length or growth coefficient k to be considered when fitting the model, was specified as 8. The notation $\lfloor x \rfloor$ represents the "floor" function, which is the largest integer less than or equal to x. Likewise, the values of k were divided into n_k classes $(1 \le \kappa \le n_k)$, where the respective mid-point, lower bound and upper bound of the κ^{th} interval of the k distribution were determined as

$$k^{\kappa} = \{\kappa - (\lfloor n_k/2 \rfloor + 1)\}\left[\frac{R\sigma_k}{n_k - 1}\right] \tag{5.8}$$

$$k^{\kappa-} = k^{\kappa} - \left[\frac{R\sigma_k}{2(n_k - 1)}\right] \tag{5.9}$$

$$k^{\kappa+} = k^{\kappa} + \left[\frac{R\sigma_k}{2(n_k - 1)}\right] \tag{5.10}$$

where σ_k is the standard deviation for the growth coefficient. The values of the two parameters at the centre of each of the resulting grid cells, denoted by L_{∞}^{ω} and k^{κ}, were used as the specific values for L_{∞} and k associated with that grid cell. The proportion of fish which lie within the grid cell, $p_{L_{\infty},k}$, was calculated from the bivariate normal distribution. The following calculations were then undertaken for each pair of values of L_{∞}^{ω} and k^{κ}.

The lengths of fish in each age class, L_j, were assumed to be described by a von Bertalanffy growth curve:

$$L_j = L_{\infty}^{\omega}\left\{1 - \exp\left[-k^{\kappa}\left(a_j - t_0\right)\right]\right\}. \tag{5.11}$$

Movement of *P. georgianus* from inshore to offshore waters was modelled as a logistic function with two parameters, where the probability that a fish in age class *j* (and thus of length L_j) has moved to the offshore region was determined as

$$P_j^{\text{offshore}} = \left\{1 + \exp\left[-\log_e(19)\frac{L_j - L_{50}^{\text{Move}}}{L_{95}^{\text{Move}} - L_{50}^{\text{Move}}}\right]\right\}^{-1} \tag{5.12}$$

and where L_{50}^{Move} and L_{95}^{Move} represent the lengths at which 50 and 95% of fish, respectively, have moved offshore. The model assumes that all fish recruit to the inshore region and become fully vulnerable to fishing prior to moving offshore. Thus, the probability that a fish in age class j still remains in inshore waters was calculated as

$$P_j^{\mathrm{inshore}} = 1 - P_j^{\mathrm{offshore}}. \tag{5.13}$$

The proportion of inshore fish in age class j that are expected to move offshore during age step Δa was determined as

$$\psi_j^{\mathrm{move}} = \left(P_j^{\mathrm{inshore}} - P_{j+\Delta a}^{\mathrm{inshore}}\right) / \, P_j^{\mathrm{inshore}}. \tag{5.14}$$

It was assumed that (i) all fish are destined to move offshore at some moment in life, if they do not die first, (ii) fish which have moved offshore do not return to inshore waters, and (iii) the vulnerability of fish, *i.e.* selectivity to the fishing gear, is the same in inshore and offshore waters. The vulnerability of fish in age class j, V_j, which was assumed to be length-dependent, was determined as

$$V_j = \left\{1 + \exp\left[-\log_e(19)\frac{L_j - L_{50}^{\mathrm{Vuln}}}{L_{95}^{\mathrm{Vuln}} - L_{50}^{\mathrm{Vuln}}}\right]\right\}^{-1} \tag{5.15}$$

where L_{50}^{Vuln} and L_{95}^{Vuln} represent the lengths of fish at which 50 and 95% are vulnerable to capture, respectively. As the model recognises that fishing mortality can differ between regions, the fishing mortality of fully vulnerable fish in region r (1 = inshore, 2 = offshore) was denoted F_r. Thus, the instantaneous rate of fishing mortality (year^{-1}) of fish of length L_j in region r, $F_{j,r}$, was calculated as

$$F_{j,r} = V_j\, F_r. \tag{5.16}$$

The instantaneous rate of total mortality (year^{-1}) for fish of length L_j in region r, $Z_{j,r}$, was determined as

$$Z_{j,r} = F_{j,r} + M \tag{5.17}$$

where M is the instantaneous rate of natural mortality (year^{-1}). M was assumed to be constant for all fish and was estimated from the maximum age of the fish species using Hoenig's (1983) mortality equation for fish:

$$M = \exp\ [1.46 - 1.01 \log_e A]. \tag{5.18}$$

The proportion of fish of length L_j in region r that survive to the end of age step Δa, $s_{j,r}$, was determined as

$$s_{j,r} = \exp\ [-Z_{j,r}\ \Delta a]. \tag{5.19}$$

The relative number of fish (with the growth parameters associated with the current grid cell of discretized values of asymptotic length L_∞ and growth coefficient k) in age class j in inshore waters, $n_{j,1}$, was calculated from the expected proportion of fish with those growth parameters $p_{L_\infty,k}$ as

$$n_{j,1} = \begin{cases} p_{L_\infty,k} & \text{for } j = 1 \\ n_{j-1,1}\, s_{j-1,1} \left(1 - \psi_{j-1}^{\text{move}}\right) & \text{for } j > 1. \end{cases} \tag{5.20}$$

Likewise, the expected relative number of fish in age class j in offshore waters, $n_{j,2}$, was determined as

$$n_{j,2} = \begin{cases} 0 & \text{for } j = 1 \\ \left(n_{j-1,2}\, s_{j-1,2}\right) + \left(n_{j-1,1}\, s_{j-1,1}\, \psi_{j-1}^{\text{move}}\right) & \text{for } j > 1. \end{cases} \tag{5.21}$$

Equations 5.20 and 5.21 rely on the assumption that fish in the population are unlikely to grow to ages greater than the specified maximum age for the species. For each region, the expected catch from age class j (and thus length L_j) for fish that had the specific growth parameters L_∞^ω and k^κ was calculated using the Baranov catch equation:

$$C_{j,r} = {}^{F_{j,r}}\!/_{Z_{j,r}}\ \left(1 - s_{j,r}\right) n_{j,r}. \tag{5.22}$$

and accumulated over all pairs of growth parameters, thus producing an estimate of the relative numbers of fish in each age or length class within the overall catch.

Because the above model was intended to be fitted to age and length data for fish collected from inshore and offshore waters, the observed data will represent numbers at integer ages rather than decimal ages of fish. To fit the model, therefore, the expected catch for each age class and region predicted by the model was now expressed in terms of integer ages and the expected length composition for each such integer age was determined. It was thus necessary to move from the earlier definition of age classes, which, to give the required precision of calculations, were based on an age interval of Δa, to an expression of the age distribution in terms of integer ages. For this, integer age classes were denoted by the subscript τ, where a_τ represents fish of integer age τ $(0 \leq \tau \leq A)$. The length classes are denoted by the subscript υ, where the lower bound of the υ^{th} length class is L_υ , and the number of length classes and the size of the class intervals were those used for the observed length composition data.

The expected catch within each length class υ, for each integer age τ and region r, $C_{\upsilon,\tau,r}$, was calculated by summing the catches for that particular length class at age over all values of ω and κ. That is,

$$C_{\upsilon,\tau,r} = \sum_{\omega} \sum_{\substack{\kappa \\ a_\tau \leq a_j \leq a_{\tau+1} \\ L_\upsilon \leq L_j \leq L_{\upsilon+1}}} C_{j,r}^{\omega,\kappa} . \tag{5.23}$$

Subseqently, the expected number of fish caught from each integer age class τ and region r, $C_{\tau,r}$, was determined as

$$C_{\tau,r} = \sum_{\upsilon} C_{\upsilon,\tau,r} . \tag{5.24}$$

The total expected catch in region r was calculated as

$$C_r = \sum_{\tau=0}^{A} C_{\tau,r} . \tag{5.25}$$

The expected proportion of fish in the catch that belong to length class υ from region r, $\psi_{\upsilon,\tau,r}$, was determined as

$$\psi_{\upsilon,\tau,r} = C_{\upsilon,\tau,r} / C_{\tau,r} . \tag{5.26}$$

Similarly, the expected proportion of fish in the catch that belong to integer age class from each region, $\psi_{\tau,r}$, was calculated as

$$\psi_{\tau,r} = C_{\tau,r} \;/\; C_r \,. \tag{5.27}$$

5.2.4 *Fitting the model to simulated and real data*

Six parameters were estimated when fitting the model to age and length data. These included the two parameters of the logistic function describing the size-dependent vulnerability of fish to fishing gear (L_{50}^{Vuln} and L_{95}^{Vuln}), the two parameters of the logistic function describing the offshore movement of fish (L_{50}^{Move} and L_{95}^{Move}), and the fishing mortality of fish in the inshore and offshore regions (F_1 and F_2, respectively). The parameters were estimated by minimising an objective function which comprised the sum of the log-likelihoods calculated for the length-at-age data and age compositions from the two regions.

Denoting the observed frequency of fish in length class υ as $f_{\upsilon,\tau,r}$, the log-likelihood associated with length-at-age data from inshore and offshore waters was calculated as

$$\lambda_1 = \sum_{r=1}^{2} \sum_{\tau=0}^{A} \sum_{\upsilon} f_{\upsilon,\tau,r} \log_e\left(\psi_{\upsilon,\tau,r}\right). \tag{5.28}$$

Likewise, denoting the observed frequency of fish in integer age class τ as $f_{\tau,r}$, the log-likelihood associated with the age composition data from the two regions was calculated as

$$\lambda_2 = \sum_{r=1}^{2} \sum_{\tau=0}^{A} f_{\tau,r} \log_e(\psi_{\tau,r}) \,. \tag{5.29}$$

An estimate of the overall log-likelihood was calculated as the sum of the individual log-likelihoods associated with the lengths at ages and age compositions of the catch. That is,

$$\lambda = \lambda_1 + \lambda_2 \,. \tag{5.30}$$

The model was fitted using Solver in Microsoft Excel, applying a phased fitting approach to estimate the six model parameters. Prior to the first fitting phase, random starting values were generated, within specified bounds, for each of the parameters. The parameter estimates resulting from each phase were then used as the starting values for subsequent fitting phases, thus progressively helping the model find a solution. Several penalty functions were implemented to ensure that the following constraints were satisfied:

(1) $L_{95}^{\mathrm{Vuln}} > (L_{50}^{\mathrm{Vuln}} + 20)$,

(2) $L_{95}^{\mathrm{Move}} > (L_{50}^{\mathrm{Move}} + 20)$,

(3) $L_{50}^{\mathrm{Move}} > (L_{95}^{\mathrm{Vuln}} + 20)$, and

(4) F_1 and F_2 lie between 0.0001 and 0.6 year^{-1} (~ 2.5 times the natural mortality).

The third of these penalties was used to satisfy the assumption that inshore fish become fully vulnerable to capture by the fishing gear prior to their movement to offshore waters. Jitter tests were used to confirm that, when the model was fitted multiple times to the same data set (using different initial starting values for the parameters that were being estimated), the same solution was reached on each occasion.

To test the robustness of the model for reliably estimating the six model parameters, the model was first fitted to simulated age and length data for *P. georgianus*. The data were generated using an operating model that essentially comprised the same formulation as that described above in Section 5.2.3. This was achieved by specifying values for the model parameters (representing a base case scenario; see Table 5.1) that were considered to approximate the "true" parameters for *P. georgianus*, based on available biological information for this species in Western Australia (Farmer *et al.*, 2005). For all fits of the model undertaken for this study, the parameters specified to describe the growth of *P. georgianus* were those estimated by the non-linear random effects model (see Table 5.2).

Cumulative frequency distributions of the expected age and length compositions for *P. georgianus*, denoted $F(\psi_{\tau,r})$ and $F(\psi_{\upsilon,\tau,r})$, respectively, were calculated from values of $\psi_{\tau,r}$ and $\psi_{\upsilon,\tau,r}$ generated by the operating model. Using the inverse method of random number generation described by Zelen and Severo (1965), observed samples of fish were then drawn from these two cumulative distributions. That is, to obtain an "observed age" for each simulated fish, a random

Table 5.1. Model parameters used for simulating age and length data for *Pseudocaranx georgianus* for the base case scenario.

Parameter	Notation	Value
Selectivity parameters		
Length at which 50% of fish are vulnerable to capture (mm)	L_{50}^{Vuln}	300
Length at which 95% of fish are vulnerable to capture (mm)	L_{95}^{Vuln}	400
Movement parameters		
Length at which 50% of fish have moved offshore (mm)	L_{50}^{Move}	450
Length at which 95% of fish have moved offshore (mm)	L_{95}^{Move}	600
Mortality parameters		
Inshore fishing mortality (year^{-1})	F_1	0.3
Offshore fishing mortality (year^{-1})	F_2	0.1

number d was drawn from a uniform distribution with values ranging between zero and one, *i.e.* $d \sim U(0,1)$. The integer age τ, for which the value of d was such that $F(\psi_{\tau+1,r}) \leq d < F(\psi_{\tau,r})$, was then assigned to the fish, and the process repeated until samples of the required sample size for fish from region r had been generated.

The model was fitted to 100 simulated data sets for *P. georgianus*, each of which had been generated by the operating model using the parameters specified for the base case scenario. The resultant estimates of the six model parameters were then compared to the known, "true" values of the parameters (*i.e.* as specified in the operating model). To determine whether the amount of data available for fitting the model has a marked influence on parameter estimation, the model fitting process was repeated using two different specified sample sizes when simulating data, including a relatively small sample of 247 inshore fish and 107 offshore fish (*i.e.* corresponding to the amount of real data currently available for *P. georgianus* in Western Australia), and a larger sample size of 1000 and 500 fish in the inshore and offshore waters, respectively. Model fits to the small and large simulated data sets for *P. georgianus* were also repeated by specifying values of fishing mortality in the inshore and offshore regions of 0.1 and 0.3 year^{-1}, respectively (*i.e.* the opposite to the values specified for the base case, see Table 5.1).

Sensitivity analyses were undertaken to explore how different assumptions about the underlying data may influenced parameter estimation. Four different scenarios, including the base case scenario, were considered in the analysis to simulate hypothetical fish stocks for which the size range over which individuals remained in inshore waters after becoming vulnerable to the fishery varied. For example, in situations where the lengths at which fish begin moving offshore are only slightly greater than the lengths at which fish become vulnerable to capture by the fishing gear, the information content in the inshore length-at-age data for estimating movement and mortality will be less than when the offshore movement occurs at a larger size. Therefore, by varying the values specified for the parameters L_{50}^{Vuln}, L_{95}^{Vuln}, L_{50}^{Move} and L_{95}^{Move} when simulating data for *P. georgianus*, the ability of the model to deal with more or less informative data sets was explored. As above, the model was fitted to 100 simulated data sets (comprising 1000 inshore fish and 500 offshore fish) generated for each of the three additional scenarios considered in the sensitivity analysis, where the inshore and offshore fishing mortality for *P. georgianus* were specified as 0.3 and 0.1 year^{-1}, respectively.

At last, the model was fitted to real age and length data for *P. georgianus* in Western Australia. These data, which comprised 247 fish caught in inshore waters and 107 fish from offshore waters, were resampled and used in the model to produce 1000 sets of bootstrap estimates for each of the six model parameters. The medians of the estimates for each parameter, as well as the lower and upper 95% confidence levels, taken as the 2.5 and 97.5 percentiles, respectively, were then calculated.

5.2.5 Per-recruit analysis

Per-recruit analyses that account for the size-dependent movement of fish from inshore to offshore waters were used to explore the implications of different levels of fishing mortality in these two regions for the overall stock status of *P. georgianus*. As the analyses were intended to provide an indication of the likely consequences of differing mortality of fish in inshore and offshore waters, rather than precise estimates for this species, a simplified version of the above offshore movement model was employed. For this, it was assumed that the lengths at ages of all fish were represented by the expected lengths at the mid-points of each age class *j* (as before, assuming a common age interval of 0.05 years) calculated from the von Bertalanffy growth curve and using the mean growth parameters for *P. georgianus* as estimated by the random effects model (see Table 5.2), *i.e.* the growth model employed in the per-recruit analysis is deterministic and does not allow for variability in growth among individual fish. The values specified for other parameters used in the per-recruit analysis to determine the numbers at age in each of the inshore and offshore regions, $n_{j,r}$, were those obtained by fitting the offshore movement model to the real data available for this species (see Table 5.3). To further simplify analyses, only the females of *P. georgianus* were considered for the per-recruit analyses.

Yield per recruit, YPR, and spawning biomass per recruit, SBPR, were calculated for different specified values of fishing mortality in each region, F_r, ranging from 0 to 0.6 year^{-1}. Assuming a maximum age of 18 years for *P. georgianus*, YPR (g) in inshore ($r = 1$) and offshore ($r = 2$) waters was calculated as

$$\mathrm{YPR}_r = \sum_{j=1}^{J} \left[\frac{F_{j,r}}{Z_{j,r}} \left\{ 1 - \exp\left(-Z_{j,r}\, \Delta a \right) \right\} n_{j,r}\, W_j \right] \tag{5.31}$$

where W_j is the weight of *P. georgianus* at length L_j, as estimated from the weight-length relationship $\log_e(W) = 2.992 \log_e(L) - 11.331$ (Farmer *et al.*, 2005). The SBPR (g) for *P. georgianus* in inshore and offshore waters was determined as

$$\mathrm{SBPR}_r = \sum_{j=1}^{J} \left[\psi_j^{\mathrm{mat}}\, n_{j,r}\;\; W_j \right] \tag{5.32}$$

where ψ_j^{mat} represents the proportion of fish of length L_j that are mature, which was determined as

$$\psi_j^{\mathrm{mat}} = \left\{1 + \exp\left[-\log_e(19)\frac{L_j - L_{50}^{\mathrm{mat}}}{L_{95}^{\mathrm{mat}} - L_{50}^{\mathrm{mat}}}\right]\right\}^{-1}. \qquad (5.33)$$

$L_{50}^{\mathrm{mat}}$and L_{95}^{mat} represent the lengths (mm) at which 50 and 95% of female *P. georgianus* are mature, *i.e.* 310 and 378 mm, respectively (Farmer *et al.*, 2005). Values of the overall YPR and SBPR for fish in inshore and offshore waters were determined by summing the values calculated for each region.

The spawning potential ratio, SPR, of *P. georgianus* (*i.e.* the level of spawning biomass of the stock at the estimated level of exploitation relative to the unfished level) was calculated from the SBPR for different specified values of inshore fishing mortality (F_1) and offshore fishing mortality (F_2) as:

$$\mathrm{SPR}_{F_1,F_2} = \mathrm{SBPR}_{F_1,F_2}/\mathrm{SBPR}_{0,0}. \qquad (5.34)$$

5.3 Results

5.3.1 Evidence for size-dependent, offshore movements

The ages and sizes of *P. georgianus* caught by rod and line fishing in marine waters on the lower west coast of Australia (*n* = 354) differed substantially between inshore waters (< 60 m deep) and offshore waters (≥ 60 m deep). For example, the maximum age of *P. georgianus* collected in offshore waters (18 years) was far greater than in inshore waters (11 years) and the length of the largest fish in offshore waters (TL = 885 mm) was considerably greater than in inshore waters (TL = 568 mm) (Fig. 5.1).

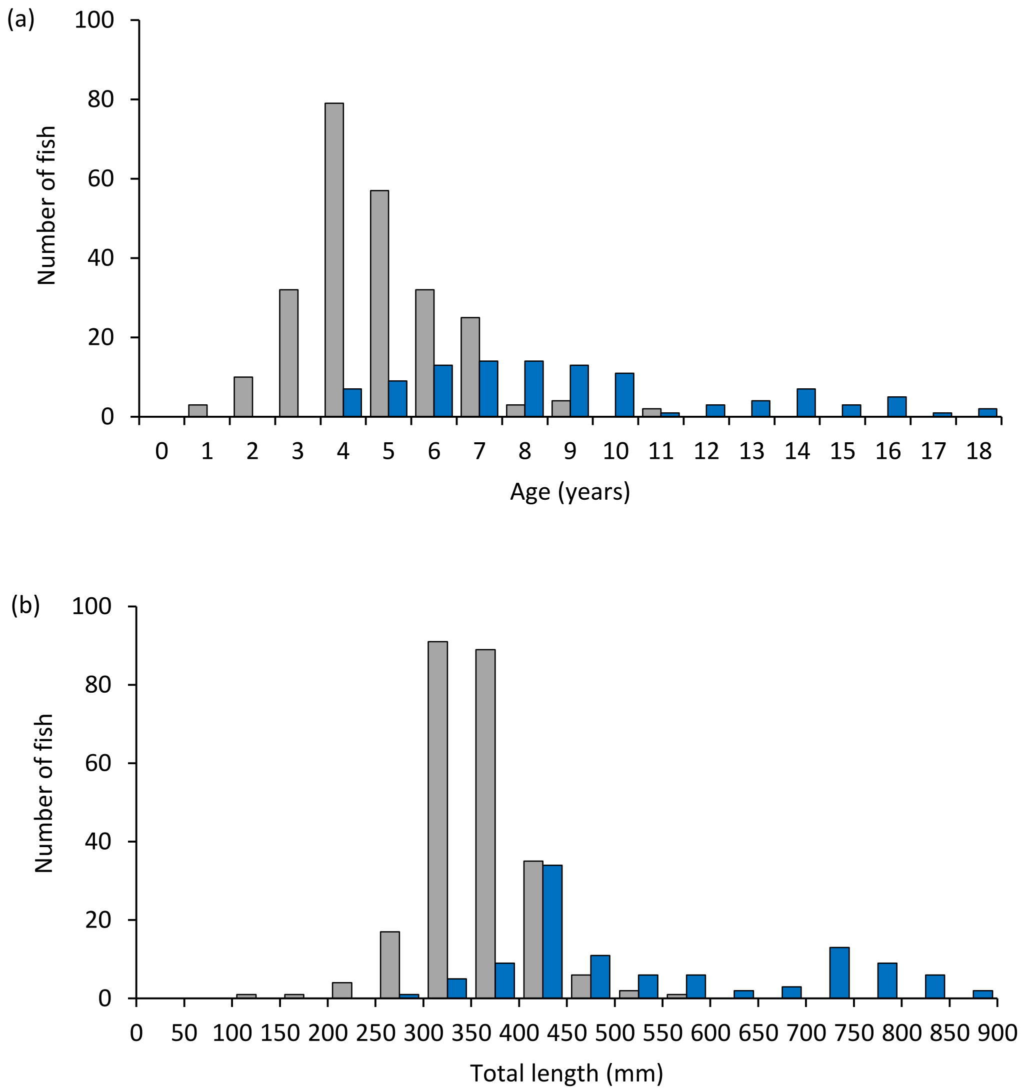


Fig. 5.1. (a) Age and (b) length frequency distributions for *Pseudocaranx georgianus* caught between November 2001 and October 2004 by rod and line fishing in inshore (grey bars; *n* = 247) and offshore (blue bars; *n* = 107) coastal waters of south-western Australia.

For each of the ages of which individuals of *P. georgianus* occurred in both inshore and offshore waters, the lengths of fish in the latter region were typically greatest (Fig. 5.2). For example, at 5, 7, 9 and 11 years of age, the mean lengths of *P. georgianus* were 414, 459, 556 and 646 mm, respectively, in offshore waters, compared with 371, 389, 442 and 530 mm, respectively, in inshore waters.

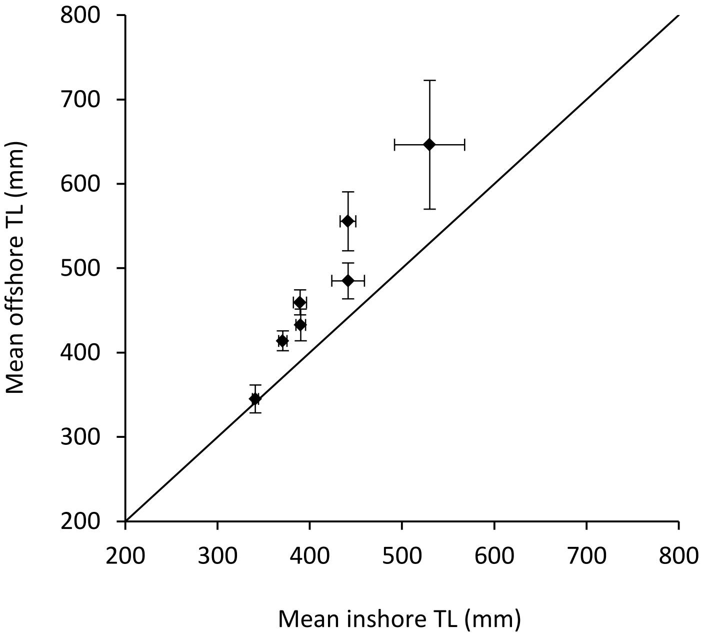


Fig. 5.2. Mean (± 1SE) total lengths (TL; mm) of *Pseudocaranx georgianus* in inshore and offshore coastal waters of south-western Australia, for the ages that were represented in both regions.

5.3.2 *Patterns of individual growth of fish*

For the 58 *P. georgianus* (ranging between 230 and 885 mm TL) for which measurements of total length and otolith radius at capture (L_c and R_c, respectively) were taken for back-calculation studies, L_c exhibited a strong non-linear (power) relationship with R_c ($R^2 = 0.73$; Fig. 5.3). Fitting the non-linear random effects model to the back-calculated lengths at age for *P. georgianus* from both inshore and offshore waters produced mean estimates of the von Bertalanffy growth parameters L_∞, k and t_0 that were 1246 mm, 0.075 year^{-1} and -0.201 years, respectively (Table 5.2). The standard deviations associated with each of these parameter estimates were relatively large (Table 5.2), as also indicated by the probability distributions for the parameter estimates obtained from the MCMC simulations (Fig. 5.4). The correlation between L_∞ and k was estimated by the random effects model as -0.829 for this species.

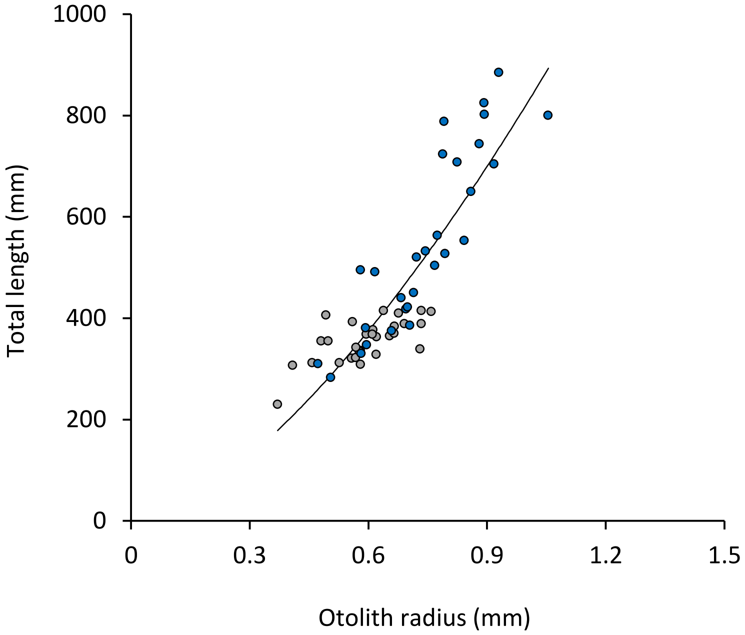


Fig. 5.3. Relationship between the total length (mm) and otoliths radius (mm) of *Pseudocaranx georgianus* caught in inshore (grey circles; *n* = 29) and offshore (blue circles; *n* = 29) coastal waters of south-western Australia.

Table 5.2. Means and standard deviations (SD) for estimates of the von Bertalanffy growth parameters and the correlation between L_∞ and k for individual *Pseudocaranx georgianus*. The estimates were obtained by fitting a non-linear random effects growth model to back-calculated lengths at age for *P. georgianus*, estimated using the body proportional hypothesis.

	Estimates	
Parameter	Mean	SD
Asymptotic length, L_∞ (mm)	1246	85
Growth coefficient, k (year^{-1})	0.075	0.007
Theoretical age at length zero, t_0 (years)	-0.201	4.161
Correlation L_∞ / k	-0.829	0.070

5.3.3 Robustness of the model for parameter estimation

Fitting the size-dependent, offshore movement model developed for estimating mortality in inshore and offshore waters to simulated data generated for the base case scenario (see Table 5.1) yielded model parameter estimates that were relatively similar to the “true” values for *P. georgianus*, as specified in the operating

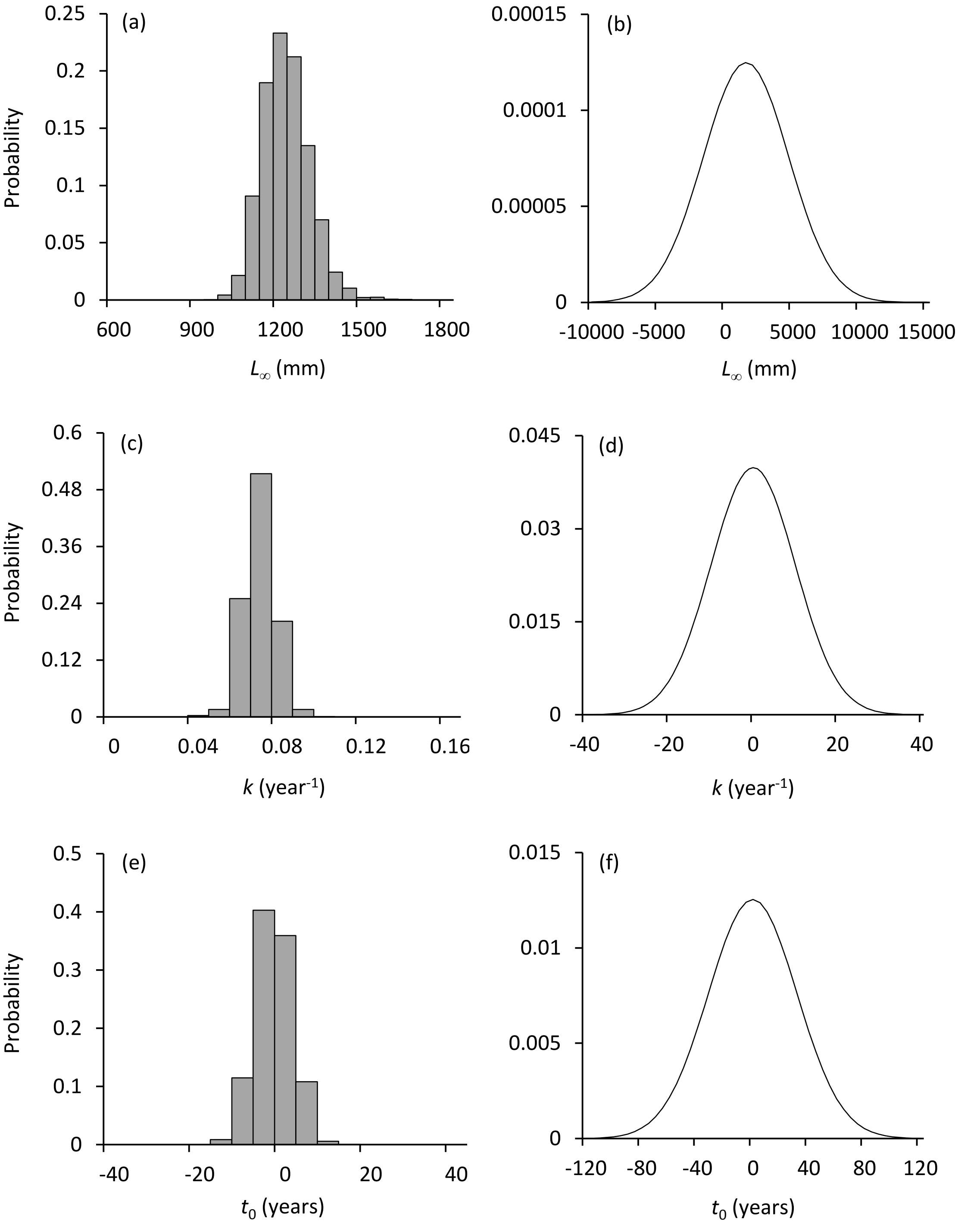


Fig. 5.4. Probability distributions (a, c, e) and prior probability distributions (b, d, f) for the three von Bertalanffy growth parameters, L_∞, k and t_0, for *Pseudocaranx georgianus* when estimated using the non-linear random effects model fitted to back-calculated lengths at age estimated using the body proportional hypothesis.

model (Fig. 5.5). For example, when the true fishing mortalities in inshore (F_1) and offshore (F_2) waters were specified as 0.1 and 0.3 year^{-1}, respectively, and the specified sample size was 247 inshore fish and 107 offshore fish, the respective median values for the estimates of F_1 and F_2 were 0.10 and 0.32 year^{-1}. For the same scenario, the median values of estimates for the two movement parameters L_{50}^{Move} and L_{95}^{Move} (451 and 601 mm, respectively) were very close to the respective true values of 450 and 600 mm. Increasing the sample size to 1000 and 500 fish in inshore and offshore waters, respectively, yielded similar median estimates for the parameters as compared with the smaller sample size scenario (Fig. 5.5).

Whilst the accuracy of parameter estimates produced by the model was similar for all of the six parameters estimated by the model, the precision of estimates of those parameters differed substantially among the parameters (Fig. 5.5). Thus, for example, when specified true fishing mortalities were F_1 = 0.3 and F_2 = 0.1 year^{-1} and for sample sizes of 247 and 107 fish, respectively, for inshore and offshore waters, the coefficients of variation (CVs) calculated for the 100 estimates of F_1 (0.89) and F_2 (0.51) were substantially larger than those for L_{50}^{Vuln} (0.06) and L_{95}^{Vuln} (0.07). Increasing the sample size of the data to which the model was fitted generally led to improved precision of parameter estimates (Fig. 5.5). For example, when the true fishing mortalities in inshore and offshore waters were specified as 0.1 and 0.3 year^{-1}, respectively, estimates of offshore mortality ranged between 0.20 and 0.44 year^{-1} for the larger sample size scenario (1000 inshore fish and 500 offshore fish), compared with 0.18 and 0.74 year^{-1} for the small sample size scenario (247 inshore fish and 107 offshore fish). Despite an increased sample size, however, it is worth noting that the precision of inshore mortality estimates produced by the model remained relatively poor (Fig. 5.5).

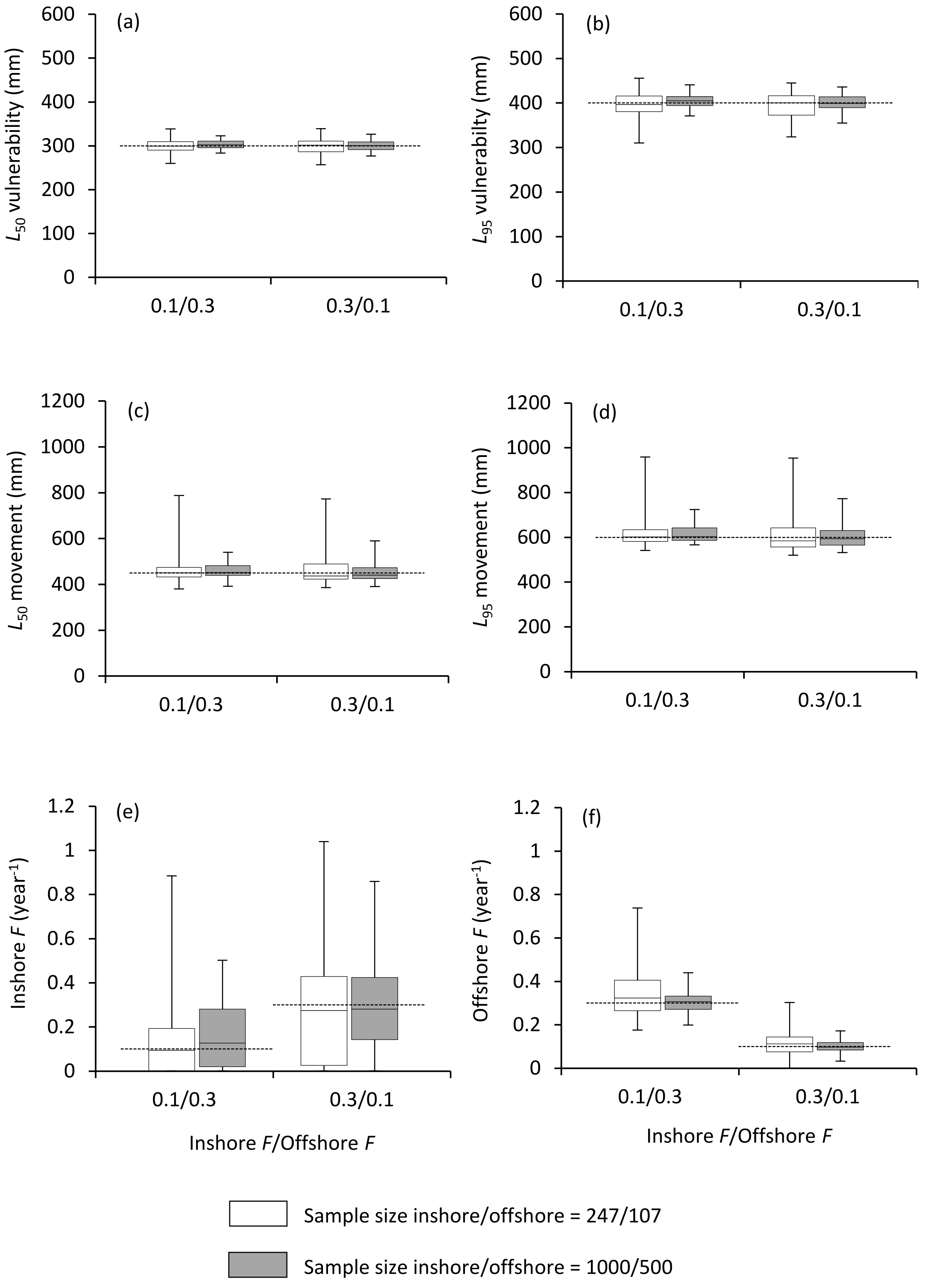


Fig. 5.5. Model estimates of (a, b) vulnerability parameters, (c, d) movement parameters, and (e, f) inshore and offshore fishing mortality (*F*). The true values for inshore *F*/offshore *F* were specified as 0.1/0.3 year^{-1} and 0.3/0.1 year^{-1}. Two different sample size scenarios were considered, where the white and grey boxes represent sample sizes in inshore/offshore waters being 247/107 and 1000/500 fish, respectively. For each scenario, the line inside the box shows the median value, the bottom and top of the box show the 25th and 75th percentiles, and the lower and upper bars show the minimum and maximum values for 100 model fits. The true values for the parameters are represented as the dashed lines.

The sensitivity analysis showed that the robustness of the model to reliably estimate mortality of fish species that undertake size-dependent movements from inshore to offshore waters varied substantially between the different scenarios undertaken (Fig. 5.6). As the size range over which individual fish remain in the inshore region after becoming vulnerable to the fishery increased, the precision of inshore mortality estimates and, to a lesser extent, offshore mortality estimates improved. That is, compared with the base case scenario, assuming that fish become vulnerable to fishing gear at smaller sizes resulted in the CV of inshore mortality estimates decreasing from 0.71 to 0.66 (*cf.* scenario 1 and 3 in Fig. 5.6). A similar

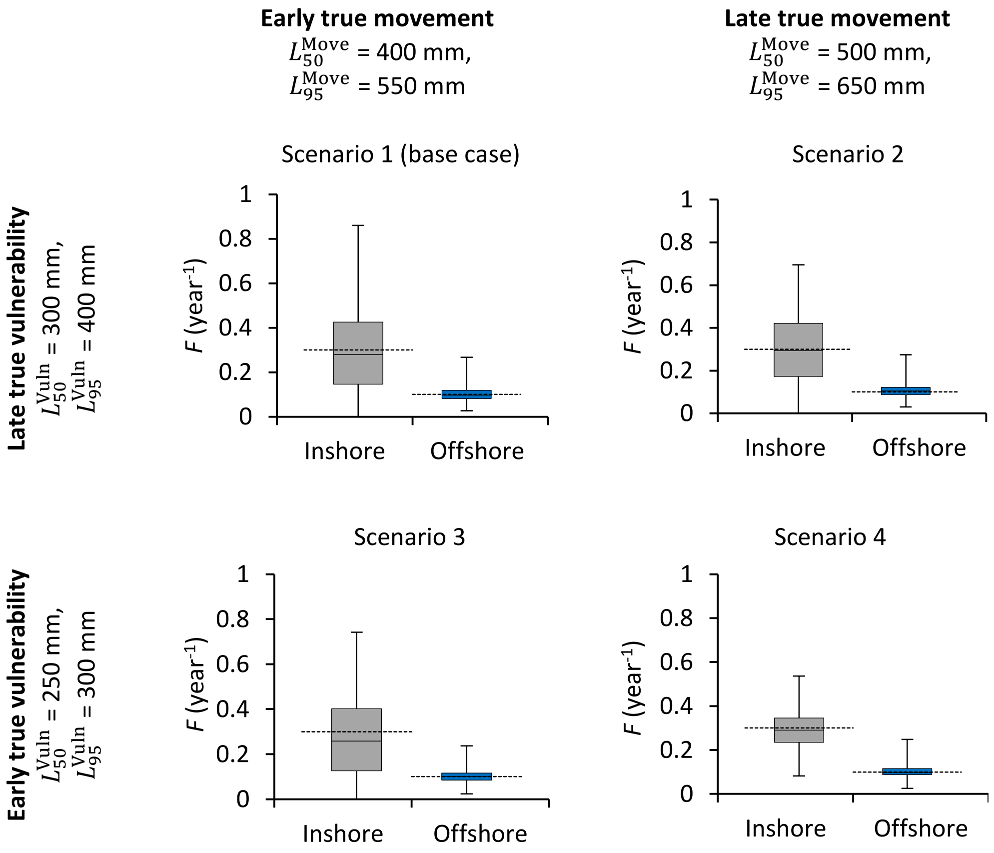


Fig. 5.6. Model estimates of inshore (grey boxes) and offshore (blue boxes) fishing mortality (*F*) when fitted to simulated data generated for four scenarios in which the sizes at which fish were assumed to become vulnerable to fishing gear and move offshore varied. For each scenario, the line inside the box shows the median value, the bottom and top of the box show the 25th and 75th percentiles, and the lower and upper bars show the minimum and maximum values for 100 model fits. The true values of inshore/offshore *F* were specified as 0.3/0.1 year^{-1} and are represented as the dashed lines.

improvement in the precision of inshore mortality estimates was obtained by assuming that the offshore movement of fish occurs at a larger size than specified for the base case scenario (*cf.* scenario 1 and 2 in Fig. 5.6). Of four scenarios explored, the one which assumed both “early” vulnerability and “late” movement of fish (scenario 4), resulted in the most precise estimates of inshore fishing mortality (CV = 0.27; Fig. 5.6).

5.3.4 Mortality of Pseudocaranx georgianus in Western Australia

The estimates of F_1 and F_2 derived by fitting the model to real data available for *P. georgianus* sampled in inshore and offshore waters of south-western Australia (*n* = 247 inshore fish and 107 offshore fish) indicate that the mortality of this species differs substantially between the two regions in which it occurs (Table 5.3). Although the median estimate obtained for F_2 (0.02 year^{-1}) indicates that fishing mortality of *P. georgianus* in the offshore region at the time of sampling was negligible, the median for F_1 (0.30 year^{-1}) was much larger and suggests that mortality in inshore waters is substantial, *i.e.* at about the level of estimated natural mortality for this species. Estimates of the parameters that describe the size-dependent vulnerability

Table 5.3. Median values of model parameter estimates and associated lower and upper 95% confidence limits (CLs; in parentheses) obtained by fitting the model to 1000 sets of resampled real age and length data for *Pseudocaranx georgianus* in south-western Australia (*n* = 247 and 107 fish from inshore and offshore waters, respectively).

Parameter	Median (± 95% CLs)
Length at which 50% of fish are vulnerable to capture, L_{50}^{Vuln} (mm)	338 (328, 348)
Length at which 95% of fish are vulnerable to capture, L_{95}^{Vuln} (mm)	414 (396, 432)
Length at which 50% of fish have moved offshore, L_{50}^{Move} (mm)	434 (416, 452)
Length at which 95% of fish have moved offshore, L_{95}^{Move} (mm)	593 (536, 630)
Inshore fishing mortality, F_1 (year^{-1})	0.30 (0.20, 0.39)
Offshore fishing mortality, F_2 (year^{-1})	0.02 (0.0001, 0.11)

and offshore movement of fish appear consistent with the length composition data for *P. georgianus* (see Fig. 5.1b).

5.3.5 Implications of size-dependent, offshore movements for management

Per-recruit analyses showed that the levels of mortality experienced by *P. georgianus* in inshore waters can have an influence on the overall yield and spawning potential of the fish stock, even if mortality in offshore waters is low. As would be expected, when the level of offshore fishing mortality was negligible, the value of overall YPR for *P. georgianus* increased markedly as the inshore mortality increased from 0 to 0.3 year^{-1} (Fig. 5.7a). As the rate of offshore mortality increased, however, the YPR curve reached a plateau and declined at a relatively similar rate, independently of the inshore fishing mortality (Fig. 5.7a). For any given level of inshore mortality, the maximum values of YPR were obtained at an offshore fishing mortality of about 0.3 year^{-1}. At this level of mortality, the values of overall YPR were 4419, 4319, 4234 and 4096 grams when the rate of inshore fishing mortality was 0, 0.1, 0.2 and 0.3 year^{-1}, respectively.

For any of the specified values for inshore fishing mortality, the overall SPR calculated for *P. georgianus* decreased as the offshore mortality increased (Fig. 5.7b). Even at a relatively low offshore fishing mortality of 0.1 year^{-1}, increasing the inshore fishing mortality from 0 to 0.1, 0.2 and 0.3 year^{-1} resulted in the overall SPR declining from 0.66 to 0.57, 0.50 and 0.44 (equivalent to percentage declines of 14, 24 and 33%), respectively. As the level of inshore fishing mortality was increased from 0 to 0.1, 0.2 and 0.3 year^{-1}, the often-used limit reference point for SPR of 0.3 (*e.g.* Goodyear, 1993; Mace and Sissenwine, 1993), is reached as the respective values of offshore fishing mortality are approximately 0.47, 0.36, 0.28 and 0.22 year^{-1}.

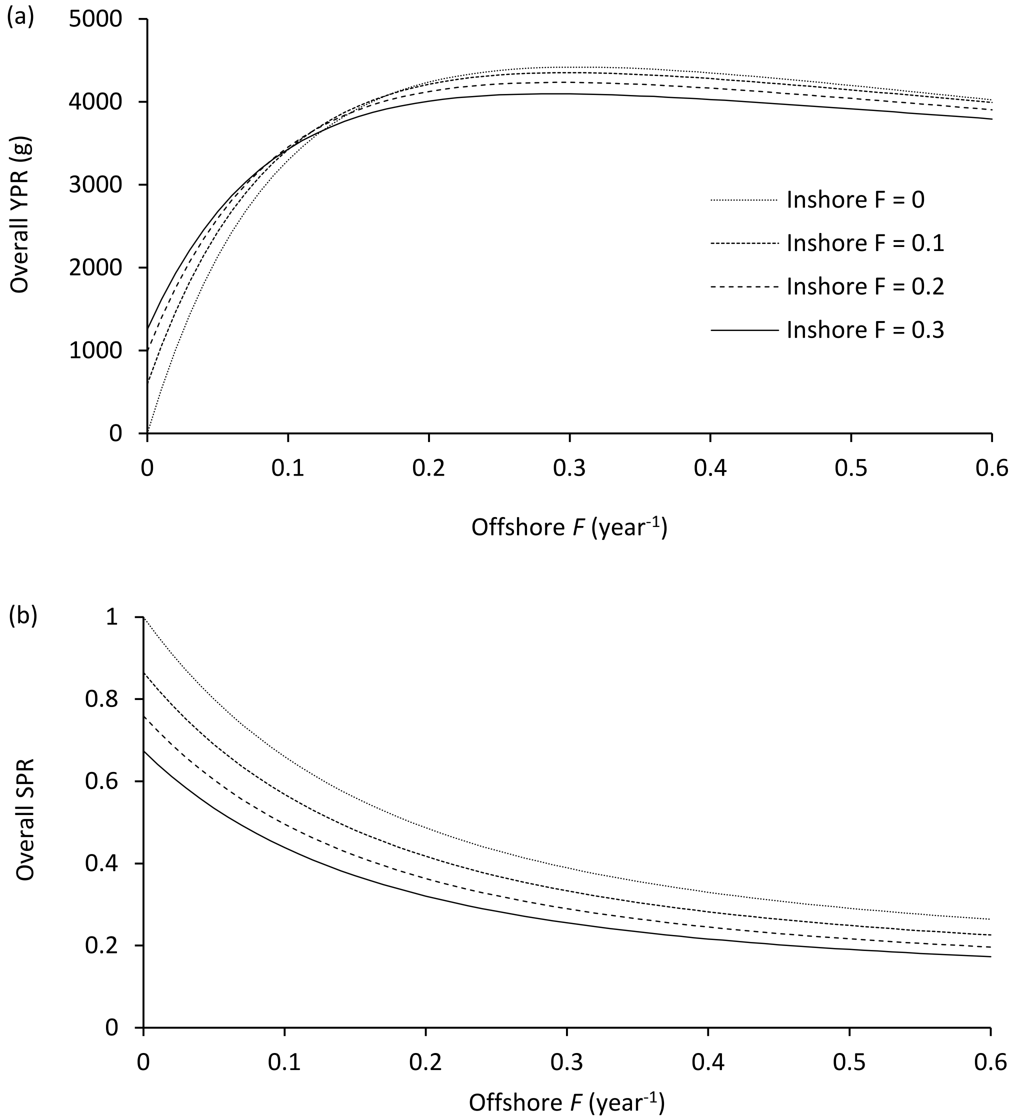


Fig. 5.7. Relationships between offshore fishing mortality and overall (a) yield per recruit and (b) spawning potential ratio based on spawning biomass per recruit for female *Pseudocaranx georgianus* in south-western Australia, given four alternative levels of inshore fishing mortality (*F*; year^{-1}).

5.4 Discussion

This study has described a method for estimating growth and mortality of fish species such as *P. georgianus*, which undertake (unidirectional) size-dependent movements, *e.g.* from inshore to offshore waters. By fitting the new model to simulated age and length data for *P. georgianus*, it was demonstrated that it can provide accurate estimates of model parameters. As was shown by sensitivity analyses, the level of precision of parameter estimates can vary markedly depending on the range of sizes and ages of fish in each region, which ultimately influences the information content in the data to which the model is fitted. The model has also been fitted to real data for *P. georgianus*, thereby further demonstrating the applicability of the approach and providing, for the first time, estimates of fishing mortality for that fish species in inshore and offshore coastal waters of south-western Australia. Per-recruit analyses that can account for size-dependent, offshore movements of fish were then used to demonstrate the importance of being able to reliably estimate mortality of species like *P. georgianus* in each of the regions in which it is exploited by fishers. As with any model, the one developed in this study has several assumptions and specific (but relatively modest) data requirements. These aspects are now discussed, together with an illustration of its application using data for *P. georgianus*.

5.4.1 Size-dependent, offshore movements of Pseudocaranx georgianus

As previously noted by Farmer *et al.* (2005), the age and size compositions of *P. georgianus* sampled in inshore waters (< 60 m deep) and offshore waters (≥ 60 m deep) off south-western Australia are conspicuously different. The substantially greater maximum age and size of fish in offshore waters (18 years, 885 mm) compared with fish in inshore waters (11 years, 568 mm) indicates that this species undertakes a pronounced offshore movement as fish become larger and older (Farmer *et al.*, 2005). This pattern of individuals moving from inshore to deeper, offshore waters has also been described for the closely related *P. dentex* in the north-eastern Atlantic (Afonso *et al.*, 2008; 2009) and in Japan (Masuda and Tsukamoto, 1999), as with many other fish species (Chen *et al.*, 1997; Russell and McDougall, 2005; Collins *et al.*, 2007).

The finding of this study that, for any given age, the mean length of *P. georgianus* is consistently larger for fish sampled in offshore waters provides strong evidence that the movement of this species in Western Australia is strongly size-dependent. This thus implies that, for the range of ages over which *P. georgianus* may move to the offshore region, it is the largest individuals in each age class which are most likely to undertake this offshore movement first. This, in turn, has several implications for obtaining reliable estimates of mortality for this species in inshore and offshore waters. Firstly, as the distribution of lengths at corresponding ages of fish in the inshore and offshore regions differs, this means that age composition data, on its own, is likely to be insufficient for estimating the rate at which *P. georgianus* moves offshore. Secondly, if mortality can be assumed to be age-dependent and if movement can be shown to be largely size-dependent, these two variables will impact on the age and length compositions of this species differently. In such cases, this difference in the ways in which the processes of movement and mortality influence age and length composition data can potentially provide a basis for allowing these parameters to be estimated.

The age and size compositions of fish in a population are strongly influenced by the growth patterns of its individuals and hence, any attempt to estimate movement and mortality will require a reliable description of growth for the fish species being studied. As the basis for disentangling the effects of movement and mortality, by the model used in this study, resides in the different ways in which these two processes influence age and length data for fish in the two regions, it was also recognised that growth modelling for species such as *P. georgianus* would need to account for the variability in growth among individuals. Fortunately, in more recent years, sophisticated approaches have been developed for estimating the individual growth variability of fish (*e.g.* Pilling *et al.*, 2002), which could be readily adopted for this study to help overcome this issue.

5.4.2 Patterns of individual growth of fish

This study is the first to describe the overall pattern of growth of *P. georgianus* throughout its depth range by accounting for the size-dependent movement of fish from inshore and offshore waters. The methods used for estimating growth also provided information about the extent to which growth patterns vary among individuals of this species. Because statistical tools such as the one applied in this study to describe individual variability in the growth of *P. georgianus* are typically based on data derived using back-calculation methods, it is important to recognise that their applicability is dependent on a number of assumptions (*e.g.* Campana, 1990; Wilson *et al.*, 2009). As pointed out by Campana (1990), growth back-calculations assume (i) that the periodicity of the deposition of growth increments on otoliths is constant over time (verified for *P. georgianus* using marginal increment analysis, see Farmer *et al.*, 2005), and (ii) that the distance between these increments directly relates to the somatic growth of fish. The observation that, throughout inshore and offshore waters, the values of total length for individuals of *P. georgianus* were strongly related with those for otolith radius suggests that the back-calculation approach was appropriate for describing the growth of *P. georgianus*.

The growth estimates obtained by fitting the (slightly modified) random effects model of Pilling *et al.* (2002) demonstrated that the growth of *P. georgianus* varies considerably among individuals, as has also been observed for a number of other species, including the sand-smelt *Atherina presbyter* (Moreno and Morales-Nin, 2003) and red snapper *Lutjanus campechanus* (White and Palmer, 2004). This variability in growth of individual *P. georgianus* is illustrated, for example, by the finding that estimates for L_∞ of different individuals varied widely, with estimates ranging from ~ 900 to 1400 mm. In discussing the growth characteristics of *P. georgianus*, it may also be worth noting that the estimate obtained for the correlation between the asymptotic length and Brody growth coefficient (-0.829) is consistent with the general perception in the fisheries ecology literature that, among species, these two parameters are strongly negatively correlated (*i.e.* often in the range of -0.8 to -0.9; see Quinn and Deriso, 1999).

5.4.3 Robustness of the model for parameter estimation

To my knowledge, the model described in this study represents the first attempt to develop a method for estimating the exploitation rate of a fish species that undertakes a size-dependent movement from inshore to offshore waters, and which relies only on age composition and length-at-age data as are typically collected in many biological studies. The model estimates the parameters that describe the movement and mortality of fish (and also their vulnerability to the fishing gear) by calculating, according to the values of these parameters and others that describe individual variability in growth, the probabilities that individuals of different ages, and their size at those ages, occur in inshore and offshore waters. The model assumes that, for the age and size ranges over which the fish species is exploited, mortality is related solely to age whereas movement is strongly size-dependent. As described above, the available age and length composition data for *P. georgianus* suggest that these assumptions are valid for this species. It is worth noting that the assumption that mortality is age dependent is also assumed by most stock assessment methods, including conventional catch curve analyses (Ricker, 1975). Moreover, the offshore movements undertaken by a number of fish species have been shown to be associated with size, *e.g.* the tarwhine *Rhabdosargus sarba* (Hesp *et al.*, 2004) and mangrove jack *Lutjanus argentimaculatus* (Russell and McDougall, 2005).

The finding that, when fitting the model to simulated data for *P. georgianus*, the values specified for the model parameters when simulating those data could often be recovered, demonstrates the potential of the approach for providing robust parameter estimates. The simulations indicated that, if substantial sample sizes for *P. georgianus* could be obtained from inshore and offshore waters, and if the values used to simulate data for this species are relatively close to the true values for this species, the model is likely to yield accurate estimates of vulnerability, movement and mortality. The simulation testing also demonstrated, however, that if samples sizes are relatively small, as is the case with available data for *P. georgianus*, then the estimates of some parameters are likely to be relatively imprecise. Sensitivity analyses also showed that, if fish only reside in the inshore region for a short period of time (and thus over a narrow age and size range), the amount of information in the inshore data is likely to be insufficient for the model to “tease out” the differential effects of movement and mortality. In this regard, it may be worth noting that the value of simulation testing as an approach for assessing the robustness of fisheries assessment models is now widely recognised among fisheries stock assessment scientists (*e.g.* Cope and Punt, 2009; Wetzel and Punt, 2011). For any future use of the model developed in this study with other fish species, it is thus recommended that the robustness of the model first be tested by simulating data using parameters appropriate for that stock.

5.4.4 Mortality of Pseudocaranx georgianus in Western Australia

Estimates of fishing mortality for *P. georgianus* produced by fitting the model to real data collected for this species in south-western Australia (Farmer *et al.*, 2005) indicated that fishing pressure on this species is substantially greater in inshore waters compared with offshore waters. Although it must be recognised that these data for *P. georgianus* were collected about a decade ago, and that the situation with this species may thus have changed, the mortality estimates are consistent with anecdotal evidence from recreational anglers and charter boat fishers that they more frequently target and catch this species in inshore waters. As access to the deeper, more offshore waters is strongly weather-dependent and mainly limited to fishers with large boats, it might be expected that the levels of fishing mortality to which this species is exposed in offshore waters is less than in the more easily accessible inshore region. Furthermore, fishers are known to target offshore *P. georgianus* only during a few months of the year, at times when these fish have been found to aggregate over artificial reefs (sunken barges) in ~ 110 m deep water.

The finding that, when the model was fitted to resampled real data for *P. georgianus*, more precise mortality estimates were produced than when fitting it to simulated data, is likely due to one of the penalty terms imposed to keep parameters within appropriate bounds. When fitting the model to real data, resultant estimates were constrained by the penalty imposed by the assumption of a minimum difference between L_{95}^{Vuln} and L_{50}^{Move}. It is likely that this result was a consequence of the lack of data, and thus information, for older and larger fish in offshore waters and, despite this constraint, the resulting estimates of the parameters describing the size-dependent vulnerability and offshore movement of *P. georgianus* appeared to match the available data well.

5.4.5 Implications of size-dependent, offshore movements for management

This study has provided a demonstration as to how per-recruit analyses can be modified to account for size-related movements of fish species such as *P. georgianus*.

Although the level of sophistication/realism of the per-recruit analyses used in this study could be enhanced through incorporating information on individual variability in growth among individual fish, the approach clearly highlights the importance of being able to obtain accurate estimates of mortality for fish in all the regions in which it is being targeted. For example, analyses indicated that, in the case of *P. georgianus*, heavy exploitation on fish in inshore waters ($F_1 = 0.35$ year^{-1}) could reduce the spawning potential of a stock of this species to a relatively low level (*i.e.* ~ 30% of the unfished level), even if mortality in offshore waters was relatively low ($F_2 = 0.1$ year^{-1}). The importance of accounting for potentially different levels of exploitation on the various components of a stock, which may also be targeted by very different fisheries, has been highlighted for some other species, including redfish *Centroberyx affinis* and tiger flathead *Neoplatycephalus richardsoni* (Chen *et al.*, 1998). Although those authors demonstrated that changes to inshore fishing mortality can have a pronounced effect on the overall yield per recruit of a fish species, the results of this current study have highlighted the importance of also evaluating the impacts of such changes on the spawning component of the stock.

5.4.6 Conclusion

In summary, this study has developed and evaluated the efficacy of an approach for assessing the stock status of species, such as *P. georgianus*, which exhibit size-dependent, offshore movements. The approach involved employing existing methods for describing variability in growth of individual fish, applying a new model to estimate parameters describing the size-dependent vulnerability and offshore movement of fish, and mortality rates in inshore and offshore waters and, at last, exploring the implications of these findings for overall stock status using per-recruit analyses. The model for estimating mortality was able to be fitted to limited data for *P. georgianus*, thereby demonstrating its potential value for data-limited fisheries. The work undertaken for this chapter could potentially be extended by exploring, through simulation, the possible benefits (*i.e.* improvements in reliability and precision) of integrating information on movement and mortality obtained from tagging studies with the outputs of the model developed in this study. The value of such research is further discussed in the final discussion chapter of this thesis.

CHAPTER 6

General discussion

6.1 Towards better assessment and management of data-limited fisheries

As efforts to assess the state of the world’s fish resources continue to increase, more and more fisheries are being identified as data-limited (Wetzel and Punt, 2011). Data limitations pose significant challenges for management of fish stocks as they lead to increased uncertainty in stock assessment information (Jiao *et al.*, 2011; Wetzel and Punt, 2011). Therefore, when fisheries scientists are asked to provide managers with stock assessment information for fish stocks for which data are limited or highly unreliable, is the solution simply to collect more data? This chapter considers some broad issues associated with assessing and managing fisheries in the face of large uncertainties and limited data, as well as some future research directions for helping to tackle these issues.

6.1.1 Implementation of participatory management systems

To ensure the sustainability of any fishery, good governance is vital (Hilborn, 2007). This point is illustrated by the fact that management of a number of large commercial fisheries has failed to conserve the fish stocks targeted by those fisheries, despite large amounts of resources being directed towards research and development of appropriate management plans (Garcia and Grainger, 2005). It has been recognised that an important contributing factor towards such failures is the often successful lobbying by fishers against recommended reductions in catch limits (Peña-Torres, 1997; Hutchings and Reynolds, 2004; Safina and Klinger, 2008). As fishers can have considerable political power, it can be difficult to gain their support for proposed management changes, even if the intent for such changes is to provide long-term economic and ecological benefits (Hilborn, 2004). This is likely to be particularly true in situations when management advice is highly uncertain because of limited stock assessment information. Such issues pose a major challenge to the sustainability of fisheries and, to resolve this, management actions need to be implemented that make sense to all the stakeholders involved in the fishery.

In addition to issues regarding the typically contrasting values and objectives of different fishery stakeholder groups, lack of effective communication between scientists and other stakeholders have often been put forward as one reason to explain the failure of fisheries management systems in the past (de la Mare, 1998; Peterman, 2004). As fisheries research is commonly undertaken in relative isolation from the fishing industry, it is not surprising to find that fishers can be sceptical of information resulting from scientific assessments, especially when they have little understanding of how this was obtained (Daw and Gray, 2005). To overcome issues associated with distrust in the science on which management decisions are based, fisheries simulation models could constitute useful vehicles for communicating stock status information, in particular to stakeholders who have limited stock assessment knowledge (see Chapters 2 and 3). For simulation models to be effective as communication and education tools, careful design of the user interface is likely to be key to ensuring that the information can be readily understood by stakeholders (Scandol, 2000). If such models can be developed, they could be valuable to help support a participatory approach to the management of many fisheries.

Critical to the success of a participatory management approach is that all stakeholders in a fishery feel represented in the process of decision-making, and that they are genuinely interested in the sustainability of the fishery (Hilborn, 2007). For recreational fisheries, mechanisms to encourage the involvement of fishers in research and management could be provided by recreational fishing organisations which benefit fishers by offering services associated with education, lobbying and advocacy (Harrison and Schratwieser, 2008). The concept of a co-management approach to fisheries management is attractive because allowing fishers to participate in decision-making may help improve compliance and support of those management decisions (Mikalsen and Jentoft, 2001; Schratwieser, 2006). Furthermore, there is often a wealth of empirical knowledge from fishers that they have accumulated through their experiences on the fishing grounds. Scientists could benefit from this extensive knowledge base, for example, when developing simulation models to be used as communication tools, by allowing fishers to provide feedback on the model design. Indeed, stakeholder workshops like those held during the early stages of developing the MSE model used in Chapters 2 and 3, in which scientists and managers were given an opportunity to trial the software, proved vital for improving the applicability and usefulness of the finalised model (Fisher *et al.*, 2011).

In the future, the work undertaken using the MSE model could be enhanced to explore, over an extensive projection period, the effectiveness of alternative fixed decision rules to regulate exploitation pressure on fish stocks with different biological attributes (*e.g.* longevity, recruitment variability, hermaphroditic *vs.* gonochoristic species), according to results produced by the assessment component of the MSE framework. The model itself could also be extended to incorporate alternative assumptions regarding how fishers respond to changes in management. The MSE framework could also be applied to investigate the impacts of different levels of compliance by fishers to different management rules (controls), and the inter-relationship between alternative management policies for directing resources towards enforcement of regulations.

6.1.2 Efficient allocation of available resources

For many small-scale fisheries like those on which this thesis has focused, investment towards monitoring the state of targeted fish stocks is often limited. Even when substantial funds are made available for monitoring programs, collection of reliable catch and effort information can be difficult due to the open-access nature of many such smaller fisheries, particularly when these operate over a wide geographical range and/or involve a large number of participants (Murray-Jones and Steffe, 2000; McPhee *et al.*, 2002). The situation becomes further complex when resources are shared by several fishing sectors, which may target multiple fish species and use a variety of different fishing methods (Wise *et al.*, 2007; Marriott *et al.*, 2011). Moreover, advances in fishing efficiency brought about by the uptake of new technologies, and changes in management arrangements for fisheries over time, further add to the difficulty associated with assessing fish stocks based on trends in catch and effort data (Ulrich *et al.*, 2002; Bishop *et al.*, 2008).

To simplify the task of assessing the state of fisheries that operate over an extensive area, a regional approach to management is often applied to divide the total fished area into smaller, more manageable units (*e.g.* Punt *et al.*, 2000; McGarvey *et al.*, 2010). Such an approach has proven practical for the management of fisheries resources in Western Australia, which expand over a vast stretch of coastline (~ 12,800 km, ranging from ~ 10˚S to ~ 40˚S), and where the species composition of catches varies substantially with latitude (Department of Fisheries, Western Australia, 2011b). To allow available resources for monitoring and assessment to be effectively accommodated, four bioregions divide the state’s coastal marine waters into broad ecological regions (Fletcher *et al.*, 2010) and, within each of these, five ecological suites (estuarine, nearshore, inshore demersal, offshore demersal and pelagic) have been identified (Department of Fisheries, Western Australia, 2011b). Assessments are then undertaken for a number of commercially and recreationally important fish species that have been selected from each suite to help prioritise research efforts to those stocks that most require them (Wise *et al.*, 2007; Department of Fisheries, Western Australia, 2011b).

In the case of the Western Australian finfish fisheries, the selected species on which assessments are undertaken differ widely with respect to their biological characteristics. For example, several of these species, such as King George whiting *Sillaginodes punctata* and silver trevally *Pseudocaranx georgianus*, undertake size-dependent movements from inshore to offshore waters (Hyndes *et al.*, 1998; Farmer *et al.*, 2005). Until the present study, no methods were available for assessing the status of these stocks due to the difficulty in obtaining samples of fish that are representative of the whole populations. The model described in Chapter 5 is, to the best of my knowledge, the only method currently available for estimating mortality and movements of such fish species based on age and length data only, noting that these are the types of data that may only be available for many data-limited fisheries.

6.1.3 Ensuring sufficient data for assessments

A crucial first step in managing any fish stock is to identify what types of data, and how much of it, are needed to inform the assessment model that is to be used (Wetzel and Punt, 2011). For example, as demonstrated by a number of simulation studies (including Chapter 4), the robustness of catch curve analyses for estimating mortality can be influenced greatly by the sample size of data to which the curve is fitted (*e.g.* Dunn *et al.*, 2002; Fisher *et al.*, 2011). Furthermore, the accuracy of catch curve estimates of mortality will also vary for different fish species depending on the number of age classes (*i.e.* data points) to which the catch curve can be fitted, and the level of variability in annual recruitment (as conventional catch curve analyses assume constant recruitment over time) (Fisher *et al.*, 2011; see also Chapter 4).

Another critical aspect for estimating the mortality of fish stocks is to ensure that the data used as input for an assessment model are representative of the underlying population. If the data used in analytical models are unreliable, then estimates of the model will most likely also be highly uncertain (Punt, 1997). Although simulation models can provide valuable tools for assessing the effectiveness of alternative methods for assessing fish stocks, it must be highlighted that the approach used in designing such models is typically to generate data on the basis that samples are drawn randomly from the fish population. In reality, sampling designs used for collecting age composition data often lead to the ages of fish caught during the same trip or trawl being more similar than those in the actual population (Pennington *et al.,* 2002; Aanes and Pennington, 2003). Consequently, the effective sample size required for any particular assessment method can be substantially smaller than the actual sample size suggested by such simulation models (*e.g.* Williams and Quinn, 1998; Hulson *et al.*, 2012). For assessment methods such as those described in Chapters 4 and 5 of this thesis, it has been assumed that the simulated age and size composition data were representative of the population or assemblage from which they were assumed to have been collected. Future work directed towards estimating the effective sample size of the age composition data to which these models are fitted could be valuable for better understanding uncertainties resulting from errors in sampling designs.

A further issue that may need to be considered in data-limited situations is that assessment methods may become increasingly unreliable as we attempt to extract more and more information from limited data. Although the simulations undertaken for Chapter 5 demonstrated that the model developed for estimating mortality for fish species that undertake size-dependent movements is able to produce relatively accurate estimates of mortality, sensitivity analyses showed that there are situations in which age and length data alone may not be sufficient to inform the model. To overcome imprecision in mortality estimates, it was proposed that additional information resulting from a tagging study may help to better inform the assessment model. Because of the significant costs associated with tagging studies, however, a desktop study involving simulation of the tag-recapture experiments could be valuable for determining how many fish would need to be tagged and recaptured to yield sufficiently precise estimates of movement and mortality. It would be worth investigating whether the costs of a tagging study may be further reduced if the estimates produced by the tagging study could be combined with those provided by the model described in Chapter 5, to produce more precise estimates of movement and mortality, and thus possibly reducing the number of fish required to be tagged.

6.1.4 Making the most of available information

A key issue when undertaking stock assessments for data-limited fisheries is that traditional assessment methods are often not applicable (Cope and Punt, 2009). As assessment models become more complex and an increasing amount of data are needed as input, resulting estimates of stock status will likely become progressively more sensitive to unreliable data (Kelly and Codling, 2006). Consequently, for fisheries where the quality of available data is poor, stock assessment scientists often rely on simplified assessment methods with limited data requirements.

One of the main concerns with having to rely on simplified assessment approaches is the strong assumptions on which these are often dependent. To improve the robustness of such assessment methods and make the most of limited data, two of the studies described in this thesis were focused on developing new approaches to mortality-based assessments that eliminate some of these challenging assumptions. For example, by removing the key assumption of conventional catch curve methods that mortality is constant for fish of all ages in the population, the mortality of fish stocks that have recently undergone a marked change in management can be more reliably estimated (Chapter 4). Moreover, for fish species that are known to undertake size-dependent movements from inshore to offshore waters, explicitly accounting for this movement in stock assessments produces unbiased mortality estimates for fish in those two regions (Chapter 5). As shown by both of the above studies, however, the mortality estimates that result from the use of such approaches can be relatively imprecise when the information content in the data is low.

In situations where a lack of scientific data may preclude the use of more complex analytical stock assessments and estimates obtained from simpler quantitative analyses are highly uncertain, it is important to also consider any other information that may be available to help inform management decisions. Risk-based assessment methods are increasingly being used in the management of fisheries to reduce the risks of over-exploiting resources, as well as to help achieve ecosystem-based management objectives (Smith *et al.*, 2007; Fletcher *et al.*, 2010). Although both quantitative (Walters, 1986; Hilborn *et al.*, 1993; 2001) and qualitative (Fletcher, 2005; Hobday *et al.*, 2007) risk assessment approaches have been described in the literature, the underlying concept of these methods is that they aim to identify and categorise the risks associated with the various uncertainties inherent in fisheries. Risk assessments have proven particularly valuable for identifying and prioritising where to target management effort, as well as for directing resources for future research (Fletcher, 2005).

In Australia, management decisions for fish stocks with limited data have often been made following "expert" deliberations about the exploitation state of targeted fish species (Scandol and Rowling, 2007; Wise *et al.*, 2007), based on what is commonly referred to as a "weight-of-evidence" approach (*e.g.* Scandol *et al.*, 2009). Commonly centred on the biological characteristics of fish species (rate of growth, size at maturity *etc.*), this approach allows the risks associated with a range of alternative available information to be assessed (Scandol and Rowling, 2007). Such an approach can thus be useful for ensuring that, in situations where there is a substantial risk to the sustainability of a resource, absence or incomplete information is not used as a reason for failing to make a decision. Qualitative assessment and decision-making procedures have the potential to be highly subjective, however, unless carried out systematically and transparently. This is becoming increasingly important as environmental organisations are putting larger pressures on fisheries to prove their sustainability to the wider community.

6.2 What future challenges await data-limited fisheries?

As global demand for seafood products continues to rise, the public are becoming increasingly conscious of the many issues threatening the sustainability of fisheries (Cummins, 2004; Daw and Gray, 2005; Garcia and Grainger, 2005). As a consequence of the growing recognition by the public that many of the world's fish stocks are over-exploited, the aim of many recent environmental campaigns has been to raise awareness of unsustainable fishing practises, often focusing on issues such as discarding and by-catch (Todd and Ritchie, 2000). Fisheries scientists and managers are now being held responsible not only by the fishing industry but also by the general public and environmental organisations.

Although there has been a long history of conflicting viewpoints between the fishing industry and environmentalists, fishers are now becoming more aware that the growing strength of the environmental movement cannot be ignored (Gray *et al.*, 1999). Even though some alliances between smaller environmental groups and fishers have always occurred at a local level (Gray *et al.*, 1999), the growing involvement of powerful non-governmental organisations (NGOs) in fisheries is leading to larger fisheries organisations starting to approach environmentalists for collaborations (Gray *et al.*, 1999). It is such initiatives that have formed the basis for the founding of fisheries certification schemes such as the Marine Stewardship Council (MSC), which was established in 1997 (Cummins, 2004; Gulbrandsen, 2009).

As an independent, non-profit organisation, the MSC aims to provide economic incentives for well-managed fisheries by setting standards for sustainability and issuing accreditation certificates to fisheries that meet those standards (Gray *et al.*, 1999). Such certification initiatives represent market-based approaches for providing fishers with better premiums for their products and greater market access, and thus represent valuable tools for providing an incentive for fisheries to demonstrate responsible practises and management of the resource to the public (Cummins, 2004). Although some small-scale fisheries are among those already certified, the approach is consumer-driven and thus relies on the fact that the products of the fishery are destined for the market. Furthermore, because the certification process can be time consuming and costly, the approach favours larger, industrial fisheries for high-value resources that can afford those costs (Gulbrandsen, 2009).

In the past, recreational fisheries have avoided close scrutiny from conservation and environmental groups (McPhee *et al.*, 2002). In more recent decades, however, fishers have started losing access to fishing grounds because of a perceived need by the conservation sector to “lock up” areas of the ocean as marine reserves (no-take zones), despite the general view of fishers, and possibly also of many scientists and managers, that these areas are already being managed appropriately. As it is becoming increasingly important for fisheries managers to demonstrate that they are meeting objectives of sustainability, it is possible that some components of certification initiatives such as the MSC could also benefit the recreational sector. For example, some of the strengths of fishery certification approaches lie in the fact that they commit fisheries to external scrutiny by society and enhance the transparency of management practises to the general public (Potts and Haward, 2007). Moreover, because the MSC represents a well-recognised and highly-trusted organisation, which although setting the criteria for certification maintains independence from those experts undertaking the assessment of the fishery and from the fishery itself, its accreditation scheme could thus also be important to overcome the level of distrust in science and decision-making often observed among fishers.

To decide whether a fishery meets the standards for sustainable fishing, it is fundamental that they are all assessed in a fair and similar manner. In the case of the MSC, development of these standards involved a consultative process through a series of workshops with scientists, fisheries experts, environmental organisations and many others. Once the standards are agreed, fisheries are assessed against these by external accreditation bodies that are independent of the MSC to ensure the evaluation process is not biased (Cummins, 2004). Although the value of such assessment procedures is clear, it is important to recognise that the substantial funds required for undertaking MSC assessments are not likely to be available for the many low-valued, small-scale fisheries on which this thesis has focused. To improve the ways in which such fisheries are managed, future research needs to focus on developing management approaches that encourage participation of multiple stakeholders. Furthermore, management decisions must be based on assessments that are sufficiently transparent to allow the status of fisheries to be effectively conveyed to the fishers and the general public, thereby aiming to restore their trust in fisheries science and management.

APPENDIX A

MSE model description

THE OPERATING MODEL

Age-, length- and sex-structure

The population may be represented as an array $\boldsymbol{N}_t$ containing the numbers of fish of each sex within each age and length class at the start of year t. Thus,

$$\boldsymbol{N}_t = \begin{pmatrix} n_{1,1,f,t} & n_{1,2,f,t)} & \cdots & n_{1,J,f,t} \\ n_{2,1,f,t)} & n_{2,2,f,t)} & \cdots & n_{2,J,f,t} \\ \vdots & \vdots & \ddots & \vdots \\ n_{K,1,f,t} & n_{K,2,f,t)} & \cdots & n_{K,J,f,t} \\ n_{1,1,m,t} & n_{1,2,m,t} & \cdots & n_{1,J,m,t} \\ n_{2,1,m,t} & n_{2,2,m,t} & \cdots & n_{2,J,m,t} \\ \vdots & \vdots & \ddots & \vdots \\ n_{K,1,m,t} & n_{K,2,m,t} & \cdots & n_{K,J,m,t} \end{pmatrix} \tag{1}$$

where $n_{k,j,s,t}$ represents the number of fish of age class j $(1 \leq j \leq J)$, length class k $(1 \leq k \leq K)$ and sex s $(f = \text{females}, m = \text{males})$ at the start of year t. The columns of this matrix are vectors that contain the numbers of fish within each of the age classes, *i.e.*

$$\boldsymbol{N}_t = \begin{pmatrix} \boldsymbol{N}_{1,t} & \boldsymbol{N}_{2,t} & \cdots & \boldsymbol{N}_{J,t} \end{pmatrix} \tag{2}$$

and where the number of fish of integer age a_j at the start of time step t, *i.e.* the number of fish in age class j, is written as the column vector:

$$\boldsymbol{N}_{j,t} = \begin{pmatrix} n_{1,j,f,t} \\ n_{2,j,f,t} \\ \vdots \\ n_{K,j,f,t} \\ n_{1,j,m,t} \\ n_{2,j,m,t} \\ \vdots \\ n_{K,j,m,t} \end{pmatrix} \tag{3}$$

The maximum age (years) of the simulated fish species considered within the model is denoted by A. Individual fish are classified into J age classes, where

$$J = \lfloor A \rfloor \tag{4}$$

$\lfloor A \rfloor$, the floor function of A, is the greatest integer age less than or equal to A, *i.e.* the greatest integer age explicitly considered in the model. The fish of integer age $a_j = j$ years are assigned to age class j. That is, the lower boundary of ages within age class j is a_j. The model considers only those fish within the population with integer ages greater than or equal to 1. Thus, recruitment is considered to represent the number of fish that recruit to age class 1, *i.e.* survive to an integer age of 1 year. Fish with integer ages greater than or equal to J are assigned to age class J (treated as a plus-group).

The model follows size cohorts of fish through time by classifying individuals into length classes according to their length at age. Individual length classes are identified using the subscript k $(1 \leq k \leq K)$, where K is the length class containing the largest fish considered by the model (*i.e.* this length class acts as a plus-group). The lower and upper bounds of length class k are denoted by L_k^{lower} and L_k^{upper}. Fish of lengths smaller than the lower bound of the first length class are assigned to length class 1. Although this specification allows for the use of length classes with different class intervals, the model that has been implemented for this study assumes that all length classes have a common length class interval, L_{int}. To ensure that the whole size range of lengths of individuals in the simulated fish species was covered, the number of length classes used in the model, which was implemented for this study, was set to:

$$K = 1.5 \max\left(L_{\infty,f}, L_{\infty,m}\right) / L_{\text{int}} \tag{5}$$

where $L_{\infty,s}$ is the asymptotic length of individuals of sex s. The lower and upper bounds of each length class, L_k^{lower} and L_k^{upper} , were determined as

$$L_k^{\text{lower}} = (k-1)L_{\text{int}} \tag{6}$$

$$L_k^{\text{upper}} = kL_{\text{int}} \tag{7}$$

L_k refers to fish of a length that is equal to the length of fish at the midpoint of length class k, and is determined as

$$L_k = (L_k^{\text{lower}} + L_k^{\text{upper}})/2 \tag{8}$$

Basic population dynamics

In broad terms, the population dynamics of the exploited fish stock is modelled as:

$$\boldsymbol{N}_{j,t} = \begin{cases} \boldsymbol{R}_t & \text{for } j = 1 \\ \boldsymbol{GXS}_{t-1}\boldsymbol{N}_{j-1,t-1} & \text{for } 1 < j < J \\ \boldsymbol{GXS}_{t-1}\boldsymbol{N}_{j-1,t-1} + \boldsymbol{GXS}_{t-1}\boldsymbol{N}_{j,t-1} & \text{for } j = J \end{cases} \tag{9}$$

where $\boldsymbol{R}_t$ is a vector containing the numbers of fish of age 1 of each sex within each length class, which recruit to the population in year t (see below), $\boldsymbol{S}_t$ is a diagonal matrix, the diagonal elements of which contain the probability that individuals of each length class and sex will survive till the end of year t, $\boldsymbol{X}$ is a matrix containing the probabilities that fish of each length class and sex will either change sex or remain of the same sex at the end of the time step, and $\boldsymbol{G}$ is a growth matrix containing the probabilities that fish will move to a new length class or remain within the same length class at the end of year t. That is, recruitment, survival, sex change and growth are considered as discrete events in the annual time step. Thus, the number of fish at the start of the time step is multiplied by the survival matrix to estimate the number of individuals surviving to the end of the year. The resulting vector is then multiplied by the sex change matrix to allow for sex change if the species is hermaphroditic. Finally, the vector is multiplied by the growth transition matrix to allow for the change in size composition that results from growth.

The number of fish within each length class and of each sex that recruit to age 1 in year t is $\boldsymbol{R}_t$, where

$$\boldsymbol{R}_t = \begin{pmatrix} R_{1,f,t} \\ R_{2,f,t} \\ \vdots \\ R_{K,f,t} \\ R_{1,m,t} \\ \vdots \\ R_{K,m,t} \end{pmatrix} \tag{10}$$

where $R_{k,s,t}$ is the number of recruits of sex s in length class k in year t. For each sex, the proportion of age 1 fish recruiting into length class k, $p_{k,s} = R_{k,s,t} / \sum_{k=1}^{K} R_{k,s,t}$, is calculated using the sex-specific von Bertalanffy growth curves, assuming a normal distribution of lengths around each age and normal distributions of the parameters around their point estimates and specified values of the respective standard deviations (see Equation 12).

The expected number of age 1 fish in length class k and sex s in year t is given by

$$n_{k,1,s,t} = p_{k,s}\phi_s R_t \tag{11}$$

where ϕ_s is the proportion of recruits that are of sex s and the scalar variable R_t is the total number of recruits (over all length classes and both sexes) in year t. The values for $p_{k,s}$ were estimated using the NORMP routine of Allen Miller (latest revision March 30, 1986), based upon algorithm 5666 from Hart *et al.* (1968), ”Computer approximations”.

Growth

The patterns of growth of fish of each sex, or if the species is hermaphroditic and the growth of the two sexes is not conspicuously different, of the sexes combined, are described using the von Bertalanffy growth equation. $L(a, s)$, the length (mm) at age a of a fish of sex s, is determined as

$$L(a, s) = L_{\infty,s}\left\{1 - \exp\left[-k_s\left(a - t_{0,s}\right)\right]\right\} \tag{12}$$

where $L_{\infty,s}$ is the asymptotic length (mm) of individuals of this species and sex, k_s is the growth coefficient determining the rate (year^{-1}) at which the lengths of individuals of this sex approach the asymptotic length, and $t_{0,s}$ is the theoretical age (years) at which the expected length would be zero.

Because the start of each model time step (*i.e.* biological year) corresponds to an assigned approximate birth date for the species, the lengths of fish determined for integer values of age, *e.g.* at a_j, the integer age of fish in the jth age class, using the above equation represent the lengths of fish of this integer age at the beginning of the time step. An estimate of length at age for a fish within the jth age class midway through the annual time step, $L(a_j + 0.5, s)$, subsequently referred to as the length at mid-age, is given by

$$L(a_j + 0.5, s) = L_{\infty,s} \left\{1 - \exp\left[-k_s \left(a_j + 0.5 - t_{0,s}\right)\right]\right\} \tag{13}$$

During each biological year, individuals in a length class will grow and may move to a larger length class, or, if growth is insufficient, will remain in their current length class. A transition matrix, $\boldsymbol{G} = \{g_{j,k,s}\}$ is used to represent the probability that a fish of length class k will move to length class j due to the growth that occurs within each annual time step. Transition between size classes is assumed to be a discrete event that occurs at the end of the biological year. The growth transition matrix may be written as:

$$\boldsymbol{G} = \begin{pmatrix} g_{1,1,f} & g_{1,2,f} & \cdots & g_{1,K,f} & 0 & 0 & \cdots & 0 \\ g_{2,1,f} & g_{2,2,f} & \cdots & g_{2,K,f} & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{K,1,f} & g_{K,2,f} & \cdots & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & g_{1,1,m} & g_{1,2,m} & \cdots & g_{1,K,m} \\ 0 & 0 & \cdots & 0 & g_{2,1,m} & g_{2,2,m} & \cdots & g_{2,K,m} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & g_{K,1,m} & g_{K,2,m} & \cdots & 1 \end{pmatrix} \tag{14}$$

where $g_{j,k,s}$ is the proportion of fish of length class k and sex s that grow to length class j during a time step. Note that the columns of $\boldsymbol{G}$ sum to one. The assumption that there is no negative growth requires that $g_{j,k,s} = 0$ for all values of $j < k$.

Growth of fish in each time step is accounted for in the model after the relative numbers of fish that survive mortality in the current year have been determined, and if the species is hermaphroditic, sex change has taken place. The number of fish in each age-, length- and sex class is calculated by multiplying the vector containing the current numbers of fish in the stock of that age class within each length class for each sex, *i.e.* $\boldsymbol{X}\boldsymbol{S}_{t-1}\boldsymbol{N}_{j,t}$ by the growth transition matrix $\boldsymbol{G}$ to produce a vector containing the numbers of individuals of each sex within each length class for the age class after surviving natural and fishing mortality, and undergoing sex change (if any) and growth. For fish in age classes $j < J$, the resulting vector represents the number of fish within the next age class at the start of the next year, *i.e.*

$$\boldsymbol{N}_{j,t} = \boldsymbol{G}\boldsymbol{X}\boldsymbol{S}_{t-1}\boldsymbol{N}_{j-1,t-1} \tag{15}$$

Weight at length and age

The weight W (g) of a fish of length L (mm) is calculated using the weight-length relationship:

$$W(L) = a_{\mathrm{WL}} L^{b_{\mathrm{WL}}} \tag{16}$$

where a_{WL} and b_{WL} are the parameters of this power-function. An estimate for the weight of fish of sex s in age class j at mid-age, $W(L(a_j + 0.5, s))$, is determined from their length at mid-age, $L(a_j + 0.5, s)$, as

$$W(L(a_j + 0.5, s)) = a_{\mathrm{WL}} L(a_j + 0.5, s)^{b_{\mathrm{WL}}} \tag{17}$$

Sex ratio

In gonochoristic species, the proportion of age 1 recruits that are of sex s (f = females, m = males), ϕ_s, is

$$\phi_f + \phi_m = 1 \tag{18}$$

Following recruitment, the proportion of fish within length class k that, for a gonochoristic species, are of a given sex is determined in the model by the growth of the individuals of each sex, and by the effects of fishing mortality and gear selectivity.

For hermaphroditic species, it as assumed that, in the absence of fishing mortality and gear selection, the probability that fish of length L are of the terminal sex s_{term}, $P_L^{s_{\text{term}}}$, is a generalised logistic function of the length. Thus,

$$P^{s_{\text{term}}}(L) = \phi_{s_{\text{term}}} + \frac{\phi_{s_{\text{term}}}^{\max} - \phi_{s_{\text{term}}}}{1 + \exp\left[-\log_e(19)\frac{L - L_{50}^{s_{\text{term}}}}{L_{95}^{s_{\text{term}}} - L_{50}^{s_{\text{term}}}}\right]} \tag{19}$$

where $\phi_{s_{\text{term}}}$ is the proportion of age 1 fish that are of the terminal sex, $\phi_{s_{\text{term}}}^{\max}$ is the maximum proportion of individuals in an unexploited stock that will ultimately be of the terminal sex, and $L_{50}^{s_{\text{term}}}$ and $L_{95}^{s_{\text{term}}}$ are the lengths at which 50% and 95% of fish are of the terminal sex. This slightly generalised form of the logistic curve allows for diandric hermaphroditism, *i.e.* where some (but not all) individuals of the terminal sex have changed sex before having first become mature as the initial sex, and also for the possibility that not all individuals will ultimately change sex.

The probability that a fish in length class k is of the terminal sex, $P_k^{s_{\text{term}}}$, is calculated as

$$P^{s_{\text{term}}}(L_k) = \phi_{s_{\text{term}}} + \frac{\phi_{s_{\text{term}}}^{\max} - \phi_{s_{\text{term}}}}{1 + \exp\left[-\log_e(19)\frac{L_k - L_{50}^{s_{\text{term}}}}{L_{95}^{s_{\text{term}}} - L_{50}^{s_{\text{term}}}}\right]} \tag{20}$$

Sex change in hermaphroditic species

The probability that fish in length class k undergo sex change at the annual time step, X_k, may be calculated from the change in length that is expected to occur. From the von Bertalanffy growth curve, fish of length L_k and sex s would be expected to grow to $L_k + (L_{\infty,s} - L_k)(1 - \exp[-k_s])$. Thus,

$$X_k = \frac{\left(P^{s_{\text{term}}}\left(L_k + (L_{\infty,s} - L_k)(1 - \exp[-k_s])\right) - P^{s_{\text{term}}}(L_k)\right)}{\left(1 - P^{s_{\text{term}}}(L_k)\right)} \tag{21}$$

The resulting probability X_k thus represents the fraction of individuals of hermaphroditic species within length class k that will change from the initial to the terminal sex over the annual time step. This may be written as $X_{k,f\to m}$ for a protogynous species, and as $X_{k,m\to f}$ for a protandrous species. For a gonochoristic or protogynous species, $X_{k,m\to f} = 0$, while for a gonochoristic or protandrous species, $X_{k,m\to f} = 0$. Thus, the sex transition matrix, $\boldsymbol{X}$, may be written as

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{X}_{f\to f} & \boldsymbol{X}_{m\to f} \\ \boldsymbol{X}_{f\to m} & \boldsymbol{X}_{m\to m} \end{pmatrix} \tag{22}$$

where the sub-matrices $\boldsymbol{X}_{f\to f}$, $\boldsymbol{X}_{m\to f}$, $\boldsymbol{X}_{f\to m}$ and $\boldsymbol{X}_{m\to m}$ represent the proportions of females remaining as females, males changing to females, females changing to males and males remaining as males, respectively. These sub-matrices may be written as

$$\boldsymbol{X}_{f\to f} = \begin{pmatrix} 1 - X_{1,f\to m} & 0 & \cdots & 0 \\ 0 & 1 - X_{2,f\to m} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 - X_{K,f\to m} \end{pmatrix} \tag{23}$$

$$\boldsymbol{X}_{m\rightarrow f} = \begin{pmatrix} X_{1,m\rightarrow f} & 0 & \cdots & 0 \\ 0 & X_{2,m\rightarrow f} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_{K,m\rightarrow f} \end{pmatrix} \tag{24}$$

$$\boldsymbol{X}_{f\rightarrow m} = \begin{pmatrix} X_{1,f\rightarrow m} & 0 & \cdots & 0 \\ 0 & X_{2,f\rightarrow m} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_{K,f\rightarrow m} \end{pmatrix} \tag{25}$$

$$\boldsymbol{X}_{m\rightarrow m} = \begin{pmatrix} 1-X_{1,m\rightarrow f} & 0 & \cdots & 0 \\ 0 & 1-X_{2,m\rightarrow f} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1-X_{K,m\rightarrow f} \end{pmatrix} \tag{26}$$

where $X_{k,f\rightarrow m}$ is the proportion of fish of length class k that change sex from female to male at the end of the time step if the species is protogynous (zero otherwise) and $X_{k,m\rightarrow f}$ is the proportion of fish of length class k that change sex from male to female if the species is protandrous (zero otherwise).

Maturity

The proportion of fish in length class k that are mature is determined for each sex of gonochoristic species, and for the initial sex of hermaphroditic species, as

$$V_k = \left\{ 1 + \exp\left[-\log_e(19) \frac{L_k - L_{50,s}^{\text{mat}}}{L_{95,s}^{\text{mat}} - L_{50,s}^{\text{mat}}} \right] \right\}^{-1} \tag{27}$$

where $L_{50,s}^{\text{mat}}$ and $L_{95,s}^{\text{mat}}$ are the lengths at which 50% and 95% of individuals of that sex are mature, and L_k, which is the length of fish at the midpoint of the length class, is assumed to represent the average length of fish in this length class. Note that, for hermaphroditic species, it is assumed that all fish of the terminal sex are mature.

Fecundity

Two alternative approaches are used in the operating model to describe the relationship between fish length and fecundity. The first method estimates fecundity (batch or annual fecundity, depending on the input parameters) from a linear relationship between the natural logarithms of length and fecundity, whilst the other employs a cubic polynomial function, as used by Wise *et al.* (2007) for the fecundity of the West Australian dhufish *Glaucosoma hebraicum*. Thus, the fecundity of females in length class k is denoted by $\mathrm{BF}_{k,f}$, and is determined from the length at the midpoint of the length class, L_k, as

$$\mathrm{BF}_{k,f} = \exp\left[a_{\text{fec}} \log_e \left(L_k\right) - b_{\text{fec}}\right] \tag{28}$$

or, in the case of *G. hebraicum* (Wise *et al.*, 2007)

$$\mathrm{BF}_{k,f} = \left(b_{\text{fec}} L_{a_j+0.5,f} - a_{\text{fec}}\right)^3 \tag{29}$$

where a_{fec} and b_{fec} are the parameters of these fecundity functions and which are specific for the fish species simulated. For immature fish where length $L_k \leq L^{\text{mat}}_{50,f}$, it is assumed that $\mathrm{BF}_{a_j+0.5,f}$ equals zero.

Spawning biomass

The contribution to the mature biomass (kg) of a fish of sex s in length class k and sex s at the beginning of each biological year (*i.e.* at the time of spawning), $S_{k,s}$, is $\psi^{\text{mat}}_{k,s} W\left(L_k\right)$, where $\psi^{\text{mat}}_{k,s}$ is the proportion of fish of that length class and sex that are mature and $W(L_k)$ denotes the individual body mass of those fish. The total spawning biomass of each sex in the stock at each time step, $S_{s,t}$, is calculated as

$$B^{\text{sp}}_{s,t} = \sum_{j=1}^{J} \sum_{k=1}^{K} \psi^{\text{mat}}_{k,s} n_{k,j,s,t} W\left(L_k\right) \tag{30}$$

where $n_{k,j,s,t}$ is the number of fish of age class j, length class k and sex s in the stock.

Stock-recruitment

$\hat{R}_t$, the expected recruitment of age 1 fish (thousands of fish) in year t is assumed to follow the Beverton and Holt (1957) stock-recruitment relationship, and is calculated from the female spawning biomass in the preceding spawning season, $S_{f,t-1}$, as

$$\hat{R}_t = \frac{B^{\text{sp}}_{f,t-1}}{a_{\text{SRR}} + b_{\text{SRR}} B^{\text{sp}}_{f,t-1}} \tag{31}$$

where a_{SRR} and b_{SRR} are parameters of this function. Equilibrium recruitment in the absence of fishing, R^0, referred to as virgin recruitment, is calculated as

$$R^0 = (\text{SBR}^0_f - a_{\text{SRR}})/(\text{SBR}^0_f b_{\text{SRR}}) \tag{32}$$

where SBR^0_f is the spawning biomass per recruit for females in an unexploited stock at equilibrium (Mace, 1994). The virgin spawning biomass (kg) of this unexploited stock at equilibrium, $S^{\text{sp},0}$, is calculated as

$$S^{\text{sp},0} = \text{SBR}^0_f R^0 \tag{33}$$

A re-parameterised form of the Beverton and Holt stock-recruitment relationship has been used in this study. This employs a steepness parameter, z, which is defined as the proportion of the virgin recruitment that is produced when the spawning biomass has been reduced to 20% of the virgin spawning biomass (Francis, 1992). Using the steepness parameter, the stock-recruitment parameters a_{SRR} and b_{SRR} can be calculated as functions of z, R_0 and S_0, where

$$a_{\text{SRR}} = S^{\text{sp},0}(1-z)/(4zR_0) \tag{34}$$

$$b_{\text{SRR}} = (5z-1)/(4zR_0) \tag{35}$$

Recruitment variability

The operating model introduces inter-annual variability in recruitment of age 1 fish to the simulated fish stock by drawing for each year a random variate, ϵ_t, from a selected statistical distribution and calculating the annual recruitment, R_t, as

$$R_t = \hat{R}_t \exp\left[\epsilon_t - \frac{\sigma_R^2}{2}\right] \tag{36}$$

ϵ_t is the natural logarithm of the annual deviation in recruitment from its expected value, $\hat{R}_t$, which is calculated from the preceding year's spawning biomass using the Beverton and Holt stock-recruitment relationship, and σ_R^2 is the standard deviation of the normal distribution of the log-transformed values of recruitment. The term $-(\sigma_R^2)/2$ provides an adjustment to the value of the annual recruitment deviation that corrects for the bias in the mean value for recruitment, which arises as a result of the logarithmic transformation.

Prior to undertaken simulations, the distribution of ϵ_t may be selected from one of three specified statistical distributions. The alternative distributions assume that

1. recruitment deviations are log-normally distributed

$$\epsilon_t \sim N(0, \sigma_R^2) \tag{37}$$

2. recruitment deviations are log-normally distributed and auto-correlated between successive years.

$$\epsilon_t = \rho\eta_{t-1} + \left(1 - \rho^2\right)^{0.5} \eta_t \text{ where } \eta_t \sim N(0, \sigma_R^2) \tag{38}$$

3. recruitment is episodic and auto-correlated. e_t is thus determined as

$$\epsilon_t = \exp\left[\rho\eta_{t-1} + \left(1 - \rho^2\right)^{0.5} \eta_t - 1\right] \text{ where } \eta_t \sim N(0, \sigma_R^2) \tag{39}$$

Selectivity

The selectivity of the fish in length class k, *i.e.* the vulnerability of individuals of the length of fish at the midpoint of the length class to being caught by the fishing gear, is denoted by V_k. This selectivity is calculated as

$$V_k = \left\{1 + \exp\left[-\log_e(19)\frac{L_k - L_{50}^{\text{Vuln}}}{L_{95}^{\text{Vuln}} - L_{50}^{\text{Vuln}}}\right]\right\}^{-1} \tag{40}$$

where L_{50}^{Vuln} and L_{95}^{Vuln} are the lengths at which fish have vulnerabilities of 50% and 95% of fish that are fully vulnerable to the fishery.

Mortality

The survival matrix that results from the combined effects of natural and fishing mortality may be written as

$$\boldsymbol{S}_t = \begin{pmatrix} s_{1,f,t} & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & s_{2,f,t} & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & s_{K,f,t} & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & s_{1,m,t} & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & \cdots & s_{K,m,t} \end{pmatrix} \tag{41}$$

where $s_{k,s,t}$ is the proportion of fish of length class k and sex s that survive both natural and fishing mortality, *i.e.* M and $F_{k,s,t}$, respectively, over the annual time step t. Note that the proportion surviving over the annual time step may be calculated as the product of the proportions surviving over each of the number of shorter time periods into which the year may be divided, thereby allowing the calculation of the effects of bag and boat limits with greater accuracy.

In the absence of fishing mortality, the total mortality of fish of sex s in length class k in year t is equal to the instantaneous rate of natural mortality. Thus, in this case, the proportion of fish that survive from the start to the end of the annual time step is calculated as

$$s_{k,s,t} = \exp\left(-M\right) \tag{42}$$

Natural mortality is estimated from the maximum age, A, of the fish species using Hoenig's (1983) mortality equation for fish, *i.e.*

$$M = \exp\left\{1.46 - 1.01 \log_e A\right\} \tag{43}$$

If the fish in the stock are subjected to fishing, and it is assumed that $F_{k,s,t}$ is the effective instantaneous rate of mortality of fish of sex s in length class k due to fishing in year t after allowing for all input and output controls, the instantaneous rate of total mortality (year^{-1}) for fish of that sex and length class in that year, $Z_{k,s,t}$, is assumed to equal the sum of the instantaneous rates of natural mortality (year^{-1}), M, and the length-, and sex-specific fishing mortality, $F_{k,s,t}$. That is,

$$Z_{k,s,t} = M + F_{k,s,t} \tag{44}$$

The fraction of fish that survive from the beginning to the end of the annual time step then becomes

$$s_{k,s,t} = \exp\left(-Z_{k,s,t}\right) \tag{45}$$

The value of the "initial equilibrium fishing mortality", F_{init}, which is specified prior to the start of the simulation runs, represents the instantaneous rate of capture of fish in the absence of input or output controls. This, in combination with the input and output controls on fishing mortality, determines the initial state of the stock, *i.e.* the state when the stock is at an exploited equilibrium. After initialising the system state to values that represent this equilibrium state, the initial management strategy that is to be imposed must be specified or determined, and the instantaneous rate of capture and input and output management controls associated with this strategy must be applied by the operating model of the MSE over the requisite/specified projection period. After application of the input controls, the resulting instantaneous rate of capture will determine the probability that fish of different lengths and sexes are caught within year t, while the various output controls associated with the management strategy will determine whether the caught fish are landed or released. The level of discard mortality will determine whether released fish die as a result of capture and release, or survive. Note that the extent to which fishers comply with the input and output controls is a factor that also needs to be taken into account.

If $F_{k,s,t}$ is now considered to represent the instantaneous rate of capture after adjusting for the effects of all input controls, where this rate is dependent on length class k, sex s and time step t, an approximation to the proportion of fish that survive from the start to the end of the time step may be calculated as

$$s_{k,s,t} = \exp\left[-\left(Z_{k,s,t}\right)\right] + \frac{F_{k,s,t}}{Z_{k,s,t}}\left[1 - \exp\left(-Z_{k,s,t}\right)\right] p_{k,s,t}^{\text{rel}}\left(1 - P^{\text{rmort}}\right) \tag{46}$$

where $Z_{k,s,t} = M + F_{k,t,s}$ represents the total mortality if all captured fish were to be retained by fishers, $p_{k,s,t}^{\text{rel}}$ is the fraction of the fish that, as a consequence of output controls, are released after capture rather than landed, and D is the proportion of fish that die after release.

The fraction of fish that die as a result of fishing, either through capture and landing or through death following release as a consequence of barotrauma or hook-related injury is

$$\frac{F_{k,s,t}}{Z_{k,s,t}}\left[1 - \exp\left(-Z_{k,s,t}\right)\right]\left(1 - p_{k,s,t}^{\text{rel}} + p_{k,s,t}^{\text{rel}} P^{\text{rmort}}\right) \tag{47}$$

while the fraction of fish that are caught and landed is

$$\frac{F_{k,s,t}}{Z_{k,s,t}}\left[1 - \exp\left(-Z_{k,s,t}\right)\right]\left(1 - p_{k,s,t}^{\text{rel}}\right) \tag{48}$$

The above equations represent only an approximation to the true proportion surviving, however, as the release of fish may be considered to be a continuous process, which reduces the instantaneous rate at which the abundance of fish in the population declines. In the case of a minimum legal length control, the proportion of fish that are released depends on size, while in the case of a bag or boat limit, the proportion released is density-dependent.

The fishing mortality to be applied throughout the projection period, taking into account the various input controls, is determined by the exploitation component of the operating model. To calculate this fishing mortality, the routine adjusts the current level of fishing mortality, which, following the initialisation step, is F_{init}, by the extent to which fishing effort is modified, and by estimating the extent to which fishing mortality is influenced by the various input controls applied by the user to regulate fishing mortality. The effect of the various input and output controls is discussed in greater detail below.

Exploitation

The exploitation component of the operating model simulates the combined effects of various input and output management controls on the fishery, and thus on the resource. The fishing intensity exerted by the recreational fishers may be calculated as $E/(AT)$, where E is the fishing effort, A is the area over which the effort is applied, and T is the period over which the effort is applied (Gulland, 1969). It is assumed in this study that effort is measured as the number of fishing trips by boats with a single recreational fisher on board. That is, the units of effort are ”fishing trips by boats with one fisher”, referred to subsequently in this document as ”fishing trips”. When calculating fishing effort, fishing trips by boats with more than one fisher on board must be converted to the equivalent number of fishing trips by boats with a single fisher.

The instantaneous rate of capture of fish, which are of sizes that are fully-vulnerable to the fishing gear, is denoted by F, and is proportional to fishing intensity. Thus,

$$F = \frac{qE}{AT} \tag{49}$$

where the constant q is referred to as the catchability coefficient. A is the area occupied by the fish stock and, for convenience, is typically assigned the value 1, in which case fishing intensity may be considered to be the average fishing effort per unit of time, where time is measured in years. In the absence of temporal closures, the period over which the recreational fishery operates is usually the full year, and thus T may also be considered to have the value 1. E is then the number of fishing trips undertaken by recreational fishers over the full year, standardised to the units in which fishing effort is measured, *i.e.* fishing trips by boats with a single fisher. In many other fishery models, F is considered to be the instantaneous rate of fishing mortality. However, as the model in this study considers the effect of output controls, which allow the release and possible survival of some of the fish that are caught, it is more appropriate in this study to refer to F as the instantaneous rate of capture of fish that are fully-vulnerable to the fishing gear.

Standardising the measure of fishing effort

The unit of fishing effort used in this study is a fishing trip by a boat with a single fisher on board. As noted above, fishing trips by boats with more than one fisher on board must be converted into the equivalent number of fishing trips by boats with a single fisher. The latter value is the number of fishing trips by a boat with a single fisher that would retain the same number of fish as would be retained by the boats with more than one fisher on board.

Effects of input management controls

Three alternative input management controls for regulating the fishing mortality being experienced by the simulated stock are considered by the model: a proportional effort reduction control, a temporal closure control, and a spatial closure control.

Proportional effort reduction

The level of fishing mortality impacting the stock after a proportional reduction in fishing effort (control 1) has been applied, and which is applied during the projection period, F_t^{applied}, is calculated as

$$F_t^{\text{applied}} = F_t^{\text{current}} \left(1 - \psi_{E_{\text{reduced}}}\right) \tag{50}$$

where F_t^{current} is the instantaneous rate of capture prior to application of the input controls associated with the management strategy that is to be applied to the fish stock, and $\psi_{E_{\text{reduced}}}$ is the proportion by which fishing effort is required to be reduced (possibly zero). At the start of the simulation, F_t^{current} is set to the value of F_{init}, *i.e.* the user-specified equilibrium value for fishing mortality for the stock in its initial state. The new level of fishing mortality, F_t^{applied}, will be used as F_t^{current} when determining the fishing mortality to be applied following the next assessment. The instantaneous rate of capture applied by fishers, F_t^{applied}, will be moderated by any temporal or spatial closures imposed by the management strategy. We discuss below the effect of imposition of a temporal closure, followed by the imposition of a spatial closure.

Temporal closure

The instantaneous rate of capture of fish in the stock, taking account of any temporal closure, F_t^{TC}, is determined as

$$F_t^{\text{TC}} = F_t^{\text{applied}} \left[1 - \psi_{t_{\text{closed}}} \text{TC}^{\text{effect}}\right] \tag{51}$$

where $\psi_{t_{\text{closed}}}$ is the proportion of the year that the fishery is closed to fishing (possibly zero) and $\text{TC}^{\text{effect}}$ is the effectiveness of the temporal closure. If the closure is 100%

effective, the above equation reflects the application of the instantaneous rate of capture over a period that is less than or equal to the full year. $\mathrm{TC}^{\mathrm{effect}}$, which is assumed to be related to the duration of the temporal closure, is described as

$$\mathrm{TC}^{\mathrm{effect}} = \left\{ 1 + \exp\left[-\log_e(19) \frac{\psi_{t_{\mathrm{closed}}} - D_{50}^{\mathrm{effect}}}{D_{95}^{\mathrm{effect}} - D_{50}^{\mathrm{effect}}} \right] \right\}^{-1} \tag{52}$$

where D_{50}^{effect} and D_{95}^{effect} are the durations for which a temporal closure is 50% and 95% effective. The latter term is introduced to compensate for fishers' behaviour, as this typically results in additional effort being applied both before and after the closed season. The extent to which fishers can compensate for the loss of time is reduced as the period of closure is increased.

Spatial closure

It is assumed that, if a spatial closure is implemented, fishing effort will be displaced from the area closed to fishing to the area that remains open. It is also assumed that there is no movement of fish between the open and closed areas. Thus, while it is currently assumed in the model that there is no interchange of fish between closed and open areas, and therefore that the fish within the area closed to fishing are exposed only to natural mortality, those fish in the open area will experience an increase in instantaneous rate of capture. The value of the instantaneous rate of capture after further accounting for any spatial closure, F_t^{AC}, is therefore given by

$$F_t^{\mathrm{AC}} = \frac{F_t^{\mathrm{TC}}}{1 - \psi_{A_{\mathrm{closed}}}} \tag{53}$$

where $\psi_{A_{\mathrm{closed}}}$ is the proportion of the fished area that is closed to fishing. It is thus this level of fishing mortality that will determine the fraction of fish that are caught within the area open to fishing, during the period open to fishing, as a result of the fishing mortality applied by fishers. Note again that, in the absence of output controls, F_t^{AC}, which by convention is termed the ”fishing mortality”, represents both the instantaneous rates of capture and fishing mortality, but when output controls are introduced, only determines the instantaneous rate of capture.

The fraction of the fish in the area closed to fishing that experience only natural mortality, is $\psi_{A_{\text{closed}}}$, while the fraction that experience the increased mortality associated with fishing is $1-\psi_{A_{\text{closed}}}$. In the absence of output controls, the proportion of the fully-vulnerable fish, which are alive at the start of the annual time step and which survive to the end of that time step, is

$$\psi_{A_{\text{closed}}} \exp\left[-M\right] + (1-\psi_{A_{\text{closed}}}) \exp\left[-\left(M + F_t^{\mathrm{AC}}\right)\right] \tag{54}$$

Thus, in the absence of output controls, the overall fishing mortality experienced by the fish stock is

$$F_t = -\log_e\left[\psi_{A_{\text{closed}}} + (1-\psi_{A_{\text{closed}}}) \exp\left(-F_t^{\mathrm{AC}}\right)\right] \tag{55}$$

The probability that a fish, which is fully vulnerable to the fishing gear, is caught is the product of the fraction of the population that is exposed to capture and the fraction of the population in the area open to fishing that is expected to be caught, *i.e.*

$$P^{\text{cap}} = (1-\psi_{A_{\text{closed}}}) \left\{ \frac{F_t^{\mathrm{AC}}}{M + F_t^{\mathrm{AC}}} \left[1 - \exp\left[-\left(M + F_t^{\mathrm{AC}}\right)\right]\right] \right\} \tag{56}$$

For fish that are not fully vulnerable to the fishing gear, the instantaneous probability of capture is reduced from F_t^{AC} by the relative vulnerability of those fish. Thus, if F_t^{AC} is the instantaneous probability of capture of fully vulnerable fish in year t, fish in length class k will experience a probability of capture in that year of

$$F_{k,t}^{\text{AC}} = V_k F_t^{\text{AC}} \tag{57}$$

Thus, the probability of capture of a fish in length class k in year t is

$$P_{k,t}^{\text{cap}} = (1 - \psi_{A_{\text{closed}}}) \left\{ \frac{F_{k,t}^{\text{AC}}}{M + F_{k,t}^{\text{AC}}} \left[1 - \exp\left[-\left(M + F_{k,t}^{\text{AC}}\right)\right]\right] \right\} \tag{58}$$

The probability of capture of a fish in length class k in a time step of duration τ in year t is

$$P_{k,t}^{\text{cap}_\tau} = (1 - \psi_{A_{\text{closed}}}) \left\{ \frac{F_{k,t}^{\text{AC}}}{M + F_{k,t}^{\text{AC}}} \left[1 - \exp\left[-\left(M + F_{k,t}^{\text{AC}}\right)\tau\right]\right] \right\} \tag{59}$$

Effects of output management controls

The output management controls considered by the model ,*i.e.* those that were implemented to regulate the catches retained by fishers, include a minimum legal length for retention by fishers, daily bag and boat limits, and a catch quota. The model also accounts for the effect of post-release mortality of fish of different sizes and ages, resulting from these controls.

Minimum legal length (MLL)

Assuming that the lengths of fish within each length class are uniformly distributed, the probability that a fish in length class k is of a size greater than the MLL specified for that fish species, $P_k^{L \geq \text{MLL}}$, is

$$P_k^{L \geq \text{MLL}} = \begin{cases} 0 & \text{for } L_k^{\text{upper}} < \text{MLL} \\ 1 & \text{for } L_k^{\text{lower}} \geq \text{MLL} \\ \frac{L_k^{\text{upper}} - \text{MLL}}{L_k^{\text{upper}} - L_k^{\text{lower}}} & \text{otherwise} \end{cases} \tag{60}$$

where L_k^{lower} and L_k^{upper} are the lower and upper bounds of length class k. The probability that a fish in length class k is captured in year t and has a length $\geq$ MLL , $P_{k,t}^{L \geq \text{MLL,cap}}$, is

$$P_{k,t}^{L \geq \text{MLL,cap}} = P_{k,t}^{\text{cap}} P_k^{L \geq \text{MLL}} \tag{61}$$

while the probability that a fish in length class k is captured in year t and has a length $<$ MLL, $P_{k,t}^{L < \text{MLL,cap}}$, is

$$P_{k,t}^{L < \text{MLL,cap}} = P_{k,t}^{\text{cap}} (1 - P_k^{L \geq \text{MLL}}) \tag{62}$$

The total expected catch of legal-sized fish over all age and size classes and both sexes, in the absence of bag limits and/or catch quota, C_t, is therefore

$$C_t = \sum_{s=f}^{m} \sum_{j=1}^{J} \sum_{k=1}^{K} P_{k,t}^{L \geq \text{MLL,cap}} n_{k,j,s,t} \tag{63}$$

The probability that a fish in length class k is caught, has a length that is $<$ MLL and dies, $P_{k,t}^{L < \text{MLL,dies}}$, is calculated as

$$P_{k,t}^{L < \text{MLL,dies}} = P_{k,t}^{L < \text{MLL,cap}} D \tag{64}$$

D is the probability that an undersized fish is illegally retained or is released and dies from injuries associated with being caught and released, and is determined as

$$D = (\psi^{\text{comply}} P^{\text{rmort}}) + (1 - \psi^{\text{comply}}) \tag{65}$$

where ψ^{comply} is the proportion of fishers complying with the fishing regulations and P^{rmort} is the probability that fish will die if caught and then released.

The probability that a fish in length class k has a length that is $<$ MLL and survives after capture and release, $P_{k,t}^{L<\text{MLL,surv}}$, is

$$P_{k,t}^{L<\text{MLL,surv}} = P_{k,t}^{L<\text{MLL,cap}} \left(1 - D\right) \tag{66}$$

The probability that a fish in length class k has a length that is $\geq$ MLL and is retained following capture because the fisher has not exceeded the bag and/or boat limit for that species, $P_{k,t}^{L\geq\text{MLL}\text{ret}}$, is described by

$$P_{k,t}^{L\geq\text{MLL,ret}} = P_{k,t}^{L\geq\text{MLL,cap}}(1 - P_{\text{BL}}^{\text{rel}}) \tag{67}$$

where $P_{\text{BL}}^{\text{rel}}$ is the probability that a fish is released because of the bag and boat limit restrictions, an input parameter specified prior to model simulations.

Initially in this study, the effect of minimum legal length was modelled by calculating the catch of undersized fish over a period of fishing $\leq$ one year. However, it was recognised that release of fish modifies the instantaneous rate of mortality of released fish. Accordingly, the approach was later changed to one which modified the instantaneous rate of capture and thus the rate at which the number of fish in the stock declined. Thus, after allowing for the effect of the minimum legal length,

$$F_{k,t}^{\text{MLL}} = F_{k,t}^{\text{AC}} \left\{ P_{k}^{L\geq\text{MLL}} + P_{k}^{L<\text{MLL}} D \right\} \tag{68}$$

where the proportion of fish of legal size that are caught and retained in the annual time step is

$$(1-\psi_{A_{\text{closed}}})\left\{\frac{F_{k,t}^{\text{AC}}P_k^{L\geq\text{MLL}}}{M+F_{k,t}^{\text{MLL}}}\left[1-\exp\left[-\left(M+F_{k,t}^{\text{MLL}}\right)\right]\right]\right\} \tag{69}$$

and the proportion that survive to the end of the annual time step is

$$\psi_{A_{\text{closed}}}\exp\left[-M\right]+(1-\psi_{A_{\text{closed}}})\exp\left[-\left(M+F_{k,t}^{\text{MLL}}\right)\right] \tag{70}$$

For a shorter time step of duration τ, the proportion of fish of legal size that are caught and retained in the time step is

$$(1-\psi_{A_{\text{closed}}})\left\{\frac{F_{k,t}^{\text{AC}}P_k^{L\geq\text{MLL}}}{M+F_{k,t}^{\text{MLL}}}\left[1-\exp\left[-\left(M+F_{k,t}^{\text{MLL}}\right)\tau\right]\right]\right\} \tag{71}$$

and the proportion that survive to the end of the time step is

$$\psi_{A_{\text{closed}}}\exp\left[-M\tau\right]+(1-\psi_{A_{\text{closed}}})\exp\left[-\left(M+F_{k,t}^{\text{MLL}}\right)\tau\right] \tag{72}$$

Bag and boat limits

This section describes the calculations in the model that estimate the proportional reduction in catch resulting from application of the output management controls, after having accounted for the input controls. The broad steps that are undertaken are as follow:

1. Determine whether, when both bag and boat limits are applied, the bag or the boat limit constrains retained catches for trips by boats with different numbers of fishers.

2. Calculate the expected numbers of fish caught (*i.e.* fish retained and released) when no bag and/or boat limit is applied.

3. Calculate the fishing effort, *i.e.* the number of boat trips, based on an estimate of catchability derived from the data supplied to the MSE prior to commencing the simulations.
4. Calculate the mean CPUE for fishers when retained catches are, and are not, constrained by bag and/or boat limits.
5. Calculate the mean CPUE for retained and released fish for boats with different numbers of fishers.
6. Calculate the relative frequency distributions for total catches (*i.e.* unconstrained) and retained catches (*i.e.* constrained) for boats with different numbers of fishers.
7. Calculate the expected numbers of fish caught and retained by fishers when a bag and/or boat limit is applied.
8. Calculate the mean total and retained catch per boat with a given number of fishers.
9. Calculate the proportion of catch retained and released for boats with a given number of fishers.
10. Calculate the overall proportion of catch retained and released.
11. Estimate the expected catch (*i.e.* as the number of fish caught and retained).
12. Determine the proportion of the fish of each sex s, age class j, and length class k that survive capture and either retention or release and post-release mortality associated with their capture.

The effect of bag and boat limits is dependent on the number of fish that are caught within each fishing trip. The output control has an effect only if this catch exceeds the bag or boat limit. The boat limit, however, is typically determined by the number of fishers on board the boat during the fishing trip. The combined bag limit for the x fishers in the fishing party is $\mathrm{BagL}_x^{\mathrm{comb}}$, which may be calculated as

$$\mathrm{BagL}_x^{\mathrm{comb}} = x\mathrm{BagL} \tag{73}$$

where BagL is the individual bag limit for a fisher. If x is such that the combined bag limit for those fishers, $\mathrm{BagL}_x^{\mathrm{comb}}$, does not exceed the boat limit, BoatL, the total catch for the trip by the fishers in the boat is constrained by the combined bag limit, otherwise the total catch is constrained by the boat limit. The control that acts to constrain catches, BL_x, is thus determined as

$$\mathrm{BL}_x = \begin{cases} \mathrm{BoatL} & \text{for } \mathrm{BoatL} < \mathrm{BagL}^{\mathrm{comb}} \\ \mathrm{BagL}_x^{\mathrm{comb}} & \text{for } \mathrm{BoatL} \geq \mathrm{BagL}_x^{\mathrm{comb}} \end{cases} \tag{74}$$

The equations that are presented below assume that, in the absence of bag and boat limits, the catch for a fishing trip by a boat with a single fisher is known and constant. However, as it is assumed that recruitment to the stock occurs only at the beginning of each annual time step, the instantaneous rate of capture is constant during the time step, and growth occurs at the end of the time step, the abundance of legal-sized fish in the stock will decline through the time step. Moreover, when bag and boat limits are introduced, some released fish will survive, and thus the decline in abundance will not be as great as that which would occur if there was no bag or boat limit.

When calculating the effects of the bag and boat limits in the model, however, it is assumed that the value of catch per unit of standard effort that would be obtained in the absence of the bag and boat limits, U_t, is the average value obtained by calculating the ratio of the theoretical catch that would be obtained in the absence of bag and boat limits and the estimate of standard fishing effort, F/q. In calculating the estimate of the theoretical catch (of retained and released fish) in the absence of a bag/boat limit, it is necessary to take the effects of the various input controls, of selectivity of the fishing gear and of the MLL regulation into account, and the resulting catch is the total over sex s, length class k and age class j.

In the initial formulation of this model, the average catch per standard boat trip over the full year was calculated using a single time step, and thus fails to take the change in catch rate within the year into account when estimating the effects of bag and boat limits. By dividing the year into n_τ smaller time steps of duration τ, a more accurate assessment of the effect of the bag and boat limit may be obtained. To facilitate the presentation of the methods that are used for this calculation, the number of fish of each sex s, within age class j and length class k, at the start of time step i (for $0 \leq i \leq I$) within year t, is denoted by $n_{k,j,s,t,i}$.

The equation used to calculate the probability of capture of a fish in length class k in year t, $P_{k,t}^{\text{cap}}$, may be modified to represent the probability of capture of these fish in a time step of duration τ. Thus, this probability, $P_{k,t}^{\text{cap}_\tau}$, may be written as

$$P_{k,t}^{\text{cap}_\tau} = \left(1 - \psi_{A_{\text{closed}}}\right) \left\{ \frac{F_{k,t}^{\text{AC}}}{M + F_{k,t}^{\text{AC}}} \left[1 - \exp\left[-\left(M + F_{k,t}^{\text{AC}}\right)\tau\right]\right] \right\} \tag{75}$$

The probability that a fish in length class k is caught within time step i of year t and has a length ≥ MLL, $P_{k,t}^{L \geq \text{MLL},\text{cap}_\tau}$, is therefore

$$P_{k,t}^{L \geq \text{MLL},\text{cap}_\tau} = P_{k,t}^{\text{cap}_\tau} P_{k}^{L \geq \text{MLL}} \tag{76}$$

The probability that a fish in length class k is caught within time step i of year t and has a length < MLL, $P_{k,t}^{L<\mathrm{MLL},\mathrm{cap}_\tau}$, is therefore

$$P_{k,t}^{L<\mathrm{MLL},\mathrm{cap}_\tau} = P_{k,t}^{\mathrm{cap}_\tau}\left(1 - P_{k}^{L\geq\mathrm{MLL}}\right) \tag{77}$$

The probability that a fish in length class k has a length that is < MLL and survives after capture and release within time step i, $P_{k,t}^{L<\mathrm{MLL},\mathrm{surv}_\tau}$, is

$$P_{k,t}^{L<\mathrm{MLL},\mathrm{surv}_\tau} = P_{k,t}^{L<\mathrm{MLL},\mathrm{cap}_\tau}\left(1 - D\right) \tag{78}$$

The number of fish of sex s, age class j, and length class k that are caught in time step i in year t is therefore

$$P_{k,t}^{L\geq\mathrm{MLL},\mathrm{cap}_\tau} n_{k,j,s,t,i} \tag{79}$$

and thus, during time step i, the expected catch per standard boat trip in the absence of bag or boat limits is

$$U_t = \frac{\sum_{s=f}^{m}\sum_{j=1}^{J}\sum_{k=1}^{K} P_{k,t}^{L\geq\mathrm{MLL},\mathrm{cap}_\tau} n_{k,j,s,t,i}}{\left(F\tau\right)/q} \tag{80}$$

The catch that is made by a boat during a fishing trip depends on the number of fishers on board the boat. Simplistically, the catch per boat trip might be expected to be proportional to the number of fishers, x. The number of fish in the immediate area under the boat is limited, however, and it is therefore likely that the catches made by individual fishers during the fishing trip will decline as x increases. That is, the relative efficiency of each fisher within a fishing party of x fishers is likely to decrease as the number of fishers increases. Thus, if U_t is the mean catch per unit of standard effort of legal-sized fish (before discard due to bag or boat limit, or catch quota) for an individual unit of fishing effort, *i.e.* a boat trip with a single recreational fisher on board, the total catch of legal-sized fish that is expected (before discard due to a bag or boat limit, or catch quota) for a boat trip when x fishers are on board, $U_{x,t}$, is assumed to be

$$U_{x,t} = xU_t \text{re}^{(x-1)} \tag{81}$$

where $\text{re}^{(x-1)}$ is the assumed relative efficiency of each individual in the fishing party when there are x recreational fishers in the fishing party. The value of an estimate of re is supplied as input to the MSE prior to the start of the simulation runs. Using this, estimates of the expected catch per trip by a boat with x recreational fishers on board, $U_{x,t}$, may be calculated for the time step.

The catch on a single fishing trip may be considered to be a random variate drawn from the statistical distribution of such catches, where the mean of that distribution is related to the abundance of fish in the population within the area open to fishing at the time of the fishing trip, the vulnerability of those fish to the fishing gear, and the number of fishers on board the boat during the fishing trip. It is assumed in this study that the total number of legal-sized fish that is caught (before bag and boat limits or a catch quota) during a boat trip with x fishers on board is a random variate from a Poisson distribution with a mean catch per boat trip equal to $U_{x,t}$. The probability of capturing exactly y legal-sized fish, $P_{x,t}^{\text{cap}}\left(y|\mu = U_{x,t}\right)$, is therefore

$$P_{x,t}^{\text{cap}}\left(y|\mu = U_{x,t}\right) = \frac{U_{x,t}^{y} \exp\left[-U_{x,t}\right]}{y!} \tag{82}$$

The probability of capturing Y or less legal-sized fish may be determined from the cumulative distribution function for the Poisson distribution and is thus

$$P_{x,t}^{\text{cap}}\left(y \leq Y|\mu = U_{x,t}\right) = \frac{\Gamma\left(Y+1, U_{x,t}\right)}{Y!} \tag{83}$$

It follows that the probability of capturing Y or more legal-sized fish is

$$P_{x,t}^{\text{cap}}\left(y \geq Y | \mu = U_{x,t}\right) = 1 - \frac{\Gamma\left(Y, U_{x,t}\right)}{(Y-1)!} \tag{84}$$

If the combination of bag and boat limits constrains the total catch for the fishing trip by a boat with x recreational fishers on board to a maximum catch of BL_x fish, then the probability of capturing y fish, where $0 \leq y \leq \text{BL}_x$ is

$$P_{x,t}^{\text{cap}}\left(y | \mu = U_{x,t}\right) = \begin{cases} \frac{U_{x,t}^{y} \exp[-U_{x,t}]}{y!} & \text{for } 0 \leq y < \text{BL}_x \\ 1 - \frac{\Gamma(\text{BL}_x, U_{x,t})}{(\text{BL}_x - 1)!} & \text{for } y = \text{BL}_x \end{cases} \tag{85}$$

From this, the proportion of fish that are retained following capture, ψ^{ret}, and the proportion that die as a result of capture, $\left(1 - p^{\text{rmort}}\right)\psi^{\text{ret}} + p^{\text{rmort}}$, may be calculated. An estimate of retained catch may then be determined as

$$\sum_{s=f}^{m} \sum_{j=1}^{J} \sum_{k=1}^{K} P_{k,t}^{L \geq MLL, \text{cap}_{\tau}} n_{k,j,s,t,i} \psi^{\text{ret}} \tag{86}$$

and the number of fish of sex s, length class k, and age class j, that survive to the beginning of time step i, after allowing for the mortality associated with capture and release is

$$\begin{aligned} n_{k,j,s,t,i} &= n_{k,j,s,t,i-1} \left\{ \psi_{A_{\text{closed}}} \exp\left[-M\right] + \left(1 - \psi_{A_{\text{closed}}}\right) \exp\left[-\left(M + F_{k,t}^{\text{AC}}\right)\right] \right. \\ &\quad \left. + P_{k,t}^{L<\text{MLL},\text{surv}_{\tau}} + P_{k,t}^{L \geq MLL,\text{cap}_{\tau}} \psi^{\text{rel}} \left(1 - P^{\text{rmort}}\right) \right\} \end{aligned} \tag{87}$$

Details of the distribution of the relative numbers of fishing trips by boats in which the fishing party contains x $(1 \leq x \leq X)$ fishers are specified as input to the MSE prior to commencing the simulation trials. The maximum number of fishers within any fishing party is denoted by X, and the proportion of trips in which there are x fishers is denoted by P_x. When bag and boat limits are applied, the average catch for a fishing trip by a boat with x fishers on board is reduced from $U_{x,t}$ to

$$\sum_{y=1}^{\mathrm{BL}_x} y P_{x,t}^{\mathrm{cap}} \left(y|\mu = U_{x,t}\right) \tag{88}$$

The number of boat trips by a vessel with x fishers on board may be converted to the equivalent standard effort, *i.e.* the number of boat trips with a single fisher on board that would retain the same catch for the trip, by multiplying by the factor

$$\frac{\sum_{y=1}^{\mathrm{BL}_x} y P_{x,t}^{\mathrm{cap}} \left(y|\mu = U_{x,t}\right)}{\sum_{y=1}^{\mathrm{BL}_1} y P_{1,t}^{\mathrm{cap}} \left(y|\mu = U_{1,t}\right)}, \tag{89}$$

Note that this factor takes the combined effect of the bag and boat limits on boat trips with different numbers of fishers into account.

If the mean catch per unit of standard effort of legal-sized fish is U_t, the average catch (retained and released fish) per trip over all fishing boats, regardless of the number of fishers on board each boat, is

$$\sum_{x=1}^{X} U_{x,t} P_x \tag{90}$$

and the average number of fish that are caught and retained per trip by each boat, regardless of the number of fishers on board, is

$$\sum_{x=1}^{X} \sum_{y=1}^{\mathrm{BL}_x} y P_{x,t}^{\mathrm{cap}} \left(y|\mu = U_{x,t}\right) P_x \tag{91}$$

The proportion of fish that are retained in the average trip when bag and boat limits are applied, ψ^{ret}, is therefore

$$\psi^{\mathrm{ret}} = \frac{\sum_{x=1}^{X} \sum_{y=1}^{\mathrm{BL}_x} y P_{x,t}^{\mathrm{cap}} \left(y|\mu = U_{x,t}\right) P_x}{\sum_{x=1}^{X} U_{x,t} P_x} \tag{92}$$

while the proportion of fish that are required to be released because of the bag and boat limits, ψ^{rel} is

$$\psi^{\text{rel}} = 1 - \psi^{\text{ret}} \tag{93}$$

Of the fish that are released, a proportion P^{rmort} are expected to die as a result of barotrauma, hooking injury, or other mortality associated with capture and release. Thus, by implementing the bag and boat limit controls, the proportion of fish that are expected to die is the sum of the proportion retained and the proportion that are released but die as a result of capture and release, *i.e.*

$$\psi^{\text{ret}} + \left\{1 - \psi^{\text{ret}}\right\} P^{\text{rmort}} \tag{94}$$

which may be simplified to

$$\left(1 - P^{\text{rmort}}\right) \psi^{\text{ret}} + P^{\text{rmort}} \tag{95}$$

It should be noted that the effectiveness of the bag and boat limit regulation will be reduced if fishers fail to comply with the regulations, or if high-grading occurs.

Catch quota

If either a catch quota is not applied, or it is applied and the size of the quota, Q, is equal to or greater than the expected retained catch, N^{ret}, the number of fish of each age, length class and sex, $N_{a_j,l_k,s}$, at the end of the time step is calculated after removing the fish that die. If $Q < N^{\text{ret}}$, then $N_{a_j,l_k,s}$ is calculated by removing the fish that die and reducing probability of capture, P^{cap}, to account for the effect of the quota. The level to which P^{cap} should be reduced because of the quota is estimated iteratively, calculating the expected number of retained fish after resetting P^{cap} as

$$P^{\text{cap}} = P^{\text{cap}}Q/N^{\text{ret}} \tag{96}$$

This process terminates when $(N^{\text{ret}} - Q)/Q$ is zero.

The unexploited stock

Determination of the values of the parameters of the stock-recruitment relationship requires an estimate of the unexploited spawning biomass to be calculated. The fishery is assumed to be at equilibrium with annual recruitment equal to the average level of recruitment. Since the virgin stock is assumed to be unexploited, input and output controls have no impact and the only source of mortality is natural mortality.

The calculation commences by calculating the proportion of the fish that will lie within each age and length class when survival is determined from natural mortality. Thus, the operating model is run with recruitment set to the level of annual recruitment, R^0, entered as input to the MSE, repeating the sequence of addition of recruitment, and calculating the effects of survival, sex change (if hermaphroditic), and growth over sufficient years for the system state to achieve an approximate equilibrium state. The spawning biomass of the unexploited stock, $S^{\text{sp},0}$, is then calculated and the values of the parameters a_{SRR} and b_{SRR} of the stock-recruitment relationship determined from $S^{\text{sp},0}$, R^0, and z.

The initial exploited equilibrium state of the stock

This section gives a brief description of the sequence of calculations undertaken by the model to establish the initial state of the simulated fish stock prior to the projection period. This initial state is set to reflect that which would be expected if the population was at an exploited equilibrium and the fishery was subject to a suite of management controls. In broad terms, when there are no bag or boar limits, the operating model determines the initial state of the stock by undertaken the following steps.

1. Calculating the expected number of fish per recruit (assuming the stock is at equilibrium) within each length class, of each sex and age, allowing for total mortality in the stock and taking into account growth and, in hermaphroditic species, sex change. This is accomplished by setting the annual recruitment to one fish, and running the model with the initial level of the instantaneous rate of capture, F_{init}, for sufficient years to ensure that the model's representation of the system state has reached equilibrium. The model takes any initial spatial and temporal closures, and minimum legal length regulations into account when these calculations are undertaken.

2. Calculating the spawning biomass per recruit and the expected level of annual recruitment to the stock when at equilibrium. The expected level of average annual recruitment is calculated by considering the equilibrium spawning biomass as the product of spawning biomass per recruit and the equilibrium level of recruitment, then solving the stock-recruitment relationship to determine the average annual level of recruitment.

3. Multiplying the expected number of fish per recruit that is caught and retained by the average recruitment to estimate the average catch.

4. Dividing the average catch by the mean catch per fishing trip for the initial equilibrium state of the fishery, which was specified to the MSE prior to commencing the simulations, to produce an estimate of the fishing effort (number of standard boat trips, *i.e.* equivalent number of trips by boats with a single fisher on board.

5. Dividing the initial instantaneous rate of capture F_{init} by the fishing effort to obtain an estimate of the catchability coefficient, q.

6. Calculating the initial age- and length-compositions of the fish stock for a time series of annual recruitment levels, where the latter are determined by randomly selecting variates from the statistical distributions that describe the deviations of annual recruitment from the average level. These calculations are thus determined by undertaking, within each year throughout the historical period, the following events:

    (a) calculate the annual recruitment R to the stock, taking into account the fact that, in accordance with the specifications provided to the MSE before commencing the simulation, recruitment may be variable or episodic, and that it may also be auto-correlated between successive years;

    (b) add the new recruits produced each year to the stock at the beginning of the annual time steps;

    (c) allow for the instantaneous rate of capture for the historical year (and the effect of input and output controls in that year), possible sex change (in hermaphroditic fish) and growth of fish in that year; and

    (d) update the age- and length-compositions of the stock at the end of the time step, after which the process is repeated for the next year of historical data, and so on, until the system state at the end of the last year of historical data has been determined.

THE OBSERVATION MODEL

The observation model simulates the collection of age- and length-composition data to be used by the assessment model to obtain information about the state of the exploited stock. These types of data are those most commonly applied to stock assessments for recreational fisheries in Western Australia (Wise *et al.*, 2007). The model estimates the age- and length-compositions of the stock from the number of fish present in the population at the beginning of the time step in which sampling is undertaken. As the samples represent catches taken by recreational fishers, samples are only drawn for fish with lengths $\geq$ MLL.

The vulnerability of fish in length class k to being caught by fishers, *i.e.* $V_{k,s}^{\mathrm{MLL}}$, which depends on the selectivity of the fishing gear for fish in that length class V_k and the length of the fish in the length class L_k relative to the MLL, $P_k^{L \geq \mathrm{MLL}}$, is

$$V_{k,s}^{\mathrm{MLL}} = V_k P_k^{L \geq \mathrm{MLL}} \tag{97}$$

The expected frequency of fish within age class j for each sex, $N'_{j,s}$, is proportional to the sum over all length classes of the product of this vulnerability and the number of fish within the length classes, *i.e.*

$$N'_{j,s} = \sum_{k=1}^{K} n_{k,j,s,t} V_{k,s}^{\mathrm{MLL}} \tag{98}$$

where $n_{k,j,s,t}$ is the number of fish of sex s in length class k and age class j. The expected frequency of fish of length class k and sex s, over all ages, $\hat{N}_{k,s}$, is calculated as

$$\hat{N}_{k,s} = \sum_{j=1}^{J} n_{k,j,s,t} V_{k,s}^{\mathrm{MLL}} \tag{99}$$

Assuming that the age- and length-compositions of the stock are multinomially distributed, samples are generated by drawing random observations, ix, from the expected distributions for age, $N'_{j,s}$, and length, $\hat{N}_{k,s}$, for the simulated population, employing the algorithm described by Devroye (1986). The arguments of the algorithm are n, the number of observations (fish), P_i, the expected proportion of fish in the age or length category i, n_{cat}, the number of age or length categories and ix_i, the i^{th} random observation.

THE ASSESSMENT MODEL

The model assesses the state of the simulated fish stock employing catch curve and per recruit analyses, the details of which are provided below.

Catch curve analysis

The model enables a range of alternative types of catch curve analyses to be employed for estimating total mortality from age composition sample data (see Fisher *et al.*, 2011). For the simulations that were undertaken using the MSE model for this thesis (Chapter 2 and 3), however, only the linear, regression-based catch curve analysis (*e.g.* Ricker, 1975) was used. This method assumes that: (i) annual recruitment is constant, (ii) the total mortality of fish above the age at which fish are fully recruited into the fishery is constant, and (iii) the frequencies of fish at age in the age composition samples are log-normally distributed about their expected values. The integer age at which fish are fully recruited into the fishery, t_c, was determined as one year above the modal age in the age-frequency sample. From these assumptions, the number of fish in age class j, *i.e.* of integer age a_j, in the age composition sample, N'_{a_j}, may be written as

$$N'_{a_j} = N'_{t_c} \exp\left[-Z\left(a_j - t_c\right)\right] \exp\left[\epsilon_j\right] \tag{100}$$

where $\epsilon_j \sim N\left(0, \sigma^2\right)$ and $t_c \leq a_j \leq a_{\text{max}}$, and where a_{max} is selected as the integer age of the last age class for which there is a non-zero frequency. By taking the natural logarithms of both sides of this equation, the relationship may be expressed as the linear regression model

$$\log_e N'_{a_j} = \log_e N'_{t_c} - Z\left(a_j - t_c\right) \tag{101}$$

where total mortality, Z, represents the negative of the slope of the regression equation.

Per recruit analyses

The estimated yield per recruit for fish of sex s at the estimated level of fishing mortality F, YPR$_{F,s}$, is calculated as

$$\text{YPR}_{F,s} = \sum_{j=1}^{J}\sum_{k=1}^{K} \frac{V_k F}{M + V_k F}\left[1 - \exp\left(-(M + V_k F)\right)\right] W(L_k)\psi_k^s \exp\left(-(M + V_k F)\right) \tag{102}$$

where $W_{L_k,s}$, is the estimated weight of fish and $\psi^s_{k)}$ is the proportion of fish of sex s in length class k. The estimate of fishing mortality used in this analysis is the value derived from the catch curve analysis. The spawning stock biomass per recruit for sex s at fishing mortality F, SBR$_{F,s}$, is determined as

$$\text{SBR}_{F,s} = \sum_{j=1}^{J}\sum_{k=1}^{K} W(L_k)\psi_k^s \psi_{k,s}^{\text{mat}} \exp\left[-(M + V_k F)\right] \tag{103}$$

where $\psi_{k,s}^{\text{mat}}$ is the expected proportion of fish of sex s and length class k that are mature. The estimated number of eggs per recruit at F, EPR$_F$, is

$$\text{EPR}_F = \sum_{j=1}^{J}\sum_{k=1}^{K} \text{BF}_{k,f} W(L_k)\psi_k^s \psi_{k,s}^{\text{mat}} \exp\left[-(M + V_k F)\right] \tag{104}$$

where BF$_{k,f}$ is the fecundity of females in length class k. The spawning potential ratio, SPR, in terms of spawning stock biomass per recruit and eggs per recruit, is calculated as

$$\text{SPR(SBR)} = \text{SBR}_{F,s}/\text{SBR}_{0,s} \tag{105}$$

$$\text{SPR(EPR)} = \text{EPR}_F/\text{EPR}_0 \tag{106}$$

where $\text{SBR}_{0,s}$ and $\text{EPR}_{0,s}$ are the estimated levels of spawning stock biomass per recruit and eggs per recruit, respectively, for the stock at its virgin state.

THE DECISION-MAKING PROCESS

Depending on the type of analysis to be undertaken, management decisions during model simulation runs can be determined according to either a fixed decision rule, or through directly specifying the management controls to be applied. Only the latter approach was employed for studies presented in this thesis. In accordance with traditional MSE models, the fixed decision rule is used to automatically adjust the management, given the current state of an exploited stock relative to user-specified reference points. The application of fixed decision rules enables prediction of the likely effectiveness of alternative sets of pre-defined management strategies over an extended time frame. Details of the two F-based decision rules that have been implemented in the model are provided in Fisher *et al.* (2011).

SOFTWARE IMPLEMENTATION

Microsoft Visual Basic.NET (version 3.5 SP1) in Visual Studio 2008 Express Edition (version 9.0.21022.8 RTM; Microsoft, 2007) was used as the primary platform for model development, with AD Model Builder (Otter Research Ltd.) being employed to undertake the catch curve analyses, some of which are computationally intensive.

APPENDIX B

MSE model user guide

INSTALLATION AND USE

The MSE model (available as an .exe file) and all files required to run the software are available upon request. To install the software: (i) save the MSE folder to somewhere on the computer, (ii) open the .zip file and copy the folders named MSEDataFiles and MSEResultFiles directly to the C drive, and (iii) copy the folders called Scenarios and Results onto the computer's desktop. Note that the above folders can be placed elsewhere on the computer, however, the directory pathways will need to be specified each time the model is run. Install the MSE model on the computer by clicking on the MSE.exe file.

An overview of the folders and files used by the model when running simulations is provided in Table B.1. The MSE model can be run in two modes; a normal "MSE simulation mode", or a "scenario testing mode" for workshop situations. When running normal MSE simulations, the model inputs parameters from the text files contained within the DefaultSpecies folder. The specified parameters are those for the West Australian dhufish *Glaucosoma hebraicum*, however, simulations can be run for any fish species for which relevant data are available. This can be achieved by changing the parameter values either directly through modifying the .txt files in DefaultSpecies, or using the user interface of the model after data have been read in. As the program does not allow for changes in the layout of the .txt files, the order and spacing of parameters must remain the same. As model simulations are completed, the MSEResultFiles folder stores all outputs in various text files (*e.g.* age and length composition data, levels of recruitment for different year classes, estimates of fishing mortality and the results of per-recruit analyses).

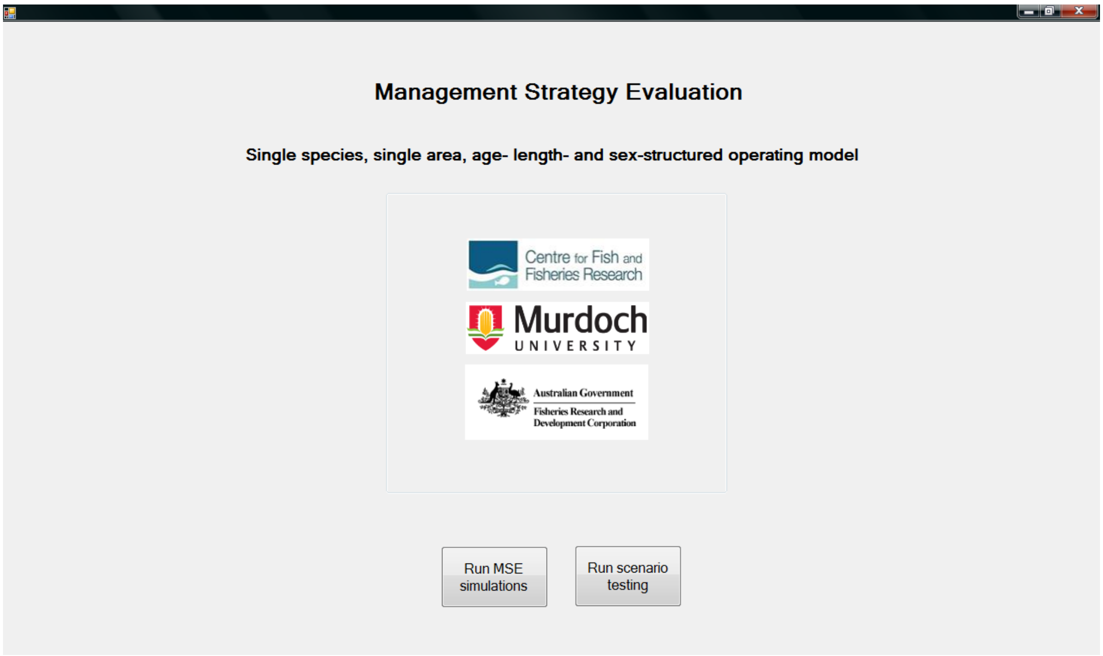
Table B.1. Overview of the data folders and data files required to run the MSE model, and their respective uses.

Data folders	Data files	General model uses
MSEDataFiles		
DefaultSpecies	SpeciesParamters.txt SimulationParamters.txt ManagementParamters.txt	MSE simulations (for *Glaucosoma hebraicum*)
TestSpecies	SpeciesParamters.txt SimulationParamters.txt ManagementParamters.txt	Scenario testing simulations (for *Sillago schomburgkii*)
Species1	SpeciesParamters.txt SimulationParamters.txt ManagementParamters.txt	Scenario testing simulations (for *G. hebraicum*)
Species2	SpeciesParamters.txt SimulationParamters.txt ManagementParamters.txt	Scenario testing simulations (for *Rhabdosargus sarba*)
CatchCurveAnalysis	Assorted	All simulations
FinalCatchCurveAnalysis	Assorted	All simulations
MSEResultFiles	Assorted	All simulations (initially empty but collects model outputs from simulations)
Scenarios	MSE.txt TrialNum.txt ReadInSpeciesForScenarios.txt ReadInLevelOfFForScenarios.txt ReadInLevelOfRecVarForScenarios.txt	Scenario testing simulations (specifies aspects of scenarios and the order in which they are undertaken)
Results		Scenario testing simulations (collects user decisions)

When run in the scenario testing mode, the MSE model presents the user with the choice to undertake a "preliminary test trial" or a "scenario trial". The former option represents a single fishery scenario for the yellowfin whiting *Sillago schomburgkii* and uses parameters from the TestSpecies folder. It is intended that this scenario can be run repeatedly to help new users become familiar with the model and the effects of the different management controls, before continuing to run the other scenario trials. By default, the model considers 12 different fishery scenarios, excluding that used for the preliminary test trial. These consider two different fish species (using data files in the folders Species1 and Species2), three initial levels of exploitation and two levels of recruitment variability.

The data files which specify aspects of the 12 fishery scenarios are contained within the folder named Scenarios. The order in which the scenarios are undertaken is detailed in MSE.txt, however, scenarios can be run multiple times by repeating the number for a particular scenario on several lines within this text file. The function of TrialNum.txt is to maintain a count of the scenarios that have been completed so that the next scenario can be read in correctly. To re-run all scenarios, delete all the values in this file except the 0 on the first line, leaving the cursor at the start of the next line before saving. The scenarios (*i.e.* fish species, initial level of exploitation and level of recruitment variability) can be modified by altering the other three .txt files in the Scenarios folder.

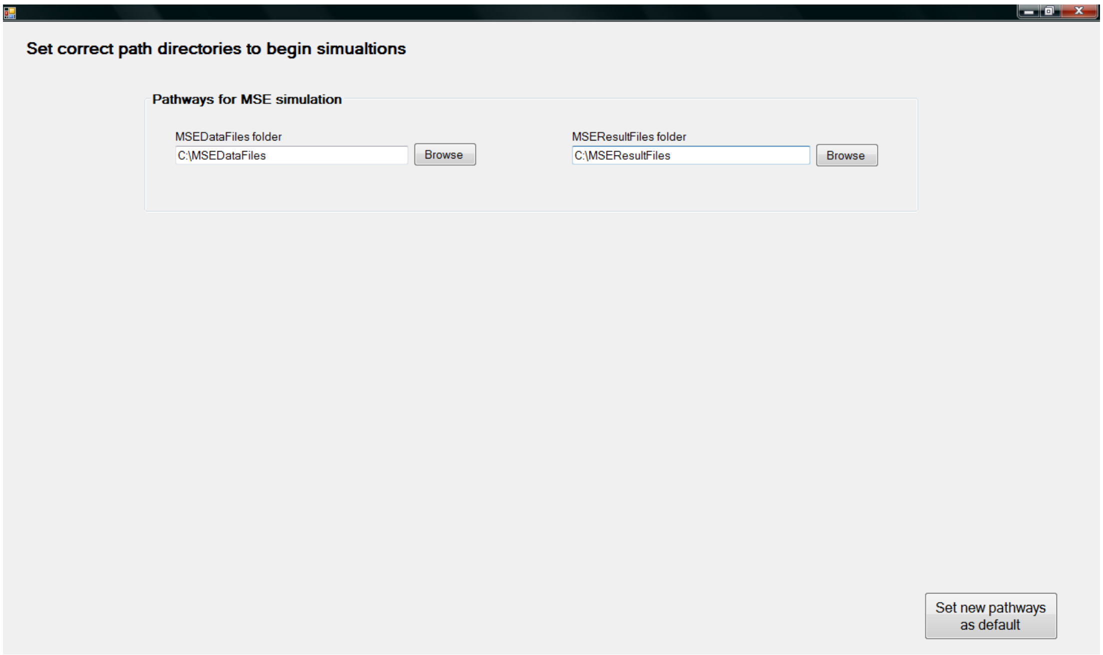
Examples of the different user screens of the MSE model are presented below, together with descriptions of the different steps required to run model simulations. At last, some notes are provided regarding the risk assessment summary screen.



Management Strategy Evaluation

Single species, single area, age- length- and sex-structured operating model

1. The above introductory screen appears when the MSE model is first opened. To use the model to undertake MSE simulations for research purposes, press "Run MSE simulations". To run the model in a scenario testing mode, press "Run scenario testing".



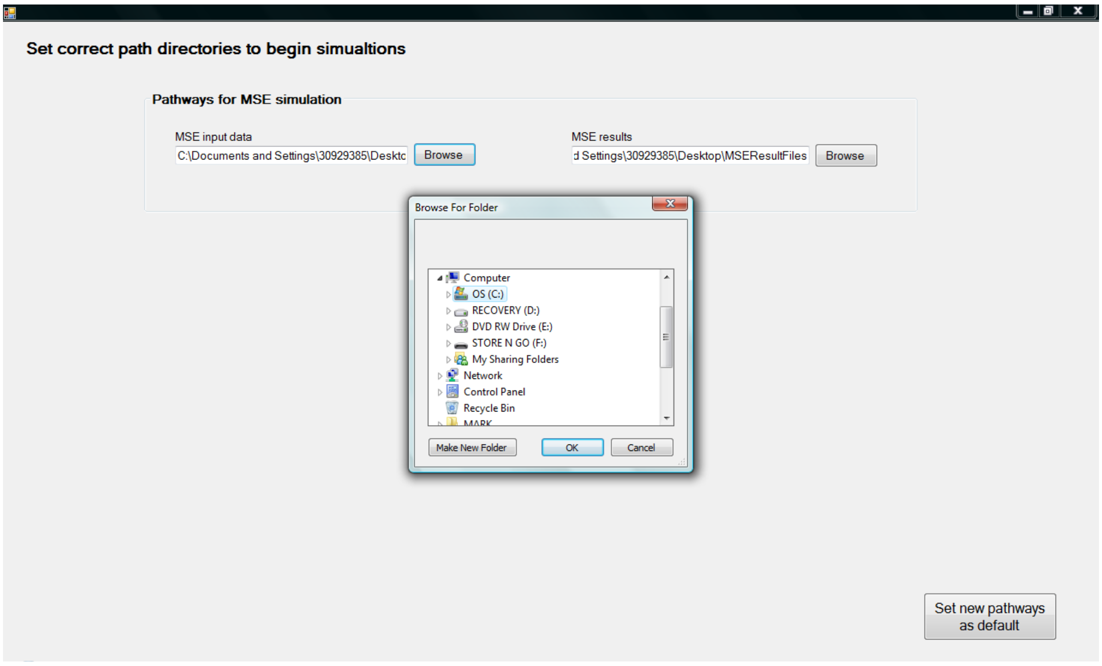
Set correct path directories to begin simualtions

Pathways for MSE simulation

MSEDataFiles folder: C:\MSEDataFiles

MSEResultFiles folder: C:\MSEResultFiles

2. Prior to commencing any type of simulation, the MSE model completes a check to ensure that the directories to all folders with required data files can be found. If they cannot be located, the above form appears to enable the correct directories to the folders containing these files on the computer to be specified.



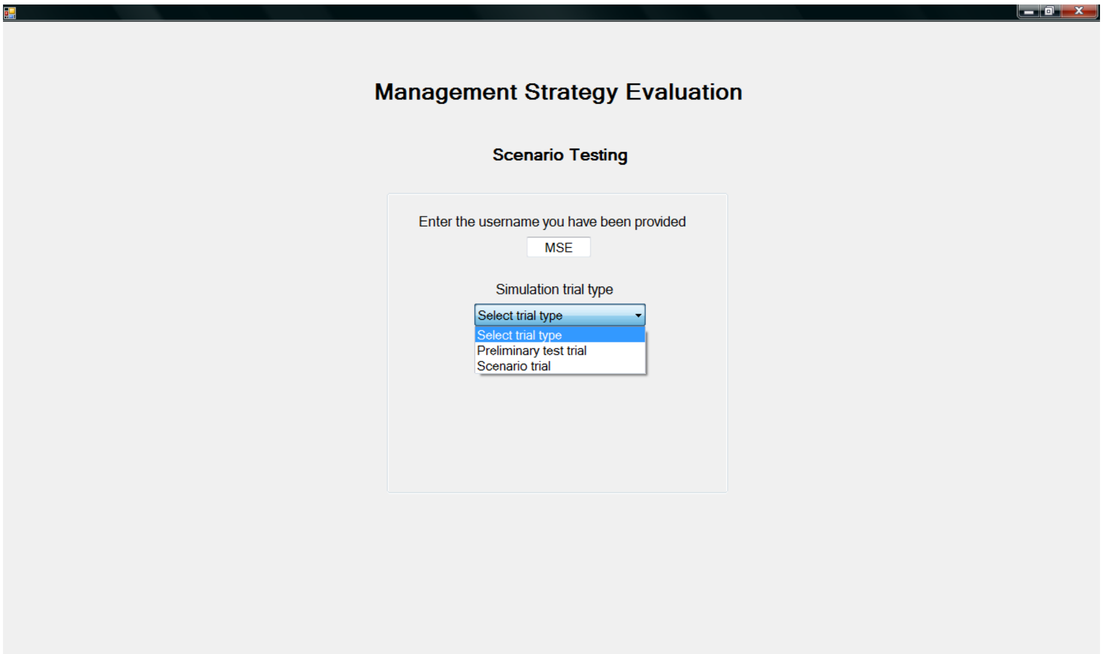
Set correct path directories to begin simualtions

Pathways for MSE simulation

MSE input data: C:\Documents and Settings\30929385\Desktc

MSE results: d Settings\30929385\Desktop\MSEResultFiles

3. Specify the correct path directories by browsing the computer directories for the correct location of the data folders. Then press “Set new pathways as default” to return to the introductory screen.



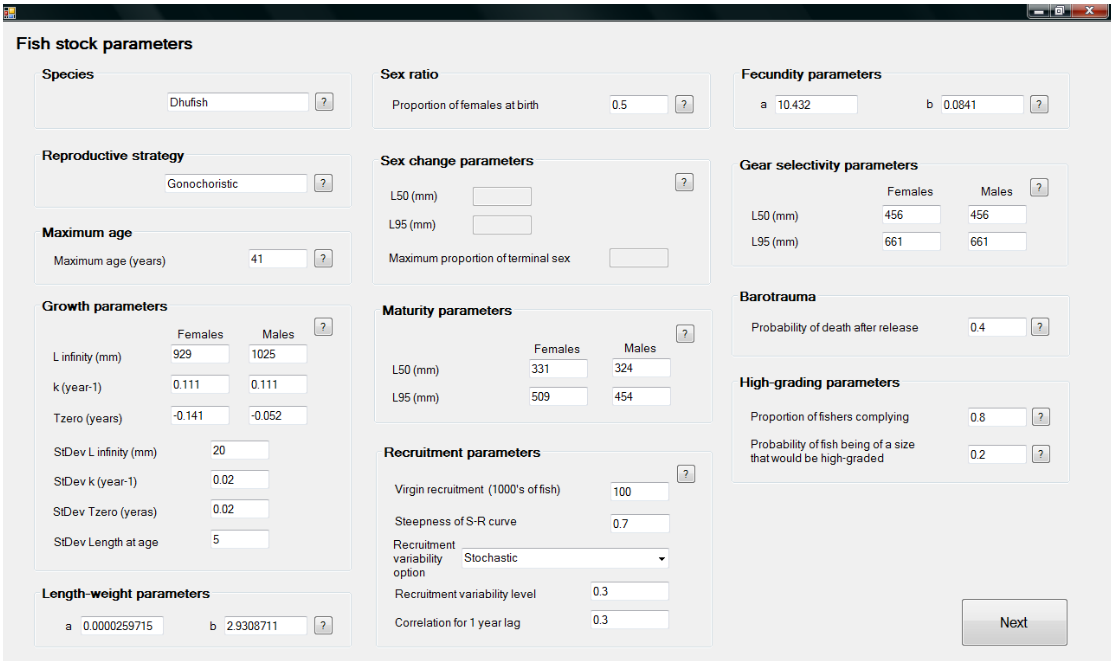
Management Strategy Evaluation

Scenario Testing

Enter the username you have been provided: MSE

Simulation trial type: Select trial type

4. This screen appears only when the model is run in scenario testing mode (or else the simulation proceeds directly to step 5). Enter the letters “MSE” as the username and click “Next”. Select either “Preliminary test trial” or “Scenario trial” before proceeding to read in data for the simulation.



Fish stock parameters

Species

Dhufish

Reproductive strategy

Gonochoristic

Maximum age

Maximum age (years) 41

Growth parameters

	Females	Males
L infinity (mm)	929	1025
k (year-1)	0.111	0.111
Tzero (years)	-0.141	-0.052

StDev L infinity (mm) 20

StDev k (year-1) 0.02

StDev Tzero (yeras) 0.02

StDev Length at age 5

Length-weight parameters

a 0.0000259715 b 2.9308711

Sex ratio

Proportion of females at birth 0.5

Sex change parameters

L50 (mm)

L95 (mm)

Maximum proportion of terminal sex

Maturity parameters

	Females	Males
L50 (mm)	331	324
L95 (mm)	509	454

Recruitment parameters

Virgin recruitment (1000's of fish) 100

Steepness of S-R curve 0.7

Recruitment variability option Stochastic

Recruitment variability level 0.3

Correlation for 1 year lag 0.3

Fecundity parameters

a 10.432 b 0.0841

Gear selectivity parameters

	Females	Males
L50 (mm)	456	456
L95 (mm)	661	661

Barotrauma

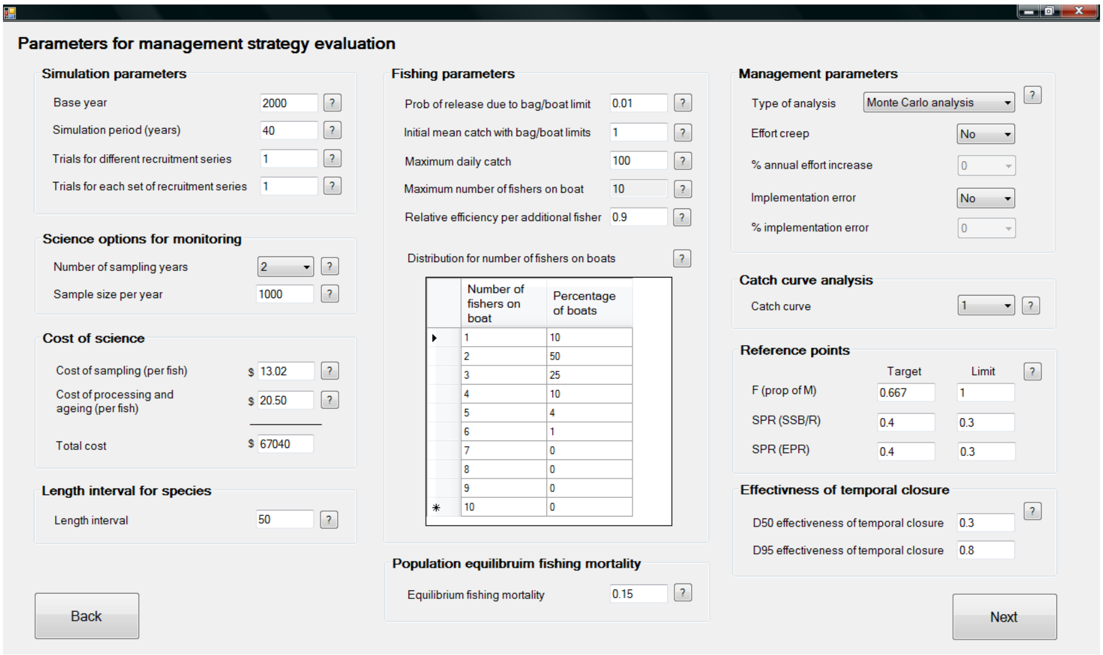
Probability of death after release 0.4

High-grading parameters

Proportion of fishers complying 0.8

Probability of fish being of a size that would be high-graded 0.2

5. Read in the required biological parameter values for the species by pressing “Read parameters” and then continue by clicking the “Next” button (which appears when the data have been read in by the model).



Parameters for management strategy evaluation

Simulation parameters

Base year 2000

Simulation period (years) 40

Trials for different recruitment series 1

Trials for each set of recruitment series 1

Science options for monitoring

Number of sampling years 2

Sample size per year 1000

Cost of science

Cost of sampling (per fish) $ 13.02

Cost of processing and ageing (per fish) $ 20.50

Total cost $ 67040

Length interval for species

Length interval 50

Fishing parameters

Prob of release due to bag/boat limit 0.01

Initial mean catch with bag/boat limits 1

Maximum daily catch 100

Maximum number of fishers on boat 10

Relative efficiency per additional fisher 0.9

Distribution for number of fishers on boats

	Number of fishers on boat	Percentage of boats
▶	1	10
	2	50
	3	25
	4	10
	5	4
	6	1
	7	0
	8	0
	9	0
*	10	0

Population equilibruim fishing mortality

Equilibrium fishing mortality 0.15

Management parameters

Type of analysis Monte Carlo analysis

Effort creep No

% annual effort increase 0

Implementation error No

% implementation error 0

Catch curve analysis

Catch curve 1

Reference points

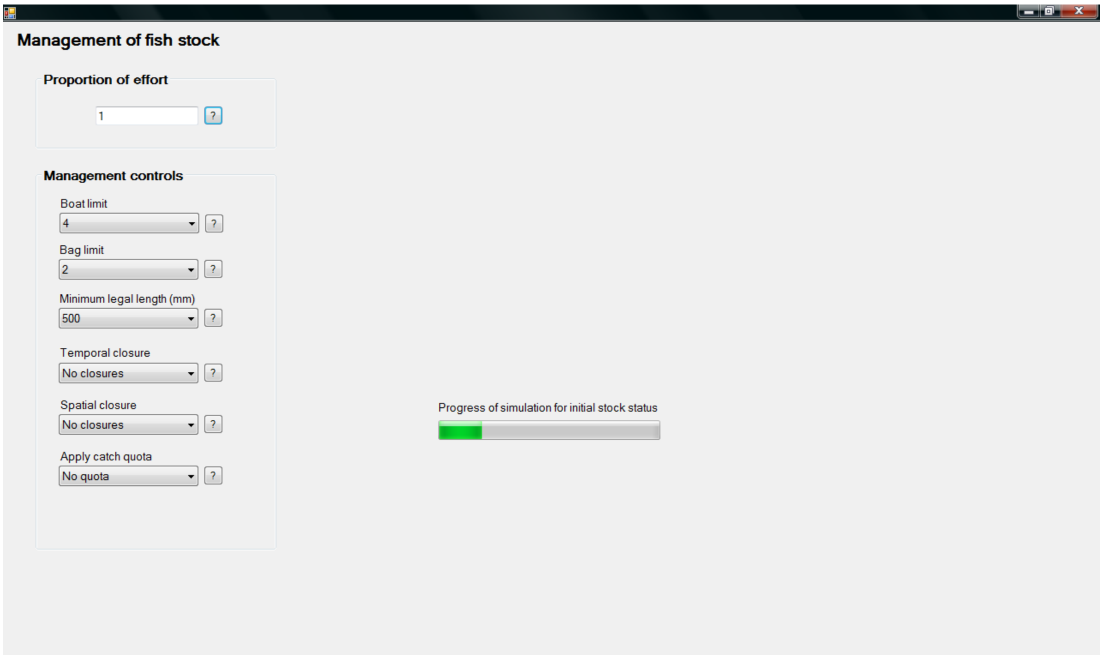
	Target	Limit
F (prop of M)	0.667	1
SPR (SSB/R)	0.4	0.3
SPR (EPR)	0.4	0.3

Effectivness of temporal closure

D50 effectiveness of temporal closure 0.3

D95 effectiveness of temporal closure 0.8

6. Read in the parameters which specify aspects of the simulation by pressing “Read parameters”. Click “Next” to proceed.



Management of fish stock

Proportion of effort

1

Management controls

Boat limit: 4

Bag limit: 2

Minimum legal length (mm): 500

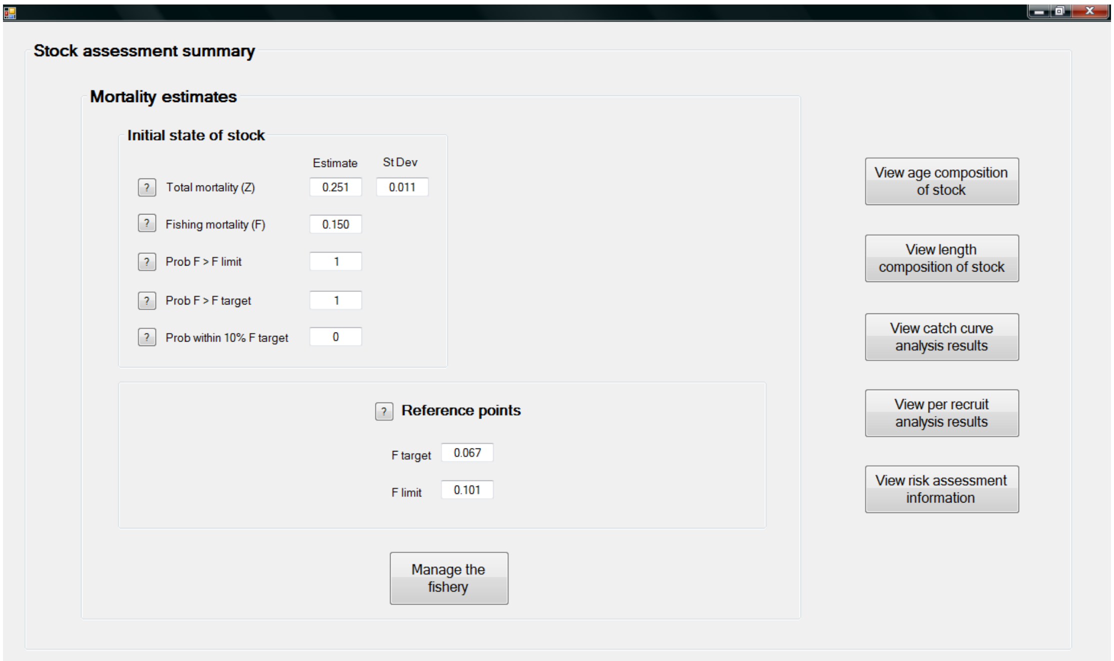
Temporal closure: No closures

Spatial closure: No closures

Apply catch quota: No quota

Progress of simulation for initial stock status

7. Press “Read parameters” to read in the values for the management controls being applied to the fish stock in its initial state. If in normal MSE simulation mode, these parameters can be changed by selecting desired values from the available lists for each control. To proceed, click “Run initial assessment” to produce information about state of the stock prior to the projection period.



Stock assessment summary

Mortality estimates

Initial state of stock

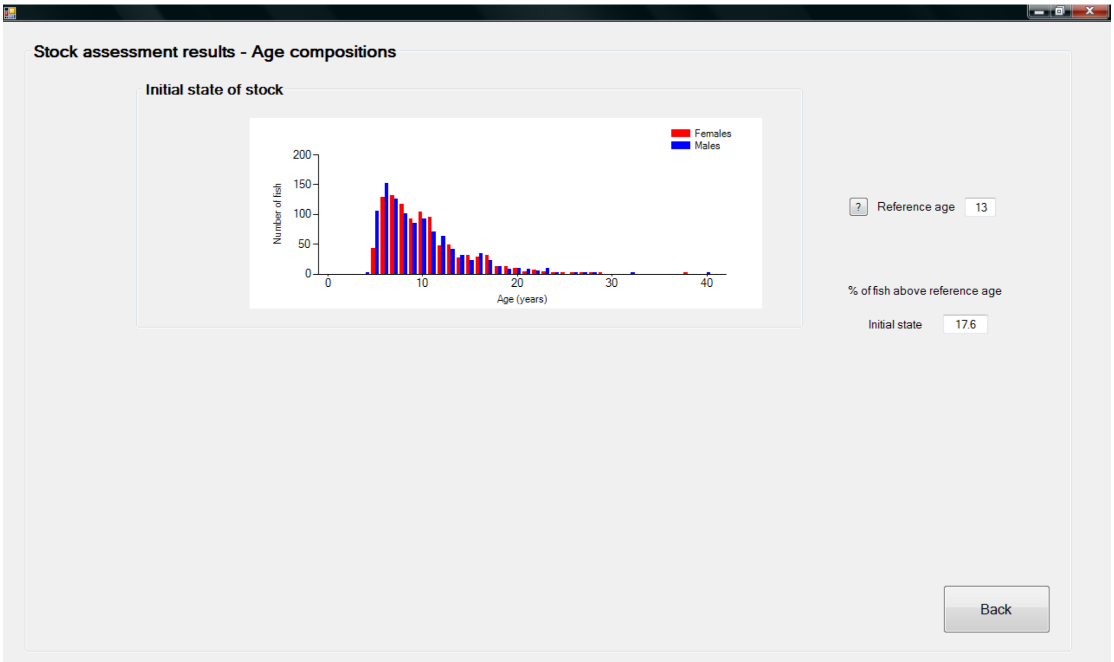
	Estimate	St Dev
Total mortality (Z)	0.251	0.011
Fishing mortality (F)	0.150	
Prob F > F limit	1	
Prob F > F target	1	
Prob within 10% F target	0	

Reference points

F target: 0.067

F limit: 0.101

8. Once the initial state of the stock has been determined and an assessment undertaken, the results of catch curve analysis are presented, as shown in the above screen. The user can view additional information about the initial stock state by selecting from the buttons to the right of the form (see steps 9 to 13).


Stock assessment results - Age compositions

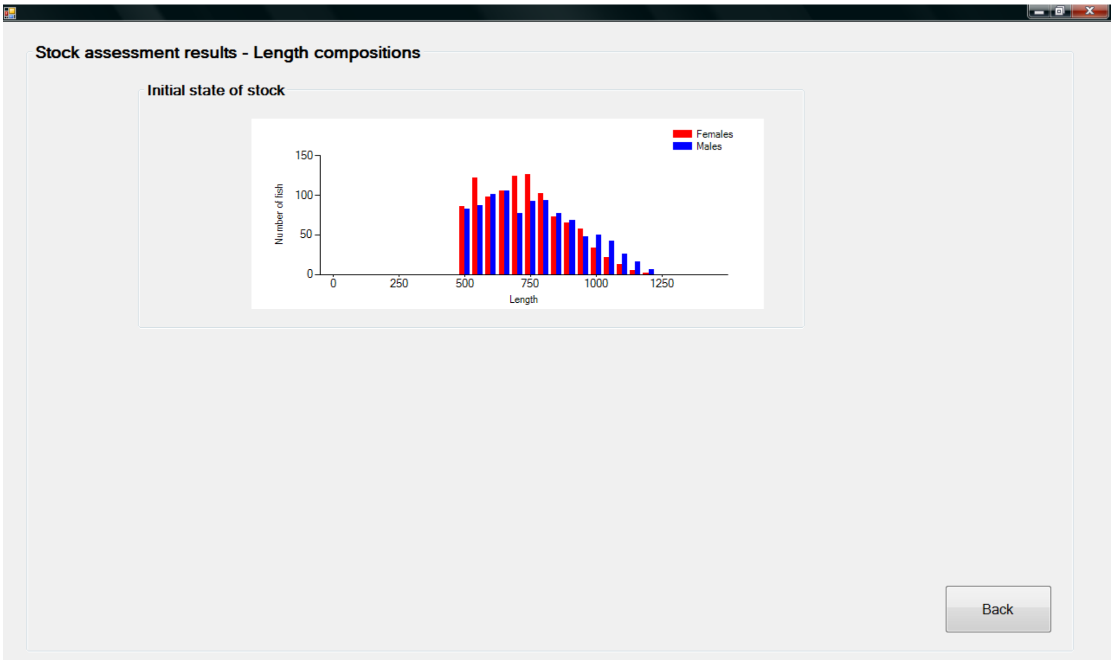
Initial state of stock

Reference age 13

% of fish above reference age

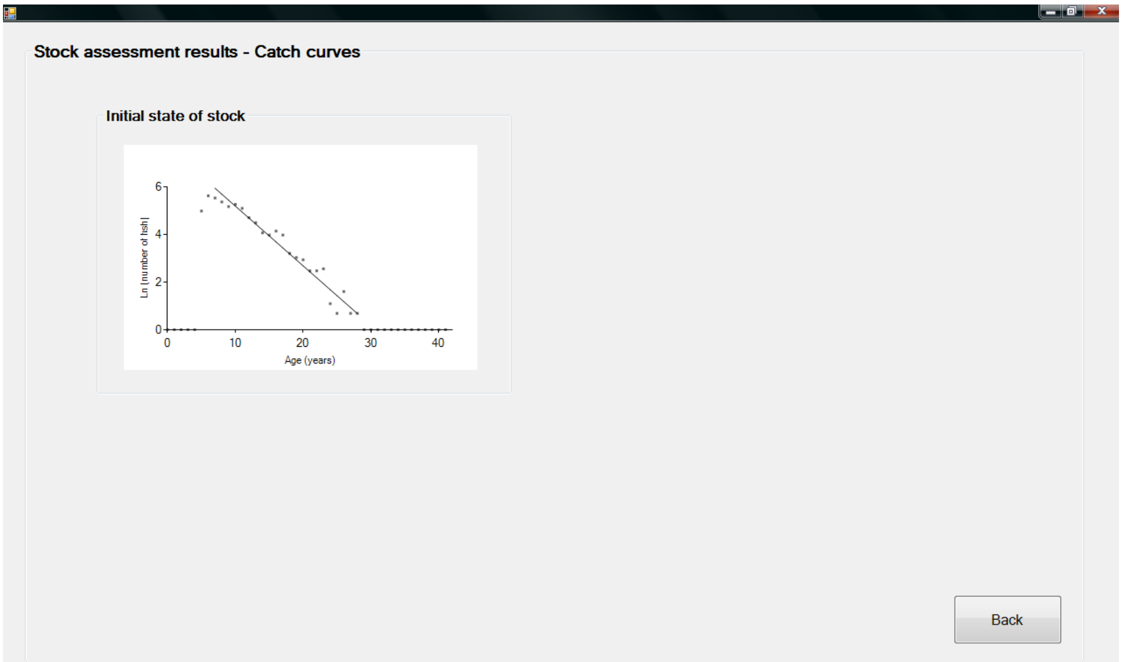
Initial state 17.6

9. Example of age composition sample data. Note, if multiple years of samples are specified in the form containing the simulation parameters, data shown on this form are pooled for the different years. To return to the previous screen, select “Back”.


Stock assessment results - Length compositions

Initial state of stock

10. Example of length composition sample data. To return to the previous screen, select “Back”.



Stock assessment results - Catch curves

Initial state of stock

11. Example of a catch curve analysis plot for a linear catch curve (*e.g.* Ricker, 1975) fitted to the natural logarithms of the frequencies of fish at age in sample data. Several other forms of catch curve analysis are available within the model (see Fisher *et al.*, 2011).

Stock assessment results - Per recruit analysis

YPR

Initial state

	Females	Males
Estimate	544	693
Prob F > F max	0 .99	
Prob F > F targ	1	
Prob F within 10% F 0.1	0	

SPR (SSB/R)

Initial state

	Females	Males
Estimate	0.257	0.239
Prob F > SPR limit	0 .99	
Prob F > SPR target	1	
Prob F within 10% SPR target	0	

SPR (E/R)

Initial state

Estimate	0.086
Prob F > SPR limit	1
Prob F > SPR target	1
Prob F within 10% SPR target	0

YPR - Yield per recruit
SPR - Spawning potantial ratio
SSB/R - Spawning stock biomass per recruit
E/R - Eggs per recruit

Reference points

YPR
F target = F 0.1
F limit = F max

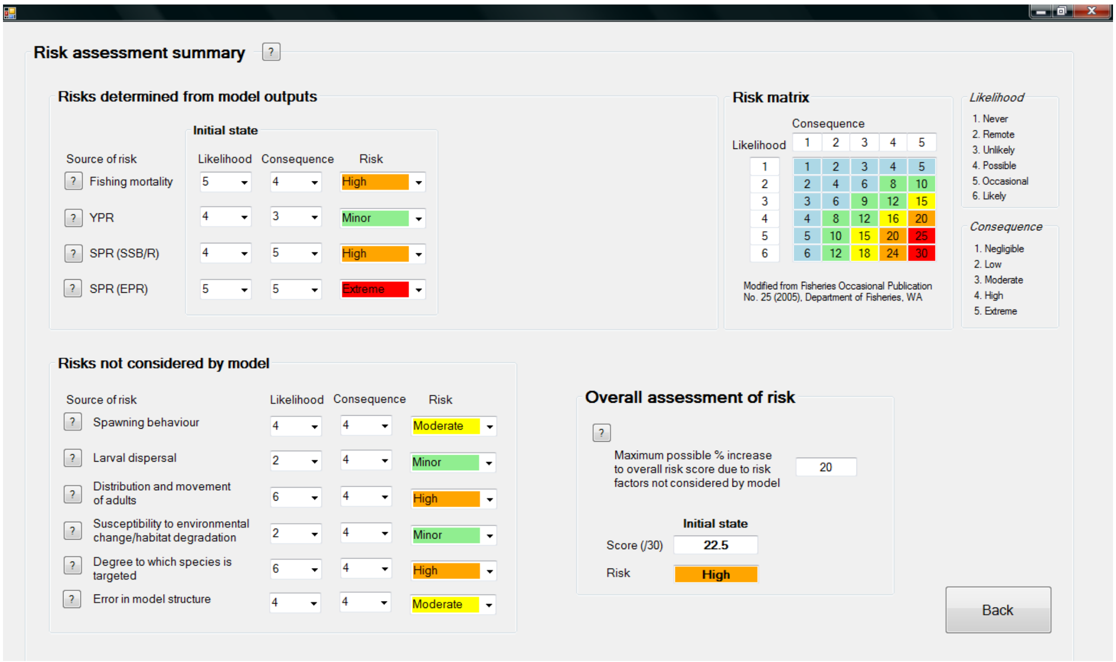
SPR (SSB/R)
F target = F 40%
F limit = F 30%

SPR (E/R)
F target = F 40%
F limit = F 30%

Color indicators for graphs

🟩	Point estimate	< Target ref point
🟨	Point estimate	> Target ref point < Limit ref point
🟥	Point estimate	> Limit ref point

12. Example of results of per-recruit analyses, including estimates of yield per recruit and spawning potential ratio (based on spawning biomass per recruit and egg per recruit).



Risk assessment summary

Risks determined from model outputs

Initial state

Source of risk	Likelihood	Consequence	Risk
Fishing mortality	5	4	High
YPR	4	3	Minor
SPR (SSB/R)	4	5	High
SPR (EPR)	5	5	Extreme

Risk matrix

Likelihood \ Consequence	1	2	3	4	5
1	1	2	3	4	5
2	2	4	6	8	10
3	3	6	9	12	15
4	4	8	12	16	20
5	5	10	15	20	25
6	6	12	18	24	30

Modified from Fisheries Occasional Publication No. 25 (2005), Department of Fisheries, WA

Likelihood

1. Never
2. Remote
3. Unlikely
4. Possible
5. Occasional
6. Likely

Consequence

1. Negligible
2. Low
3. Moderate
4. High
5. Extreme

Risks not considered by model

Source of risk	Likelihood	Consequence	Risk
Spawning behaviour	4	4	Moderate
Larval dispersal	2	4	Minor
Distribution and movement of adults	6	4	High
Susceptibility to environmental change/habitat degradation	2	4	Minor
Degree to which species is targeted	6	4	High
Error in model structure	4	4	Moderate

Overall assessment of risk

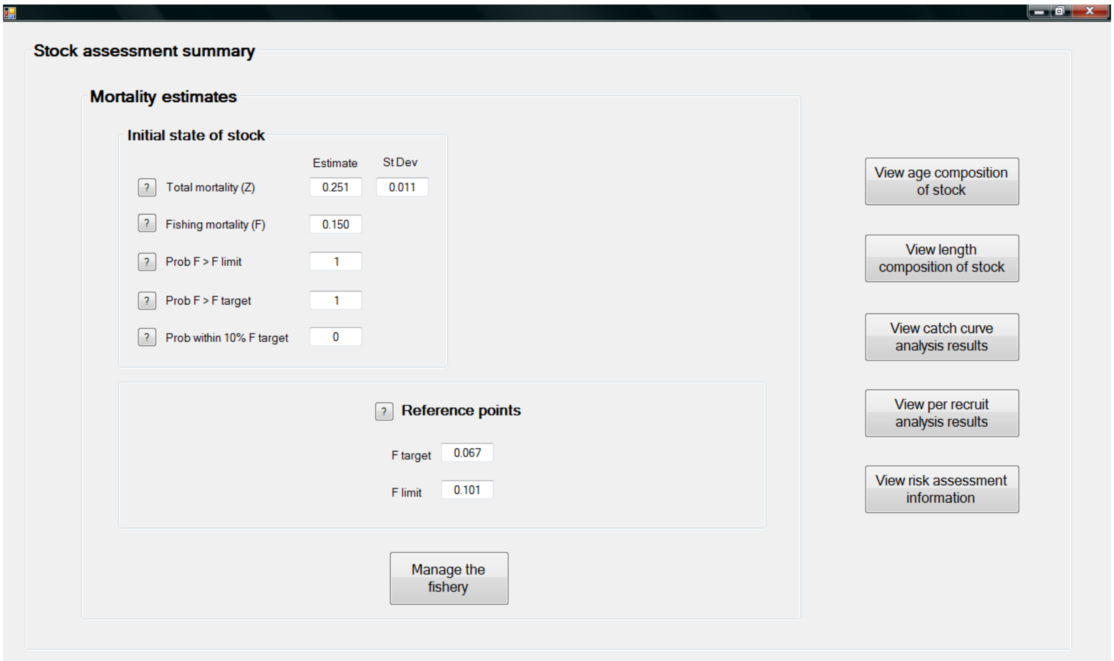
Maximum possible % increase to overall risk score due to risk factors not considered by model: 20

Initial state

Score (/30): 22.5

Risk: High

13. Example of results from a risk assessment for the stock in its initial state, based on mortality-based model outputs and other risks not considered directly by the model (assessed subjectively). Note that the risks associated with subjective criteria are added to the risks calculated from mortality estimates (see below for more details on risk calculations).



Stock assessment summary

Mortality estimates

Initial state of stock

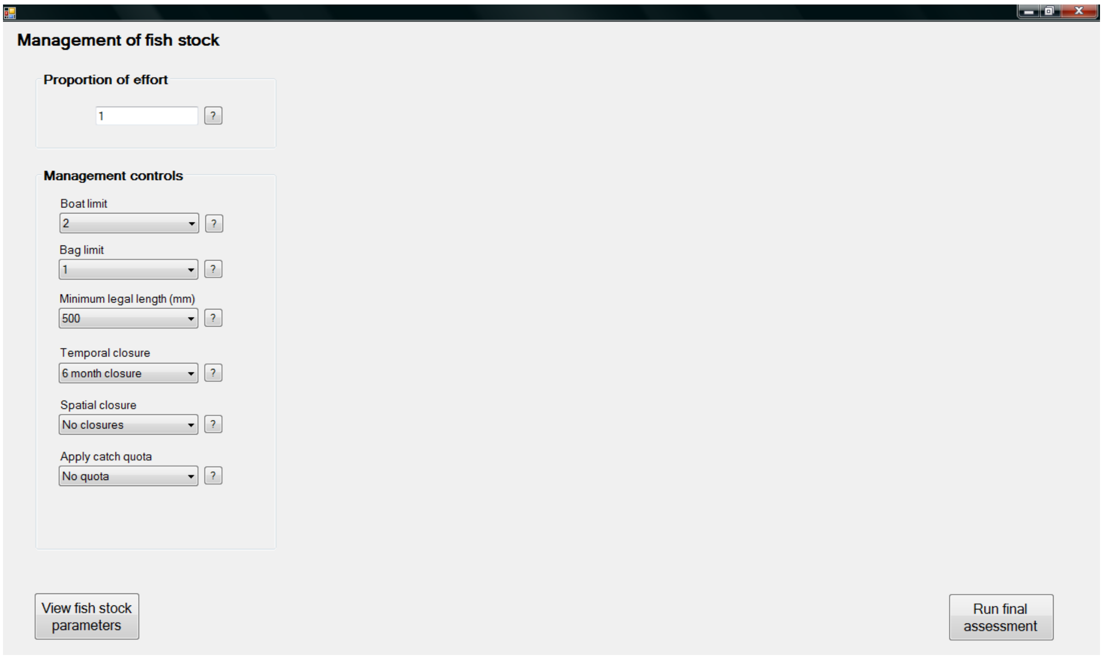
	Estimate	St Dev
Total mortality (Z)	0.251	0.011
Fishing mortality (F)	0.150	
Prob F > F limit	1	
Prob F > F target	1	
Prob within 10% F target	0	

Reference points

F target: 0.067

F limit: 0.101

14. After viewing information about the initial state of the fish stock and returning to the "Stock assessment summary" screen, click on the "Manage the fishery" button.



Management of fish stock

Proportion of effort

1

Management controls

Boat limit: 2

Bag limit: 1

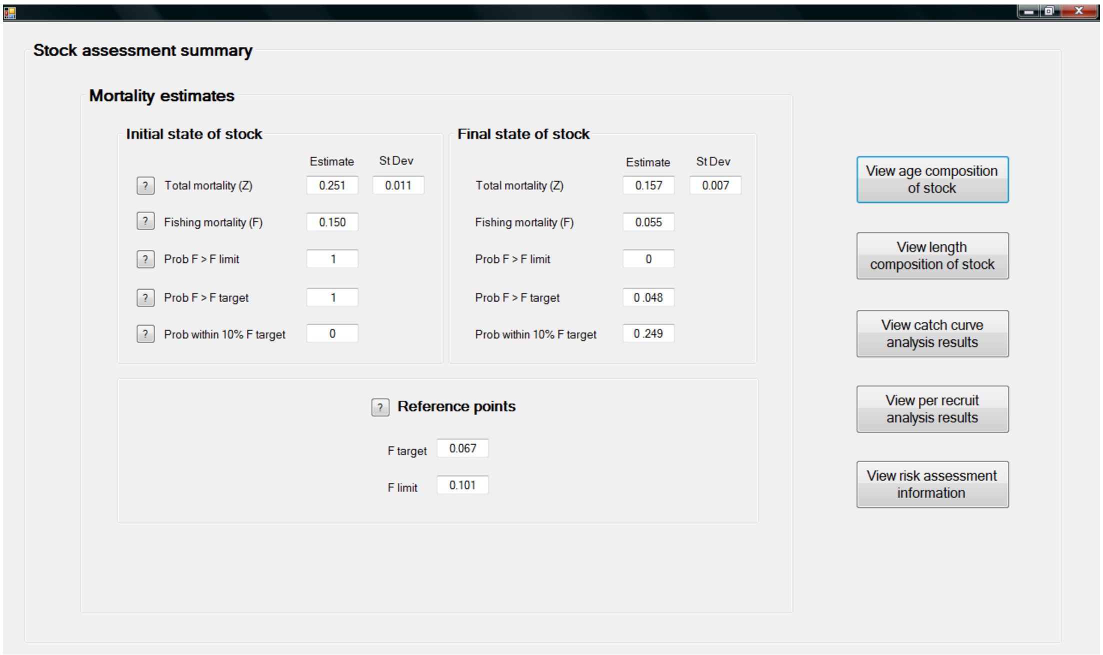
Minimum legal length (mm): 500

Temporal closure: 6 month closure

Spatial closure: No closures

Apply catch quota: No quota

15. Change none, some or all of the values for management controls and click “Run final assessment” to run the simulation over the specified projection period and produce information about the stock in its final state.



Stock assessment summary

Mortality estimates

Initial state of stock

	Estimate	St Dev
Total mortality (Z)	0.251	0.011
Fishing mortality (F)	0.150	
Prob F > F limit	1	
Prob F > F target	1	
Prob within 10% F target	0	

Final state of stock

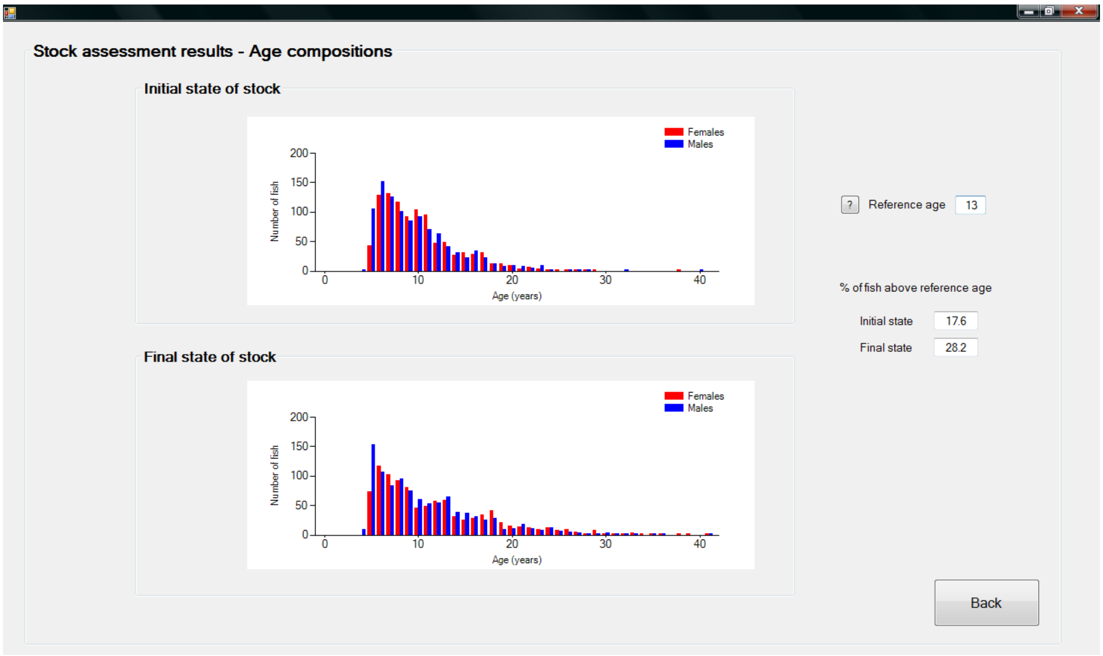
	Estimate	St Dev
Total mortality (Z)	0.157	0.007
Fishing mortality (F)	0.055	
Prob F > F limit	0	
Prob F > F target	0.048	
Prob within 10% F target	0.249	

Reference points

F target: 0.067

F limit: 0.101

16. Example of information produced by catch curve analysis for the stock in its initial and final state. Additional information about the stock in its final state is presented in steps 17-21.



Stock assessment results - Age compositions

Initial state of stock

Final state of stock

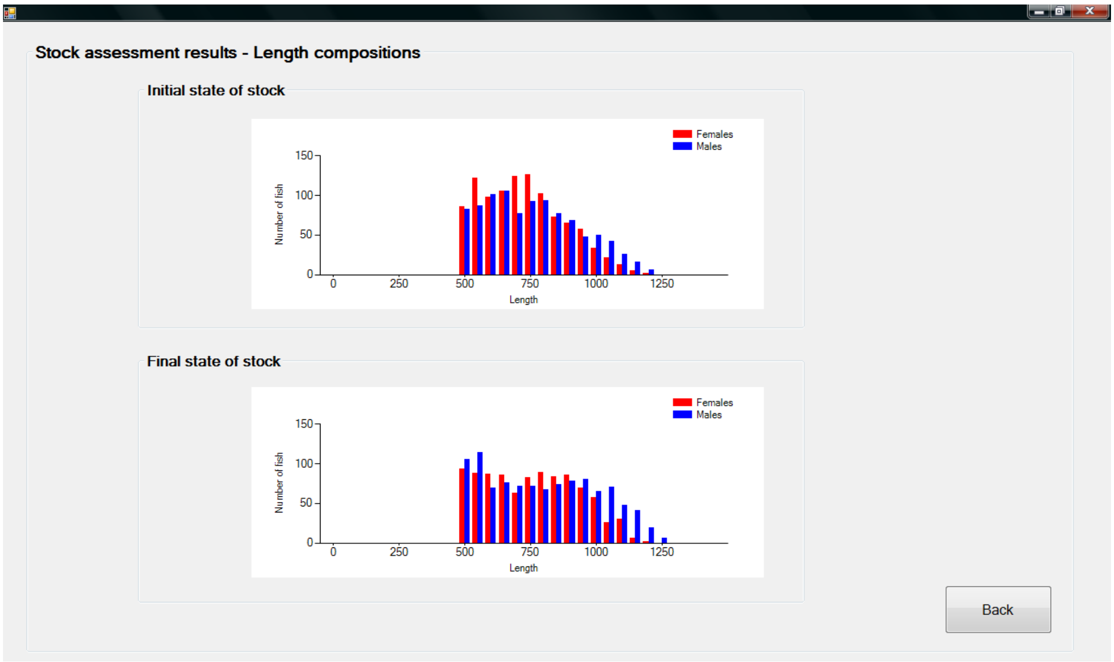
Reference age: 13

% of fish above reference age

Initial state: 17.6

Final state: 28.2

17. Example of age composition sample data for the stock in its initial and final state.

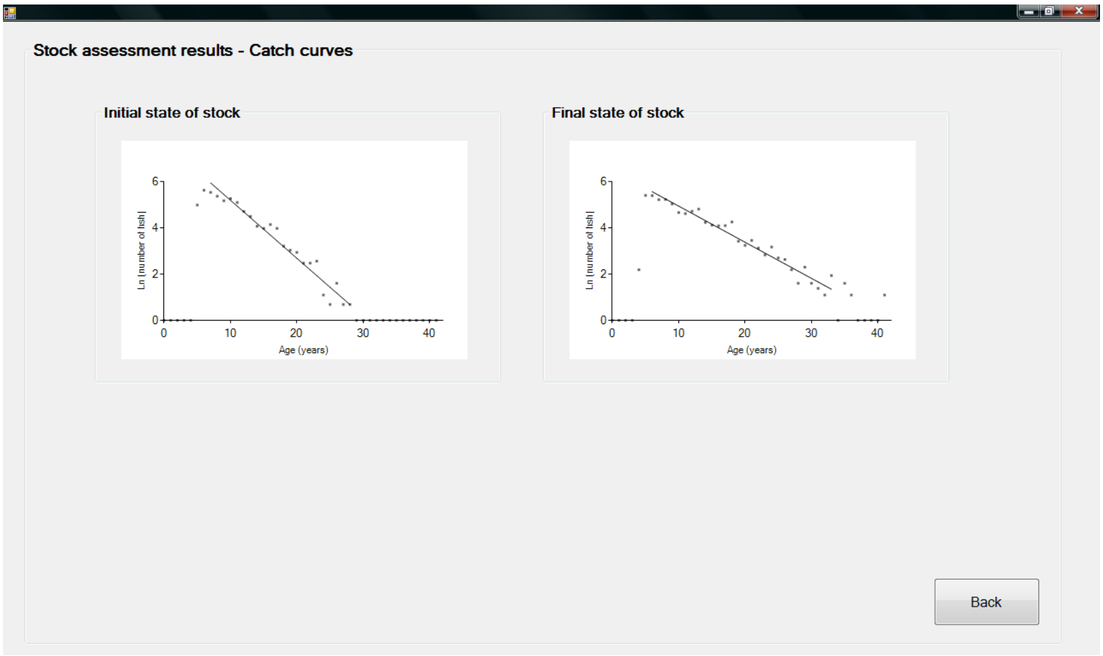


Stock assessment results - Length compositions

Initial state of stock

Final state of stock

18. Example of length composition sample data for the stock in its initial and final state.



Stock assessment results - Catch curves

19. Example of linear catch curve analysis plots for the stock in its initial and final state.

Stock assessment results - Per recruit analysis

YPR

	Initial state		Final state	
	Females	Males	Females	Males
Estimate	544	693	456	603
Prob F > F max	0 .99		0	
Prob F > F targ	1		0 .02	
Prob F within 10% F 0.1	0		0 .04	

SPR (SSB/R)

	Initial state		Final state	
	Females	Males	Females	Males
Estimate	0.257	0.239	0.524	0.507
Prob F > SPR limit	0 .99		0	
Prob F > SPR target	1		0	
Prob F within 10% SPR target	0		0	

SPR (E/R)

	Initial state	Final state
Estimate	0.086	0.335
Prob F > SPR limit	1	0 .24
Prob F > SPR target	1	0 .9
Prob F within 10% SPR target	0	0

YPR - Yield per recruit
SPR - Spawning potantial ratio
SSB/R - Spawning stock biomass per recruit
E/R - Eggs per recruit

Reference points

YPR
F target = F 0.1
F limit = F max

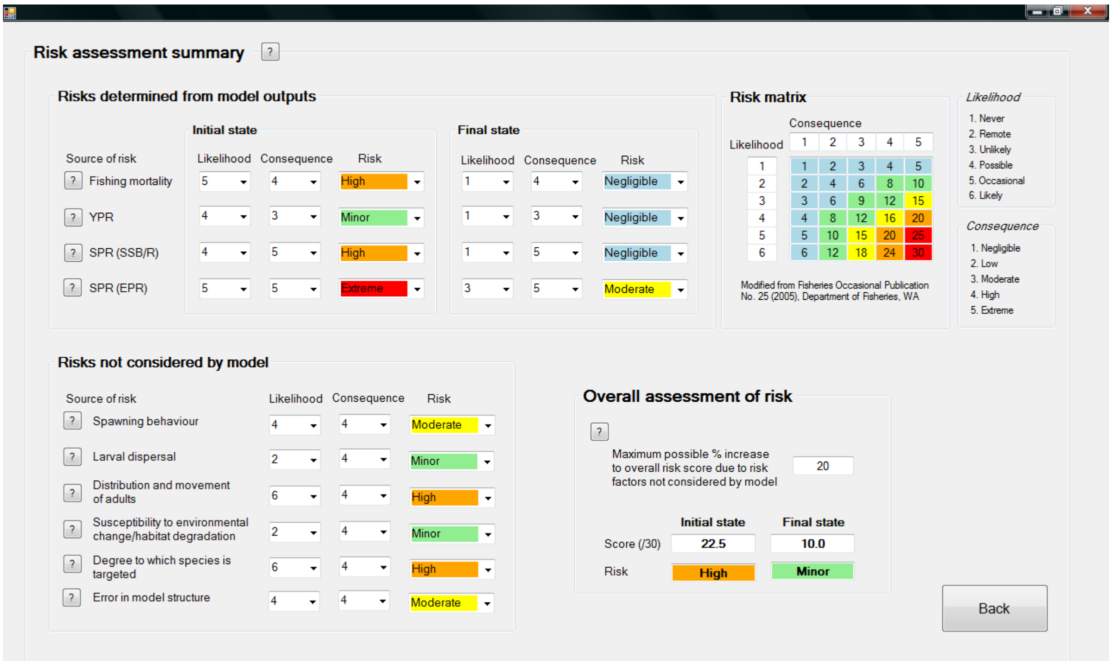
SPR (SSB/R)
F target = F 40%
F limit = F 30%

SPR (E/R)
F target = F 40%
F limit = F 30%

Color indicators for graphs

🟩	Point estimate	< Target ref point
🟨	Point estimate	> Target ref point < Limit ref point
🟥	Point estimate	> Limit ref point

20. Example of results of per-recruit analyses for the stock in its initial and final state.



Risk assessment summary

Risks determined from model outputs

	Initial state			Final state		
Source of risk	Likelihood	Consequence	Risk	Likelihood	Consequence	Risk
Fishing mortality	5	4	High	1	4	Negligible
YPR	4	3	Minor	1	3	Negligible
SPR (SSB/R)	4	5	High	1	5	Negligible
SPR (EPR)	5	5	Extreme	3	5	Moderate

Risk matrix

Likelihood \ Consequence	1	2	3	4	5
1	1	2	3	4	5
2	2	4	6	8	10
3	3	6	9	12	15
4	4	8	12	16	20
5	5	10	15	20	25
6	6	12	18	24	30

Modified from Fisheries Occasional Publication No. 25 (2005), Department of Fisheries, WA

Likelihood

1. Never
2. Remote
3. Unlikely
4. Possible
5. Occasional
6. Likely

Consequence

1. Negligible
2. Low
3. Moderate
4. High
5. Extreme

Risks not considered by model

Source of risk	Likelihood	Consequence	Risk
Spawning behaviour	4	4	Moderate
Larval dispersal	2	4	Minor
Distribution and movement of adults	6	4	High
Susceptibility to environmental change/habitat degradation	2	4	Minor
Degree to which species is targeted	6	4	High
Error in model structure	4	4	Moderate

Overall assessment of risk

Maximum possible % increase to overall risk score due to risk factors not considered by model: 20

	Initial state	Final state
Score (/30)	22.5	10.0
Risk	High	Minor

21. Example of risk assessment information for the stock in its initial and final state.

Notes on risk assessment approach

The methods used by the MSE model to provide risk assessment information are adapted from those described for an ecological risk assessment for the western rock lobster *Panulirus cygnus* (Department of Fisheries, Western Australia, 2005). The levels of risk that various "hazardous events" may pose to a fish stock are estimated according to the likelihoods of those events occurring and the levels of consequence of their occurrence. The likelihood of an event occurring is given a score ranging from 1 (never) to 6 (likely), and the level of consequence of an event is given a value ranging from 1 (negligible) to 5 (extreme). The product of the two values provides a risk score for each hazard (see risk matrix in figure above).

The risk assessment is separated into two parts; one with the risk factors that are considered by the MSE model (*i.e.* level of fishing mortality, yield per recruit, spawning biomass per recruit and eggs per recruit), and another with risk factors which are not addressed in the model itself but are subjectively specified. These include various characteristics of the fish species (spawning behaviours, larval dispersal *etc.*), as well as error in the MSE model structure. For hazardous events that are related to fishing mortality-based reference points (as assessed by the MSE model using catch curve and per-recruit analyses), the likelihood of an event occurring is calculated according to different conditions (Table B.2), whilst those not considered by the model are specified subjectively. For all hazards, scores for the levels of consequence are subjectively assigned a value.

The risk scores for the hazardous events associated with fishing mortality reference points are averaged, as are also those for the other identified hazards. An overall risk score is calculated by adding the average risk score for the hazards considered by the model to 20% of the average risk score for the subjectively addressed hazards.

Table B.2. Conditions applied to determine the likelihoods of hazardous events associated with reference points based on fishing mortality (*F*) in the risk assessment approach used in the MSE model.

Condition	Likelihood of event occurring	Score
Probability of F exceeding $F_{\text{target}} = 0$	Never	1
Probability of F exceeding $F_{\text{target}} > 0.5$	Remote	2
Probability of F exceeding $F_{\text{target}} = 1$	Unlikely	3
Probability of F exceeding $F_{\text{limit}} > 0$	Possible	4
Probability of F exceeding $F_{\text{limit}} > 0.5$	Occasional	5
Probability of F exceeding $F_{\text{limit}} = 1$	Likely	6

REFERENCES

Aanes, S. and Pennington, M. (2003). On estimating the age composition of the commercial catch of Northeast Arctic cod from a sample of clusters. *ICES Journal of Marine Science* **60**, 297-303.

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