

The effect of multiple uncertainties on the performance of bioeconomic models for fishery management

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Declaration of Originality

I, Eriko Hoshino, hereby certify that this thesis has been written by me, that it is the record of work carried out by me and that it has not been submitted in any previous application for a higher degree.

Abstract

An approach known as management strategy evaluation (MSE) provides a framework for identifying robust management strategies in the presence of multiple management objectives and system uncertainties, and has been increasingly used as a practical fisheries management framework in recent years. However, few examples exist that incorporate economics in MSEs. Meanwhile, there has been increased attention given to economic instruments for sustainable management of fishery resources, including the use of bioeconomic target reference points (RPs). However, investigation of the causes of errors and bias in the estimates of bioeconomic parameters is scarcely documented compared to their biological counterparts, and the implications of simplified assumptions concerning both the biological and economic parts of the bioeconomic models have not been adequately investigated.

In this thesis, I used three case study fisheries to illustrate how economics can be explicitly integrated within the MSE framework, and demonstrated the usefulness of this flexible approach as a rigorous tool for the evaluation of the effect of uncertainties in key parameter estimates from bioeconomic fisheries models, as well as highlighting the merits of including economics in MSE in general. The interaction between life history characteristics, fisheries variables and economic systems strongly affect the behaviour and robustness of the bioeconomic target RPs for the case studies fisheries. It was clear from these examples that the MSE approach has the potential to radically improve the robust estimation of bioeconomic RPs as well as the construction, evaluation, and implementation of economically-oriented harvest strategies.

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Chapter 1. Introduction

1.1 Problem statement

Management failures and a paradigm shift

Globally some 120 million people are directly dependent on capture fishing and post-harvest industries for their livelihoods (World Bank et al. 2010). However, the world's fisheries are in crisis as a result of overfishing and overcapacity of fishing fleets (Clark 2006). The 2005 Millennium Ecosystem Assessment Report regarded marine and coastal ecosystems as one of the most deteriorated ecosystems in need of immediate conservation attention. According to the Food and Agriculture Organisation of the United Nations (FAO), out of the 441 stock or species groups where assessment information was available, approximately 25% are considered overexploited or depleted and an additional 52% are fully exploited, 20 % are moderately exploited, and 3 percent are underexploited (FAO 2005a). Numerous scientific and popular articles have pointed to the failures of fisheries management that have caused this crisis (Beddington et al. 2007). The FAO (1995c) has identified three major causes of management failure in fisheries: (i) institutional inability to implement scientific recommendations; (ii) economic or environmental forces beyond the control of industry or management; and (iii) failure to recognize uncertainty and errors in stock assessment. Some examples of management failures resulting from uncertainties in stock assessment include the Canadian northern cod stock and the Peruvian anchoveta stock, where errors in the estimation of stock abundance and subsequent predictions of large sustainable yields resulted in the rapid reduction of these stocks (Hilborn and Peterman 1995).

The traditional approach to fishery resource management is first to determine “optimal” level of harvests or fishing efforts, and then to control fishing to achieve that objective. However, to quote Clark (2006), this approach has “*often failed to prevent overfishing.*” Maximum equilibrium yield, commonly known as the Maximum Sustainable Yield

(MSY) is one such example of an equilibrium policy that has been adopted widely as a primary objective of fisheries management since the 1950s (see Chapter 2). After the management failure of some well-known stocks in the 1990s, such as the Newfoundland cod fishery for example, fisheries management has undergone a paradigm shift from the "equilibrium" approach with a single (optimal) objective to an approach with multiple objectives that may be sub-optimal but are robust to various types of uncertainties. An approach known as management strategy evaluation (MSE) provides a framework for identifying robust management strategies as well as for sensibly comparing alternative strategies in the presence of multiple management objectives and system uncertainties (Kirkwood and Smith 1996; Cooke 1999). MSE has been increasingly used in general fisheries modelling and actual management of fish stocks (Kirkwood and Smith 1996; Butterworth and Punt 1999; Punt and Smith 1999; De Oliveira and Butterworth 2004; Campbell 2005; Butterworth et al. 2010). However, very few examples exist that incorporate economics (Dichmont et al. 2008; Holland and Herrera 2009; Punt et al. 2010).

Shift from managing the resource to managing resource users

Fisheries economists have long argued that the biomass that produces the largest discounted economic profits from fishing (B_{MEY}) is normally greater than the biomass that maximises the sustainable yield (B_{MSY}), as has been repeatedly demonstrated in the literature (Clark 1990; Grafton et al. 2007). Given the perceived failure of biologically oriented management, there has been increased attention given to instruments that provide appropriate social and economic incentives for sustainable resource use, including the Maximum Economic Yield (MEY) that aim to constrain the long-term equilibrium output (or effort) to levels that maximise the expected economic net returns from a fishery. Dichmont, et. al. (2010) argue that fisheries management has been experiencing “a *paradigm shift from a focus on managing the resource to a focus on managing resource users*,” as evident from the recent adoption of MEY as an Australian Commonwealth fisheries policy, and its consideration elsewhere (Dichmont et al. 2010). However, unlike biological target reference points (TRPs) such as MSY, that have been adopted widely and whose limitations have been well documented, bioeconomic TRPs

such as MEY have rarely been operationalised and there is limited real world experience of their use, with the Australian Northern prawn fishery being the first attempt at estimating MEY as an actual management target (Dichmont et al. 2010). Moreover, investigation of the causes of errors and bias in the estimates of bioeconomic TRPs is scarce compared to their biological counterparts, and the effects of simplified assumptions concerning both the biological and economic parts of the bioeconomic models have not been adequately investigated.

1.2 Aims and objectives

The aim of my thesis is to develop a bioeconomic MSE framework to i) investigate the errors and bias in the estimates of bioeconomic TRPs and demonstrate the risks of neglecting various types of uncertainties in this traditional equilibrium approach, using the examples of three fisheries targeting contrasting life history traits, and ii) to demonstrate the merits of incorporating economics into MSEs.

These aims are met through the following objectives:

1. Estimate bioeconomic TRPs (in terms of economically optimal levels of effort, harvest and biomass) in selected case study fisheries targeting both short-lived and long-lived species using standard bioeconomic models, and illustrate the relative robustness of model results for different life histories.
2. Develop bioeconomic operating models to test the performance of alternative management procedures based on bioeconomic TRPs for several case study species in a simulation-based MSE compared to the existing harvest control rules derived from traditional stock-based TRPs, using multiple performance criteria.
3. Extend the bioeconomic operating models to explore the limitations and biases of standard bioeconomic analyses; to determine whether simple bioeconomic models are capable of summarising the dynamics of a complex system and to what degree of accuracy; and to explore the implications of my findings for the development

of efficient management systems for fisheries.

My thesis fills the gap of the lack of substantive economics in MSEs, and the gap between the theoretical work done to estimate bioeconomic TRPs (such as MEY) and the operationalisation of these TRPs in the management of real fishery systems.

1.3 Case studies

I examine three case studies in two different geographic areas. Two of the case studies focus on Japanese fisheries targeting short-lived, highly fluctuating stocks, the Japanese common squid *Todarodes pacificus* and Pacific saury *Cololabis saira*, where recent profits from the fisheries have been minimal or negative; while the third is the long-lived, slow growing Patagonian toothfish *Dissostichus eleginoides*, and the associated highly profitable toothfish fishery in the island of South Georgia in Antarctic.

Table 1-1: List of Case Studies

Case	Fishery	Target Species		Gear	Area	Economics
1	Japanese common squid fishery	<i>Todarodes pacificus</i>	Pelagic	angling	Japan	Low profitability
2	Pacific saury fishery	<i>Cololabis saira</i>	Pelagic	stick-held dip net	Japan	Low profitability
3	Patagonian toothfish fishery	<i>Dissostichus eleginoides</i>	Demersal	longline	South Georgia	High profitability

Each case study has its own specific objectives, such as evaluating the performance of input-based control measures as an alternative to the current management regimes, as well as contributing to the objectives of the thesis as a whole.

1.4 Structure of the thesis

This thesis consists of seven chapters.

In Chapter 2, I provide background and literature reviews on three closely related topics that are central to my research: 1) the standard equilibrium approach in fisheries management; 2) the management issues arising from the standard approach; and 3) an alternative - the simulation-based modelling approach known as Management Strategy Evaluation (MSE). I do not aim to provide a comprehensive literature review on the applications of these approaches, but rather to explain the basic concepts and provide some examples of their applications in the management of fisheries resources. I then summarise the three case study fisheries, giving descriptions of historical trends in abundance of the stocks and their management.

The next chapter (Chapter 3) provides a case study for developing a framework for MSEs of short-lived exploited species, using the examples of the fisheries for Pacific saury *Cololabis saira* and Japanese common squid *Todarodes pacificus* off the coast of Japan. These fisheries are currently managed by a total allowable catch (TAC) system based on the MSY principle, which makes implicit assumptions concerning the deterministic and stable nature of harvested populations. However, short-lived pelagic stocks do not fulfil such assumptions, and adopting constant harvesting policies based on MSY may be impractical, potentially leading to economic inefficiencies or resource depletion. In this chapter, I develop an adaptive management framework, as opposed to traditional fixed input/output policies, for these stocks. As the fisheries targeting these stocks have been suffering from low profitability, the goal is to identify strategies which make the fisheries more profitable and maintain the sustainability of the resources. This approach is potentially useful for other stocks with similar biology.

Chapter 4, in contrast, develops an MSE framework for long-lived species, using the example of the Patagonian toothfish (*Dissostichus eleginoides*) fishery around the island of South Georgia. This chapter proposes an economically optimal harvesting strategy which would maximise the long-term economic returns from the fishery, and compares it to the current biologically-focused management target set by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR). It also investigates gradual effort reduction paths designed to achieve economically optimal conditions over

CCAMLR's management time-frame of 35 years.

Using the case studies fisheries presented in Chapter 3 and 4, the next two chapters (Chapter 5 and 6) explore and compare the implications of multiple uncertainties for the reliability of the estimates from bioeconomic fisheries models; and for their utility in providing robust economically-based management advice. In Chapter 5, the primary emphasis is on the effect of life-history and of biological structural uncertainties, reflecting a lack of knowledge about the nature of the fishery system, on the predictions of bioeconomic models. In contrast, Chapter 6 primarily focuses on economic structural uncertainties.

Chapter 7 brings the themes of the previous chapters together to provide discussions and recommendations for future research. It is abundantly clear that the MSE approach has the potential to radically improve the estimation of bioeconomic reference points as well as the construction, evaluation, and implementation of economically-oriented harvest strategies.

Chapter 2. Background to the literature and case studies

This Chapter provides background information and literature reviews on three closely related topics that are central to the theme of this thesis: 1) the standard equilibrium approach in fisheries management; 2) the management issues arising from the standard approach; and 3) an alternative - the simulation-based modelling approach known as Management Strategy Evaluation (MSE). The Chapter does not attempt to provide a comprehensive literature review on the applications of these approaches, but rather explains the basic concepts, provide some examples of their application in the management of fisheries resources, and identify the gaps in the current research in bioeconomic MSE. The second part of this chapter provides overviews of the three case study fisheries.

Part 1: Literature Review

2.1 Equilibrium approach to fisheries management

The equilibrium approach, and the idea of maximum sustainable yield (MSY) in particular, has played a central role in fisheries management for more than 5 decades. Although its uses and applications have changed over time, to some extent it remains as a key paradigm in fisheries management (Punt and Smith 2001; Hilborn and Stokes 2010). This section provides a brief history of how this key paradigm has evolved, and demonstrates the links to other closely related important concepts in fisheries management, including maximum economic yield (MEY), fisheries reference points, and the precautionary approach.

2.1.1 Management objectives and the concept of MSY

Traditionally, a primary objective of fisheries management has been to exploit the

largest possible catch which is nevertheless sustainable in the long term, i.e. catch at a level equal to MSY. The foundations of the concept of MSY were laid in the 1930s (Russell 1931; Hjort et al. 1933; Graham 1935). It gained popularity in the 1950s with the advent of the surplus-production approach, which explicitly estimates MSY (Mace 2001), initially developed by Schaefer (1954), and the yield-per-recruit approach developed by Beverton and Holt (1957). The 1950s is regarded as the “*golden age for the concept of MSY*” (Larkin 1977). MSY was recognised as the basic objective in fisheries management in the 1958 United Nations Conference on the Law of the Sea (Mardle et al. 2002). MSY was also adopted as a primary management goal by several regional fisheries management organisations (e.g. International Whaling Commission, Inter-American Tropical Tuna Commission, International Commission for the Northwest Atlantic Fisheries) as well as individual countries (Mace 2001). MSY achieved worldwide recognition and adoption after being advocated in the 1982 United Nations Convention on the Law of the Sea (UN 1983), followed by the 1992 “Rio Declaration” and the 2002 World Summit on Sustainable Development (WSSD) Implementation Plan (WSSD 2002). The Food and Agriculture Organizations of the United Nations (FAO) also gave considerable support and emphasis to management based on MSY (Punt and Smith 2001).

Criticisms of MSY

While MSY as a management objective was incorporated in the major international agreements and policy agendas, by the 1970s the scientific community was beginning to question the appropriateness and effectiveness of MSY as a management goal (Gulland and Boerema 1973; Doubleday 1976; Beddington and May 1977; Larkin 1977; Sissenwine 1978). Punt and Smith (2001) divided the criticisms of MSY into three categories: i) the ability to estimate MSY given uncertainty regarding models and data; ii) appropriateness of MSY as a management goal given other objectives for management; and iii) the ability to implement a harvest strategy based on MSY. The first category of criticism largely stems from the “steady-state” (equilibrium) assumption of the model in estimating MSY, while in reality fish populations are seldom at equilibrium (Sissenwine 1978; Caddy and Gulland 1983). Other problems include statistical difficulties in

parameter estimation (e.g. regressing the catch-per-unit-effort on fishing effort), lack of reliable information of catch and effort, and growth data (e.g. growth rates and the shape of the stock-recruitment relationship), and lack of consideration of random fluctuations (Beddington and May 1977; Larkin 1977; Sissenwine 1978). Moreover, MSY is basically a single-species concept, and setting a single-species quota for multi species fisheries has promoted catch misreporting and discarding (Caddy 1999). The main issues in applying this traditional equilibrium approach to the actual management of fisheries are outlined in Section 2.2.

2.1.2 The concept of MEY

Economists have long argued that a harvest policy based on MSY is misleading and undesirable from an economic perspective. Graham (1935) pointed out that the same equilibrium catch could be taken at two different levels of effort, opening the way for economic analysis (Larkin 1977). Scott Gordon (1954) argued that the optimal allocation of fishing effort to a fishery would occur at the point at which marginal cost equals marginal revenue, so resource rent is maximised. This point is referred to as the maximum economic yield (MEY) level (Gordon, 1954; Anderson, 1986). The Gordon-Schaefer model shows that in the absence of any controls or property rights, and with positive harvesting costs, the bionomic equilibrium (the point at which total revenue equals total cost) of fishing effort, E_{∞} , exceeds both E_{MEY} (denoted as E^* in Figure 2-1), the effort which maximises the net profits from a fishery, and E_{MSY} . Economists pointed out that if harvesting costs rise as population size declines, a rent maximising policy will automatically lead to biological conservation, with an equilibrium population in excess of the population corresponding to MSY. However, Clark (1973a, b) demonstrated that a rational sole owner of a fishery could deliberately drive the resource to extinction under certain conditions (including invariant costs relative to population size, and high discount rates), using whale stocks and demersal stocks on the George Banks as examples.

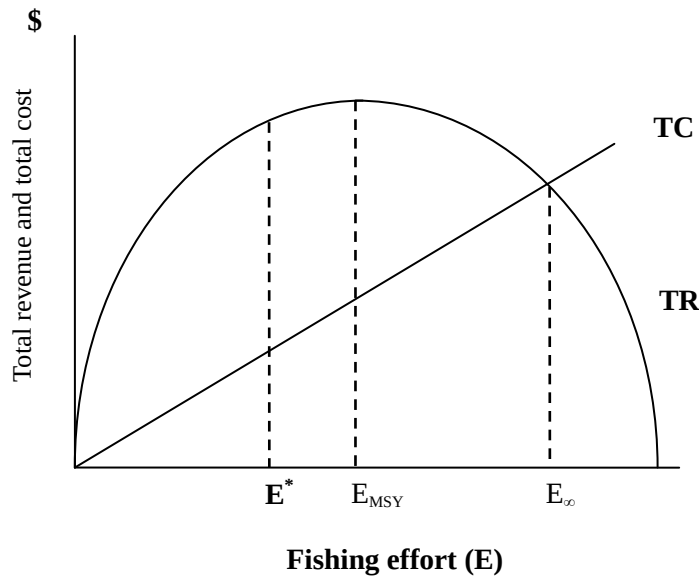


Figure 2-1: The Gordon-Schaefer model (sustainable yield-effort curve). E^* is the optimal effort, where the distance between TR (total revenue) and TC (total cost) is maximised, hence maximising profits. E_{MSY} is the effort which gives MSY, and E_∞ is the open access effort where profits are zero.

While the static Gordon-Schaefer model provides insights into equilibrium conditions, it does not consider the “optimal path” to get to the rent maximising levels of biomass, nor does it consider the consequences of discounting (Grafton et al. 2004). Fisheries in the real world are dynamic systems in which individual fishers respond to changes in parameters such as the cost of fishing and price of fish. In the 1970s, economists began to question the adequacy of the static model, since extinction is theoretically impossible with this model as well as it did not explain the apparent decline in some fishery stocks (Clark 1973a). Capital theory was integrated into the economics of fisheries by Clark by the mid 1970s, including an article with Munro (Clark and Munro 1975) and his famous book, “*Mathematical Bioeconomics*” (Clark 1976). He argued that society’s basic resource management problem is to determine the optimal consumption (harvest) time path with the objective of maximising the social utility from the stock, based on the assumption that society is willing to make current sacrifices to benefit future generations. He then showed how to derive an analytical solution to the dynamic optimisation problem (in terms of the time-path indicating the optimal amount to be extracted in each period) using the “maximum principle” (Bellman 1957; Pontryagin 1962). Bjørndal and

Munro (1998) later noted that the shift from static to dynamic economic models of the fishery occurred with the advent of optimal control theory, which made the dynamic models tractable, “*not because of a sudden revelation about the inadequacies of the static model.*”

Meanwhile another alternative concept, known as “optimal yield”, was introduced by Roedel (1975). It is defined as a deliberate modelling of biological, economic, social and political values designed to produce the maximum benefit to society from a given stock of fish. Although it was intended to integrate environmental and socio-economic considerations into the MSY concept, optimal yield was never used to a great extent as the definition was too vague so that no agreement could be reached on how to estimate it (Garcia 1996).

The 1980s and 1990s saw the introduction to fisheries management of three closely linked concepts: fisheries reference points, the precautionary approach, and feedback control decision rules; each of these have had an important impact on the utility of MSY in fisheries management (Punt and Smith 2001).

2.1.3 The concept of reference points

A reference point (RP) is defined as “*a conventional value derived from technical analysis, which represents a state of the fishery or population and whose characteristics are believed to be useful for the management of the unit stock*” (Caddy and Mahon 1995). A target reference point (TRP) indicates a state of a fishery corresponding to a situation considered as “desirable”, while limit reference point (LRP) and threshold reference points\ (ThRP) are indicative of a state corresponding to an “undesirable” situation (Garcia 1996). The three key RPs around maximum sustainable yield are the MSY itself, the biomass that produces MSY (B_{MSY}), and the fishing mortality rate that produces MSY (F_{MSY}). F_{MSY} can be converted to the effort that produces MSY (E_{MSY}) if the catchability coefficient is known.

Their economic counterparts, MEY, E_{MEY} , B_{MEY} and F_{MEY} , are defined as the optimal

(economically efficient) levels of yield, effort, biomass and mortality in a static sense, where total sustainable net returns from a fishery are maximised (Anderson and Seijo 2010). They are called bioeconomic RPs (Defeo and Seijo 1999), also referred to as economic RPs (Caddy and Mahon 1995) or bioeconomic indicators (Seijo and Caddy 2000).

The earlier biological F -based RPs, such as F_{MSY} and F_{MAX} (the level of fishing mortality which maximises the average yield from each recruit entering the fishery) were found often to give values of fishing mortality that were too high for the fishery to be sustainable (Gulland and Boerema 1973; Deriso 1987; Sissenwine and Shepherd 1987). Doubleday (1976) argued that aiming at 2/3 of the effort that produces MSY as a target RP would reduce risk of stock collapse. Gulland and Boerema (1973) suggest that the use of $F_{0.1}$, the fishing mortality at which the slope of the yield-per-recruit-curve is 10% of the slope at the origin, is a more appropriate target RP, given that it is roughly equivalent, in terms of effort exerted, to the economists' F_{MEY} . The use of $F_{0.1}$ rapidly spread through fisheries assessment and management (Sainsbury and Polacheck 1993).

One of the major limitations of biological RPs based on yield-per-recruit analyses such as F_{MAX} and $F_{0.1}$ is that the effects on both the spawning population and the related recruitment levels are essentially ignored (Quinn and Deriso 1999). Since the 1980s, a wide variety of recruitment-based RPs derived from spawning biomass per recruit (SPR) and spawner-recruitment data have been developed (Shepherd 1982; Beddington and Cooke 1983; Sissenwine and Shepherd 1987; Mace and Sissenwine. 1989; Goodyear 1993; Mace and Sissenwine 1993; Myers et al. 1994).

There are numerous alternative benchmarks at lower rates of fishing (see Caddy and Mahon 1995, Garcia 1996, and Gabriel and Mace 1999). However, Garcia (1996) noted that these alternatives are “*yet to be formally agreed and codified, so MSY remains a necessary universal benchmark*”. In fact, MSY was not abandoned by scientific communities despite the continuous debates, but instead its role appears to have shifted from a management target to an “upper limit” since the introduction of precautionary

principles in the 1990s.

2.1.4 Precautionary principles

By the 1990s, both scientific communities and decision makers became aware of the problem of uncertainties in stock assessments and associated recommendations for management measures. As several well-known stocks have collapsed despite the effort to manage them sustainably, “precautionary principles” became prevalent.

Principle 15 of the Rio Declaration of the UN Conference on Environmental and Development (UN 1992) states that the States shall apply the precautionary approach widely and the lack of full scientific certainty should not be used as a reason for postponing cost-effective measures to prevent environmental degradation. Following the Rio Declaration, the precautionary approach was adopted in the 1995 FAO International Code of Conduct for Responsible Fisheries (the Code). The General Principles and Article 6.5 of the Code prescribe a precautionary approach to all fisheries regardless of their jurisdictional nature. The Code further outlines the uncertain factors to be considered when implementing the precautionary approach, including size and productivity of stocks, levels and distribution of fishing mortality and species interactions, discards of non-target species as well as environmental and socio-economic factors (FAO 1995b).

Annex II of the 1995 UN Straddling Stocks Agreement (UN 1995) defined two “precautionary reference points”: limits and targets RPs. The Agreement states that F_{MSY} should be regarded as a minimum standard for limit reference points, while B_{MSY} for overfished stocks can act as rebuilding target (UN 1995). The concept of F_{MSY} as a limit was incorporated into the US Magnuson-Stevens Fishery Conservation and Management Act (Mace 2001).

Several alternative definitions for MSY which incorporate the precautionary principle have also been developed. For example, in New Zealand, two alternative definitions for MSY, called “maximum constant yield (MCY)” and “maximum average yield (MAY)”

were introduced. MCY is defined as the maximum constant catch that is estimated to be sustainable, with an acceptable level of risk, at all future levels of biomass, while MAY is defined as the maximum average catch that arises from applying a constant level of fishing mortality (Annala 1993). The calculation of MAY and MCY are based on models that allow for variability in recruitment (Punt and Smith 2001).

2.1.5 Types of uncertainties

Uncertainties in fisheries can be grouped into three major categories: (1) random fluctuations; (2) uncertainty in parameter estimates and states of nature; and (3) structural uncertainty that reflects a basic lack of knowledge about the nature of the fishery system or misunderstanding about variable choice and model form (Walters and Hilborn 1978; Charles 1998). Caddy and Mahon (1995) and Kell et al. (2007) provided more detailed classes of uncertainties in fish stock assessment and management. They are:

- process error—caused by disregarding variability, temporal and spatial, in dynamic population and fishery processes;
- observation error—sampling error and measurement error;
- estimation error—arising when estimating parameters of the models used in the assessment procedure;
- model error—related to the ability of the model structure to capture the core of the system dynamics;
- implementation error—where the effects of management actions may differ from those intended.

The model error in this classification reflects the misspecification of model structure and is equivalent to structural uncertainty in the earlier classification, although some authors refer to model error as potentially relating to both structural and parameteric uncertainty. In fact, many of these error types are interdependent and cannot always be decomposed in constituent types (Kell et al. 2007).

Since the 1990s, considerable progress has been made in incorporating uncertainty into

fisheries research, and estimates of the uncertainty surrounding stock assessments have become integral components of the scientific advice given to decision makers. Formal risk assessments are routinely incorporated in many stock evaluations in the United States, Canada, Europe, and New Zealand (Rosenberg et al. 1993). A wide range of uncertainties, including observation, process, model and implementation uncertainty, are all now included regularly when evaluating management procedures (Punt 2006).

2.1.6 Bioeconomic models under uncertainty

Uncertainty was introduced into bioeconomic models in the early 1970s, around the same time as the MSY concept was coming under heavy criticism. A review of the literature on stochastic bioeconomics is given by Andersen and Sutinen (1984) and more recently by Nøstbakken and Conrad (2007). A comprehensive survey of stochastic bioeconomic models is out of the scope of my thesis, but here I present a brief overview of the uncertainties that have been dealt with using stochastic bioeconomic models.

2.1.6.1 Dealing with fluctuating stocks

The problem of determining an optimal harvest policy for fluctuating stocks of a fishery resource has been addressed by various authors in the fisheries economics literature, including Ludwig (1979), Reed (1979), Lewis (1981), Kirkwood (1986), and Costello et al. (1998; 2001). There have been extensive arguments over whether deterministic bioeconomic models provide good approximations to stochastic models under uncertainty, and whether a constant-escapement (measured stock minus fixed harvesting quota to leave a fixed number of breeding individuals at the end of the fishing season) policy is optimal under a stochastic system.

Reed (1979) used a stochastic stock-recruitment model and showed that when unit harvesting costs satisfy certain conditions, a constant-escapement policy maximises the expected present value of economic rents. He compared the optimal escapement in this model with that in the corresponding deterministic model, and concluded that in most cases, the optimal stochastic escapement is no less than the optimal deterministic escapement. Based on the work by Ludwig (1979) and Smith (1980), Andersen and

Sutinen (1984) concluded that deterministic policies are reasonably good substitutes for stochastic policies on average.

Clark and Kirkwood (1986) modified Reed's model by introducing the assumption that the recruitment level is not known accurately prior to the harvest (due to measurement errors), and showed that constant escapement policies are not optimal, unlike in the original Reed model. Interestingly, they found that the optimal policy is not always more precautionary than the constant escapement policy, with rare cases where the optimal strategy was to harvest the population to extinction. By contrast, some studies suggest a conservative harvesting strategy is optimal under uncertainty. For instance, Lewis (1981) investigated the effects of both stock size and price uncertainty on the optimal harvest of the Eastern Pacific yellowfin tuna fishery, and found the optimal strategy became more conservative when uncertainties in prices, growth and catch rates were greater, with the effect of reducing downside fluctuations in population size. Costello et al. (1998) used dynamic programming to investigate the economic gains from improving El Nino forecasts in the management of coho salmon in the Pacific Northwest. They concluded that a constant escapement rule was not optimal, and optimal management in the face of uncertainty involved a more conservative management strategy. Saphores (2003) noted that uncertainty does not lead to a monotonic change in the optimal harvest rate. Rather, increases in uncertainty at low levels lead to conservative behaviour, but at high levels of uncertainty the possibility of extinction leads to more aggressive harvests because the resource has no existence value when uncertainty was high enough and extinction became optimal (Saphores 2003). A study of optimal resource allocation for terrestrial species with high extinction risks came to a similar conclusion (Possingham et al. 2002).

While many studies have attempted to find the optimal harvesting strategy with stochastic stock growth or other single sources of uncertainty, relatively few studies have attempted to incorporate multiple uncertainties simultaneously (Nøstbakken 2006). Following several instances of fisheries closure along the US Atlantic Coast in the 1990s due to the collapse of fish stocks, Roughgarden and Smith (1996) introduced three sources of uncertainty into bioeconomic models - environmental variability which affects stock

growth rates, stock measurement error, and inaccurate implementation of harvest quotas - and investigated how these uncertainties affected optimal strategies and the risk of collapse, using the Newfoundland cod fishery as an example. They suggested that ignoring uncertainty can lead to the collapse of fish stocks and that the constant-escapement level should be as high as 75% of carrying capacity. It is important to note that they implicitly assumed that a constant escapement policy was optimal.

Sethi et al. (2005) challenged the approach and conclusions of Roughgarden and Smith (1996) by examining whether the constant escapement policy is, in fact, optimal under these three sources of uncertainty. They explored low uncertainty; a single source of high uncertainty; and multiple sources of high uncertainty. They found that a constant-escapement policy is appropriate only if there is high uncertainty in growth or implementation, while higher measurement errors imply lower expected escapement, suggesting that the constant-escapement policy is not optimal. Moreover, they found that the combination of high uncertainties in both growth and implementation did not lead to a significant change in the optimal escapement policy, while including all three uncertainties at a high level changed the optimal conditions significantly.

2.1.6.2 Dealing with fluctuating prices and costs

Uncertainty in economic variables, such as output prices (Lewis 1981; Pindyck 1981; Andersen 1982; Pindyck 1984; Clark 1985; Hanson and Ryan 1998; Sandberg 2005; Nøstbakken 2006) and extraction costs (Reed 1974, 1979; Lewis 1981; Spulber 1982; Defeo and Seijo 1999), has also been studied. Assumptions concerning price fluctuations are generally either purely random (e.g. Anderson 1982) or follow a Wiener processes with drift (growth or decline on average), a random walk through time (e.g. Pindyck 1981), or extensions of the two (Hanson and Ryan 1998, Nøstbakken 2006). Hanson and Ryan (1998) incorporated uncertainty in both population size and price, assuming that price variation comprised a combination of small continuous-time fluctuations (following a Brownian motion/Wiener process) and occasional large random changes. They found that random price fluctuations that include large inflationary increases against a

background of continuous inflationary growth strongly affect optimal returns but have a much less significant impact on optimal effort. Nøstbakken (2006) studied regime switching in a fishery subject to price and stock uncertainty, while making the additional assumption that changing the harvest rate incurs fixed adjustment costs. She concluded that with stock and price uncertainty there is no steady-state and it is optimal to switch back and forth between minimum and maximum harvest rates. In many cases, price has been treated as exogenous and therefore it was assumed that the quantity harvested had no effect on the price, although some authors assumed that the price was endogenous and stochastic, and incorporated an inverse demand function with uncertainty (Pindyck 1984; Campbell et al. 1993; McDonald et al. 2002; Kugarajh et al. 2006).

Reed (1979) investigated the impacts of the cost function on optimal escapement levels, and concluded that unit harvesting costs which vary with population abundance can be important in determining the relative sizes of the optimal escapements. Lewis (1981) analysed the effect of increased uncertainty about the extraction costs, resource prices and future stock size on optimal conditions, and concluded that “cyclical fishing” (also known as “pulse fishing”), where a large effort is allocated when the population is large and the fishing is closed as the population decreases, is optimal for situations of decreasing average costs of effort over time. Based on the work by Reed and Spulber, Andersen and Sutinen (1984) conclude that the structure of harvest costs is a principal determinant of expected difference between stochastic and deterministic outcomes.

2.1.6.3 Other uncertainties

Although stochastic bioeconomic models can integrate over several sources of uncertainty, these models alone cannot be used to explore robustness to other types of uncertainty, such as structural uncertainty (see Chapter 5 for detail discussion). Indeed, the most recent survey of stochastic bioeconomic models by Nøstbakken and Conrad (2007) acknowledged that the most bioeconomic models developed to date focused on the uncertainties related to random effects and parameters.

Despite the various examples above, the assumption of constant cost and price over time

still dominates bioeconomic fisheries models. Most of the past studies using stochastic bioeconomic models appear to focus on how the magnitude of the uncertainty, or different types of errors, affect optimal conditions in a theoretical setting, with few empirical examples or real-world simulations being carried out. Where empirical examples do exist, less attention has been paid to the differences in the life history characteristics of the fish or the interaction between these characteristics and fisheries variables. Moreover, the objective in most literature is to maximise “expected” or mean present values of future benefits, thus ignoring the probabilistic distribution of optimal conditions. More than 10 years ago, Seiji et al (1998) noted “*the incorporation of risk and uncertainty in bioeconomic modelling and a formal decision analysis has been scarcely documented in the fisheries literature.*” Unfortunately, this observation appears to remain true even now. This is perhaps because there is limited real world experience of the use of bioeconomic RPs as targets, compared to biological RPs. Recently, Dichmont et al. (2010) reported the first attempt at estimating MEY as an actual management target for the Australian Northern prawn fishery, and highlighted substantial complexities “*generally unconsidered by fisheries economists*” which made it difficult to operationalise MEY in a real fishery.

2.2 Management issues under the traditional equilibrium approach

In this section I present some examples of fisheries management issues arising from applying the traditional equilibrium approach to real fisheries. Since the management issues are different for species with different life histories, the section briefly describes the characteristics of fisheries management for fisheries targeting species with different life histories, and then discusses the issues of applying an equilibrium approach to these species, and how scientists overcame some of these issues.

2.2.1 Management of short-lived species (fluctuating stocks)

Short-lived species, such as cephalopods and small pelagic species are subject to large fluctuations in abundance and respond rapidly to many factors such as changes in oceanographic conditions, biological interactions, and fishery exploitation. Assessment of

such stocks faces many difficulties. Setting an “optimal” level of fishing pressure (catch, effort etc.) has been a challenge for resource managers, given the variability in stock abundance and the uncertainty concerning the factors that may affect future abundance.

There are several general problems associated with estimating the abundance of cephalopods in particular. These include their short life spans, variable growth rates and weak stock–recruitment relationships (Caddy 1983; Pierce and Guerra 1994; Young et al. 2004). Pierce and Guerra (1994) conducted a major review of cephalopod assessment methods. They divided the assessment methods into three categories: pre-season assessment; in-season assessment; and post-season assessment. The first method is based on fishing survey data before the fishing season has begun, while the second method often uses incomplete data sets as the season progresses to estimate the point at which fishing should cease, generally using the Leslie-DeLury depletion method (Payne et al. 2006). Depletion methods examine how measured removals of fish influence the relative abundance of the remaining fish, the latter being estimated by an abundance index, often catch rate data (CPUE), normally considered proportional to population size (Smith and Addison 2003). Despite the success of depletion methods applied to some fisheries, the *Ilex argentinus* and *Loligo gahi* fisheries in the Falkland Islands are the only examples where the method has been used consistently for a number of years (Boyle and Rodhouse 2005; Payne et al. 2006) and post-season assessments, often used for the assessment of finfish, are routinely attempted (Payne et al. 2006)—these include the use of stock-recruitment relationships, surplus production models (FAO 1986) and cohort analysis (Royer et al. 2002), each with varying degrees of success (Payne et al. 2006).

Management of small pelagic species also faces a great challenge due not only to their short lifespan and high variability in recruitment and abundance, but also the schooling behaviour of the fish, which makes them vulnerable to possible stock collapse as fishing remains economical even at very low stock abundance (Pitcher 1995; Mackinson et al. 1997). Applying conventional management, aimed at maintaining a constant catch level (e.g. MSY), has been criticized for small pelagic species as it is likely to cause stock collapse (Beddington and May 1977) and the use of yield-per-recruit target RPs (e.g.

F_{MAX}) for long-term management of pelagic fisheries has been specifically discouraged (Patterson 2002), largely because they can lead to recruitment overfishing. Some of the world's most famous stock collapses have involved small pelagics, including the Japanese and South American pilchard (or sardine) stocks *Sardinops melanosticta* (Miller 2004; Takasuka et al. 2007) and *S. sagax* (Gaughan et al. 2004). In addition, the fishing industries targeting short-lived species are prone to “overcapitalization” (Fréon et al. 2008). This is because short-lived species tend to experience irregular periods of high and low abundance, and industry investment grows rapidly in response to periods of high stock abundance, while disinvestment does not occur to the same degree during periods of low biomass.

A major problem of using traditional biological RPs such as MSY and F_{MSY} for highly fluctuating stocks arises because they are mainly derived from conventional equilibrium catch-effort surplus production models and fishing effort is strongly dependent on the catchability coefficient q , which in turn is extremely sensitive to environmental and technological variables (Defeo and Seijo 1999). Bioeconomic RPs such as MEY and F_{MEY} derived from surplus production models suffer the same problems as they are based on the same underlying population model. However, it is recognised that bioeconomic RPs generally occur at lower levels than MSY and F_{MSY} , which may enable their use as precautionary RPs (Defeo and Seijo 1999). However, Caddy and Mahon (1995) argue that bioeconomic RPs may not be practical for the management of straddling stocks and highly migratory stocks, because each national fleet may have a different economic optimum depending on costs and national market prices, and it is not easy to identify F_{MEY} in fisheries involving several fleet with different gears and fishing practices.

2.2.2 Management issues for long-lived species

Long-lived species are generally characterized by slow growth and late maturity and tend to be particularly vulnerable to overexploitation because long periods of time are required for populations to rebuild once reduced (Adams 1980; Hoenig and Gruber 1990; Jennings et al. 1998; Musick 1999). Life-history traits influence recovery because of their intimate association with the maximum intrinsic growth rate (Hutchings and Reynolds 2004),

which is a product of age at maturity and age/size specific rates of survival and fecundity. Hutchings (2000, 2001) showed that clupeid species (e.g. herring) that mature early in life are more likely to recover to previously experienced population sizes after prolonged decline, while many gadoids (e.g. cod, haddock) and other non-clupeids (e.g. flatfishes) have experienced little or no recovery, despite considerable reductions in fishing mortality. Jennings et al. (1998) studied abundance trends relative to the life history of 18 intensively exploited fish stocks from the north-east Atlantic, and found that larger and later maturing species are less able to withstand a given rate of fishing mortality than their smaller earlier maturing counter-parts. Similar results were reported for the Pacific ocean shark species (Smith et al. 1998), skates and rays (Dulvy and Reynolds 2002), and coral reef fish species (Russ and Alcala 1998). Reynolds et al. (2005) reviewed 15 comparative studies that have tested for vulnerability in marine fishes and their correlation to life history traits, and concluded that large body size and late maturity are the best predictors of vulnerability to fishing. Recent studies have pointed out that older and larger fish are more productive and their offspring have a higher survival probability under unfavourable ocean conditions than those produced by younger fish (Berkeley et al. 2004a; Berkeley et al. 2004b; Birkeland and Dayton 2005), and that a population depleted of older fishes might not recover after a shift from a prolonged period of poor productivity to a more productive oceanic ecosystem regime (Beamish et al. 2006). Therefore, treating them equally as “biomass” in a management model can be misleading and not precautionary (Beamish et al. 2006).

Well-documented cases of collapsed fisheries for long-lived species include the striped bass (*Morone saxatilis*) fishery on the Atlantic coast (NOAA 2008) and the porbeagle shark (*Lamna nasus*) fishery in the North Atlantic (Anderson 1990). Deepwater commercial fisheries tend to show signs of overexploitation within a short period after the beginning of the fishery (Watson and Morato 2004). Such examples include orange roughy (*Hoplostethus atlanticus*) fishery off the waters of New Zealand (Clark 1999), Australia (Lack et al. 2003) and Namibia (Boyer et al. 2001), and the Atlantic redfish (*Sebastes marinus*) fishery in the high seas (Hareide et al. 2001). Other stocks that are heavily overexploited and facing risks of possible extinction include, e.g. Nassau grouper

(*E. striatus*) (Carter et al. 1994), and jewfish (*E. itajara*) that are candidates for the Endangered Species List in the USA (Sadovy and Eklund 1999), and Atlantic bluefin tuna (*Thunnus thynnus*) which is recently proposed for an Appendix I CITES (Convention on International Trade in Endangered Species) listing and international trade ban.

Given the sensitivity of long-lived species to fishing pressure and their slow recovery, the management of long-lived species requires special attention to ensure the precautionary principle is met. Traditional F -based biological RPs, such as F_{MSY} and F_{MAX} assume that the abundance of recruits is independent of the abundance of the parent stocks. Scientists urge that applying these traditional TPRs could lead to “recruitment overfishing” - the situation when a population has been fished down to a point where recruitment is substantially reduced or fails (Gulland and Boerema 1973; Deriso 1987; Sissenwine and Shepherd 1987). $F_{0.1}$ proposed by Gulland and Boerema (1973) is commonly understood to be more conservative than F_{MSY} , and has been widely adopted for the management of Northwest Atlantic groundfish stocks and is often used in establishing catch quotas (Rivard and Maguire 1993). However, several stocks managed under $F_{0.1}$ criteria have experienced declines largely because of the inaccuracy of commercial catch reporting and associated incorrect estimates of current F -values (Caddy and Mahon 1995). Moreover, $F_{0.1}$ still ignores the effects on the spawning population and related recruitment levels.

Since the early 1980s, spawner-per-recruit (SPR) related RPs have received much attention as a means to preserve the reproductive potential of the population (Quinn and Deriso 1999). For example, the fishing mortality which corresponds to observing between 20% and 35% of the spawner biomass per recruit seen in the absence of fishing ($F_{\%SPR}$) have been widely adopted as a recruitment overfishing threshold (Mace and Sissenwine 1993). Mace and Sissenwine (1993) carried out a survey of 91 stocks and recruitment data for Europe and North America. They found that $F_{0.1}$ as a management target does not always guard against recruitment overfishing, and advocated $F_{20\%SPR}$ for the well-known stocks with average resilience to over-fishing, and $F_{30\%SPR}$ for less well-known stocks (e.g. deep water fish) or those considered to have low resilience to over-fishing (e.g. small pelagics). The International Council for the Exploration of the Sea

(ICES) adopted three recruitment-based RPs, namely F_{low} , F_{med} , and F_{high} corresponding to the lower 10-percentile, 50-percentile, and upper 90-percentile of the observed recruit (R)/spawning stock biomass (SSB) ratios, respectively, in the North Atlantic (ICES 1984; Gabriel and Mace 1999). These RPs used by ICES are found to be more robust to the consequences of assuming an incorrect value of natural mortality M than F_{MAX} and $F_{0.1}$ levels (Jakobsen 1992). Mace and Sissenwine (1993) noted that 60% of the definitions of “overfishing” by the time of their writing had been based on SSB/R analysis, with typical value ranging from 20-35% of virgin stock levels.

A reference biomass of 20% of virgin or unexploited biomass ($20\%B_0$) is another commonly adopted overfishing threshold (Beddington and Cooke 1983; Getz and Haight 1989). Kirkwood and Smith (1996) suggest that the degree of precaution may be assessed in terms of the probability that the spawning stock falls below the 20% threshold in a fixed period. This method has been used by the Convention of Antarctic Marine Living Resources (CCAMLR) for the management of Patagonian toothfish in the Southern Ocean (Agnew 2004). Mace (1994) suggest that $50\%R_{MAX}$ (the spawning biomass corresponding to 50% of the maximum recruitment in a stock recruitment relationship) as an alternative overfishing threshold. Myers et al. (1994) examined 72 finfish stocks to identify spawning stock biomass thresholds for overfishing, and concluded that $50\%R_{MAX}$ was generally preferable over $20\%B_0$ as it resulted in higher levels of recruitment above the threshold.

2.3 An alternative approach: Management Strategy Evaluation

2.3.1 Risk evaluation and the concept of “robust” policy

Following the Rio Declaration in 1992, the importance of explicitly accounting for uncertainty, and of employing the precautionary approach in fisheries management, was gaining general acceptance, but it was unclear how to put it into effect operationally (Butterworth 2007). The practice of risk evaluation was rare until the early 1990s, but some failures in the management of well-studied stocks brought this issue to the scientific forefront in the 1990s (Caddy and Mahon 1995). Several international workshops and

scientific meetings were held during this period, specifically focused on uncertainties and risk evaluations in fisheries management. These include the 1990 Northwest Atlantic Fisheries Organization (NAFO) session “Management under Uncertainties”(Shepherd 1991), the 1991 workshop “Risk Evaluation and Biological Reference Points for Fisheries Management”(Smith et al. 1993) sponsored by Canadian Atlantic Fisheries Scientific Advisory Committee (CAFSAC), the 1995 FAO “Technical Consultation on the Precautionary Approach to Capture Fisheries” (FAO 1996) and the 1998 International Commission for the Exploitation of the Sea (ICES) symposium on “Confronting Uncertainty in the Evaluation and Implementation of Fisheries-Management Systems” (Stokes et al. 1999).

One of the major outcomes of the 1995 FAO Technical Consultation meeting was a set of guidelines on the precautionary approach, including for the quantification of uncertainty, and for the determination of management strategies which are robust to major sources of uncertainty. The guidelines state that:

“A precautionary approach requires that the feasibility and reliability of the management options be evaluated. A management plan should not be accepted until it has been shown to perform effectively in terms of its ability to avoid undesirable outcomes.... The evaluation should attempt to determine if the management plan is robust to both statistical uncertainty and to incomplete knowledge on factors such as uncertain stock identity and abundance, stock dynamics, and the effects of environmental variability and trends. As well, evaluations should consider the dynamic behaviour of the harvesting sector and managers’ ability to change harvest levels.” (FAO 1995b)

This statement was understood as an implicit endorsement of the approach known as management strategy evaluation (MSE) developed by the International Whaling Commission (IWC). MSE provides a framework for identifying robust management strategies in the presence of multiple management objectives and system uncertainties, and has been increasingly applied to the management of fisheries resources in recent years. Since the 1990s fisheries management has undergone an important paradigm shift from traditional, single objective policy based on “optimal” harvest (such MSY) to the

robust policy that provides adequate performance with multiple criteria over a wide range of uncertainties.

2.3.2 Basic concept

MSE is a simulation-based approach that provides a framework for identifying robust management strategies as well as for sensibly comparing alternative strategies in the presence of multiple management objectives and system uncertainties (Kirkwood and Smith 1996; Cooke 1999).

The major advantages of MSE are: 1) it is by design compatible with the precautionary approach by making appropriate allowance for various forms of scientific uncertainties and the proper evaluation of risk (as it enables evaluation of the sensitivity of the results to the various sources of uncertainty); 2) it allows for the evaluation of the trade-offs among mutually conflicting objectives (e.g. maximising catches, minimising inter-annual catch variability for industrial stability, and minimising the risk of substantial depletion of the population) by simulation testing; 3) it provides a framework for interactions with stakeholders in developing management objectives; and 4) it enables scientists to spend less time haggling over scientific recommendations (Kell et al. 2006b; Butterworth 2007). The experiences of the South African Rock Lobster Scientific Working Group provide a classic example of saving haggling time: a total of 40 meetings needed in the previous year to finalise a TAC recommendation was reduced to 4 meetings after the adoption of a MSE approach (Butterworth 2007).

A key feature of this approach is that an optimal strategy or solution is not provided, but instead policies are sought that are feasible, robust to uncertainty and provide adequate management performance with respect to multiple criteria. This approach has been increasingly used as an alternative to the traditional reference point-based approach in the provision of scientific recommendations for fisheries management measures.

2.3.3 Components of MSE and terminologies

A conceptual diagram of the processes involved in an MSE is given in Figure 2-2. The

key component of MSE is a mathematical representation of the “true” population dynamics, termed the “operating model.” An operating model (OM) is defined as a mathematical and statistical model used to describe the actual resource dynamics in simulation trials and to generate resource monitoring data when projecting forward (Rademeyer et al. 2007).

Observation of the resource system by managers is always imperfect. In MSE this is covered by the “observation model” (Figure 2-2) whereby the statistical features of the collection of relevant data are simulated, including both error and potential associated bias. For example, abundance indices such as catch-per-unit-effort (CPUE) from commercial fisheries and/or from fishery independent surveys often involve observation (measurement) errors - the differences between the measured value of some resource index and the corresponding actual value in the OM.

The observation data are then passed to the “management model.” The management model can be further divided into stock assessment model, estimation model, and harvest control rules (defined by Rademeyer et al. 2007 as a set of defined rules used for determining a management action). The (stock) assessment model uses the outputs of the observation model and produces estimates of key variables relating to the population of concern, using some mathematical population model (e.g. a depletion model) and may include estimates of parametric and process errors. The estimation model produces the key target reference points (e.g. F_{MSY} , E_{MEY}) and parameters (e.g. catchability coefficient) based on either the results from the assessment and observation models or other information, such as life-history or economic information. If estimates of TRPs are not required or only biological aspects are accounted for, the estimation model can be identical to the assessment model. However a separate estimation model is generally required to produce bioeconomic RPs to incorporate production function parameters (e.g. coefficient of harvest mortality per unit effort) and economic parameters. The HCR takes the status information from the assessment, and in combination with other information (such as biological & socioeconomic reference points), produces a management action in the form of a harvest or effort level.

The “implementation model” simulates the process of the operationalisation of the management actions (e.g. TAC), and may include implementation errors—the differences between intended limits and those actually achieved. The implementation of the management actions then feed back into the OM to simulate the impacts these actions have on the resource and the associated fishery. This feedback feature provides a “self-correction” mechanism, even if some of the assumptions made in developing a “best assessment” were wrong (Butterworth and Punt 1999).

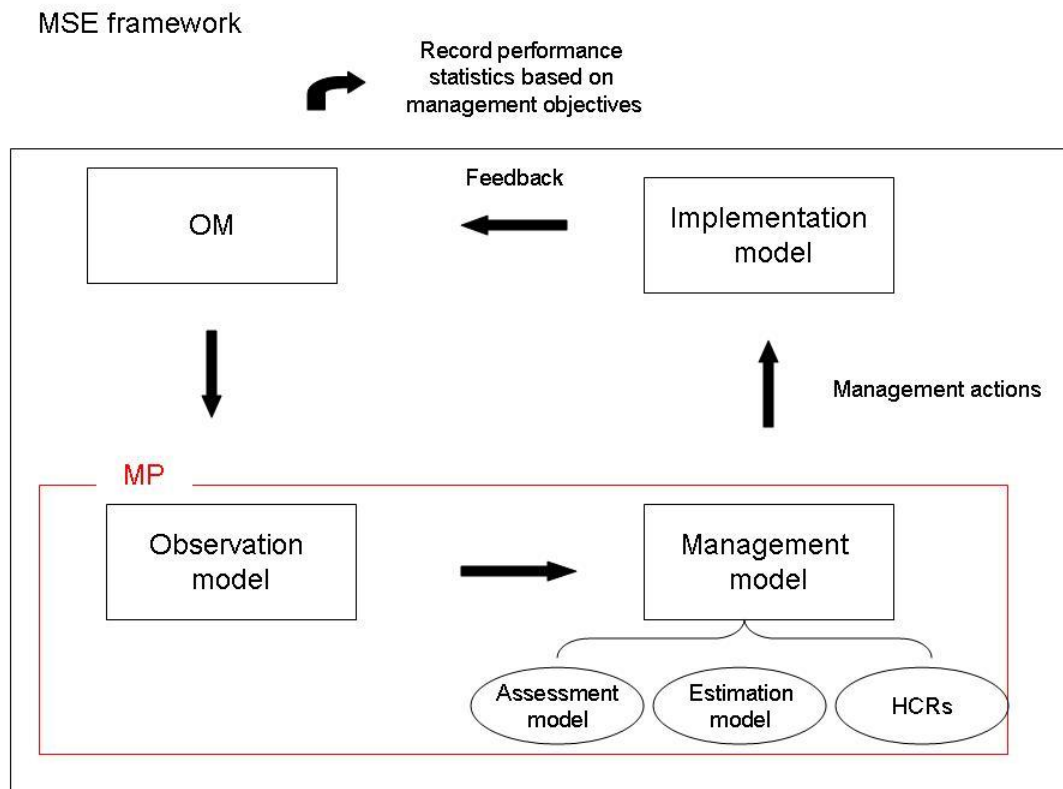


Figure 2-2: Conceptual diagram of the processes of a Management Strategy Evaluation (MSE). The OM (operating model) represents the “true” dynamics of the population. The observation model simulates monitoring of the system. The data obtained are passed to the management model, consisting of the assessment model, estimation model, and harvest control rules (HCRs), which produce the management actions. The implementation model simulates the process of implementing those actions and feeds back into the OM to produce impacts on the stock and the fishery. The impacts of all those process are evaluated via simulation based on pre-defined performance criteria that reflect multiple management objectives. This whole framework is called MSE.

The process from data collection to the determination of management actions is called a “management procedure (MP)”. There are several definitions of MP. Some authors

include the implementation model as a part of the MP. Butterworth defines an MP as a set of rules which utilises available data to provide recommendations for management actions (Butterworth and Punt 1999; De Oliveira et al. 2009). In this thesis, I adopt Butterworth's, and define the MP as including not only the process of data collection and the stock assessment procedure, but also a decision rule that uses information on the observed status of the system to provide management advice. This is also similar to the "implicit definition of MP" given by Rademeyer et al. (2007).

In the above definition, the MP is separate from the evaluation through simulation trials. The procedure of testing the robustness of the MP through simulation was described by Smith et al. (1999) as "management strategy evaluation". This term has various synonyms, including "management procedure evaluation", "management procedure approach", "operational management procedure", "management algorithm evaluation", "simulation modelling approach", and "operating model approach". The term "management procedure approach" is most often used as synonymous with MSE, but to avoid confusion between the MP (not including evaluation) and the MP approach (including evaluation), I do not use the term "MP approach" in this thesis.

The term "management strategy (MS)" is also commonly used as synonymous with MP in the literature, but some authors use it to mean a harvest control rule (Rademeyer et al. 2007). In this thesis, I avoid using "MS", and interpret the use of MS and similar terms in the literature as referring to MPs.

2.3.4 Types of OM

Kell et al. (2007) classified OMs into four types based on their information requirements and complexity: 1) the OM mimics the current stock assessment model, implying that the assessment model describes the true dynamics almost perfectly (the least demanding approach); 2) the OM represents all available data, and its parameter estimates depend almost exclusively on the data; 3) in addition to (2), prior probabilities are assigned to alternative hypotheses and data from sources other than a specific fishery (e.g. from a meta-analysis) is incorporated; and 4) in addition to (3), focus is given to *a priori*

information and expert belief about the process that may affect the management system in the future, rather than focusing on fitting historical data. The OM and assessment model are identical in the first approach, while the OM does not need to be identical to the assessment (estimation) model in (2)-(4).

To give an example, suppose we choose a simple Schaefer bioeconomic model as an estimation model, which provides an estimate of optimal effort E^* , hence providing a management advice, and choose an HCR, such as a fixed input control measure aiming to ensure the fleet operates at E^* , to simulate management action. In evaluating the outcomes of such a management action, however, we may use either the same Schaefer model or use a more complex bioeconomic OM (e.g. based on a Beverton-Holt model) to simulate the whole fishery management system. Since the OM is used for simulation purposes, it is sometimes referred to as a “simulation model” distinguished from an estimation model or assessment model. OMs often contain a greater level of complexity and knowledge than that used within the stock assessment models, allowing for the evaluation of the consequences of contrasting hypotheses about the real dynamics of the system (Kell et al. 2007). However, when OMs are used to calculate management measures to be applied in practice, simpler models rather than the “best assessment model” are often to be found preferable (Kirkwood and Smith 1996; Punt and Smith 1999; Parma 2002; Butterworth et al. 2010).

In this thesis, only type 1 and 2 OMs were used. When an OM was designed to be more complex than the available stock assessment model, it was conditioned using only the available data, not any prior information on parameters or hypotheses.

2.3.5 Types of MPs

There are two broad types of MPs: model-based; and empirical (also called model-free). A model-based MP involves estimation of the status of the resource through the use of some population model, while an empirical MP does not involve a population model, but instead uses empirical observations (e.g. upwards and downwards trends in abundance indices from fishery-independent surveys) to provide recommendations for management

measures. Empirical approaches are typically simple to develop and easily understood by stakeholders (Rademeyer et al. 2007). However, model-based MPs tend to perform better in terms of producing less inter-annual variability in TACs (Butterworth and Punt 1999; Punt and Smith 1999). This is because empirical approaches tend to estimate short-term trends considering only data for the most recent years, while model-based MPs reflect the behaviour of the resource over much longer periods (Rademeyer et al. 2007).

2.3.6 Examples of MSE applications

The MSE approach in a fishery context was first developed by the Scientific Committee of the International Whaling Commission (IWC) during the late 1980s (De la Mare 1986; Butterworth 2007). The IWC's analyses explored many functional forms for the harvest control rule while taking into account uncertainties in estimates of whale abundance (Peterman 2004). They also examined model performance under numerous combinations of uncertainty, concerning stock identity in multi-stock fisheries and temporal trends in abundance of whales resulting from environmental changes or interactions with other species (Peterman 2004). The history of MSE, its applications, advantages and disadvantages have been reviewed by Butterworth (2007). Kell et al. (2006a) provides extensive examples of MSE applications. Rademeyer et al. (2007) have developed guidelines for designing MSEs, which include the descriptions of OM types, consistent nomenclature, and how to construct OMs.

MSEs have been explored quite extensively by the International Council for the Exploitation of the Sea (ICES; Hilborn and Walters 1992). South Africa is one of the pioneering countries which has been applying the MSE systematically and widely in the assessment and management of marine fisheries stocks. For instance, a MSE framework was developed for fisheries for Cape hake *Merluccius spp.* by Punt (1992), and South African anchovy *Engraulis capensis* by Butterworth and Bergh (1993). MSE formed the basis for setting TAC and total allowable bycatch (TBC) for pilchard (sardine) and anchovy in the purse-seine fishery since 1991 (De Oliveira and Butterworth 2004). A model-free MSE framework has also been developed for the South African west coast rock lobster (*Jasus lalandii*) fishery (Butterworth 2005).

MSE has also been widely applied in the management of Australian fisheries (Smith et al. 1999). Punt and Smith (1999) carried out MSE for the eastern stock of gemfish, *Rexea solandri* using OMs that included uncertainty about historical catches, the comparability of survey estimates, the form and autocorrelation of the stock–recruitment relationship, and the quantity and quality of the data available for assessment purposes. Dichmont et al. (2006a, b, c) have carried out MSE for the Australian Northern prawn fishery incorporating implementation errors (inability to predict the size of the stock, behaviour of fishers etc.).

Most applications of MSE to date have focused on harvest strategies for target species (Fulton et al., 2005), but it has also been used for identifying the harvest limit for bycatch species, including determining cetacean bycatch limits in the U.S. (Wade 1998), and harbour porpoise bycatch limits in the North Sea (Winship 2008). Other examples include Namibian fur seals *Arctocephalus pusillus pusillus* (Butterworth et al. 1998), Namibian hake (*Merluccius capensis* and *M. paradoxus*) resource (Butterworth and Geromont 2001) and the New Zealand rock lobster (*Jasus edwardsii*) fishery (Starr et al. 1997). Peterman (2004) draws a general conclusion from past work on this topic and states that “such comprehensive simulations of sources of uncertainties provide different recommendations to decision makers than if only a subset of those uncertainties were analysed”.

Most applications, including the examples mentioned above, have focused on yield or stock status objectives, and very few MSE studies have explicitly considered economics (Dichmont et al. 2008; Holland and Herrera 2009; Punt et al. 2010).

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2.4 Simulation-based bioeconomic modeling

Over the past decade, a number of simulation-based bioeconomic models have been developed as practical management tools, of which a few use operating models. Tingley (2005) compiled a brief review of some of the well known bioeconomic simulation

models that have been developed to assess the possible impacts of management measures. One of the early simulation models widely applied for the fisheries is the Bio-Economic Analytical Model (BEAM; series 1 to 5) developed by FAO, which was originally developed for the analysis of tropical shrimp fisheries (Garcia and Zalinge 1982). The underlying biological model is an age/length based yield-per-recruit model of Thompson and Bell (1934). It is a spreadsheet based simulation model, which allows assessment of the impact of changes in management regimes, including the biological and economic consequences. EIAA (Economic Interpretation of ACFM Advice) is also a spreadsheet-based simulation model developed in 1998-2000 and subsequently used in 2002-2004 to assess the economic consequences of the TACs proposed by the EU's Advisory Committee for Fisheries Management (ACFM). These spreadsheet-based models are deterministic, and do not take uncertainties in the input parameters and variables into consideration.

Another example of an earlier model is the General Bioeconomic Fisheries Simulation Model (GBFSM) funded by US National Marine Fisheries Service (NMFS). GBFSM is a multiple species, length-based model using cohort analysis and instantaneous mortality (Griffin no date) and was initially developed to evaluate management policies proposed for the shrimp fisheries in the Gulf of Mexico in the late 1970s.

More recently, a large number of bioeconomic simulation models have been developed for European fisheries, including BEMMFISH (Bio-economic simulation model of Mediterranean fisheries), TEMAS (Technical Management Measures) for Danish fisheries in the North and Baltic Seas, and IBEM/MOSES (Italian Bio-Economic Model based on Models for Optimal Sustainable Effort in the Seas). Prellezo et al. (2009) provides a review of 14 bioeconomic simulation models within the EU. Most common platforms used are GAMS, R, and Excel. Many of these models are area-specific, except for those models based on FLR (Fisheries Library in R, Kell et al. 2007). While some of these simulation models are deterministic (e.g. COBAS, ECONMULT, MOSES), a few are stochastic models that allow uncertainty in parameter estimates and the models themselves. FLR is a collection of tools in the R statistical language that facilitates the

construction of bioeconomic simulation models of fisheries and ecological systems (<http://flr-project.org/>). Initial development of FLR was part of the EU-funded FEMS (Framework for the Evaluation of Management Strategies, QLRT-2001-01824) research project. Prellezo et al. (2009) noted that the possibility of including uncertainty in any process or variable is one of the main advantages of using FLR. FLR has been used for the construction of simulation models for the evaluation of fisheries management procedures for a number of EU fisheries. For instance, Tserpes et al. (2009) used it to carry out a MSE for the Mediterranean swordfish stock to evaluate the biological and economic implications of temporal fisheries closures. Hoff and Frost (2008) used FLR to assess the economic and biological effects of recovery plans under the new CFP (Common Fisheries Policy of EU) for the Dutch beam trawl fishery in the North Sea, although the model they used (AHF-model) does not directly include observation and measurement errors and uncertainty for the input parameters and variables (Prellezo et al. 2009). Given the ability to incorporate uncertainty in the whole fishery process, I used FLR for all of the parameterization and simulation modelling work in subsequent chapters.

Outside the EU, Christensen (1997) developed a simulation framework to evaluate alternative management regimes for the Greenland shrimp fishery, taking fleet behaviour and uncertainties in biological and economic data into account, and found that the losses associated with implementation errors, such as high-grading of catches, could be more significant than the losses due to incomplete knowledge of the underlying system.

All of the above examples of bioeconomic simulation models focus on the evaluation of harvest strategies rather than investigating the causes of errors and bias in the estimates of bioeconomic target RPs. The use of MSE for the purpose of testing and validating the robustness of the estimates from bioeconomic models under multiple sources of uncertainty is conspicuously absent from the literature. This is the gap that I hope to fill in this thesis.

Part 2: Overviews of case study fisheries

This section first provides an overview of the Japanese fisheries case studies, namely for the fisheries for Pacific saury *Cololabis saira* and Japanese common squid *Todarodes pacificus* off the coast of Japan (Section 2.5). It then provides an overview of the fishery for Patagonian toothfish around the island of South Georgia (Section 2.6).

2.5 Japanese fisheries case studies

2.5.1 Introduction

In 1996 Japan ratified the UN Convention of the Law of the Sea and as a consequence established an Exclusive Economic Zone (EEZ) of 200 nautical miles. Subsequently, the total allowable catch (TAC) system was introduced in 1997 and the total allowable effort (TAE) system was also introduced following an amendment in 2001 (Matiya et al. 2006). The central government sets TAC and TAE for each species, and supervises and controls total fishing levies, while the allocation of quotas and the determination of access rules are the responsibility of fishers' organizations (Matiya et al. 2006).

As of late 2009, seven species are subject to the annual TAC system: Pacific saury (*Cololabis saira*), Alaska Pollack (*Theragra chalcogramma*), Japanese sardine (*Sardinops melanostictus*), Japanese jack mackerel (*Trachurus japonicas*), chub mackerel (*Scomber japonicas*), blue mackerel (*Scomber australasicus*), common squid (*Todarodes pacificus*), and snow crab (*Chionoecetes opilio*). TAC species are selected if the species meets one or more of the following criteria: 1) they are economically and socially important to the Japanese people; 2) they are in immediate need of resource management due to low stock levels; and 3) the stock is harvested by neighbouring countries. The TAE system sets upper limits on the number of fishing days and number of operating vessels in a specific area within the EEZ. The TAE system applies to the fisheries targeting the depleted stocks that are managed under restoration plans for rebuilding the stocks. These are mainly flatfish stocks including flathead flounder (*Hippoglossoides dubius*) in the western Japan Sea, roughscale flounder (*Clidoderma asperrimum*) and willow flounder

(*Tanakius kitaharai*) in the Northern Pacific Ocean, brown sole (*Pleuronectes herzensteini*) in the Northern Japan Sea, marbled sole (*Pleuronectes yokohamae*) at Suoh Nada, Japanese Spanish mackerel (*Scomberomorus niphonius*) in the Seto Island Sea, tiger puffer fish (*Takifugu rubripes*) in Ise Bay & Mikawa Bay, sand lance (*Ammodytes personatus*) in the Soya Strait, and spear squid (*Loligo bleekeri*) in the South Pacific Ocean. Since the TAE system can be introduced without the detailed scientific data necessary to calculate the TAC, the TAE system is considered to be suitable for the management of species whose abundance is declining conspicuously or whose abundance level fluctuates widely depending on the oceanographic conditions or other natural factors rather than fishing (OECD 1997).

The TAC is set based on Acceptable Biological Catch (ABC) and ABC decision rules. ABC targets and limits are based on biological RPs, including MSY. However, the majority of the TAC-managed stocks are pelagic stocks that are subject to substantial environmentally-driven fluctuations. Problems have been pointed out for the output control system using TAC, e.g. the reliability of the stock assessment, for such fluctuating stocks (Kishida and Wada 2003). Moreover, given that recent harvest levels are considerably below the TAC levels for some stocks (Table 2-1), the current TAC-based output control system seems insufficient as a practical management tool.

Table 2-1: TAC versus observed harvest (000 tonnes) for Japanese common squid and Pacific saury, 2004-2006

Fishing season	Japanese common squid			Pacific saury		
	TAC (000 t)	Harvest (000 t)	Harvest as % TAC	TAC (000 t)	Harvest (000 t)	Harvest as % TAC
2006	359	203	57%	286	234	82%
2005	385	210	54%	286	209	73%
2004	530	225	42%	334	270	81%

As an alternative to the current system, Kishida and Wada (2003) proposed optimal capacity management for the Japanese sardine *Sardinops melanostictus*, and chub mackerel *Scomber japonicus*. Using a simple stock dynamics model, and separate production functions to represent high, low, and average stock levels, they suggested that

the optimal fishing capacity to achieve the maximum discounted future profit is about a quarter of the maximum fishing capacity corresponding to the bionomic equilibrium (open access level where revenue is zero) in a high stock abundance period. Their model, however, used a deterministic stock dynamics model, disregarding uncertainty in stock abundance. Moreover, their models are based on a linear model where the revenues obtained from fishing were assumed to be directly proportional to the harvest, and the problem of “flooding the market” and driving down the price of fish by harvesting at a high rate was not accounted for. Pacific saury, for instance, has a downward sloping demand relationship, so the result of applying a linear model to such a fishery requires investigation.

As most Japanese fisheries are multi-species, multi-gear fisheries, and revenue and cost data are not available on a species-by-species basis, the following two single-species fisheries were selected for empirical analysis; the saury stick-held dip net fishery; and the coastal squid angling fishery.

2.5.2 Pacific saury stick-held dip net fishery

2.5.2.1 Overview of the fishery

Japan has well-developed pelagic fisheries, due to its complicated oceanographical conditions that favour pelagic fish. Pacific saury *Cololabis saira* is one of the important pelagic species in the waters around Japan, accounting for 4.6 % of total capture fisheries production in 2002, worth 30.6 billion yen, approximately US\$342 million (MAFF 2004), using the exchange rate as of Aug 2009 (1USD=94.4yen). Called *sanma* in Japanese, saury is a seasonal delicacy prepared in the autumn in Japanese cuisine and is of great economic importance.

Pacific saury is a straddling stock, found from Japan eastward to the Gulf of Alaska and southward to Mexico; 67°N - 18°N, 137°E - 108°W (Froese and Pauly 2008). The map of native distribution of *Cololabis saira* is given in Figure 2-3. The spawning season of

saury starts in September in the transitional waters between the Kuroshio Extension and the subarctic Oyashio front off northern Japan and active spawning is observed in October and November but tends to decline in December (Watanabe et al. 2003). The lifespan of the Pacific saury is estimated to be about 2 years.

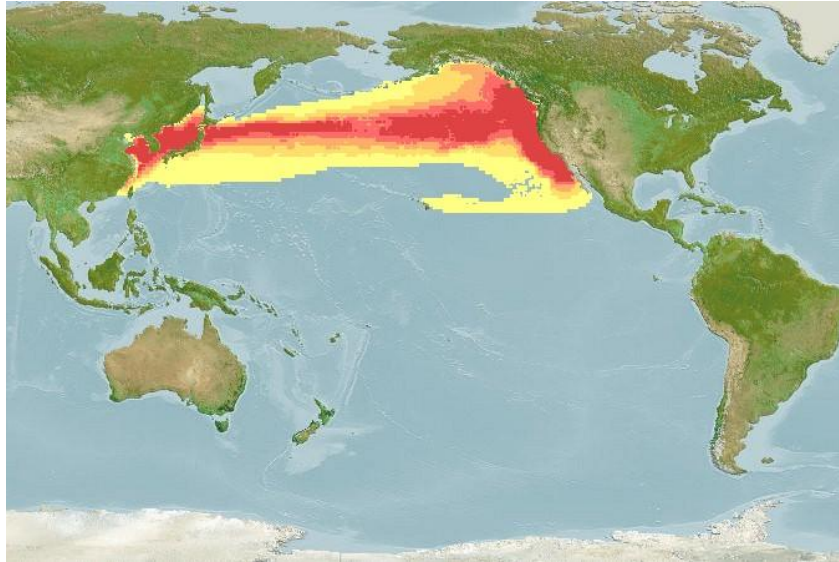


Figure 2-3: Computer generated native distribution map of *Cololabis saira*. The colour indicates the relative probabilities of occurrences. For instance, dark red indicates the probability of 0.8-1.0, and pale yellow indicates the probability 0.01-0.19. Source: www.fishbase.org

The global catch of Pacific saury increased in the 1950s after the introduction of an effective fishing gear known as the “stick-held dip net” (Watanabe et al. 2003). The fishing method involves fish aggregating light, a square or rectangular net with bamboo poles, sinkers and ropes (Figure 2-4). The annual catch of saury peaked at around 600,000 tonnes in 1958 then declined in the 1960s down to the lowest annual catch of 120,000 tonnes in 1969. It rapidly recovered by the 1970s, since then the catch has generally fluctuated between 200,000 and 400,000 tonnes (Figure 2-5).

About 60% to 80% of the total catch was caught by Japan, followed by Russia, Taiwan (China), and South Korea. China also entered into the fishery in 2004, but the catch volume is unknown. Although Japan remains the dominant fishing nation for Pacific

saury, a preliminary estimate indicated that the Japanese share appears to have declined to less than 50% in 2005 due to the increase in catches by other nations (Ueno et al. 2006).

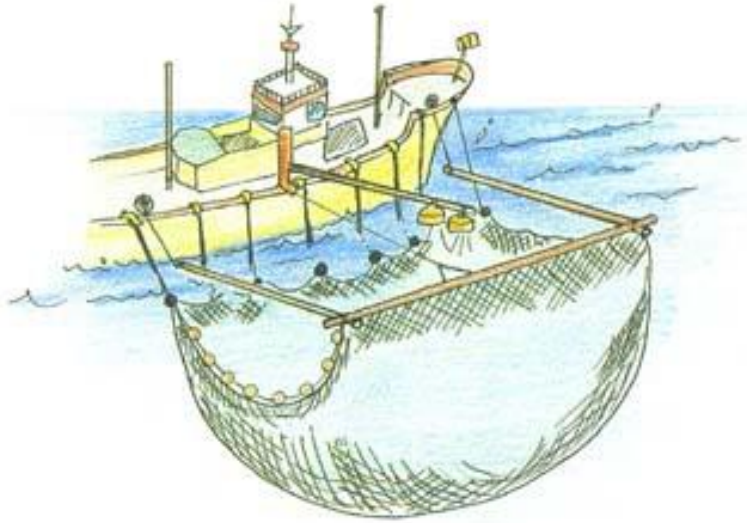


Figure 2-4: Image of saury stick-held dip net fishing method
Source: <http://www.pref.mie.jp/ONOKAN/HP/>

The Japanese commercial fishery exploits the stock of saury using stick-held dip nets from August to December. Fishing operations of the fisheries begin in August off the Pacific side of the Kuril Islands, after which the fishing ground there closes and shifts south to the regions off the Sanriku and Joban coasts (Watanabe et al. 2006). The operations usually decrease in mid-December, and the span of operations is approximately 140 days. The stick-held dip net fishery accounts for 95 percent of the total saury catch in the country (MAFF 2005). Small numbers of saury are also caught by the gill nets and drift nets fisheries.

In Japan saury is caught mainly by vessels over 100 tonnes in terms of volume, although vessels less than 20 tonnes are dominant in terms of number of operators. Total participants in this fishery in 2005 were 228 vessels (those who have obtained fishing permits from the Fisheries Minister and whose income from saury comprises the majority

of their fishery income). Note that vessels smaller than 10 tonnes do not require Ministerial permits, but require permission from local government.

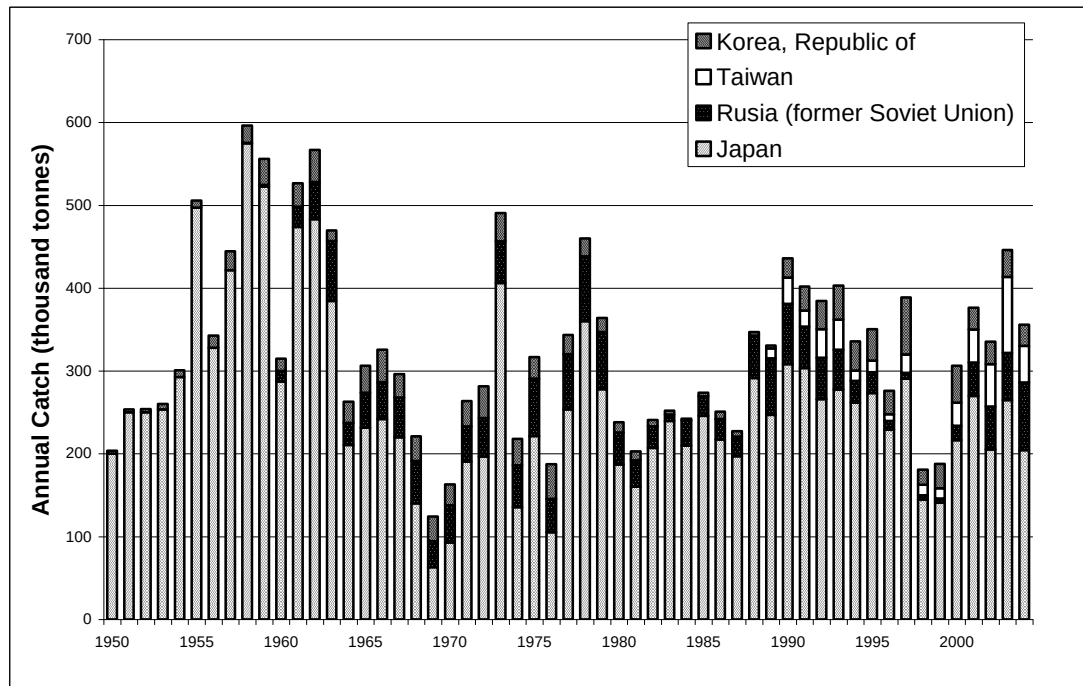


Figure 2-5: Global Annual Capture Production for Pacific Saury, by Country, 1950-2005, Tonnes/Year. Source: FAO Fishstat.

Taiwanese fishers target saury with vessels larger than 500 tonnes mainly using the stick-held dip nets from June to October in the waters around 150°E -160°E just outside of the Russian EEZ (Ueno et al. 2006). According to Ueno et al. (2006), around 100 vessels participate in the saury fishery in Taiwan, with most of them also operate in the squid angling fishery during the off-season. South Korean fishers appear to operate in similar locations and during the same season as Taiwan, accounting for an estimated 20 vessels (Ueno et al. 2005). Russian vessels targeting saury operate throughout the period from August and December mainly use stick-held dip nets. However, they also target saury using trawlers equipped with fish aggregation lights in some areas. Since the saury fishing season is limited to the months of August to December in Japan, most of the large vessels are used to operate other fisheries outside the saury fishing season, such as the salmon drift net fishery, tuna longline fishery and a large set net fishery. However, earnings from these other fisheries have been low or negative in recent years, and the

declining income of saury fishery operators has grown into a serious concern for Saury Fishermen Cooperatives.

2.5.2.2 Abundance trend

The time series abundance trend of Pacific saury obtained from the FRA is given in Figure 2-6. Their abundance estimates are based on a non-parametric production model using standardized CPUE from the reported global capture production (including responses to questionnaires from relevant agencies overseas) and the best available estimates of global fishing efforts by the four countries participating in the fishery, as well as swept-area abundance estimates from mid-water trawl surveys (Ueno et al 2006). The saury stock has fluctuated widely from year to year. Causes and mechanisms of the large variations in abundance are not well understood (Tian et al. 2004), but several authors have indicated a strong influence of environmental factors, including sea surface temperature and a possible link between saury abundance and the climate regime shifts occurred in the Kuroshio region. Since the late 1990s, fishermen have begun to use fish sorting machines in order to land only high grade saury (Ueno et al. 2006). The effect of the use of fish sorting machines for the 2005 assessment was assumed negligible as larger fish makes up the majority of the catch (Ueno et al. 2006), but the assessment in this year could potentially underestimate the true fishing mortality.

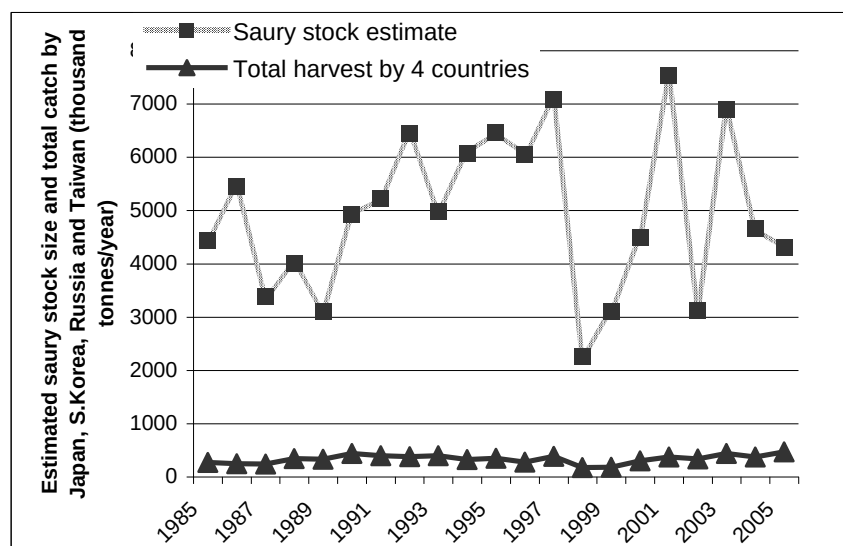


Figure 2-6: Abundance Trend for Pacific Saury, 1985-2005. Source: Ueno et al. 2005 and 2006.

2.5.2.3 Economic trend

The average annual expenditure of the major fleet (100-200GT class) varied from 111 million yen/year per operator (US\$945,000) to 205 million yen/year (US\$1.4 million) per operator during the 1985-2004 fishing seasons. During 1985-2000 where the detail expenditure data is available, labour is the largest source of cost (Figure 2-7), accounting for about 40 percent of the total expenditure in 2000. The relative proportion of different costs appears to be quite stable, except for fuel, which declined from about 20% of the cost share in 1985 to 8% in 2000. Expenditure has increased slightly over time, but the average fishery revenue also increased, particularly between 1995 and 2000 (Figure 2-7). Average annual revenue of sampled operators increased until 2000, however the more recent report (MAFF 2005) indicated that the profit has fallen since 2003 due to the low price of saury.

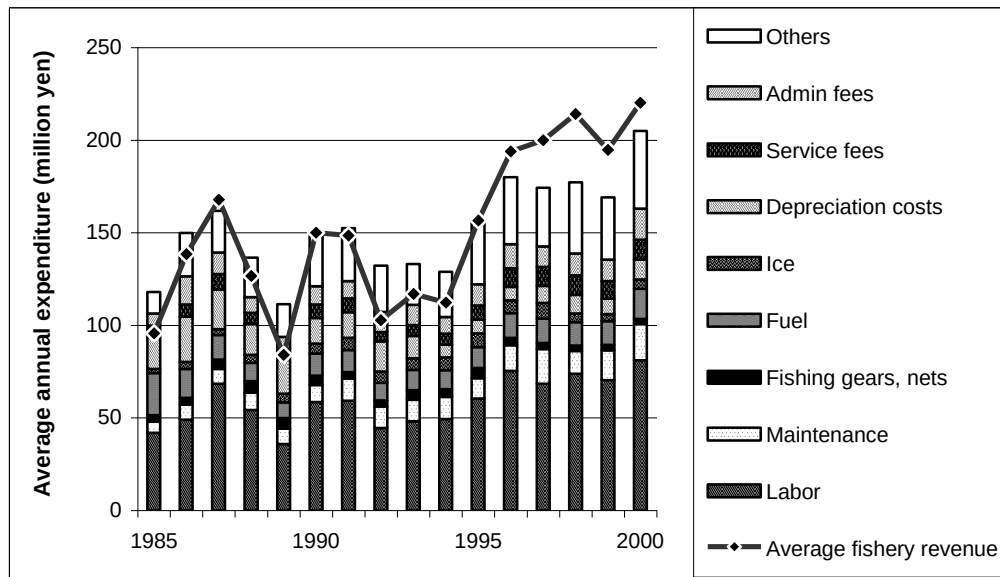


Figure 2-7: Average annual expenditure of sampled operators (part-time, 100-200GT class) for Pacific saury stick-held dip net fishery, million yen/year, 1985-2000.
Source: Survey Report on Fishery Economy, 1985-2000, MAFF.

The ex-vessel price of saury is relatively stable in participating countries other than Japan because most of the fish caught are landed either in frozen or canned form (Ueno et al. 2006). On the other hand, the ex-vessel price of saury in Japan is highly unstable as most

harvests are landed fresh and the price declines substantially during good fishing seasons, ranging from 66 yen/kg to 211 yen/kg (real prices) over the period between 1990 and 2005 (Figure 2-8). Such price fluctuations contribute to the low profitability of the fishery (Ueno et al. 2006).

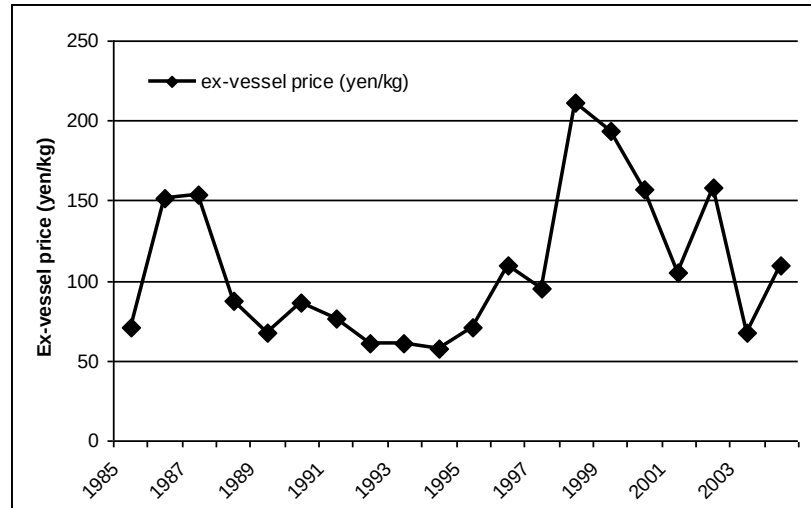


Figure 2-8: Ex-vessel price (yen/kg) of Pacific saury in Japanese market, 1985-2005. Source: Annual Report of Fish Marketing Statistics. MAFF, 1961-2005

2.5.3 Japanese common squid angling fishery

2.5.3.1 Overview of the fishery

Squid is the most consumed type of seafood in Japan, with the annual purchase of raw squid per household estimated at about 6 kg, twice the amount of the second-most consumed seafood, tuna (Fukuda and Okazaki 1998). The Japanese common squid or Japanese frying squid, *Todarodes pacificus*, is the most important species in the Japanese squid fisheries and constitutes the majority of Japanese squid catch, approximately 40% in 2006 (MAFF 2007). The catch of common squid accounted for 4.17 % of the total capture production in 2003 (MAFF 2004). Squid fisheries employ a large number of fishery workers and squid angling fisheries (excluding distant water fishing) alone employ about 18,000 workers (Mori and Nagasawa 2006), contributing significantly to the employment in coastal communities.

The Japanese common squid is an oceanic and pelagic species that occurs within a broad temperature range from about 5° to 27° C, and usually at a depth of 0 to 100 meters, and to a minor extent, down to 500 meters (FAO/FIGIS 2009). Three independently breeding subpopulations can be distinguished in Japanese waters. The main group spawns in winter in the East China Sea, the second in the autumn, west of Kyushu, and the third, minor group during the summer in the Sea of Japan as well as off northeastern Japan. The lifespan of the common squid is estimated to be 1 year (Mori and Nagasawa 2006). Japanese common squid stocks are managed as two separate sub-stocks: the winter spawning stock and the autumn spawning stock. The distributions, migration patterns and major fishing grounds are given in Figure 2-9.

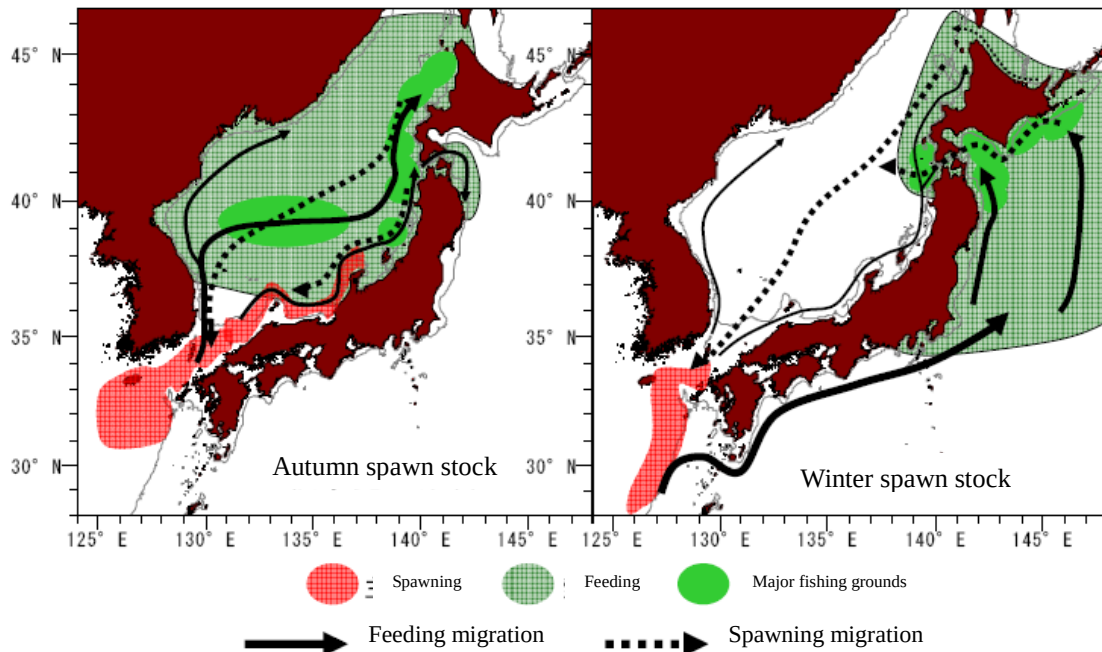


Figure 2-9: The patterns of spawning and feeding migration, and fishing grounds for *Todarodes pacificus* around Japan. Source: Kidokoro et al. 2006

Up to the 1940s, the Japanese common squid fishery remained relatively small-scale, exploited by non-powered boats of 1 to 2 tonnes, and taking less than 100,000 tonnes per year in landings (FAO/FIGIS 2009). In the 1940s, well equipped, engine-powered boats were introduced and the global capture production of common squid steadily increased through the 1950s. Annual production peaked at 560,000 tonnes per year in 1968, but

catch declined in the 1970s and remained at a low level in the 1980s (Figure 2-10). Parallel to this decline in catches of *T. pacificus*, other species such as *Ommastrephes bartrami* are becoming more heavily exploited (FAO/FIGIS 2009). The catch of common squid increased again in the 1990s and declined sharply in 1998, and has experienced substantial fluctuations ever since (Figure 2-10).

Harvests of the winter spawning sub-stock of common squid (caught mainly in the Pacific Ocean) used to dominate Japanese capture fisheries, accounting for 84 percent of Japan's total capture production when it reached its peak in 1968 (Ueno et al. 2006). However, the catch has declined and the current catch levels (including catch from Korean operators) have stagnated around 200,000 tonnes over the past 5 years, less than half the historical peak. Similarly, the catch taken from the autumn spawning sub-stock (caught mainly in the Sea of Japan) has declined since peaking in the 1970s, with a recent harvest of 100,000 tonnes in 2005. The Japanese common squid fishery has been subject to a TAC management system since 1997.

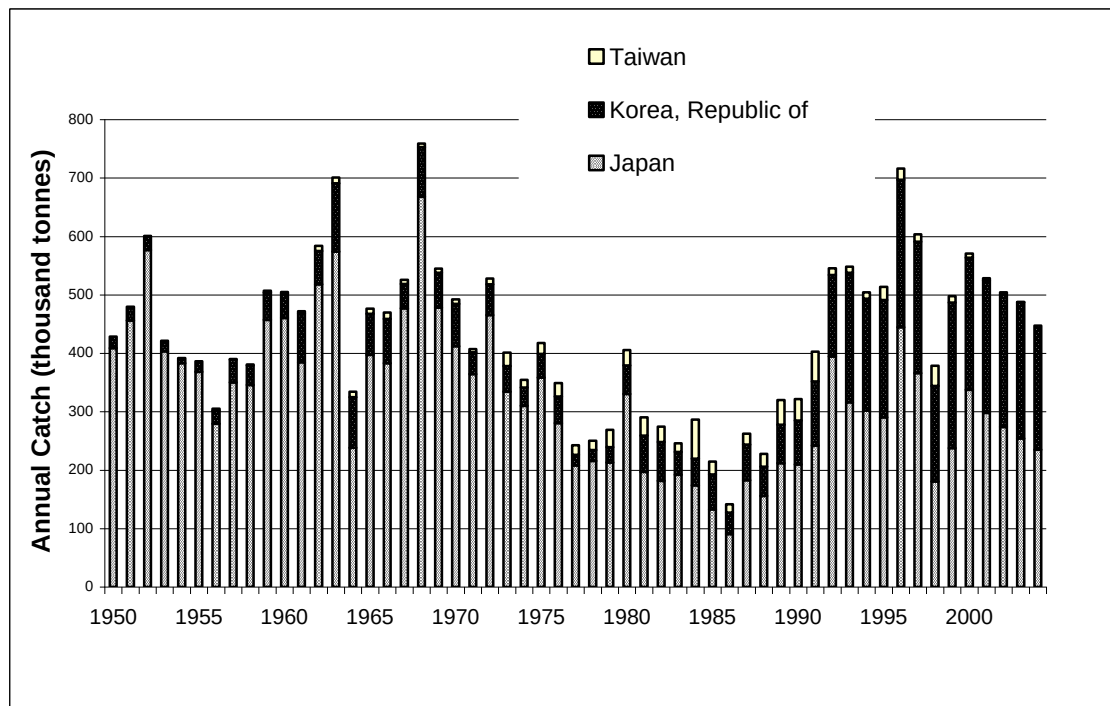


Figure 2-10: Global Annual Capture Production for Japanese Common Squid, by Country, 1950-2005, 1000 tonnes/year. Source: FAO Fishstat.

Until recently, Japan dominated the global catch of common squid, but South Korea has exceeded Japanese catch since 1999 and the recent catches of both winter and autumn spawning stocks by South Korea are estimated to represent around 55% of the global catch (Mori and Nagasawa 2006). China and North Korea also target the winter spawning sub-stock, but the catch amounts of these countries are unknown. However, based on the catch reported to the FAO, the Fisheries Research Agency (FRA) estimated the capture production by countries other than Japan and South Korea to be around 34,000 tonnes per year from 1998 to 2002 (Mori and Nagasawa 2006). In the Pacific, Japanese common squid (winter spawning sub-stocks) is mainly caught by a coastal angling fishery using a small-scale fleet (vessels smaller than 30 tonnes), but is also caught in gill nets and by the bottom trawl fishery. Catches from fisheries other than angling have increased steadily since 1995, accounting for 56 percent of the total catch of common squid in 2004. On the other hand, offshore angling fishery by a medium-size fleet (vessels of 30 -185 tonnes, although the category used until 2001 was 30-138 tonnes) dominates the catch of the autumn spawning sub-stock in the Sea of Japan. In 2005, the small-scale coastal angling fishery received the largest share (about 30 %) of the TAC for Japanese common squid, amounting to 108,000 tonnes per year.

2.5.3.2 Abundance trends

The time series abundance trend of Japanese common squid estimated by the FRA is given in Figure 2-11. Stock size estimates are based on the CPUE from commercial fisheries and/or vessel surveys, using assumptions of catch efficiency (Kawabata 2005), as well as larval surveys. For the autumn stock, the number of animal in a year is calculated from the average CPUE of all the sampling stations (annual stock index) multiplied by a catchability coefficient estimated from historical CPUE data. A Beverton-Holt stock-recruitment relationship was assumed for the autumn spawning stock. For the winter spawning stock, the stock-recruitment relationship is not well understood, so they use the density of squid from the survey abundance index and scale this to the full population given the survey coverage.

The size of the winter spawning sub-stock has been estimated by the RFA at less than

300,000 tonnes per year up to 1989, but it has steadily increased since, peaking at 1.3 million tonnes in 1996 (Figure 2-11).

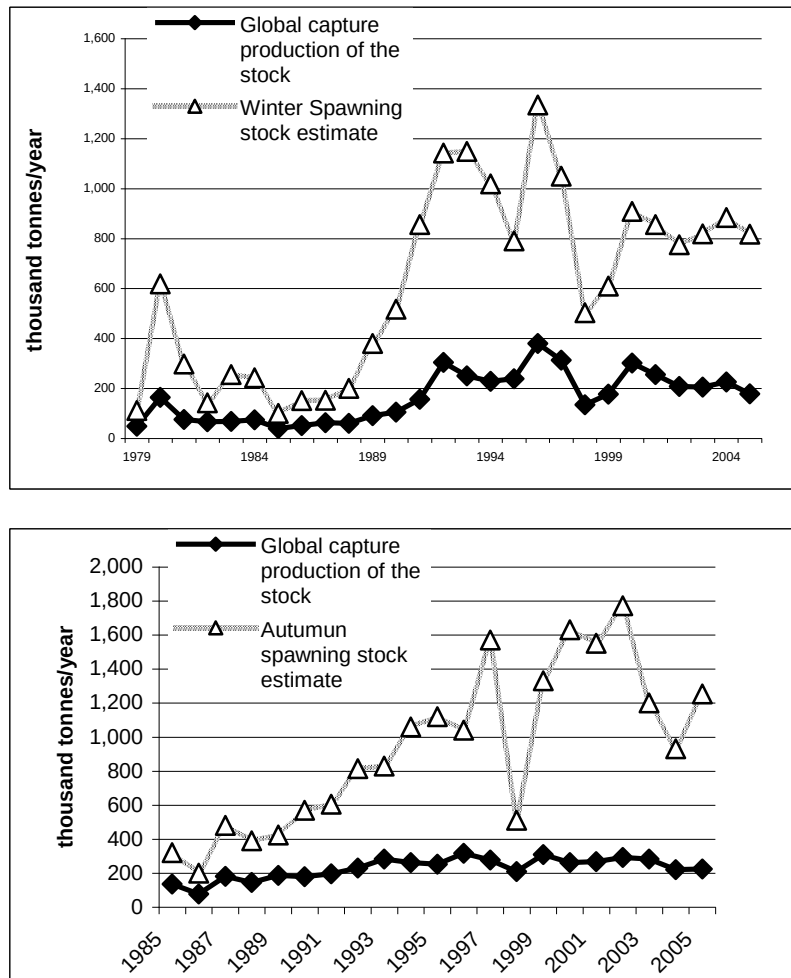


Figure 2-11: Annual capture production of winter spawning sub-stock (top) and Autumn spawning sub-stock (bottom) of *T. pacificus* (1000 tonnes/year) by Japan and South Korea in relation to estimated stock size, 1979-2005. Source: Mori and Nagasawa, 2006 and Kidokoro et al., 2006.

The size of the winter stock then declined in 1998, increased again by 2000 and has remained relatively stable since. In 2005, the stock size of the winter spawning sub-stock was estimated at about 840,000 tonnes. The large annual variation in stock abundance is believed to be associated with interdecadal climatic regime shifts over the North Pacific (Sakurai et al. 2000). In the western North Pacific, environmental conditions have shifted from a warm regime beginning in the late 1940s, to a cool regime in the late 1970s, and

back to a warm regime in the late 1980s (Minobe 1997; Sakurai et al. 2000). These regime shifts appear to coincide with the variation in *T. pacificus* stock abundance as well as catches (Sakurai et al. 2000; Kidokoro et al. 2006) as the stock size and catch decreased particularly during the early 1980s and increased during the late 1980s (Figure 2-11).

Similarly, the autumn spawning stock experiences large fluctuations in abundance (Figure 2-11). The estimated stock size of the autumn spawning sub-stock has been historically low: less than 500,000 tonnes per year until the 1980s due to the high fishing mortality and oceanographic conditions that were unfavourable to the stock. Since the early 1990s, stock size has recovered, reaching between 1.5 and 2 million tonnes per year by 2000. The sharp decline in the stock level in 1998 is believed to be associated with the unpredicted climate change event which was unfavourable with respect to recruitment to the stock (Kidokoro et al. 2006). Over the past few years, however, the stock size has been in decline.

2.5.3.3 Economic trend

The average annual expenditure of the major fleet operators (10-30GT class) varied from 17.7 million yen/year (US\$149,800) to 55.6 million yen/year (US\$ 472,000) during 1985-2004. The detailed expenditure data in the period of 1985-2000 indicate that fuel and labour are the two major sources of costs for this fleet (Figure 2-12). In 2000 fuel and labour jointly accounted for about 35% of the total expenditure of sampled operators. This share changes slightly over time, between 35% and 42%, largely associated with the fuel share change, although the relative proportion of other cost items remain relatively stable. The average annual profits of sampled operators have been either very low or negative over the last twenty years.

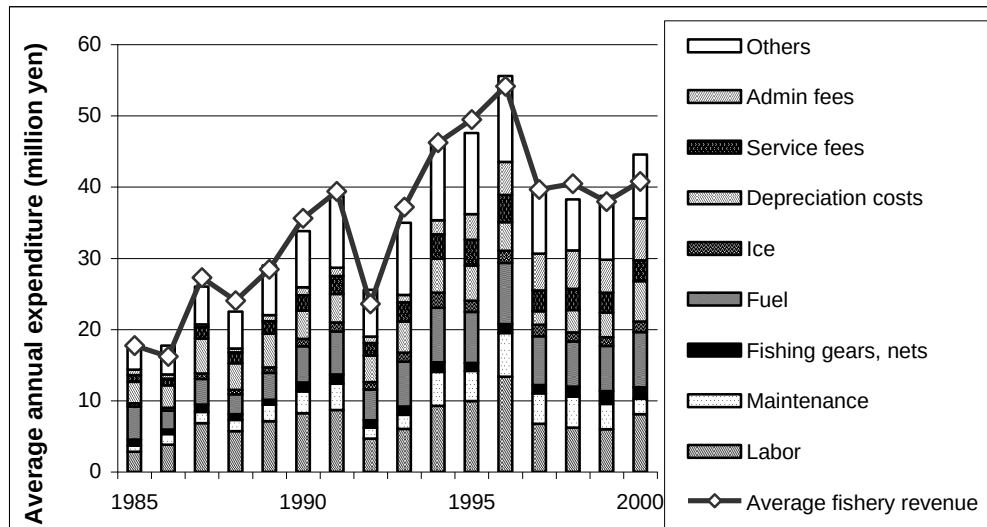


Figure 2-12: Average annual expenditure of sampled operators (full-time, 10-30GT class) for coastal squid angling fishery, million yen/year, 1985-2000. Source: Survey Report on Fishery Economy, 1985-2000, MAFF.

Ex-vessel price of Japanese common squid landed as fresh in the mid 1980s were much higher than the current levels, e.g. the price in 1986 was nearly 3 times higher than the price in 2004. This exceptionally high price was due to the historical low levels of catch. The stock recovery in the early 1990s together with the expansion of alternative squid fisheries (i.e. fishery targeting *O. bartrami*) and increased in cheap imported squid products coincided the decline in common squid prices during 1986 and 1991. As a result, prices in more recent years (between 1992 and 2004) appear to have arithmetic mean around 200 yen/kg with random fluctuation between 149 yen/kg and 343 yen/kg (real prices), without any apparent upward/downward trends (Figure 2-13). Frozen squid was generally slightly cheaper, with its ex-vessel price varying from 135 yen/kg to 295yen/kg over the same period.

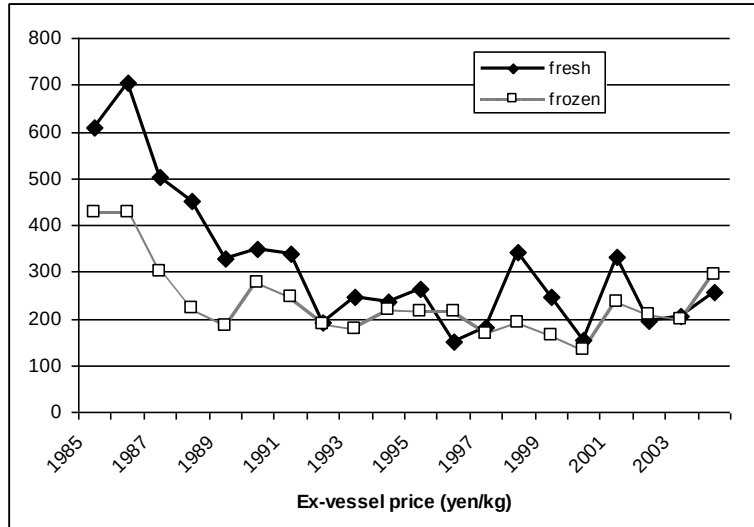


Figure 2-13: Changes in ex-vessel price (yen/kg) of Japanese common squid in Japanese market, 1985-2004. Source: Annual Report of Fish Marketing Statistics. MAFF, 1961-2005

2.6 Patagonian toothfish fishery case study

2.6.1 Overview of the fishery

The Patagonian toothfish occurs in the Exclusive Economic Zones (EEZ) of southern Chile and Argentina, and sub-Antarctic islands under the sovereignty of Australia, France, New Zealand, South Africa and the United Kingdom (Catarci 2004).

The South Georgia toothfish fishery occurs within both the Convention Area of the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) Subarea 48.3, and the South Georgia Maritime Zone (SGMZ) managed by the Government of South Georgia and the South Sandwich Islands (GSGSSI), and is confined to a depth between 500 and 2000 metres. South Georgia and Shag Rocks toothfish are considered a single stock, separate from all other stocks in the Southern Ocean or Patagonian Shelf off South America (Agnew 2004). Toothfish is fished in deep water (600m – 2000m) using bottom longlines (CCAMLR 2000).

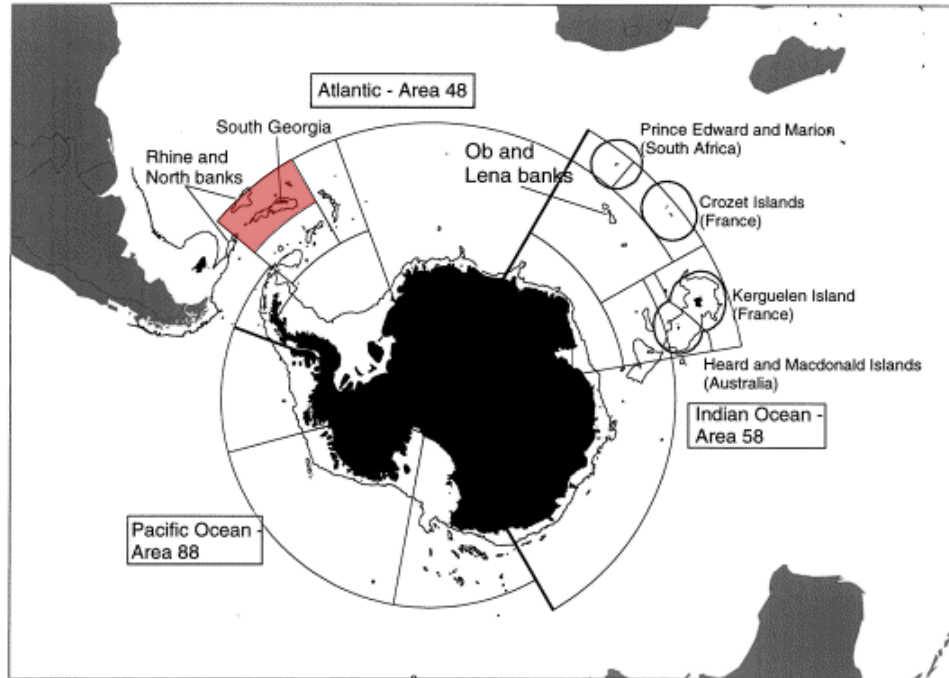


Figure 2-14: Map of the Convention Area. Subarea 48.3 is highlighted. Source: Agnew, 2000

There were three major periods in the development of the toothfish fishery in Subarea 48.3 (SC-CAMLR 2006). Juvenile toothfish had been a minor by-catch species in a general trawl fishery in South Georgia by Polish and Soviet Union vessels since the mid 1970s. At that time it was not recognized as a potentially lucrative fishery because the bulk of the toothfish population lived at depths inaccessible to bottom trawls (Agnew 2004). However, in late 1988 the Soviet Union initiated a longline fishery in the area, with catches rising to a peak of 8,311 tonnes in the 1989/1990 season (Figure 2-15) but they quickly came to a halt following the break-up of the Soviet Union (Agnew 2004). In 1991/1992 Chilean vessels fished for the first time at South Georgia, and the number of participating countries and vessels increased substantially in the following years (Figure 2-15).

From 1993 the fishery entered a second phase. In 1993/1994 CCAMLR designated the South Georgia toothfish fishery a special area for protection and a number of conservation measures were put in place. The key management changes include the shift from a summer fishery to a winter fishery in 1995 and an associated requirement for

night-time setting of longlines to mitigate the by-catch of seabirds. Observers were also introduced in 1994. This led to an immediate change in longline configuration with fewer, longer lines containing more hooks per set each day.

CCAMLR considers the period from 1997 to the present as the third phase in the development of the fishery, which is characterized by multinational fleet. There is very little overlap of vessels between the first and third phases. Thirty vessels fished only in the first phase and up to 1995 of the second phase, 36 vessels fished only from 1996 in the second phase and in the third phase (SC-CAMLR 2006).

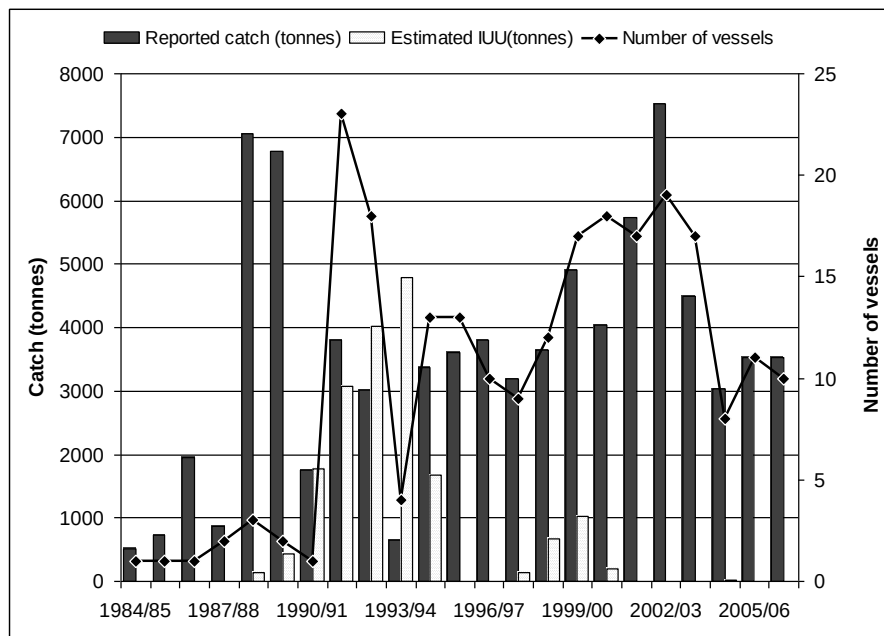


Figure 2-15: Catches of Patagonian toothfish in the Subarea 48.3, South Georgia, 1984/85-2007/08. Data were obtained from SC-CAMLR, 2008. Catch from IUU fleet were estimated by CCAMLR.

Total catch quota is set annually by CCAMLR for Subarea 48.3 and smaller management areas in recent years. Catch quota and mitigation measures are also set on major by-catch species such as macrourids and skates / rays.

GSGSSI allocates individual vessel quotas within this overall limit to a set number of

vessels for a defined season (May – August) at a level that will take the quota within the season. In 2007/2008 season, fishing licences were given to 10 vessels from 7 nations.

2.6.2 IUU fishing

Illegal, Unreported, and Unregulated fishing, or so called “IUU fishing” (For the definition of IUU fishing in the area, see Agnew 2004) has been a feature of the Southern Ocean toothfish fisheries since the early 1990s (Agnew 2004). CCAMLR has made estimates of IUU catch in Subarea 48.3, based on the evidence from sightings of IUU vessels and estimates of the likely duration of fishing and catch rates of the vessel sighted. There are a number of sources for such information, but the most reliable is a systematic searching performed by fisheries protection vessels (FPVs). A comprehensive FPV data are only available from 1998, and over the following four years, FPV activity increased considerably at South Georgia, with the result that the number of sightings of IUU vessels rapidly decreased (Agnew and Kirkwood 2005). Only one further incident of IUU has been recorded since, when the Guinean flagged vessel Elqui was caught fishing illegally inside the SGMZ highlighting the effective surveillance of the SGMZ. IUU catches of this stock of toothfish are currently estimated to be zero (SC-CAMLR 2008).

2.6.3. Abundance trends

Since 2005, assessments and estimates of long-term yields for this stock were made using the CASAL assessment model (Hillary et al. 2006). It is an integrated assessment method, capable of fitting to a variety of different types of input data, including catch length-frequencies in the official CCAMRL catch data, standardised CPUE data, mark–recapture data from the UK mark–recapture experiment in Subarea 48.3, and estimates of recruitment by age and year class from bottom trawl surveys around South Georgia. The estimated historical stock dynamics are given in Figure 2-16. The current (2005) estimate of the spawning stock biomass (SSB) is some 69% of virgin spawning biomass (X_0).

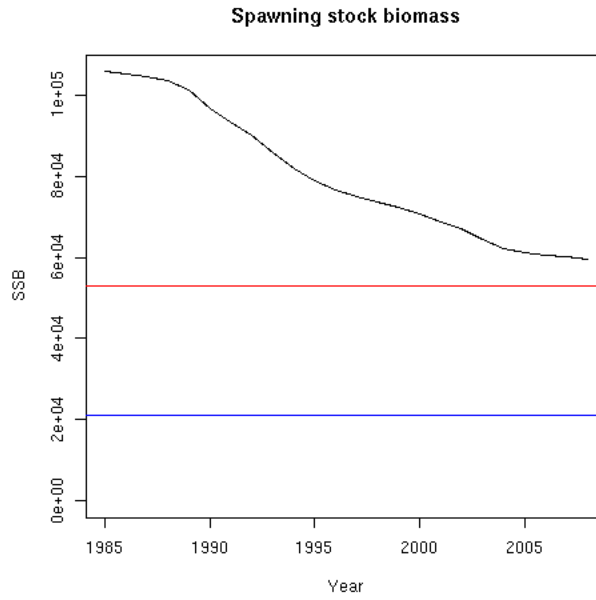


Figure 2-16: Historical stock dynamics of Patagonian toothfish in the Subarea 48.3, South Georgia. SSB = spawning stock biomass) with the red and blue lines denoting 50% and 20% of the mean unfished SSB (X_0), respectively. Source: SC-CAMLR(2008)

Chapter 3. Developing a framework for bioeconomic MSEs of short-lived species: A case study of Pacific saury (*Cololabis saira*) and Japanese common squid (*Todarodes pacificus*)

Abstract

Standard fixed output control policies, based on the concept of maximum sustainable yield (MSY), have the implicit assumption of deterministic and stable harvested populations. Short-lived pelagic stocks that are subject to large environmentally-driven fluctuations do not fulfil these assumptions, and hence total allowable catch (TAC) policies based on the MSY may be impracticable, potentially leading to economic inefficiencies or resource depletion. The fish stocks currently being managed by the TAC system in Japan, for example, are potentially affected by these issues. In this chapter, I develop an adaptive harvest strategy, as opposed to traditional fixed input/output strategies for the stocks of Japanese common squid and Pacific saury, aiming to identify the strategies which make the fisheries more profitable and maintain the sustainability of the resources. It was found that for both fisheries, fixed and adaptive input-based management procedures (MPs) with bioeconomic objective were superior to the constant TAC-based MP in terms of achieving higher economic profits, while maintaining or improving the probability of keeping the stock at sustainable levels. The adaptive MPs were found to be preferable to the fixed input control for both fisheries, as they were capable of generating higher economic profits and minimising the economic losses from the fisheries, while maintaining the precautionary principle. This approach is potentially useful for other stocks with similar biology especially for fisheries that are borderline profitable.

3.1 Introduction

Populations of small pelagic fish (e.g. anchovy and sardine) and coastal squid support important fisheries worldwide. These species are typically short-lived, have rapid growth rates, and play an important role in the marine food web. Great challenges for managing these short-lived species arise because the populations tend to expand rapidly in abundance when feeding and spawning conditions are favourable, but decline rapidly when ocean conditions change (EUR-OCEANS 2008). Consequently the prediction of future abundance for short-lived species is very difficult and the management of such species faces many challenges (Caddy 1983; Patterson 1992; Pierce and Guerra 1994; Fréon et al. 2008).

Conventional static harvesting policies, such as TAC based on MSY, are not necessarily helpful as they have little flexibility and are potentially unsuitable for a dynamic system whose parameters are known imprecisely and are subject to large natural variability. Although static harvest measures for highly fluctuating stocks have been frequently criticised (Beddington and May 1977; Patterson 1992; Kishida 2003), conventional static biological reference points (e.g. MSY, F_{MSY}) continue to provide a means of guiding fisheries management decisions (Punt 2006), including for Japanese fisheries targeting short-lived species.

As an alternative to stationary decision rules, adaptive management or adaptive control of the fisheries system in the form of feedback control rules has been proposed (Walters and Hilborn. 1976; Walters 1986). Optimal feedback control systems are a subfield of optimal control theory in which the control variables are determined as functions of the current state of the system (McGraw-Hill 2002). Here it is assumed that there is uncertainty in the dynamics of the system, so that the optimal control at any future time will depend upon the state of the system at that time, rather than on time alone (Walters and Hilborn 1978). Feedback rules provide resource managers with an adaptive method of regulating resource use to achieve defined objectives, and allow them to evaluate the performance of alternative management regimes (Grafton et al. 2000).

Adaptive management based on feedback controls has been advocated by various authors in the fisheries literature (Clark and Munro 1975; Walters and Hilborn. 1976; Walters and Hilborn 1978; Walters 1986; Conrad and Clark 1987) but has rarely been operationalised and even fewer applications exist that compare actual management with management using a feedback rule (Grafton et al. 2000). One of the few examples of an adaptive scheme is the Falkland squid fishery, where weekly in-season fishery data are used to provide resource managers with up-to-date abundance indices of the resource. The fishery is closed when the target stock biomass escapement of 40% is reached during the fishing season prior to the “official” end of the fishing season (Basson et al. 1996). Adaptive management is also used for the management of the South African pelagic fisheries, where the Management Strategy Evaluation (MSE) approach has been used since 1991 and forms the basis of setting TAC and total allowable bycatch (TBC) for pilchard (sardine) and anchovy in the purse-seine fishery (De Oliveira and Butterworth 2004).

Feedback control rules have been used for economic evaluations of the history of a fishery by comparing the actual harvest pattern over a period with the optimal pattern. Such rules can be introduced as either deterministic or stochastic control systems. A deterministic feedback rule was used by Grafton et al. (2000) for Canada’s Northern cod fishery and by Arnason et al. (2004) for the Norwegian cod fisheries. Their models are applications of the model developed by Sandal and Steinsham (2001b). Using a similar procedure, McDonald et al. (2002) used both a deterministic and stochastic model to identify the stock level at which a harvest moratorium is optimal using data for the Southern bluefin tuna fishery. All of the above examples reached the general conclusion that the fishery of concern was economically overexploited in some period in the past, and a harvesting moratorium should have been imposed. However, what has been missing in the literature is an evaluation of the future performance of the current management, economically optimal input control management, and custom designed feedback control rules which adapt to population and economic changes and/or objectives over time.

Another area where feedback control has been applied to fisheries is using MSE (Holt and de la Mare 2009). The MSE approach in fisheries has been given increasing attention in recent years due to the ability of the approach to incorporate adaptive and precautionary principles (see Chapter 2). The MSE approach involves assessing the consequences of a range of management procedures (MPs) and presenting the results in a way that demonstrates the trade-offs in performance across a range of management objectives (Smith et al. 1999). A detailed overview of this approach is provided in Chapter 2.

Although input-controlled fisheries for short-lived species are common (Dichmont 2006), most applications of MSE have focused on longer-lived species managed using output controls (Dichmont et al. 2006a), except for a few examples, e.g. the Australian Northern prawn fishery (Dichmont et al. 2006c). Moreover, few MSE studies have explicitly considered economics (Dichmont et al. 2008; Holland and Herrera 2009; Punt et al. 2010).

A novelty of this study is the development of an in-season adaptive scheme, where the adjustment in permitted effort levels during the fishing season is based on the detected changes in the abundance and catchability coefficient - the key parameter for a stock assessment, often assumed to be constant. Catchability variation is likely to be the greatest source of error in models based on catch per unit effort with an assumed constant catchability (Ricker 1975; Arreguín-Sánchez 1996), but has not been taken into account in the existing examples of adaptive management for fisheries resources. Catchability variation can be caused by a number of factors, including daily and seasonal cycles, changes related to stock abundance, changes in the efficiency of the fishery (e.g. improved gear), changes in regulations, fishers' behaviour, and environmental factors (Gulland 1983; Hannesson 1983; Wilberg et al. 2010). Gulland (1983) noted that the most important sources of variation in catchability are essentially random. Catchability change also occurs when the fishery, or the survey from which the abundance index is derived, does not cover the full area of the stock (Wilberg et al. 2010). Higher catchability means that fish are easier to catch on average given the same level of inputs. This

scheme might permit resource managers to set a more aggressive harvesting strategy (e.g. higher levels of effort/catch) when environmental conditions are favourable, and also enables them to make the necessary adjustments when economic conditions (e.g. fish price, fuel price) change. Thus, a higher profitability might be obtained from the fishing operation under such a scheme while maintaining the precautionary principle. An additional obvious advantage is the self-correction mechanism when the true catchability is different from the long-term average catchability, as assumed in traditional methods. There is a potential issue of obtaining unbiased estimates of catchability separately from biomass, given that there is a known negative correlation between them (Hilborn and Walters 1992). However, the depletion assessment method is included in the simulation framework, as is the simulation of observation error in the key input data, so this potential bias is already factored into the evaluation process. I also explore how the key factors influencing this bias (depletion level/exploitation rate and observation error) can affect the estimates of catchability and biomass in the depletion method.

The aim of this chapter is to develop an approach to MSEs for short-lived species that includes economic as well as biological considerations. Since the case study fisheries are suffering from low profitability, the focus is on exploring whether adaptive strategies have the potential to make the fisheries more profitable, while maintaining the sustainability of the resources. The chapter illustrates how an input-based adaptive management scheme with bioeconomic objectives can be constructed for fisheries targeting short-lived species as an alternative to output controls (TAC), based on the actual example of evaluating management procedures for the Pacific saury *Cololabis saira* and Japanese common squid *Todarodes pacificus* fisheries off the coast of Japan.

The chapter first identifies the optimal stationary (fixed) effort using stochastic bioeconomic models, which incorporate uncertainties in both stock abundance and economic parameters. This is the first alternative harvest control rule proposed here to the annual TAC-based control rule. Secondly, custom designed feedback control rules, which adapt to population and economic changes, are developed as a second alternative scheme. Finally the performance of the TAC management, constant effort control management,

and adaptive management are compared using a simulation-based MSE approach. The results are used to identify whether the feedback control scheme performs better than the traditional fixed harvest/effort control management schemes, based on economically optimal effort, with performance assessed in terms of the resource rent. The chapter does not provide an evaluation of the performance of the current management regime because the necessary data were not available to me, but rather use real fisheries to demonstrate a method of constructing a bioeconomic adaptive management scheme using the MSE framework, and to illustrate its advantages relative to more traditional approaches. I used the available stock abundance estimates and life-history information to (a) parameterise the bioeconomic estimation models, and (b) to condition the bioeconomic operating models used in this chapter.

This chapter is organized as follows: Section 3.2 describes the methods for constructing bioeconomic models, adaptive management procedures, and a management strategy evaluation comparing output versus input-based harvest strategies. Section 3.3 gives the results. Discussion and conclusions of the chapter are given in Section 3.4.

3.2 Methods

This section has three major parts. In section 3.2.1, I outline the method used to construct stochastic bioeconomic models (basic models) for the two selected Japanese fisheries for the purpose of identifying the bioeconomic equilibrium. Subsequently, I construct bioeconomic operating models, which are used as the basis for both an adaptive management procedure (section 3.2.2) and a full simulation of the performance of candidate management procedures (section 3.2.3). The bioeconomic operating models being developed here are complex enough to explain the dynamics of systems and data, including the full population dynamics, environmental conditions, management actions and their interactions, but simple enough to be able to solve for dynamic optimisation problems. Hence, they are “minimum realistic” models.

3.2.1 Constructing stochastic bioeconomic models

I developed stochastic bioeconomic models to estimate the steady-state effort level in terms of the number of participants in each of the two fisheries which would maximise the sum of discounted annual profits over a long-term (100 year) time horizon. Due to the lack of availability of economic data for all participating fleet categories, the steady-state conditions were derived for the major fleet only and the fishing mortality by other Japanese and non-Japanese fleets was specified as “external” and treated as random variables with known mean. As the external fishing mortality cannot be known precisely, the equilibrium conditions for the fleet concerned are indicative and the use of the model is limited to performing a comparison of alternative management regimes under realistic scenarios of external mortality. The aim is to identify approximate optimal stationary policies that can serve as a base for an adaptive management framework.

3.2.1.1 Biological data

Stock estimates for the Pacific saury and Japanese common squid were obtained from the Resource Assessment Report, published annually by the Fisheries Research Agency of Japan (FRA). Stock assessments of the western North Pacific stock of Pacific saury have been carried out by FRA since 2003 based on a non-parametric production model using the global capture production and best available estimate of global fishing efforts by the participating 4 countries. Mid-water trawl surveys have also been used to improve the stock assessments. See Chapter 2 for full details of the case study fisheries.

3.2.1.2 Economic data

Income and expenditure data were obtained from the Annual Survey Report on Fishery Business Management (1985-2000; and 2001-2005), Ministry of Agriculture, Forestry and Fisheries (MAFF). These reports are based on sampling surveys. The published income and expenditure data are aggregated to the fishery level, and report only either the sum or the average values for each fishery. Vessel-level data are not available from the MAFF due to confidentiality obligations. Thus, the calculation of fishing costs are based on aggregated/average costs data from sampled vessels and operators. The historical

record of ex-vessel prices for Pacific saury and common squid were obtained from the Annual Report of Fish Marketing Statistics. MAFF, 1961-2005. To account for the effects of inflation, economic data were adjusted using the Consumer Price Index (CPI) reported by the Statistics Bureau of Japan. A summary of the key historical abundance trends, and management information for the stocks of Pacific saury (*Cololabis saira*) and Japanese common squid (*Todarodes pacificus*) can be found in Chapter 2.

As Pacific saury are caught mainly by 100-200GT class vessels, I selected this category to extrapolate the costs of fishing for the saury stick-held dip net fishery. Japanese common squid are caught mainly by a small-scale angling fleet with vessels of less than 30 tonnes. Due to data availability, I selected the 10-30GT class category to infer the cost of fishing for the coastal angling fishery, which accounts for approximately 50% of common squid catch. The coastal angling fleet comprised of vessels smaller than 10GT also catches a great amount of common squid, but the information on how many participants actually exist is limited, as some prefecture governments do not require a license registration for the vessels smaller than 5GT. As a result, I have excluded them from my analysis. This will, however, lead to an underestimation of the true effort size.

3.2.1.3 Model for Pacific saury

Stock dynamics of Pacific saury

Ueno et al. (2006) used a simple surplus production model to describe the population dynamics for *C. saira* in their stock assessment work. In order to account for random variation in stock abundance, I used a stochastic difference equation, similar to Reed (1979), to describe saury biomass dynamics:

$$X_{t+1} = Z_{t+1} \left[X_t + F(X_t) - Y_t - \xi_t^{Ext} X_t \right] \quad (3-1)$$

$$F(X_t) = rX_t \left(1 - \frac{X_t}{K} \right) \quad (3-2)$$

where $F(X_t)$ is the logistic growth function, Y_t is the size of harvest by the dominant Japanese fleet (100-200GT class), Z_{t+1} are random variables with $E\{Z_{t+1}\}=1$. This can be written as $Z_{t+1} = e^{\varepsilon_{t+1}^X - \sigma_X^2/2}$, where ε^X are normally distributed error terms with mean zero and variance σ_X^2 . In this formulation, biomass X becomes a random variable. In the above equation, ξ_t^{Ext} is the external harvest rate expressed as a proportion of the modelled harvest with a normal distribution with known mean μ_{Ext} and variance σ_{Ext}^2 . Based on the historical estimates of biomass, an assumption was made that the coefficient of variation CV_X is roughly 25-30%. The standard deviation σ_X - the square root of the variance - can be then calculated as follows:

$$\sigma_X = \sqrt{\log(1 + CV_X^2)} \quad (3-3)$$

The estimates of the biological parameters, namely K and r , obtained from Ueno et al. (2006), are given in Table 3-1. Based on these values, σ_X was estimated at approximately 0.23-0.29.

Table 3-1: Carrying capacity (K), MSY, growth rate (r) and standard deviation for biomass

Biological parameters (95% CI)		
K (million tonnes)	8.15	(7.7; 11.4)
MSY (000 tonnes)	966	(888; 1,143)
r	0.474	(0.449; 0.522)

Source: Ueno et al. (2006)

Price dynamics of Pacific saury

The inverse demand function is an abstraction of the market for fish (Grafton et al. 2000) and can be specified in either linear models (McDonald et al. 2002; Arnason et al. 2004) or non-linear models (Grafton et al. 2000; Sandal and Steinshamn 2001a). After fitting the observed price and historical harvest data to several candidate models, it was found that although the linear model fitted relatively well ($R^2=0.72$), it underestimated the

demand at high harvest levels. Comparing a simpler non-linear model (1 parameter) used in Grafton et al. (2000) and Sandal and Steinshamn (2001a) to a more complex (2 parameter) non-linear model, the latter non-linear form fit much better with a smaller residual standard error and adjusted R^2 of 0.71 compared to 0.36 under the 1-parameter model (see observed versus estimated inverse demand curve in the Results). ANOVA confirmed that the improvement from a simpler to more complex model is highly significant (see Results). Thus, a 2-parameter model was selected to explain the price dynamics of Pacific saury:

$$P(Y) = \frac{P_{\max}a^n + P_{\min}Y^n}{a^n + Y^n} + \varepsilon^P \quad (3-4)$$

where $P_{\max}$ and $P_{\min}$ are the maximum and minimum historical ex-vessel prices of Pacific saury in the period of 1986-2004, Y is the observed harvest of Pacific saury by 100-200GT class operators, a and n are parameters to be estimated. The ε^P are normally distributed error terms with mean zero and variance σ_p^2 . The standard deviation σ_p is obtained by calculating the standard deviation of the residual standard error from the fitted model.

Uncertainty in costs

The cost per operator was reported to be about 168.8 million yen per fishing season in 2004, based on a sampling survey from approximately 10% of the participating operators. This is very similar to the average annual cost per operator over the past 15 years (1990-2004) of approximately 165 million yen. Since the true average cost for all participating operators is unknown, I accounted for this key uncertainty by allowing the cost to have a uniform distribution +/- 15% of the value in 2004 using the parametric bootstrap method. I assumed that this can also capture uncorrelated year to year variation in costs due to e.g. changes in fuel costs. Although this is a realistic assumption, given the historical variation in the major cost items including fuel (See 2.5.2 for economic trends), it requires further investigation if future changes in fuel price exceed the historical variation.

Production function

I assumed that the harvest of Pacific saury in period t by the stick-held dip net fleet follows a production function:

$$Y_t = Y(q, E_t, X_t, \alpha, \beta, ENSO) \quad (3-5)$$

where Y_t is the aggregated harvest by fleet at time t , q is the catchability coefficient, and E_t is the aggregated fishing effort in period t . The term α is the effort output elasticity and β is the stock output elasticity. ENSO is a dummy variable included as a proxy for the sea surface temperature (SST) anomalies in the Pacific, which are believed to affect the abundance of pacific saury (Watanabe et al. 2003; Tian et al. 2004). The ENSO index (<http://www.coaps.fsu.edu/jma.shtml>) developed by the Japan Meteorological Agency (JMA) classified three phases of ENSO: El Niño (warm SST anomalies in the Pacific), El Viejo (cool SST anomalies), and neutral, based on an index derived from observed SST anomalies. The harvest function expressed as a logarithmic scale is:

$$\ln Y_t = \ln q + \alpha \ln E_t + \beta \ln X_t + \gamma ENSO_t + u_t \quad (3-6)$$

where ENSO is a categorical variable (warm, cold, neutral). Bjørndal and Conrad (1987) found that the number of participating vessels may be an appropriate effort measure for schooling fisheries. Historical data show that the number of operators and the number of participating vessels are very similar, and having data on cost per operator, the number of operators was taken as an appropriate measure of fishing effort for Pacific saury. The estimated parameters for the production function by OLS regression are given in the Results.

Optimisation

Optimal policies were based on the usual criterion of maximising the discounted sum of net present value of annual profits subject to the population and price dynamics of Pacific saury expressed in equation (3-1) and (3-4), and $X_t, Y_t \geq 0$. Unit harvesting cost was assumed constant over time.

The sum of future discounted profits, or net present value (NPV), was defined according to:

$$NPV = \sum_{t=1}^T \pi_t (1 + \delta)^{-t} \quad (3-7)$$

where δ is the discrete discount rate. The profit function, π_t , is defined as follows:

$$\pi_t = pY_t - cE_t \quad (3-8)$$

p and c are the price and cost variables, respectively, and depending on the case are either assumed as fixed or random variables with the previously outlined distributions. Rather than trying to identify the single point estimate of optimal steady-state effort, I adopt a stochastic method using a Monte Carlo (MC) approach to obtain many possible future values for optimal effort, given the time horizon parameter T . To ensure the sustainability condition was met I chose a suitably large value of T (100 years). In all cases 500 MC trials were performed to obtain the samples of optimal effort. The distribution of optimal effort for both stocks is given in the Results section.

3.2.1.4 Model for Japanese common squid

Stock dynamics of Japanese common squid

The model describing population dynamics for *T. pacificus* is based on the work by Maruta (1989). A Beverton-Holt discrete time age-structured model was used to define the population dynamics for the autumn spawning stock of *T. pacificus* (Kidokoro et al. 2006). The spawner-recruit relationship can be expressed as:

$$S_t = N_t \exp(-M - F_t - F_t^{Ext}) \quad (3-9)$$

$$N_t = \frac{aS_{t-1}}{1 + bS_{t-1}} \cdot e^{\varepsilon} \quad (3-10)$$

where S_t is the number of spawners at time t , N_t is the number of surviving squid at time t , M_t is the rate of natural mortality at time t , F_t is the rate of fishing mortality by the dominant Japanese fleet at time t , F_t^{Ext} is the rate of external fishing mortality at time t , and $\exp(-M - F_t - F_t^{Ext})$ is the proportional survivorship. a and b are Beverton-Holt parameters. The external fishing mortality, other than the mortality from dominant Japanese fleet, has known mean μ_{Ext} and variance σ_{Ext}^2 . The ε are normally distributed error terms with mean zero and variance σ_R^2 . The variance term (log-normal deviations) was included to account for the uncertainty in the stock-recruit relationship. Kidokoro et al (2006) used $\sigma_R = 0.238$ for the autumn spawning stock, thus I used this value as a baseline. I also considered higher levels of σ because the inter-annual fluctuation of the sizes of the winter spawning stock is believed to be higher than that of the autumn stock.

Substituting (3-10) into (3-9), I obtained:

$$N_t = \frac{aN_{t-1} \exp(-M - F_t - F_t^{Ext})}{1 + bN_{t-1} \exp(-M - F_t - F_t^{Ext})} \quad (3-11)$$

The catch in weight in period t is given by the Baranov (1918) catch equation:

$$Y_t = \frac{F_t}{F_t + M} (1 - \exp(-M - F_t)) N_t w_t \quad (3-12)$$

where w_t is the average squid weight at period t . The stock-recruitment parameters for the autumn stock of Japanese common squid, average squid weight, and natural mortality were derived based on the works by Kidokoro et al. (2006) and Mori et al. (2006). The Japanese common squid is a special case where the lifespan is assumed to be 1 year.

Table 3-2: Stock recruitment parameters (a,b), natural mortality (M) and squid weight (w)

a	7.76
b	0.105
M	0.6
w	280g

Source: Kidokoro et al. (2006) and Mori et al (2006)

Price and cost uncertainty

Unlike the Pacific saury case where the inverse demand function was used to predict the price of saury given the harvest level, the Japanese common squid price is assumed constant (fixed) and independent of harvested quantity. I considered this assumption reasonable because the ex-vessel price is relatively constant over the whole period considered: the real ex-vessel price in 2004 (257 yen-per-kg) was approximately the same as the median ex-vessel price of common squid in the period between 1985 and 2004 (p=260 yen/kg).

The cost per operator was reported to be about 22.3 million yen per fishing season in 2004. Similar to the Pacific saury case, the cost information was obtained from a sampling survey and the true cost is unknown. Thus, the uncertainty in cost was included by allowing the cost to have a uniform distribution +/- 15% of the subsample cost value in 2004. Although the price of Japanese common squid has been relatively stable since the early 1990s, I also accounted for the price uncertainty by allowing the price to have a uniform distribution of +/- 15% of the price in 2004.

Stock-recruitment parameter estimate for a combined stock

The stock-recruitment (S-R) relationship for the winter stock is not well understood. The FRA argues that environmental conditions have large effects on the abundance of this stock, and used a simple linear model, which assumes an density-independent mortality, rather than using Ricker and Beverton-Holt models (Mori and Nagasawa 2006), where density-dependent mortality is assumed. They assume that the number of the winter stock can be explained by:

$$N_t = S_{t-1} \times RPS \quad (3-13)$$

$$S_t = N_t \times e^{(-F-M)} \quad (3-14)$$

where S_t is the number of spawners at time t , and RPS is the recruit-per-spawner. However, this model is rather unrealistic as the number of squid can increase infinitely at a high population density. Thus, I assume that the Beverton-Holt model is more appropriate. As my interest was to estimate the equilibrium effort level for the coastal squid angling fleet, which harvests both stocks indistinguishably, in this chapter I use a single population model which can explain the population dynamics of both stocks, rather than having a separate biological model for each stock. A separate biological model is constructed for each stock in Chapter 5 in order to test the sensitivity of this assumption. Beverton-Holt parameters for the autumn stock cannot be used for the winter stock, because one of the S - R parameters (b) is dependent on the stock size of spawners, and the S - R relationships for different sub-stocks may be different. However, it is reasonable to assume that both stocks have the same or very similar steepness of the stock-recruitment curve, since both sub-stocks have a similar life history. In general, the estimation of steepness can be informed by estimates from related stocks (Myers et al. 1999; Punt and Hilborn 2001; Rose et al. 2001; SFSC 2009). I used the reported S - R parameters for the autumn stock to extrapolate the indicative S - R parameters for the combined stock. The steepness parameter z is defined by a consideration of the deterministic number of recruits arising when the mature biomass is reduced to 20% of its virgin level (Haddon 2001) and given by:

$$zR_0 = \frac{0.2aS_0}{1 + 0.2bS_0} \quad (3-15)$$

where the a and b are the Beverton-Holt parameters, S_0 is the total mature biomass under the absence of fishing (virgin mature biomass), and R_0 is the virgin recruitment observed in the absence of fishing. The parameters in equation (3-15) can be rewritten as:

$$a = \frac{4zR_0}{S_0(1-z)}, b = \frac{5z-1}{S_0(1-z)} \quad (3-16)$$

After calculating the steepness from the autumn stock using the available *S-R* parameters (Table 3-2), and assuming that the global R_0 is the carrying capacity for the combined stock divided by the mean weight of squid, it is possible to estimate an indicative stock-recruit relationship for a combined stock. To estimate the carrying capacity for the combined stock, the carrying capacity for the autumn spawning stock was first estimated using the X_{MSY} and the corresponding MSY reported by Kidokoro et al. (2006). The growth function parameters r and carrying capacity K_A for the autumn spawning stock were calculated as follows:

$X_{MSY} = K/2 = 1.05$ million tonnes, $MSY = rK/4 = 428,000$ tonnes, thus:

$K_A = 2.1$ million tonnes.

$r = 0.812$

For the winter spawning sub-stock, information on MSY, X_{MSY} , and F_{MSY} are not available. Thus an assumption was made that the winter spawning sub-stock has the same value of r . Myers et al. (1997c) showed that r was similar for all populations of Atlantic cod (*Gadus morhua*) at colder temperatures, thus, this assumption was considered reasonable. During 1985-2005, the estimated biomass of the autumn sub-stock was about 80% of the biomass of the winter sub-stock. It is assumed that the carrying capacity for the winter spawning sub-stock, K_W can be estimated by K_A multiply by a factor of 0.8, the average ratio of the winter sub-stock biomass and autumn sub-stock biomass, since the levels of catches as a proportion of stock biomass are similar between the two stocks. Thus I used this average ratio to obtain K for the winter sub-stock (K_W):

$K_W = K_A * 0.8 = 1.7$ million tonnes

K for the combined stock is thus estimated at 3.8 million tonnes.

Production Function

I considered two frequently encountered functional forms for fisheries production (Conrad 1999): an exponential form and a Cobb-Douglas form. The exponential model is more realistic than the Cobb-Douglas as the level of harvest will never exceed the level of available stock biomass, but there is a trade off as a Cobb-Douglas form has several advantages (Conrad 1999). Hence both functional forms were employed and an evaluation of fit was made post hoc.

A) the Cobb-Douglas production function is expressed as:

$$Y_t = Y(E_t, X_t) = q E_t^\alpha X_t^\beta e^{u_t} \quad (3-17)$$

Here, u_t is assumed to be a normally distributed error term. The number of operators was used as a crude measure of actual fishing effort. For angling fisheries, the number of hooks multiplied by soaking time would be a better indicator of fishing effort, but this information is not available. I considered the number of registered vessels as an alternative, but the information on the number of vessels was only available after 1991.

The estimating equation for the production function can be expressed in logarithmic form:

$$\ln Y_t = \ln q + \alpha \ln E_t + \beta \ln X_t + u_t \quad (3-18)$$

B) Exponential Production Function

With an exponential production function, the harvest of Japanese common squid can be explained by:

$$Y_t = X_t (1 - e^{-qE_t}) \quad (3-19)$$

The estimating equation is expressed as:

$$\ln\left(\frac{X - Y}{X}\right) = -qE + \varepsilon \quad (3-20)$$

where X is the global biomass of squid, Y is the aggregated harvest by squid angling operators, q is a catchability coefficient, E is an aggregated fishing effort index, and ε is an error term. Note that the number of squid in the population model was converted into biomass by multiplying the numbers by the mean weight w in Table 3-2.

For both production models, the number of squid angling operators in the 10-30GT class was used as a fishing effort index. The data for stock estimates, harvest, and the effort index between 1985 and 2004 ($n=20$) were fitted to estimate the parameters, but the exponential model did not perform well in predicting the observed harvest level given the 2004 effort level; it underestimated the historical catch levels while overestimating recent catch levels. Therefore, I used a subset of time-series data between 1998 and 2004 for which the predictions from the model were relatively good ($R^2 = 0.955$). The Cobb-Douglas model had a relatively good fit to the entire period of available data with $R^2 = 0.85$ - 0.86 . The resulting parameters and residual plots as well as predicted versus observed harvest levels are given in the Results.

3.2.2 Developing adaptive management procedures

This section provides the methods used for developing adaptive management (feedback control) procedures in a simulation framework, which involved the construction of an underlying population model, here termed an “operating model”, the simulation of the stock assessment process and harvest control rules with feedback to the population model.

Feedback control policies can be specified in an infinite number of ways. For squid, one possible idea is to use a Leslie-Delury depletion analysis (Leslie and Davis 1939; DeLury 1947) in order to account for the potential seasonal changes in the catchability coefficient, q . Such analyses have been used in biological feedback models for short lived stocks such as the Patagonian squid *Loligo gahi* fishery off the Falkland Islands (Agnew et al.

1998; Roa-Ureta and Arkhipkin 2007), and the Australian Northern prawn fishery (Dichmont 2006; Dichmont et al. 2006a). However, the necessary data are not currently available for the case studies and the generation of fine-scale catch and effort data and the application of the model is done instead in a simulation framework.

For saury, a similar mid-season depletion analysis could be considered, but implementation error bias could be an issue, as the fishery takes only a small fraction of the global stock. As an alternative, pre-season assessment is proposed for this fishery.

As a first step, an age-structured seasonal population model with a stock-recruitment relationship was developed as a biological operating model (OM) which mimics the “reality” of the population dynamics of Pacific saury and Japanese common squid (section 3.2.2.1). I chose this rather complex model rather than the specific models developed in section 3.2.1 for stock assessment purposes in order to generate fine-scale catch and effort data applicable to a depletion analysis, and also to include the most important uncertainties, such as stock-recruitment parameter uncertainty, and errors associated with imperfect stock assessment (observation errors).

Once the OM was “conditioned”, the term used to describe the process of adjusting the parameter values to ensure that the model is consistent with the data and the hypotheses about how they were generated (Kell et al. 2007; Rademeyer et al. 2007), feedback control rules which adapt to population and economic changes and/or objectives over time were developed (section 3.2.2.2). Two adaptive schemes were considered: in-season adjustment based on the stock-assessment results; and pre-season adjustments based on pre-season surveys. Finally, a set of management actions according to pre-defined harvest control rules, which take into account the outcome of the assessment, was developed (also in section 3.2.2.2). The performance of the adaptive management procedures developed here was then evaluated through simulation trials in comparison to the constant output management, and constant effort management regimes in the following section 3.2.3.

3.2.2.1 Biological operating model

Mathematical specifications of the seasonal biological OM were obtained from the FLR framework (Fisheries Library for R) and adopted to suit to the population dynamics of the Pacific saury and Japanese common squid. For details of the general model, see Hillary (2009). This is a type 2 OM, according to the classification in Kell et al. (2007), because it is more complex than the assessment model, but is based on data (see 2.3.4). I assumed a maximum of two age-classes (0 and 1) and 4 seasons.

Population model

The number of animal in year t at age j , in season s can be written as:

$$N_{t,j,s} = N_{t,j,s-1} (1 - \psi_{t,j,s-1}) e^{-M_{t,j,s-1}} \quad (3-21)$$

where $\psi_{t,j,s}$ is the exploitation rate, $M_{t,j,s}$ is the natural mortality. For age 0, $N_{t,0,s} = 0$ for the seasons before recruitment. For the seasons following recruitment, it is:

$$N_{t,0,s} = N_{t,0,s-1} (1 - \psi_{t,0,s-1}) e^{-M_{t,0,s-1}} \quad (3-22)$$

For age 1, which only applies to Pacific saury, the number of animals in the first season ($s=1$) is:

$$N_{t,1,1} = N_{t-1,0,4} (1 - \psi_{t,0,4}) e^{-M_{t,0,4}} \quad (3-23)$$

and the numbers in the following seasons ($s=2,3,4$) are:

$$N_{t,1,s} = N_{t-1,1,s-1} (1 - \psi_{t,1,s-1}) e^{-M_{t,1,s-1}} \quad (3-24)$$

Stock-Recruitment Relationship

The number of recruits can be express as the following Beverton-Holt stock-recruitment relationship:

$$N_{t,j,s} = \frac{aSSB}{1+bSSB} e^{\varepsilon_R} \quad (3-25)$$

where a and b are Beverton-Holt stock-recruitment parameters, SSB is the spawning stock biomass in the spawning season, and ε_R is the normally distributed error term with mean zero and standard deviation σ_R . This error term was included to account for year to year random variation in recruitment. For Japanese common squid, parameters a and b are known (see 3.2.1). For Pacific saury, it is possible to estimate the stock-recruitment parameters from available life history parameters of the species. Following the method detailed in Myers et al. (1997c), the a parameter was estimated by solving the Euler-Lotka equation:

$$\sum_j^{\infty} e^{-rj} l_j m_j w_j a = 1 \quad (3-26)$$

where l_j is the probability of surviving to age j , m_j is the maturity at age j , w_j is the weight at age j , and r is the intrinsic growth rate, which is assumed to be known. After estimating the parameter a , the steepness parameter of the stock-recruitment curve, z , and parameter b can be calculated in equations (3-15) and (3-16). Mori et al (2006) used $m_j = 0, 0.5$, and 1 at age 0 for their stock assessment work, and I selected the value of 0.5 for age 0 . At age 1 full maturity is assumed.

Defining exploitation rate

The exploitation rate, $\psi_{t,j,s}$ can be defined in two ways: input-based; and output-based.

The input based exploitation rate can be defined as:

$$\psi_{t,j,s} = \kappa_{t,j,s} \times q_t E_{t,s} X_{t,s}^{\beta-1} + \xi_t^{Ext} \quad (3-27)$$

where $\kappa_{t,a,s}$ is the selectivity function, q_t is the catchability coefficient, and $E_{t,s}$ is the effort at year t , in season s , ξ_t^{Ext} is the external harvest rate with normal distribution with known mean μ_{Ext} and variance σ_{Ext}^2 , β is the stock output elasticity from the production function, and finally $X_{t,s}$ is the exploitable stock biomass.

I assumed the age selectivity is equal to one because both Pacific saury and Japanese common squid are short-lived (up to 2 years for saury, up to 1 year for squid) and there is no evidence that a specific age class is targeted by fishermen. So equation (3-27) is simply reduced to $\psi_{t,j,s} = q_t E_{t,s} X_{t,s}^{\beta-1} + \xi_t^{Ext}$

The current management of the fisheries uses annual TACs - an output-based control. The catch biomass for each season at year y is expressed as:

$$Y_{t,s} = \frac{TAC_t}{FS} \quad (3-28)$$

where TAC_t is the TAC at year t , and FS is the number of fishing seasons. For both fisheries, there are two fishing seasons: June to August, and September to December. An equal share of TAC was assumed for the two seasons. This assumption is considered reasonable based on the actual landing statistics in 2006 season where about 43%, and 56% of Pacific saury catches were taken by Japanese fleet in the first and the second fishing season, respectively, and about 43% and 47% of Japanese common squid catches were taken in the first and the second fishing seasons, respectively. Note that the rest of the catch (10%) is taken outside of the two fishing seasons, but this is due to the fact that the monthly production statistics provided by MAFF is the aggregated production by all fleets, and it is likely that other fleets (e.g gillnet) are operating outside of the angling fishing seasons.

Total exploitable stock biomass is:

$$X_{t,s} = \sum_{j=0}^J w_{j,s} \cdot N_{t,j,s} \quad (3-29)$$

where $w_{j,s}$ is the weight at age j in season s . The output-based exploitation rate can be then defined as the ratio of catch biomass to total exploitable stock biomass, and written as:

$$\psi_{t,j,s} = \frac{Y_{t,s}}{X_{t,s}} \quad (3-30)$$

3.2.2.2 Adaptive Management Procedures (AMPs)

The adaptive management procedure consists of two parts: simulating a process of stock assessment; and setting of management actions according to pre-defined harvest control rules, which take into account the outcome of the assessment.

a) AMP with in-season stock assessment (depletion method)

An adaptive management procedure (AMP) based on an in-season stock assessment was proposed for the coastal angling fishery for Japanese common squid. The in-season stock assessments are based on weekly catch and effort data using the depletion method similar to those used in assessments of other cephalopod species (Rosenberg et al. 1990; Basson et al. 1996; Agnew et al. 1998; Young et al. 2004). The AMP with in-season assessment was set up as follows: Prior to the start of the fishing season, when the population abundance of squid was unknown, fishing effort was based on the optimal steady-state effort derived from the bioeconomic modelling in section 3.3.1. Once fishing had started and data were available for assessment, in-season adjustments of effort were made based on the detected changes in abundance and the catchability coefficient to avoid risks of negative profits and to maintain the population at sustainable levels. The basic idea was similar to the existing adaptive management used in the Falkland Islands squid fishery, where the effort is limited by both initial effort controls (number of licenses), based on the historical average recruitment and the target escapement (biological reference point), and in-season adjustment of the length of the fishing season. However, in this model the

initial effort is set based on a bioeconomic reference point. Moreover, the effort adjustment scheme developed here was designed to capture annual catchability variation, which in turn might permit resource managers to set a more aggressive harvesting strategy (e.g. higher levels of effort/catch) when environmental conditions are favourable, and also enables them to make necessary adjustments when economic conditions change for the worse. Thus, a higher profitability might be obtained from the fishing operation under such a scheme while maintaining the precautionary principle.

The performance of the AMP was evaluated through the MSE approach in section 3.2.3. The approach here does not attempt to find optimal solutions, but to find a policy under which the fisheries are profitable, the populations sustainably harvested, and the system is robust to the key uncertainties. The schematic diagram of the models and simulation framework is given in Figure 3-1.

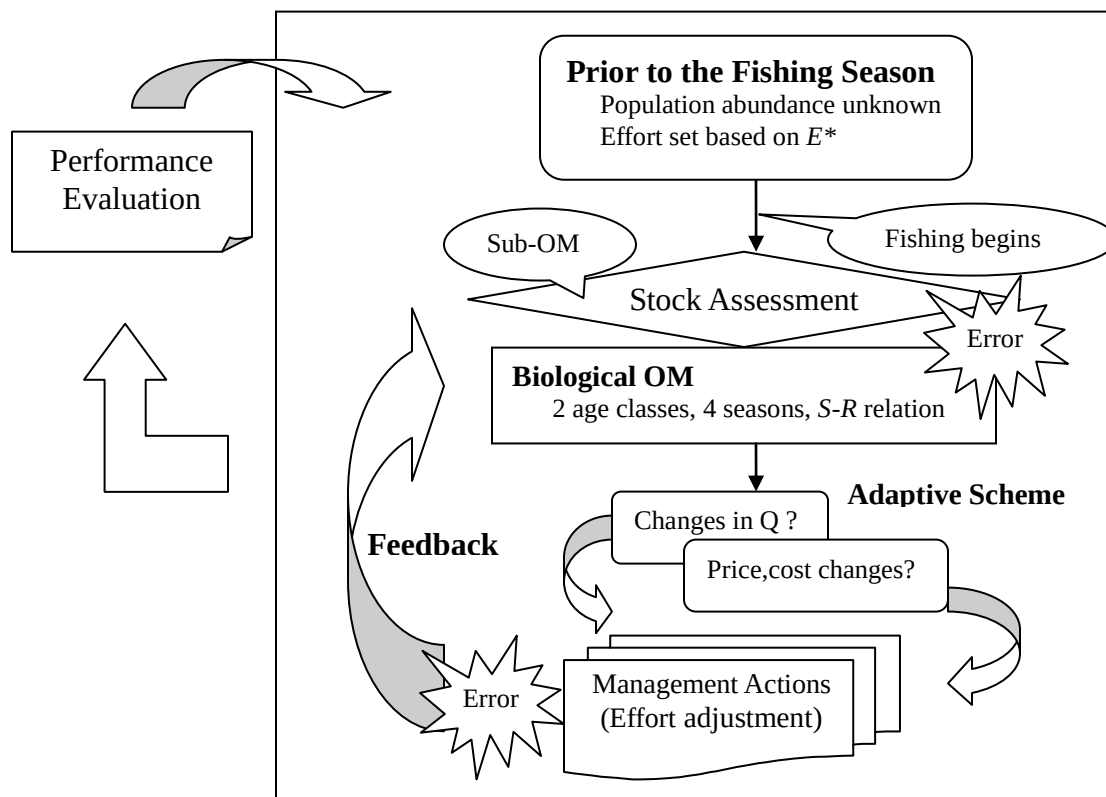


Figure 3-1: Schematic representation of the operating model, in-season adaptive scheme and management evaluation simulation framework for the Japanese common squid angling fishery

The in-season assessments are based on incomplete time-series data from commercial fisheries. However, the necessary data are not currently available and so the fine-scale catch and effort data necessary for depletion analysis were generated through simulation modelling. For this purpose, a secondary feature (sub-OM) was built into the OM to simulate the true weekly dynamics of the stocks. Simulated data is then fed to an “observation error model” (OEM) which simulates weekly CPUE during the first fishing season. This is then fed to an “assessment model” (AM). A graphical representation of the simulation cycle is given in Figure 3-2.

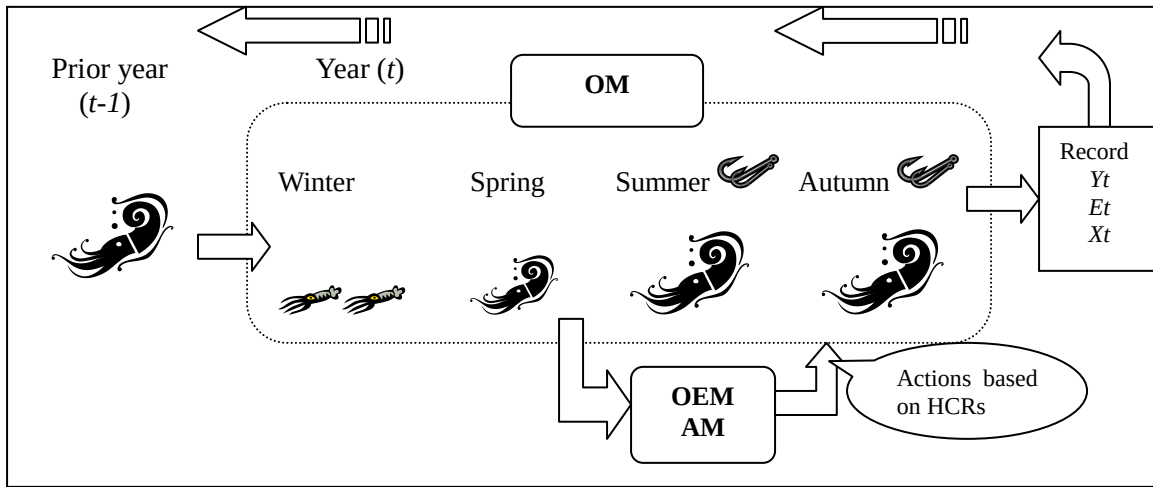


Figure 3-2: Roles of the operating model (OM), observation error model (OEM), assessment model (AM) and harvest control rules (HCRs) in a simulation cycle for the population dynamics of *T. pacificus*.

The modelling steps and the roles of the OM, OEM, and AM are as follows:

1. Reported stock abundance and effort in 2004 were used to initialize the OM. The first season is winter, where recruitment occurs, and no fishing takes place.
2. Stock abundance in the second season, spring, is derived from the winter abundance minus losses to natural mortality. No fishing occurs in spring and the abundance at the beginning of summer is derived from the spring abundance minus losses to natural mortality.
3. The fishing seasons are summer and autumn where both natural and fishing mortality is accounted for. Surviving autumn spawner abundance is then used to generate the new recruits for the following winter which completes the annual cycle.

4. Meanwhile using the biomass levels prior to the summer fishing season as a starting point, the OM (sub-OM to be specific) generates weekly biomass. Using these data, the OEM simulates the observation process by generating weekly CPUE data during the summer season, and the AM estimates the initial (summer) stock biomass and year-specific catchability coefficient Q_t , using the depletion method. The estimated biomass $\tilde{X}_t$ is distinguished from the “true” biomass X_t in the OM, because the assessment process involves observation/estimation errors. The estimate of Q , and changes in economic variables, are then used to form the management decision (effort adjustment) for the autumn, the second fishing season.
5. Such management actions are then fed back into the OM, and total catch, effort and biomass at the end of the fishing seasons every year are recorded for the simulation period (10 years).

Note that the parameter Q_t above is distinguished from the constant catchability coefficient q_t estimated from the bioeconomic estimation models in Section 3.3, because q_t was obtained from historical annual biomass and effort, while Q_t is obtained from incomplete in-season weekly catch and effort data. Although their values might be different, it is reasonable to assume that their relative changes in response to the environment and technology are the same since both models use the same commercial data from the same fleet. The following sections are based on this assumption.

Depletion assessment method

The expected total catch biomass from all fleet at week w is defined as:

$$Y_w = Q_t E_w \tilde{X}_w^\beta + \xi_w^{Ext} \tilde{X}_w \quad (3-31)$$

Where Q_t is the year (t) specific catchability coefficient, E_w is the effort at week w , and $\tilde{X}_w$ is the estimated exploitable biomass of animal at week w and ξ_w^{Ext} is the external harvest rate. The estimated biomass $\tilde{X}_w$ can be expressed in relation to the initial

exploitable biomass:

$$\tilde{X}_w = S_{w-1}(X_1 - C_{w-1}) \quad (3-32)$$

where S_{w-1} is the proportion surviving to week w , and C_{w-1} is the cumulative catch biomass taken prior to week w . The initial exploitable biomass, X_1 , was assumed equal to the exploitable biomass generated from the main biological OM at the start of the first (summer) fishing season.

Effort data were available only for the major Japanese fleet, and the generation of weekly CPUE is thus based on the weekly catches of the Japanese fleet Y_w^J and its effort. Using (3-31) and (3-32) I obtain:

$$Y_w^J = Q_t E_w (S_{w-1}(X_1 - C_{w-1}))^\beta \quad (3-33)$$

Including observation error

In depletion analysis, catch per unit effort (CPUE) is often used as a key index to measure the relative abundance of the stock. Given that there will be always an observation error in measuring such an index, CPUE at week w can be written as:

$$CPUE_w = Y_w^J / E_w = Q_t (S_{w-1}(X_1 - C_{w-1}))^\beta e^{\varepsilon_o} \quad (3-34)$$

where ε_o is the observation error with mean zero, variance σ_o^2 . Non-linear least squares methods were used to estimate the key parameters X_1 and Q_t .

Because the external harvest rate cannot be known precisely, I also included observation error for this process.

$$\zeta_t^{Ext} = \zeta_t^{True} \times e^{\varepsilon_E} \quad (3-35)$$

where ε_E is the observation error for the external harvest rate with mean zero, variance σ_E^2

Harvest control rules

Harvest control rules (HCRs) can be defined in a number of possible ways, but one possible example is to use year to year changes in the catchability coefficient, Q_t . The target effort level is varied from year to year relative to the mean catchability coefficient $\bar{Q}$ estimated from the assessment above (after at least a few years of observations) and the pre-defined optimal effort level, E^* , given q used in the bioeconomic model. The key assumption here is that the true changes in q (which was estimated from historical annual catch and effort) can be tracked by changes in the estimates of Q from depletion analysis (which was estimated from incomplete in-season weekly catch and effort data). One can argue that E^* estimated in section 3.3.1 has a known variation around the mean value, and using the mean value of E^* as the basis of a HCR would introduce an additional uncertainty. However, the main focus of this chapter is to identify comparative advantages of using an adaptive HCR in which the initial effort is set at a fixed level (e.g. mean E^*), but adjusted within the fishing season, versus the conventional fixed effort policy, in which the effort level remains the same throughout the fishing season.

Here I considered two sets of HCRs using the detected changes in Q_t relative to $\bar{Q}$: (i) the reactive version where the effort level in the second fishing season is increased by the estimated *proportional increase* in Q_t , and (ii) the less-reactive version where the effort level at second fishing season is increased by a fixed amount if an increase in catchability is detected. The purpose of these HCRs is to increase effort when catchability is higher, while closing down the fishery if the catchability and/or the stock biomass are low enough to suggest the continuation of the fishery is likely to be unprofitable. As noted in the Introduction, higher catchability means that fish are easier to catch on average given the same level of inputs, so that the HCR which allows higher catch rates with higher catchability may have a potential to increase profitability.

a-i) Reactive HCRs

Before defining the HCRs, I first explain why the effort should be increased when catchability is higher than normal and economic conditions are favourable, while maintaining it at E^* when these conditions are unfavourable (rather than reducing it), as long as the expected profits are non-negative.

Justification for increasing effort when $\varphi > 0$

Let assume that catchability coefficient at year t can be expressed as:

$$Q_t = \bar{Q}(1 \pm \varphi) \quad (3-36)$$

where φ represents a proportional change relative to $\bar{Q}$. The annual industry profit at base year ($Q_t = \bar{Q}$) is written as:

$$R1 = P_t \bar{Q} \tilde{X}_t^\beta E^* - cE^* \quad (3-37)$$

If the proportional change is positive ($\varphi > 0$), and the effort level is maintained at E^* , the annual profit for the industry at year t will increase due to the positive change in Q_t :

$$R2 = P_t \bar{Q}(1 + \varphi) \tilde{X}_t^\beta E^* - cE^* \quad (3-38)$$

The difference in the annual profits due to positive change in Q_t is:

$$\Delta(R2 - R1) = \varphi P_t \bar{Q} \tilde{X}_t^\beta E^* \quad (3-39)$$

Alternatively, the industry could increase the effort by a factor of $1 + \varphi$ as long as the total effort does not exceed the pre-defined upper bound effort limit, which will be detailed later in this section. The annual profit is then:

$$R3 = P_t \bar{Q}(1+\varphi)^2 \tilde{X}_t^\beta E^* - c(1+\varphi)E^* \quad (3-40)$$

The difference in the annual profits due to increase in effort plus positive change in Q_t is:

$$\Delta(R3 - R2) = \varphi E^* \left(P_t \bar{Q}(1+\varphi) \tilde{X}_t^\beta - c \right) \quad (3-41)$$

The equation above shows that if $\varphi > 0$, and $c < P_t \bar{Q}(1+\varphi) \tilde{X}_t^\beta$, or $\tilde{X}_t > \sqrt[\beta]{c / P_t \bar{Q}(1+\varphi)}$ the above equation is always positive. In other words, it is always profitable to increase effort by the factor of $1+\varphi$.

Justification for maintaining the effort when $\varphi < 0$

When the proportional change is negative ($\varphi < 0$), managers can choose to either maintain or reduce the effort. If the effort level is maintained at E^* , the annual profit for industry at year t will be:

$$R4 = P_t \bar{Q}(1-\varphi) \tilde{X}_t^\beta E^* - cE^* \quad (3-42)$$

If the industry decreases the effort by a factor of $1-\varphi$, the annual profit becomes:

$$R5 = P_t \bar{Q}(1-\varphi)^2 \tilde{X}_t^\beta E^* - c(1-\varphi)E^* \quad (3-43)$$

The difference in the annual profits due to the reduction in effort and changes in Q_t is:

$$\Delta(R5 - R4) = \varphi E^* \left(c - P_t \bar{Q}(1-\varphi) \tilde{X}_t^\beta \right) \quad (3-44)$$

The above equation shows that if $\varphi < 0$, decreasing effort by the factor of $1-\varphi$ is more profitable than maintaining the effort at E^* only when $c > P_t \bar{Q}(1-\varphi) \tilde{X}_t^\beta$ or $\tilde{X}_t < \sqrt[\beta]{c / P_t \bar{Q}(1-\varphi)}$. These conditions are independent of the levels of effort. In other

words, when the above conditions are satisfied, it will be unprofitable regardless of the levels of effort. Thus, the most economical choice is to close down the fishery (zero effort) to minimise losses, rather than employing reduced levels of effort. Therefore, the effort is maintained at E^* when $\varphi < 0$ is detected.

Defining lower and upper bounds of effort

If the industry is to remain economical, the unit harvesting cost should be at least equal to or smaller than the unit harvesting revenue, thus $P_t Q_t \tilde{X}_t^\beta E \geq cE$. Hence, target effort should be zero (or fishery should be shut down) if:

$$P_t Q_t \tilde{X}_t^\beta < c \quad (3-45)$$

To ensure the long-term sustainability of the stock, upper bounds of effort can be specified as, e.g. the effort which gives 75% of MSY.

In summary, the HCRs can be defined as follows:

Table 3-3: Harvest control rules for the adaptive scheme with depletion method

i)	$E_t^{TARG} \leq E_{0.75MSY}$	Effort cap
ii)	$E_t^{TARG} = 0$	if $P_t Q_t \tilde{X}_t^\beta < c$
iii)	$E_t^{TARG} = (1 + \varphi) \times E^*$	if $\varphi > 0$ and $c \leq P_t \bar{Q}(1 + \varphi) \tilde{X}_t^\beta$
iv)	$E_t^{TARG} = E^*$	Otherwise

a-ii) Less reactive adaptive scheme

The adaptive scheme proposed above is based on the proportional change in Q_t , and the effort adjustment is reactive as the target effort changes frequently according to year to year changes in Q . However, the accuracy of detecting changes in Q_t depends strongly on the precision of the in-season stock assessments and, hence, is highly sensitive to observation error. Thus, in practice, an adaptive scheme with gentle effort adjustment may be more appropriate. For this reason, I simplified the HCRs so that the target effort

is increased by a fixed percentage θ , rather than by the empirically derived proportional change, φ , when $Q_t > \bar{Q}$ is detected. All other rules are as before.

Table 3-4: Simplified (less reactive) harvest control rules

i)	$E_t^{TARG} \leq E_{0.75MSY}$	Effort cap
ii)	$E_t^{TARG} = 0$	if $P_t Q_t \tilde{X}_t^\beta < c$
iii)	$E_t^{TARG} = (1 + \theta) \times E^*$	if $\varphi > 0$ and $c \leq P_t Q_t \tilde{X}_t^\beta$
iv)	$E_t^{TARG} = E^*$	Otherwise

To decide the values of θ , one needs to make sure that the target effort does not exceed the levels that ensure the long-term sustainability of the stock. I selected 15% increase ($\theta=0.15$) because in practice any larger a year to year change in the target effort is unlikely to be accepted by the stakeholders. In EU fisheries, for instance, year to year changes in quota are set at no more than 15% as a general rule based on industry preferences (EC 2007).

Relationship between harvest rates & observation error

In order to demonstrate the relationship between the harvest rate of Japanese common squid and bias from the depletion assessment, a simulation evaluation of the accuracy of the estimates was carried out by varying the levels of observation error CV (5%, 15%, and 30%) and harvest rates (10%, 20% and 30%) and calculating the distributions of biomass estimates.

b) AMP with pre-season assessment

Ricker (1958) noted that intense fishing effort that reduces the abundance considerably leads to informative data for the depletion model. Hilborn (1979) also noted that the most informative data scenario in general with the depletion method is the one that includes a period of quite heavy exploitation, followed by a period where the stock is allowed to rebuild to an intermediate level, after which the exploitation rate increases

again. Given the low exploitation rate of Pacific saury (Ueno et al. 2006), adaptive management based on depletion methods using in-season fisheries data might be inappropriate for this fishery, as the commercial fisheries take only a small fraction of the stock, not large enough to result in significant depletion. For this reason, an adaptive management procedure based on the pre-season survey data was proposed as an alternative adaptive scheme for the Pacific saury stick-held fishery. Pre-season surveys have already been used as a part of stock assessment practices for Pacific saury in Japan, thus in practice, this approach could be easily implemented in the near future. The schematic diagram of the models and simulation framework is given in Figure 3-3.

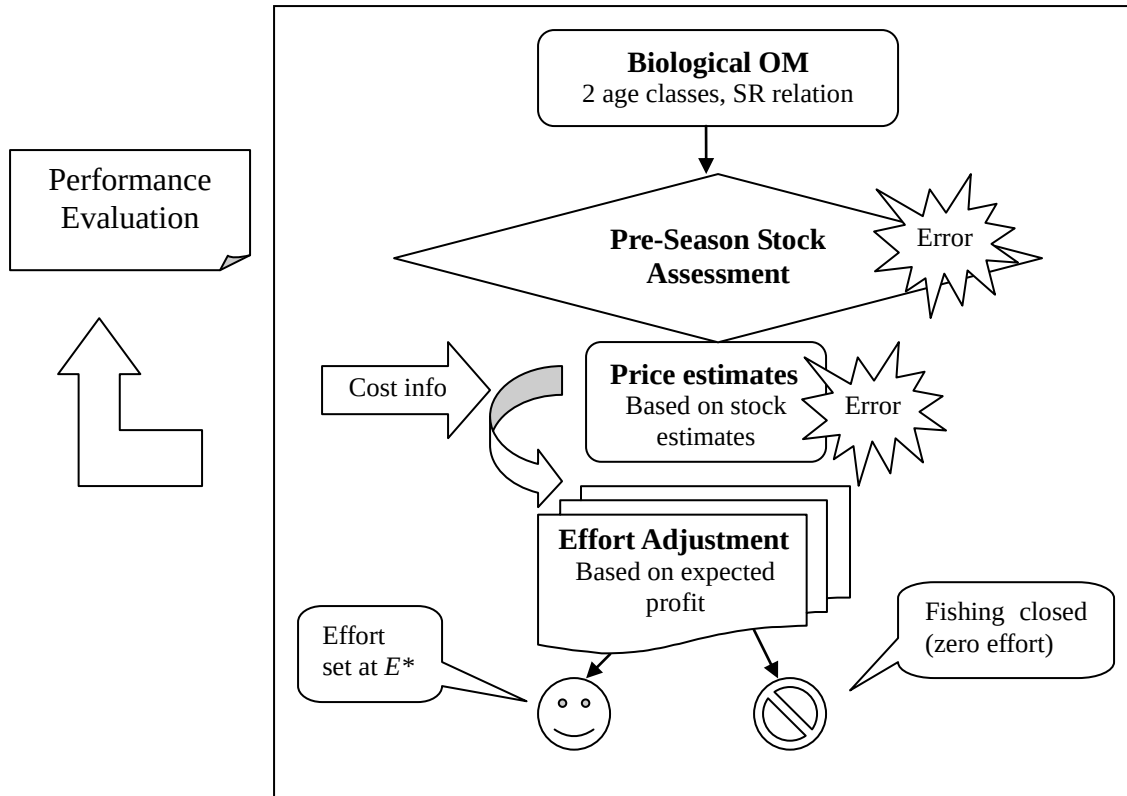


Figure 3-3: Schematic representation of the operating model, pre-season adaptive scheme and management evaluation simulation framework for the Pacific saury stick-held dip net fishery

Including imperfect survey precision

The survey biomass each year was generated through the OM. In order to account for imperfect survey precision, observation error for survey was introduced.

$$X_t^{Survey} = X_t^{True} \times e^{\varepsilon_s} \quad (3-46)$$

where ε_s is the observation error from survey with mean zero, variance σ_s^2 . This assumes that the survey biomass to stock biomass calibration has already been performed.

Including imperfect prediction of the price of saury

The adaptive scheme with a pre-season survey method involves predicting the prices of fish given the survey stock biomass. However, the functional relationship between the prices of fish and biomass from the survey data is unknown. As an alternative, I used the predicted harvest Y_t^{Pred} of fish given the level of E^* and survey biomass, X_t^{Survey} .

$$Y_t^{Pred} = qX_t^{Survey}E^* \quad (3-47)$$

Y_t^{Pred} was then used to predict the price of fish (P_t^{Pred}) using the inverse demand function for Pacific saury described in section 3.3.1. The annual expected profit based on the survey biomass is expressed as:

$$\pi_t^{Pred} = qP_t^{Pred} X_t^{Survey}E^* - cE^* \quad (3-48)$$

Defining harvest control rules

The fishery is closed when the expected profit is below zero or $qP_t^{Pred} X_t^{Survey} < c$. Otherwise, the target effort is E^* (Table 3-5).

Table 3-5: Harvest control rules for pre-season survey adaptive scheme

i)	$E_t^{TARG} = 0$	if $qP_t^{Pred} X_t^{Survey} < c$
ii)	$E_t^{TARG} = E^*$	Otherwise

3.2.3 Management Strategy Evaluation (MSE)

3.2.3.1 Candidate management procedures

To identify the relative advantage of an input-based management strategy over the fixed output-based (TAC) strategy, as in the current practice, as well as to explore the usefulness of adaptive input management over fixed management, the following three candidate management strategies were considered: 1) The fixed output control management based on an annual TAC determined according to the pre-specified target fishing mortality; 2) Fixed input control based on an annual effort allocation with the mean optimal effort as the target effort; 3a) For the common squid, a variable input control, where the annual effort is adapted mid-season according to the results of a depletion assessment and the relevant harvest control rule (HCR); and 3b) For the saury, a variable input control where the annual effort is decided according to a pre-season survey of stock biomass and the associated HCR.

1) Annual TAC Management based on constant fishing mortality

Seven major fisheries around Japan, including the Pacific saury and Japanese common squid, are managed by the TAC system. TAC is based on Acceptable Biological Catch (ABC) decision rules. The ABC target for both Pacific saury and Japanese common squid is based on yield-per-recruit RPs ($70\%-80\%F_{MSY}$). In setting TAC, socio-economic factors are incorporated and TAC can be either higher or lower than ABC. Since the introduction of the system, considerable differences between scientific ABC recommendations and TACs set by the government agency have been reported (Takagi Committee 2007; JFA 2008) with some exceptional cases of TACs up to 10 times higher than the ABC (Takada 2010). This led to the setting of a cap for the TAC up to twice the ABC level since 2003 (MAFF 2003).

ABC for Pacific saury

FRA considers the limit fishing mortality, F_{limit} to be F_{MSY} , this was estimated by Ueno et

al. (2005) at 0.32 in the 2004 season. The target ABC (global) is set to be 80% of the catch taken at F_{limit} (hence, $F_{\text{target}} = 80\%F_{\text{MSY}}$). The target ABC for Japan is then calculated by multiplying 0.66, the average Japanese catch share relative to the estimated global catch between 2000 and 2004, as reported in Ueno et al. (2005). According to the recent reports (Ueno et al. 2006; 2008), the use of F_{limit} based on $F_{\% \text{SPR}}$, the spawner-per-recruit (SPR) is reduced to 50-70% of unfished SPR, has been considered since 2006, and thus in reality the values of F_{target} may vary over time. However, I assume F_{target} remains constant to demonstrate the comparative advantages of adaptive management over a conventional fixed output/effort management. TACs for Pacific saury have been set lower than the ABC level (JFA 2008) since the introduction of the TAC system, roughly around 70-80% of ABC. To mimic this, a uniform random multiplier between 0.7 and 0.8 of ABC was used in setting the actual TAC. It is then assumed that about 90% of the TAC is allocated to the 100-200GT class fleet, also to mimic the current system.

ABC for Japanese common squid

The ABC for the autumn stock is set to attain the target fishing mortality at 70% of the F_{MSY} level. Kidokoro et al. (2006) estimated MSY for the autumn stock to be 4.28 million tonnes, and F_{MSY} to be 0.737, thus target F (global) for the autumn stock is set around 0.51. For the winter spawning stock, MSY is unknown and the ABC is set as follows: F_{limit} is set to the maximum F that results in a 60% probability of spawning stock biomass (SSB) being above the predefined $\text{SSB}_{\text{limit}}$ (590 thousand tonnes for the 2006 assessment) after a 5 year projection. The target F is 70% of F_{limit} and the target ABC is set to achieve the target F . For the 2007 season, target F (global) for the winter stock was set at 0.3. Since the two sub-stocks were treated as a single stock in the bioeconomic model developed earlier in previous section, I set a target F level (global) between 0.3 and 0.5 for the combined stock. The target ABC for Japan is obtained by multiplying the ABC global for combined stock with 0.54, the average Japanese catch share relative to the estimated global catch of these stocks between 2001 and 2005. TACs for Japanese common squid have been almost identical to the ABC levels during 2004-2008, thus I assume that $\text{ABC}=\text{TAC}$. It is assumed that about 30% of the TAC is allocated to 10-30GT

class fleet, as per actual practice.

2) Constant effort management

The mean optimal effort in terms of the number of participating operators derived from the stochastic bioeconomic models (section 3.4.1) defines the management advice in this scenario. The constant effort level is set at 43.5 operators for 100-200 GT class operators for Pacific saury, while it is 1,291 operators for 10-30 GT class operators for the Japanese common squid.

3) Adaptive management

The target effort every year in terms of the number of participating operators, defined by the pre-defined harvest control rules (Table 3-4 and Table 3-5) dictates the management advice in this scenario.

Treatment of external fishing mortality

As both Pacific saury and Japanese common squid are harvested by neighbouring countries, it is necessary to take into account the fishing mortality from fisheries other than Japanese fleet when evaluating the impacts of management actions in one country on the status of the shared stock. However, the biological, economic and technical interactions of the fishing agents in these fisheries are poorly understood and extremely difficult to quantify. As a compromise, one can assume that the technology among all participants is similar, and treat the entire fleet as a single fleet. However, a major flaw of this assumption is that the harvest rate of the non-Japanese fleet is assumed to change in accordance with the Japanese HCR. While this assumption may be reasonable in the cases where the Japanese fleet dominates the global harvest of the stocks, it is not appropriate if the harvest from the fleet accounts for a relatively small fraction of global catch. Instead, the external fishing mortality was accounted for by using the recent catch levels in external fleets, or “external” catch, to calculate empirical estimates of the historical exploitation rates, which has mean and rough variance estimates, for both fisheries, as an external exploitation rate, based on the assumption that future catches in these fleets are randomly distributed, with known mean and variance. These levels would not be affected by the HCR restrictions. However, this approach also has shortcomings,

as the model assumes that that future catches by the non-Japanese fleet will have no average trend and are taken independent of both the fishing pressure of the Japanese fleet and stock depletion. It would be interesting to explore the effect of this assumption in future work.

3.2.3.2 Simulation of future stock biomass and profits

The SSB for Pacific saury and Japanese common squid, as well as the net present value of annual profits from the fisheries at a 4% discount rate, were projected into the future from 2004 to 2014 (10 years), under the three candidate MPs described above. A thousand Monte Carlo trials were undertaken in the simulation for each scenario. I assumed fluctuations in Q were purely random and an arbitrary CV between 0.1 and 0.3 was used to simulate year to year changes in Q .

For the adaptive MP with the depletion method, observation error of the stock estimates was initially set at a negligible level in order to simulate the performance of the depletion method under a perfect stock assessment. An arbitrary observation error of CV= 0.1 was then introduced for comparative purposes. The sensitivity of the depletion method with respect to the size of observation error CV was also explored later in the section. For the survey-based adaptive scheme, values of survey CV between 0.1 and 0.3 were used in simulating the precision of pre-season surveys.

Performance indices

Five indices were used to evaluate the performance of alternative MPs. Biologically-based indices were the probabilities that, after 10 years of management, the SSB in season 4 (spawning season) in the final year either dropped below 20% of SSB_0 (Index 1) or was $\geq 50\%$ of SSB_0 (Index 2). Economically-based indices were the sum of the net present value (NPV) of discounted annual profits, at a 4% discount rate over a 10 year period (Index 3) and the probability of the annual profits being negative (Index 4). The total loss of profits (sum of the loss projected from each Monte Carlo sample) was also included as another economic indicator (Index 5) to see if adaptive management worked to minimise the economic losses in bad years.

3.3 Results

3.3.1 Parameter estimates

3.3.1.1 Pacific saury

The estimated inverse demand function for Pacific saury is given in Table 3-6 and Figure 3-4. Compared to the observed price of Pacific saury, the estimated inverse demand curve fits relatively well under the 2-parameter model, with a residual standard error (SE) of 24.5 compared to the SE of 36.9 for the 1-parameter model. The ANOVA result showed that the residual sum of squares for a complex model is less than half of a simpler model, confirming that the improvement from a simpler to more complex model is highly significant (F-value =22.48, P-value <0.000).

Table 3-6: Estimates of inverse demand function parameters for Pacific saury

Inverse demand parameters	Estimates	t-value	d.f.	Pr(> t)
a	1.225e+05	14.14	17	0.000
n	3.741	4.63	17	0.000
σ_p	24.2			

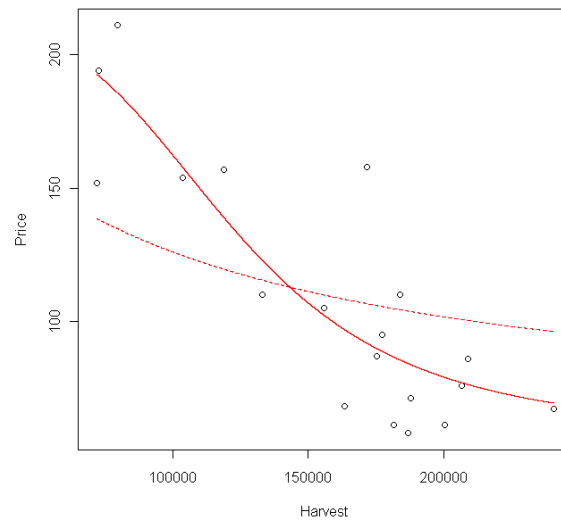


Figure 3-4: Inverse demand curves and observed ex-vessel price of Pacific saury. The solid line represents the 2-parameter model, and the dashed line represents the 1-parameter model.

The production function parameter estimates for Pacific saury are given in Table 3-7. The coefficient for the ENSO was not statistically significant, thus it was excluded from the models. Under the non-restricted model, the parameter β estimate was between zero and one, indicating that the harvest decreases with decreasing stock size but is less than proportionately sensitive to changes, probably due to the schooling behaviour of saury. However, t-tests indicate that the coefficient values of both α and β were not significantly different than one. Thus I re-ran the OLS fixing $\alpha = \beta = 1$ (Table 3-7). I also considered the model where $\alpha = 1$ but in this case the intercept (catchability coefficient) was not significant.

Table 3-7: Estimation of production function parameters for Pacific saury sick-held dip net fishery, 100-200GT class, 1985-2000 (n =16). Y_t = harvest, E_t = effort, X_t = biomass at time t . Standard error in parentheses. ** indicate the p-value less than 0.000, and * less than 0.05

<u>Non-restricted model</u>		
$\ln Y_t =$	$-7.408 + 1.252 \ln E_t + 0.865 \ln X_t$	$(R^2 = 0.740,$
$\bar{R}^2 = 0.683)$	$(3.43)^* (0.25)^{**} (0.19)^{**}$	
<u>Restricted (Schaefer) model ($\alpha=\beta=1$)</u>		
$\ln Y_t =$	$-8.289 + \ln E_t + \ln X_t$	$(R^2 = \bar{R}^2 = 0.704)$
	$(0.06)^{**}$	

To choose between the non-restricted model and the restricted model, a likelihood ratio test was carried out to assess the significance of the improvement from a simpler model to the more complex model. The null hypothesis is that the non-restricted model is not better than the restricted model. The Chi-squared test indicated that the probability of the null hypothesis being true is 0.419, suggesting that there is no evidence that the more complex model is significantly better than the simpler model; this was confirmed with an ANOVA table (Table 3-8). Based on parsimony, I conclude that the restricted (Schaefer) model is the best to explain the harvest of Pacific saury in Japan. Approximately 70.4% of variability of Pacific saury harvest is explained by this model (Figure 3-5).

Table 3-8: Analysis of Variance (ANOVA) table for model selections. Res.Df.= residual degree of freedom, RSS= residual sum of squares, SS=sum of squares

<u>(1) non-restricted model vs (2) one-parameter model ($\alpha=1$)</u>						
	Res.Df	RSS	Df	SS	F value	Pr(>F)
1	13	0.73539				
2	14	0.79173	-1	-0.05635	0.9961	0.3365
<u>(1) one-parameter model vs (2) restricted (Schaefer) model ($\alpha=\beta=1$)</u>						
	Res.Df	RSS	Df	SS	F value	Pr(>F)
1	14	0.79173				
2	15	0.83809	-1	-0.04635	0.8196	0.3806

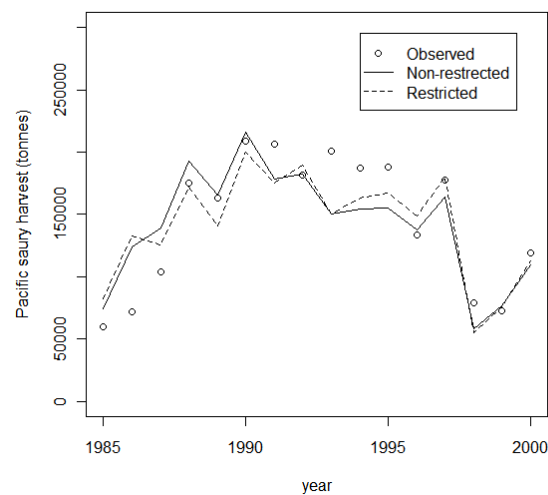


Figure 3-5: Observed vs predicted harvest by the model.

The residual plot and normal QQ plot (Figure 3-6) indicate a poor fit to the model especially in the data in early years. In order to detect the presence of autocorrelation in the residuals from the selected model, a Durbin–Watson test was carried out. The null hypothesis was that there was no autocorrelation. The Durbin-Watson d-statistic was 2.087, with p-value of 0.51, thus it was concluded that there was no evidence of autocorrelation.

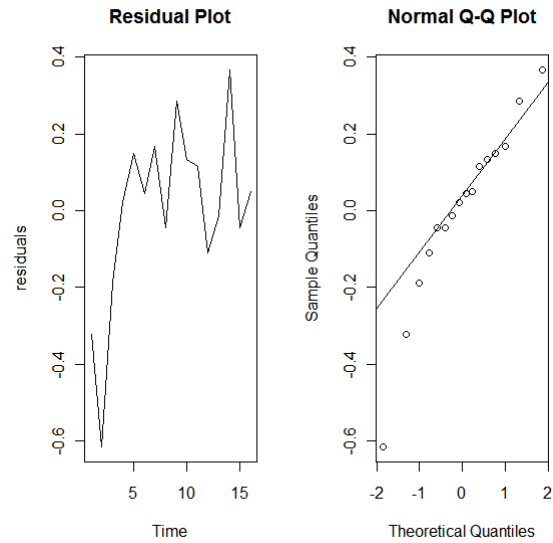


Figure 3-6: Residual plots for Pacific saury production function

3.3.1.2 Japanese common squid

The estimates of stock-recruitment parameters are given in Table 3-9. The estimates of the production function parameters for the Japanese common squid fishery, standard error, and p-value are reported in Table 3-10.

Table 3-9: Estimated steepness (z) and indicative stock-recruitment parameters (a, b) for a combined stock of Japanese common squid

z	0.5488
a	7.76
b	0.035

Table 3-10: Estimate of production function parameters for the Japanese common squid coastal angling fishery 10-30GT class. h_t = harvest, E_t = effort, X_t = biomass at time t . Standard error in parentheses. **indicates a p-value less than 0.000, and * less than 0.05

A) Cobb-Douglas form. 1985-2004 (n =20)		
<u>Non-restricted model</u>		
$\ln Y_t = -7.024 + 1.18 \ln E_t + 0.68 \ln X_t$	$(R^2 = 0.865, \bar{R}^2 = 0.835, df=17)$	
(1.95)* (0.15)** (0.07)**		
<u>Restricted model ($\alpha=1$)</u>		
$\ln Y_t = -4.69 + \ln E_t + 0.61 \ln X_t$	$(R^2 = 0.853, \bar{R}^2 = 0.838, df=18)$	
(0.48)** (0.00)**		
B) Exponential form. 1998-2004 (n=7)		
$q = 3.29 \times 10^{-5} (95\%CI : 4.06 \times 10^{-5}, 2.51 \times 10^{-5})$	$R^2 = 0.955$	
(2.89e-06)**		

With the Cobb-Douglas model, I tested whether the coefficients in the non-restricted model were significantly different from one. The t-tests suggest that α (=1.18) was not significantly greater than one (one-tailed t test, p-value = 0.123), but β (=0.68) was significantly smaller than one (one-tailed t test, p-value < 0.0001). Therefore, I re-ran the OLS regression while fixing $\alpha = 1$ (restricted model), and obtained new values for q and β (Table 3-10). The restricted model had a slightly better adjusted R-squared and the standard errors for q and β were significantly reduced. ANOVA confirmed that there was no evidence that the non-restricted model was better than the restricted model in describing the variance (Table 3-11). For this reason, I concluded that the restricted model was superior to the non-restricted model in predicting the harvest of Japanese common squid. The R-squared indicates that 85.3% of the variability in the harvest of Japanese common squid can be explained by this model.

Table 3-11: Analysis of Variance (ANOVA) table for Cobb-Douglas model selection. Res.Df.= residual degree of freedom, RSS= residual sum of squares, SS=sum of squares

<u>(1) non-restricted model vs (2) restricted model ($\alpha=1$)</u>						
	Res.Df	RSS	Df	SS	F value	Pr(>F)
1	18	0.16059				
2	17	0.14736	1	0.01323	1.5263	0.2335

In order to detect the presence of autocorrelation in the residuals from the selected regression model (restricted model), a Durbin–Watson test was carried out. Based on the Durbin–Watson d-statistic (1.58) and p-value (0.167), it was concluded that there was no evidence of autocorrelation. The plot of residuals against lagged residuals also confirmed that there was no significant sign of autocorrelation.

Only the data between 1998 and 2004 ($n=7$) were fitted to the exponential form. The figure of observed versus predicted is given in Figure 3-7. Although the exponential form fit relatively well for the time period specified here, the Cobb-Douglas form was better at explaining the variance of harvest in a longer-time frame. Thus, the Cobb-Douglas form was used in calculating the optimal steady-state conditions for Japanese common squid as well as for performance evaluation. The residual plot and normal QQ plot of the residuals are given in Figure 3-8.

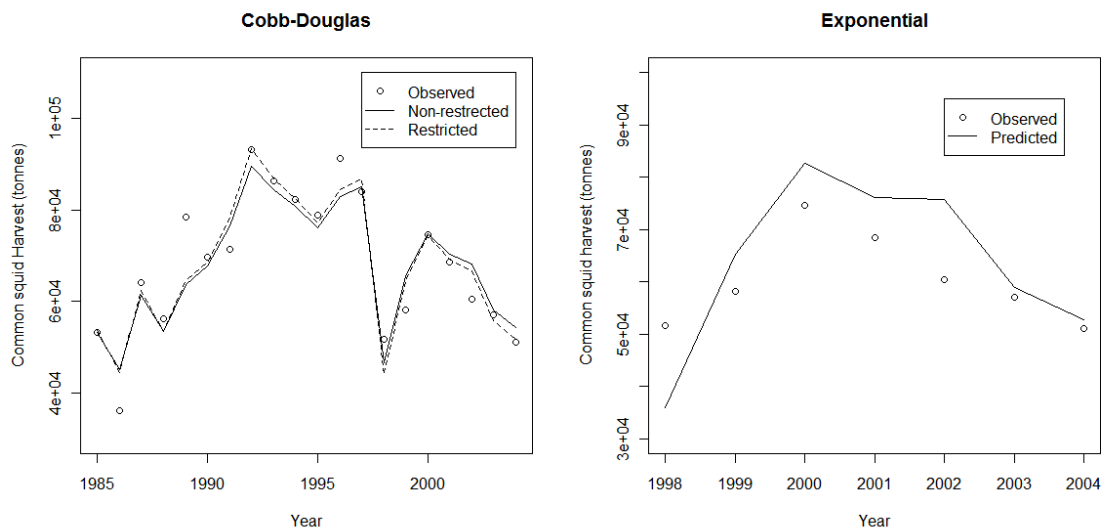


Figure 3-7: Observed versus predicted harvest of common squid with a Cobb-Douglas form (left) and an exponential form (right)

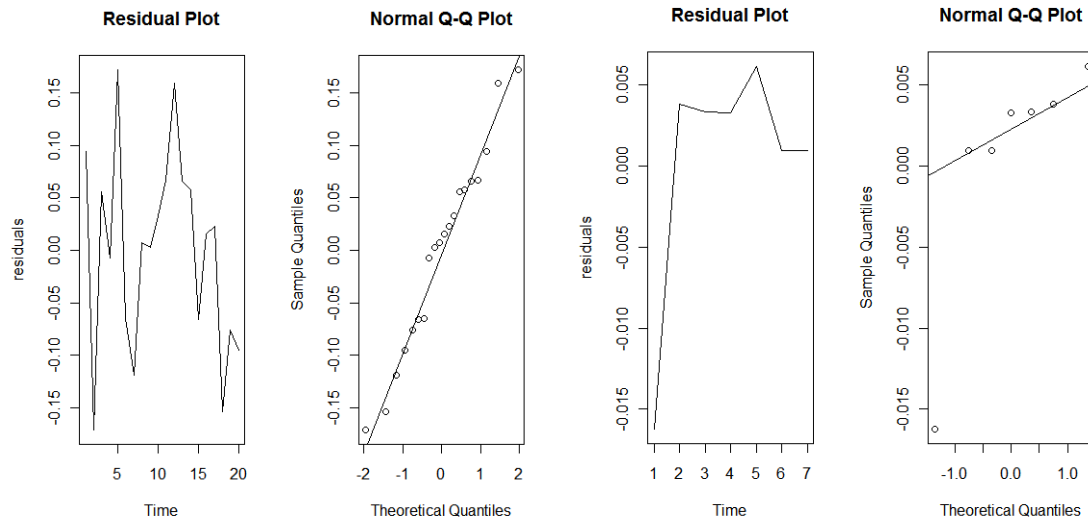


Figure 3-8: Residual plots for Japanese common squid production function with a Cobb-Douglas form (left) and an exponential form (right)

3.3.2 Optimal steady-state effort

3.3.2.1 Pacific saury

Taking into account the random fluctuations in price, cost and stock abundance, the distribution of the optimal steady-state effort, E^* , in terms of the number of 100-200 GT class fleet operators, and corresponding steady-state harvest, Y^* , of Pacific saury by the same fleet were calculated (Table 3-12). The median and mean E^* was estimated at 43.2, and 43.6 operators respectively at 4% discount rate, with $CV_X = 30\%$. This was approximately 60% of the number of operators in 2004. The median h^* for this fleet was estimated at about 82,543 tonnes, less than half of the observed harvest by the same fleet in 2004.

The median steady state biomass, X^* , assuming that the harvest rate by other fleets and overseas operators were randomly fluctuating with known mean and variance, was 7.4 million tonnes or about 90% of the carrying capacity. The effects of the magnitude of the uncertainty in stock abundance on the steady-state effort was relatively minor (Figure 3-9), given that the changes in values of CV_X were relatively small.

It is also important to bear in mind that the optimal conditions here were set to maximise the discounted future profits for the industry/operators, which does not necessarily mean they were “socially optimal” because social benefits, such as providing cheaper fish for local consumption or generating jobs, were not accounted for.

Table 3-12: Steady-state levels of effort (number of 100-200GT class operators) E^* and corresponding harvest h^* , and global optimal biomass X^* of the Pacific saury

	Levels of random variation in saury abundance					
	$CV_X = 0.25$ ($\sigma_X = 0.23$)			$CV_X = 0.3$ ($\sigma_X = 0.29$)		
	Median	95% CI		Median	95% CI	
E^* 100-200GT (Operators)	44.1	39.2	50.0	43.2	38.4	49.8
Y^* 100-200GT (tonnes)	82,543	73,601	93,343	81,662	70,846	93,099
X^* (1000 tonnes)	7,373	7,336	7,409	7,378	7,339	7,415

Note: Discount rate = 4% is used. Cost per unit effort are based on 2004 data $\pm$ 15%. σ_X corresponds the levels of variation in stock abundance.

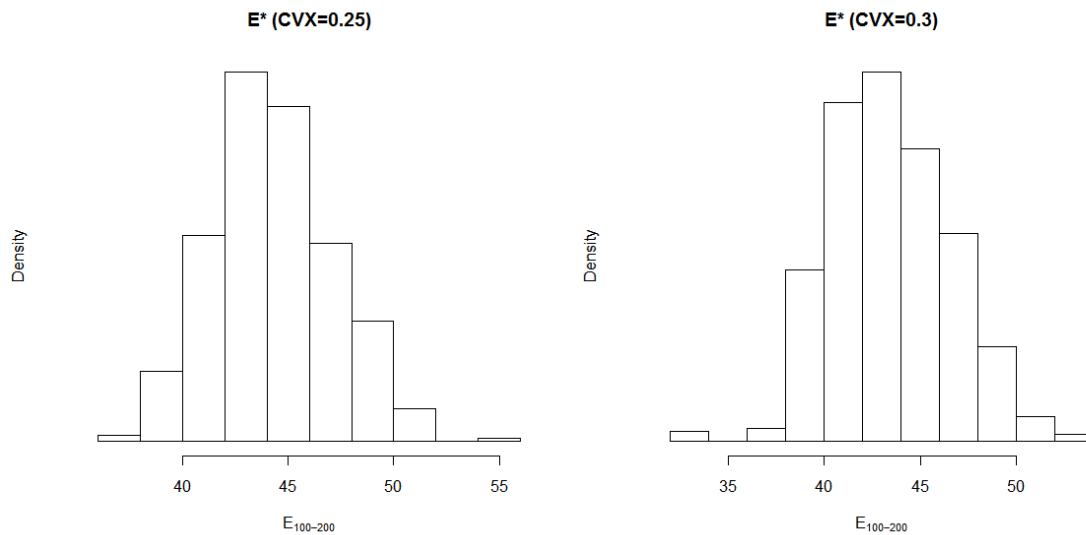


Figure 3-9: Distribution of steady-state effort (E^*) for 100-200GT fleet when $CV_X = 0.25$ (left) and $CV_X = 0.3$ (right)

3.3.2.2 Japanese common squid

The steady-state effort (E^*) in terms of the number of 10-30GT class operators of the Japanese common squid angling fishery, and the associated harvest, are given in Table 3-13. Estimates of E^* were highly variable, ranging between 0 and 6,866 operators when

uncertainties in both price & cost and the stock-recruitment relationship were taken into account (Table 3-13, Figure 3-10). A higher value of the standard deviation in S - R uncertainty ($\sigma_R = 0.3$) made the mean estimates of E^* and Y^* about 9-12% smaller, which can be interpreted that a higher σ_R resulted in slightly conservative harvesting strategy. The distribution of E^* (Figure 3-10) showed a bi-modal pattern with the highest frequency around zero, with the median value zero. The mean values were about the same as the observed effort level in early 1990s, and as twice as large as the 2004 level (897 operators). The median value of Y^* under a smaller σ_R of 0.238 was estimated at 66,000 tonnes, which was roughly the same as the observed harvest level by the fleet in 2001.

The distribution of E^* implies that the coastal squid angling fishery, on average, is profitable (as predicted by the positive mean) when economic and recruitment conditions are favourable, but there is a large probability (160 out of 250 runs, or 64%) that the fishery becomes unprofitable when these conditions are unfavourable and the optimal effort is therefore zero. In fact, negative profits are common for this fishery. Based on the average annual revenue and expenditure data from sampled operators between 1985 and 2004 (20 years), negative profits were reported approximately 40% of the time (see Chapter 2).

Table 3-13: Steady-state levels of effort (number of 10-30GT class operators) E^* , corresponding harvest Y^* for Japanese common squid angling fishery and optimal stock biomass X^*

	With uncertainty in price and cost						No uncertainty in price and cost					
	$\sigma_R = 0.238$			$\sigma_R = 0.3$			$\sigma_R = 0.238$			$\sigma_R = 0.3$		
	50% (mean)	95% CI		50% (mean)	95% CI		50% (mean)	95% CI		50% (mean)	95% CI	
E^* 10-30GT (Operators)	0 (1,480)	0	6,866	0 (1,291)	0	6,837	0 (273)	0	2,303	0 (179)	0	2,144
Y^* 10-30GT (1000 tonnes)	6.6 (124)	0	562	0 (108)	0	561	0 (15.5)	0	199	0 (23.9)	0	185
X^* (million tonnes)	3.3 (3.3)	3.0	3.3	3.3 (3.3)	3.0	3.3	3.4 (3.3)	3.3	3.4	3.4 (3.3)	3.3	3.4

Note: Discount rate = 4% is used. Price of squid and cost per unit effort are based on 2004 data $\pm$ 15%.

σ_R corresponds the levels of variation in the S - R relationship.

For comparative purposes, the distribution of E^* was re-calculated without taking into account the uncertainty in price and cost. Under this assumption, the upper 95% confidence interval of E^* became much narrower, ranging between 0 and 2,303 operators when a smaller σ_R of 0.238 was assumed, and between 0 and 2,144 under a larger σ_R of 0.3 was assumed (Table 3-13). Without the price and cost uncertainties, the mean values of E^* became smaller, between 179 and 273 operators, approximately 20-30% of the 2004 level, and the median values remained zero. This suggests that there is more than a 50% probability that the fishery is unprofitable if the current economic conditions remain, given the stochastic nature of the stock. However, the cost data are highly uncertain as the information on costs was obtained from sampling surveys, and the true costs of operation cannot be known precisely. Thus, it is unrealistic to assume that economic parameters are known accurately. It can be concluded that there is no steady-state equilibrium effort for this fishery under the levels of uncertainties in both economic parameters and S-R uncertainty considered here. The corresponding distribution of Y^* for 10-30 GT fleet were also highly variable, ranging between zero and 562 thousand tonnes. The highest value exceeds the annual TAC set for this species in 2004 (530 thousand tonnes). The estimates of X^* for this species were relatively stable, with a median value of approximately 3.3 million tonnes. This equates to about 86.8% of the carrying capacity.

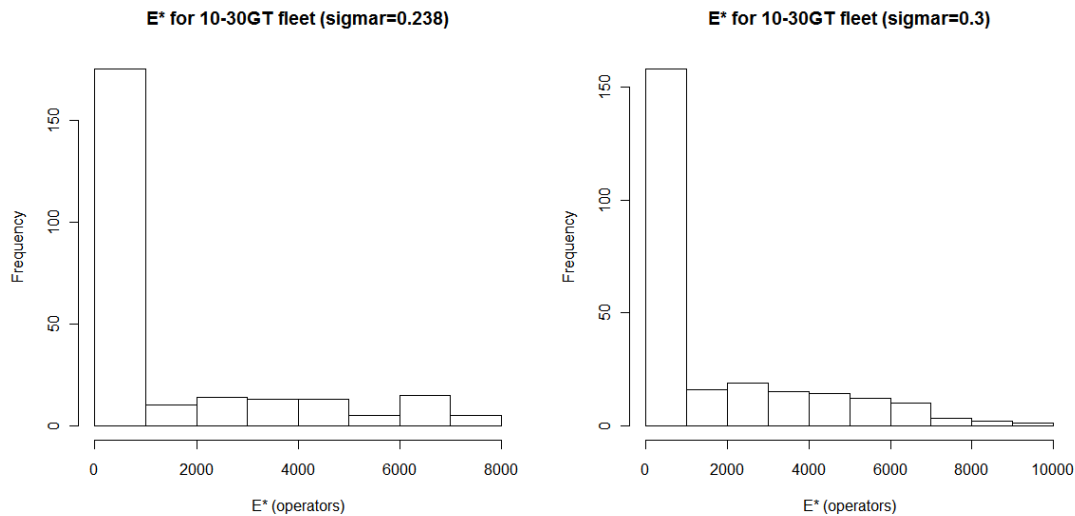


Figure 3-10: Distribution of steady-state effort (E^*) for 10-30GT fleet targeting Japanese common squid with price and cost uncertainty (mean $\pm 15\%$) under different values of S-R uncertainty. 250 Monte Carlo run. $\sigma_R = 0.238$ (left) and $\sigma_R = 0.3$ (right).

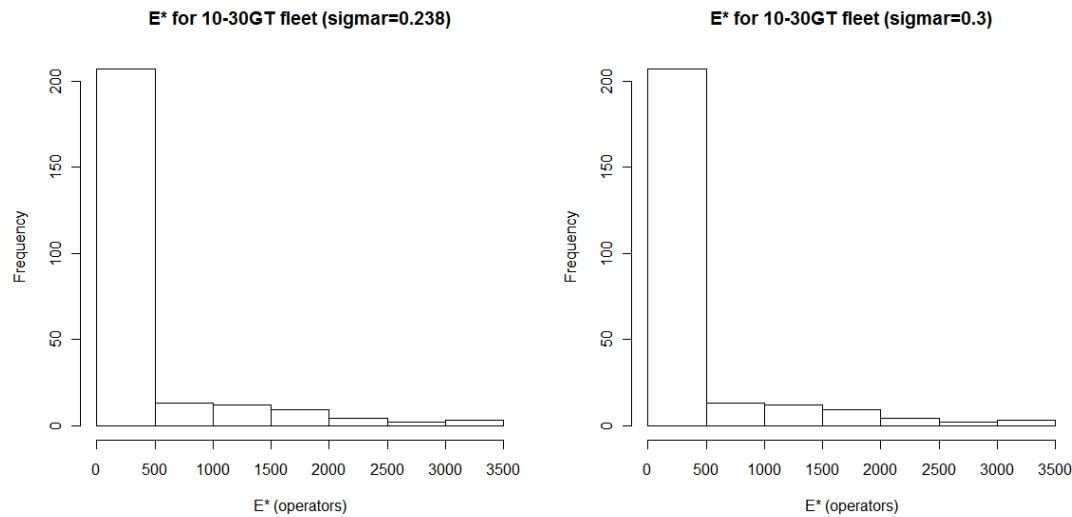


Figure 3-11: Distribution of steady-state effort (E^*) for 10-30GT fleet targeting Japanese common squid without price and cost uncertainty under different values of S - R uncertainty. $\sigma_R = 0.238$ (left) and $\sigma_R = 0.3$ (right)

3.3.3 Performance testing simulation results

3.3.3.1 Pacific saury

In terms of the SSB indices, most MP scenarios performed well, with negligible risks of recruitment overfishing and a high chance of the final year SSB being above 50% of virgin SSB level, although the effort-based MPs performed better than the TAC –based MP, since the two effort-based MPs were predicted to maintain the final year SSB levels above 50% of virgin SSB level for over 80% of the time (Table 3-14).

In terms of economic-based indices, the TAC-based MP performed poorly (Table 3-14) with negative discounted annual profits projected for most years during 10-year projection period, while the constant effort MP and adaptive MP generate significantly higher positive discounted profits over 10 years (Table 3-14). A comparative plot of annual discounted profits (Figure 3-12) shows that the probability of annual profits being negative is significantly reduced for the adaptive scheme.

Table 3-14: Performance indicators for Pacific saury management procedures. The level of annual variability in catchability coefficient (CV_Q) was 0.1. Discount rate = 4%, Monte Carlo trials =1000

Management Procedure	Biological Indices		Economic Indices		
	Prob. of $SSB_{final} < 20\% SSB_0$	Prob. of $SSB_{final} \geq 50\% SSB_0$	Sum of dis. profits in 10 years, median value (Billion yen)	Prob. of annual profits being negative*	Ave. total loss* (Million yen)
A) TAC	0.006	0.62	-128	0.944	128,740
B) Fixed Effort	0.001	0.84	49.7	0.018	111
C) Adaptive					
Survey cv =0.1	0	0.84	48.7	0.003	10.6
Survey cv =0.2	0	0.83	48.4	0.005	17.6
Survey cv =0.3	0	0.83	44.5	0.009	46.7

* Excluding the initial year.

The probability of negative annual profits was only 0.3% for the adaptive MP compared to 1.8% under the constant effort MP. This positive effect may seem small in practice to justify the adaptive management if possible adjustment costs are high. However, I assumed such costs are negligible for this particular fishery, given that pre-season surveys are already in place as the current stock assessments, and the most participants in the dominant fleet are part-time operators, thus their opportunity costs of not remaining in the fishery are lower than those for full-time operators. The average total loss (from 1000 Monte Carlo samples) over 10 years was 10.6 million yen for the adaptive MP with relatively good survey precision ($CV_{survey} = 0.1$), compared to 111 million yen in the constant effort MP, suggesting a 90% reduction in the total loss of profits. This indicates that, with reliable survey precisions, the adaptive MP performs better than constant effort management as it minimises the economic losses while maintaining roughly the same average level of discounted profits.

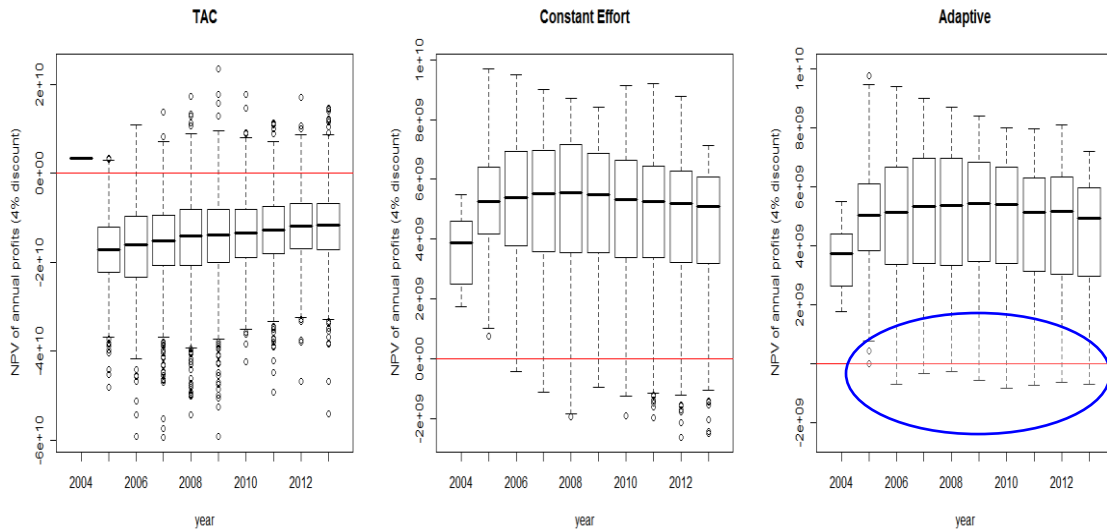


Figure 3-12: 10 year projection of discounted annual profits (Yen, 4% discount) under the current TAC management (left), constant effort management (middle), and adaptive effort management with survey CV 0.1 % (right). Red line shows zero profits. One can see how negative profits are reduced for the adaptive management procedure.

In the case of reduced survey precision ($CV_{survey} = 0.3$), the probability of the annual profit being negative increased from 0.3% to 0.9% in the adaptive MP. Total losses also increased from 10.6 to 46.7 million yen, which is approximately 50% less than the losses from the constant effort MP (Table 3-14). This indicates that the survey precision is important to ensuring the reduction of potential losses through the adaptive scheme, but that even with low precision, the adaptive HCR still outperforms a constant effort policy. If annual variability in Q ($CV_Q = 0.2, 0.3$) is assumed to be higher, this increases the probability of negative annual profits, but does not affect the relative performance of each management scenario as this trend is observed equally across all scenarios.

3.3.3.2 Japanese common squid

All three MPs performed equally well in terms of the SSB indices, with no risk of recruitment overfishing and a high probability that the final year SSB was above 50% of virgin SSB level (Table 3-15). The average exploitation rates during the fishing season, including external fishing mortality, were estimated at 26.6%, 24.3%, and 24.3 % for the TAC management ($F_{targ}=0.5$ by Japanese fleet), constant effort management (based on

1,291 operators), and the effort-based adaptive management procedure, respectively. Given the moderate exploitation rates, the stock was maintained at high levels under all MPs.

Table 3-15: Performance indicators for Japanese commons squid management scenarios. SSB = spawning-stock biomass. The level of annual variability in catchability coefficient (CV_Q) was 0.1

Management Procedures	Biological Indices		Economic Indices		
	Prob. of $SSB_{final} < 20\% SSB_0$	Prob. of $SSB_{final} \geq 50\% SSB_0$	Sum of dis. profits in 10 years, median value* (Billion yen)	Prob. of annual profits being negative**	Ave. total loss** (Billion yen)
A) TAC (F _{targ} =0.3)	0	0.99	25	0.292	9.9
(F _{targ} =0.4)	0	0.99	36	0.282	12.2
(F _{targ} =0.5)	0	0.99	47	0.291	14.7
B) Fixed Effort	0	0.99	28	0.282	10.1
C) Adaptive	0	0.99	37	0.267	6.0
With CV=0.1obs. error	0	0.99	37	0.270	6.2

* NPV was calculated based on the mean E* effort of 1,291 operators ($\sigma_R=0.3$) at discount rate of 4%.

** Excluding the initial year.

In terms of the sum of discounted annual profits over a 10-year projection period, the TAC with F_{target} =0.5 scenario yield the highest (roughly 10 billion yen). This was due to the higher harvest rate relative to the two alternative MPs. The total loss over the projection period was, however, the highest under TAC-based MP: compare to the adaptive MP, the total losses are about 3- 8 billion yen higher with all F_{target} level. The risks of negative annual returns appear to be slightly reduced (up to 3.5%) under the adaptive MP, although the effect was considered minimal.

In comparing the adaptive vs. constant effort MPs, the adaptive MP yield significantly higher (26-27%) sum of discounted profits over the 10 year period than the constant effort MP (Table 3-15), although the exploitation rates were about the same as constant effort. Moreover, the average total loss (from 1000 Monte Carlo samples over 10 years) was reduced from 10.1 billion yen under the constant effort MP to around 5.6-6 billion yen under the adaptive MP. This was due to a combination of increased effort in productive years when catchability was detected to be higher than the base year, and

fishery closure in non-productive years.

Introducing an observation error with a CV of 10% did not change the estimated sum of discounted profits, while increasing the losses slightly (3%) compared to the negligible observation error case (Table 3-15), but the effect was minimal.

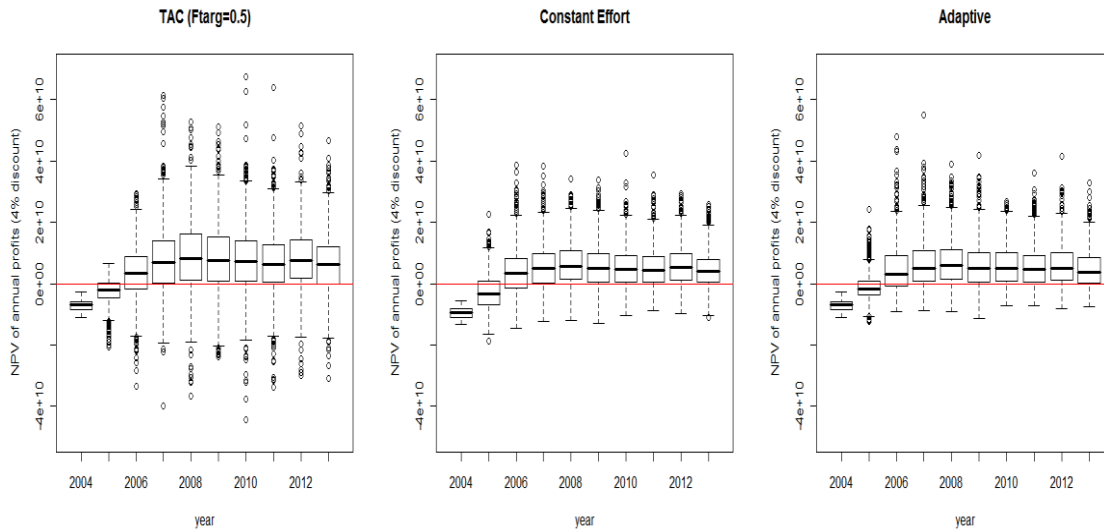


Figure 3-13: 10 year projection of the net present value (Yen, 4% discount) of annual profits under the TAC management with $F=0.5$ (left), constant effort management (middle), and adaptive management with negligible observation error (right). Red line shows zero profits. $CV_q = 0.1$ was assumed for all management procedures.

Advantage of adaptive scheme with larger CV_Q

The discounted annual profits tend to increase at higher levels of CV_Q , but the slight increase in frequency of negative profits at higher CV_Q was observed only for the TAC-based MP and constant effort-based MP. In fact, the larger the values of CV_Q , the better the adaptive MP performed (Figure 3-14), as the adaptive MP maintained the lower risk of negative profits. This provides evidence that adaptive MP is superior in minimising losses from fisheries targeting fluctuating stocks with significant uncertainties.

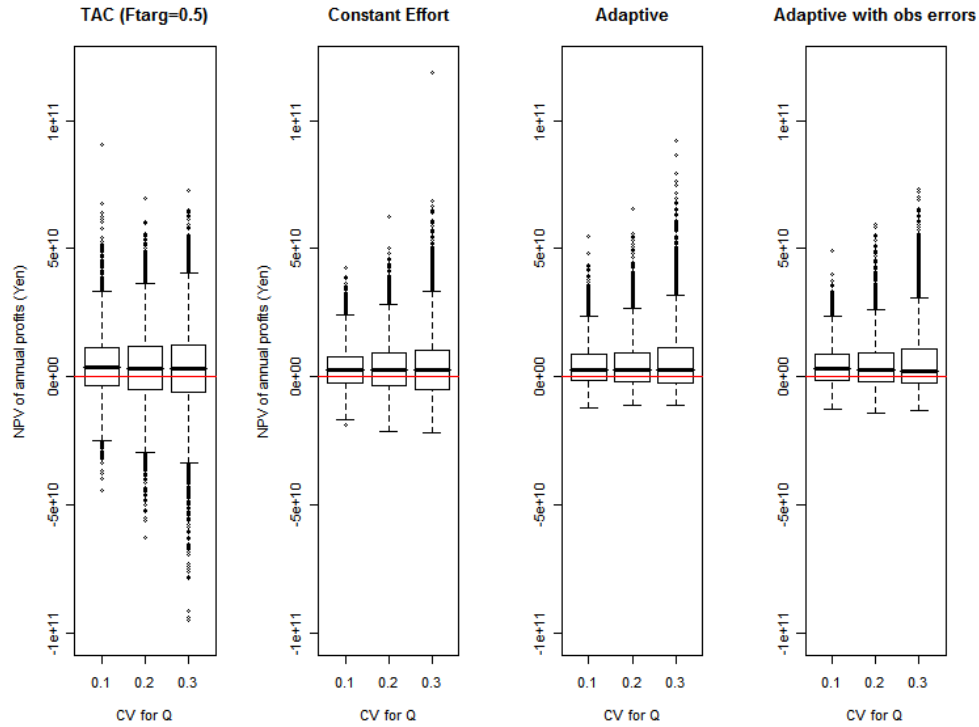


Figure 3-14: Distribution of discounted profits (Yen, 4% discount rate) with different levels of CV_Q . TAC ($F_{targ}=0.5$) management (left), constant effort management (left middle), adaptive management with negligible observation error (right middle) and adaptive management with 10% observation errors (right).

Bias from low harvest rates & high observation error

In order to demonstrate the relationship between the harvest rate of Japanese common squid and bias from the depletion assessment, a simulation evaluation of the accuracy of the estimates was carried out by varying the levels of observation error CV and the harvest rates. The plots of biomass estimates with different observation errors (Figure 3-15) indicate that the biomass was consistently overestimated (positively biased) by the depletion stock assessment method in the presence of observation error. As the observation error CV increased from 0.05 to 0.25, the bias became progressively larger in terms of the mean, although the median estimates were relatively stable around the true biomass of around 1.8 million tonnes (Figure 3-15). Mean estimates were positively biased due to large upward skewed errors. The error became smaller as harvest rate increased, and the observation error CV was reduced. At a harvest rate of 0.3 the estimates of mean biomass, except for the 0.25 observation error CV case, fell within the

90th quintiles, suggesting that the bias in the biomass estimates under the presence of observation error became smaller with higher harvest rates. Low harvest rates tend to lead biased estimates, because in a depletion method, the catchability coefficient is estimated from the negative of the slope of a linear regression model, where CPUE is fitted on cumulative catch, and the initial population size is the intercept when CPUE hits zero due to depletion of the stock (see Methods). In the case of a low exploitation rate, the data used to fit the lines are far from the intercept, resulting in large errors on the estimates of both slope and intercept.

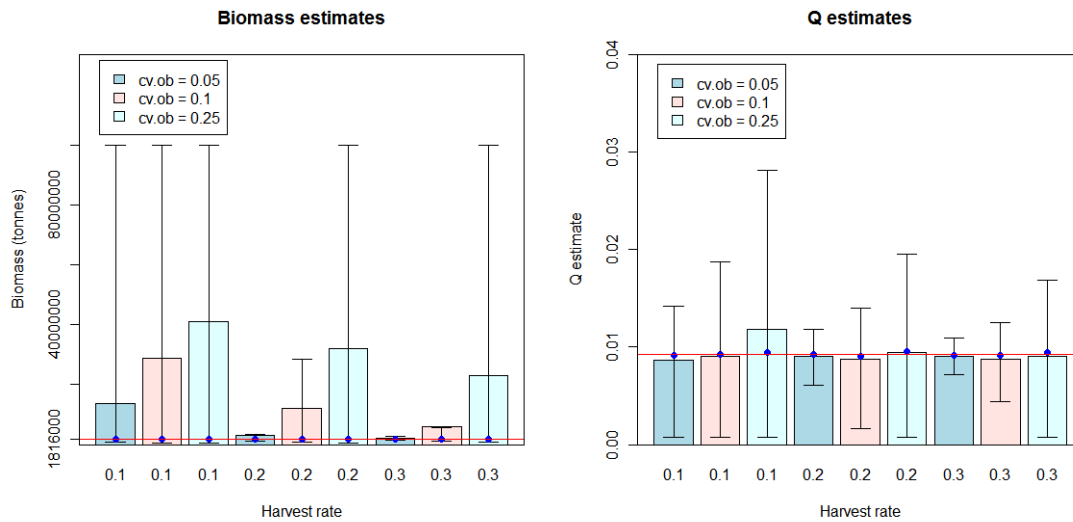


Figure 3-15: The relationship between the distribution of biomass estimates (left), catchability coefficient Q (right) in relation to the observation error CV and harvest rates from 10% to 30%. Mean values are the height of the bars, and blue dots are medians. The whisker lines show the upper and lower 90th percentiles. The true biomass and catchability estimates are shown in the red lines.

On the contrary, the bias in the estimates of Q was less serious. The large discrepancy between the mean (height of the bars in Figure 3-15) and median (blue dots) estimates of Q was observed only under the situation with high observation error CV (0.25) combined with low harvest rate (0.1), due to large upward skewed errors. The errors appear to be normally distributed around mean for the rest. Similar to the biomass estimates, the errors around Q estimates became smaller as the harvest rate increased, and as observation error CV reduced.

It was found that the estimated biomass and Q were strongly negatively correlated. This means that when biomass is overestimated, Q is underestimated. This negative correlation between biomass and Q was consistent with the observation by Hilborn and Walters (1992). Based on this result, a harvest rate of 0.24 appeared to be adequate to obtain unbiased estimates of Japanese common squid biomass, with relatively good stock assessment precision (i.e. observation error CV less than 0.1).

For the Pacific saury fishery, the average harvest rate from commercial fishing, when the mean effort E^* was used, was estimated at less than 0.1. This implies that the adaptive scheme with depletion method may not be so appropriate for the saury fishery, as the low harvest rate may result in biased estimates for biomass. This provides a justification for the pre-season survey adaptive scheme for the Pacific saury fishery.

3.4 Discussion

In this Chapter, I illustrated how an input-based adaptive management procedure with bioeconomic objectives can be constructed for fisheries targeting short-lived species, using the empirical examples of evaluating management procedures for two of the Japanese fisheries currently being managed by an annual TAC system.

As alternatives to the current TAC-based management, two effort-based MPs were proposed; constant effort management and adaptive effort management, both based on the optimal equilibrium effort designed to achieve a long-term bioeconomic objective. In finding the economically optimal effort levels, stochastic bioeconomic models were developed for the fisheries targeting Pacific saury and Japanese common squid, taking into account random fluctuations in stock abundance, as well as key economic parameters. While most studies with bioeconomic models in fisheries commonly assume constant price and cost, I incorporated uncertainty in these key parameters using the parametric bootstrap method and Monte Carlo trials. I also applied an inverse demand function to take into account the negative relationship between demand and supply in the

bioeconomic model for Pacific saury. Uncertainty in this function was also incorporated using the historical variation in prices in relation to harvest by the fleet considered. These enabled me to obtain a probability distribution of equilibrium effort levels that would maximise the net present value of future profits from the relevant fisheries.

The prediction of steady-state effort, E^* , for the Pacific saury fishery was relatively robust with low variance around the median value, while it was highly variable for the coastal angling fishery for Japanese common squid. The uncertainties in the stock-recruit relationship made the estimates of E^* for the Japanese common squid angling fishery more conservative, while the bi-modal distribution of E^* , and the highest frequency around zero (64%), suggesting that fishery closure is optimal about two third of the time. Thus, it is concluded that there is no steady-state effort for the Japanese common squid angling fishery given the levels of uncertainties involved.

These results lead to the general conclusion that uncertainties in stock abundance and the general lack of good economic data significantly affect the precision of the estimates, as clearly demonstrated by the volatile probability distribution of equilibrium effort levels for Japanese common squid. Thus, a simple illustration of the “expected” value of optimal effort estimated from a deterministic method, commonly seen in the fisheries literature, gives insufficient information with regards to the bioeconomic analysis of fluctuating stocks such as these. Bioeconomic modelling is sometimes perceived as unreliable by policy makers (Pascoe 2007). Providing a probability distribution gives decision makers more information on the precision of their estimates, and a stochastic analysis has such an advantage. Currently the information on operating costs for Japanese fisheries is limited to “average” values from sampled operators, and there is a clear need to improve the quality of economic data to obtain robust estimates in the future.

It was found that the effects of uncertainties related to the stock abundance and economic parameters on optimal conditions were different between the two fishery models, despite the fact that both species are characterized as short-lived, highly fluctuating stocks. The major differences in the two models were 1) the supply-demand specification, and 2) the

population dynamics specification (age-structured versus biomass dynamic). The Pacific saury fishery has a downwards sloping demand, which implies that maintaining the supply at relatively small levels even in years of high stock abundance is more profitable than saturating the market. This is probably why the optimal conditions for Pacific saury fishery were relatively stable regardless of the uncertainties in price and costs. The different specification of population dynamics is another possible reason for the different behaviour of the two bioeconomic models. These speculations will be tested in detail in Chapter 5 and 6.

While there is a need to continue the development of reliable bioeconomic modelling through a better understanding of the biology and improvement in economic data, it was demonstrated that the MSE approach can be very useful in providing a means of testing and evaluating the possible outcomes of input control measures based on bioeconomic reference points, particularly when considerable uncertainty is expected, e.g. for the management of short-lived species. The adaptive MPs based on a bioeconomic reference points proposed here were capable of generating higher economic profits (in the case of the Japanese common squid fishery) and minimising the economic losses from both fisheries targeting fluctuating stocks, while maintaining the precautionary principles.

Under the adaptive management regime developed for the coastal angling fishery for Japanese common squid, in-season adjustments in the effort were possible based on the stock assessment results, detected changes in catchability coefficient, and economic changes over time. As it is adaptive in nature, finding the “right” level of initial effort is less important as it can be adjusted later within the fishing season compared to the situation with conventional constant harvest/effort strategies where such in-season adjustments are not permitted. Such an advantage was clearly demonstrated by the results with improved performance of the adaptive MPs over the constant effort MP.

However, the effort-based MPs for the common squid have limited practical applicability, since the better performance of both constant and adaptive effort management strategies for this species is based on an increase in the effort level by approximately 35% of the

2004 level. Given that the observed harvest levels of Japanese common squid have only been about half of TAC levels in recent years, it is unrealistic to expect a higher harvest level given the declining trend in the number of participants. Moreover, in-season assessment is likely to increase the management costs. Since the analysis suggests that the fishery is profitable on average, the decline in the number of participants may be due to either 1) social reasons, such as aging population and general lack of interest in fishing by the young generation, or 2) the high risks of negative profits, or the combination of both. The ex-vessel price of Japanese common squid today has declined to less than half of what used to be in the mid 1980s as a result of globalization and price competition between the cheaper imported seafood products, while the operating cost has increased by approximately 30% since 1985. Such structural changes in the market together with the fluctuations in the stock abundance and profits make the fishery relatively unappealing from a business perspective.

On the other hand, the applicability of the two effort-based MPs developed for the Pacific saury stick-held dip net fishery appear to be more promising, given the effort reduction from the current to equilibrium level is within a realistic range, and pre-season surveys have already been used as a part of stock assessment practices. Ueno et al. (2006) has reported that the prices of Pacific saury tend to drop in the Japanese market in years when the stock is abundant (hence, a large supply), perhaps due to the lack of primary processing capacity to handle large quantities of fresh saury. *Ad hoc* advice to cut the fishing effort to avoid the price drops in good seasons has already been provided by the Pacific saury fishermen's organization. Although the equilibrium effort used here was indicative, the results presented here still provide an economic justification for reducing the fishing effort for the Pacific saury stick-held dip net fishery in Japan in good years. Fresh saury receives a high price premium in the Japanese market, and the competition with frozen, imported products is considered minimal. Since the supply of fish by the Japanese fleet is highly influential on the market price, it is recommended for policy makers to take into account not only the sustainability of the stock, but also the possible economic impacts in setting the annual catch limit for this species.

One important limitation of this Chapter was an exclusion of implementation errors for effort-based strategies. For the output control simulations (TAC-based MP) implementation error can be accounted for using the observed discrepancies between TAC set and actual catch taken, while there is no such available information with regards to potential input control. It is likely that the level of implementation error will vary based on the input variables themselves: controlling the number of jigs could be much harder than controlling the number of vessel operators. Clearly implementation issues require further attention.

The management of short-lived species involves complexities, and requires one to take into account year to year fluctuations in abundance and other key parameters and large environmental and economic variability. The existing examples of adaptive management tend to have focused on biological reference points alone (Basson et al. 1996; De Oliveira and Butterworth 2004), but the potential benefits of incorporating bioeconomic indicators is clearly demonstrated from the case studies in this chapter. Moreover, most applications of adaptive or feedback control rules in the fisheries economic literature have been focused on the economic evaluation of the history of a fishery (Grafton et al. 2000; Sandal and Steinshamn 2001a; McDonald et al. 2002; Arnason et al. 2004), rather than an evaluation of the future performance of alternative harvest strategies.

In these studies, however, social objectives, such as providing jobs in coastal communities or supplying fresh seafood to a local market, are not included. Social objectives are key to coastal nations, such as Japan, and in reality they are sometimes given priority over others. The comparative advantage of adaptive MP with economic consideration may be undermined by the relative importance of other objectives. For instance, if the social objective is more important than economic objectives, a stationary effort control may be more appropriate, i.e. for the Pacific saury fishery, as the fishery remains open even when the expected profit is negative. There is further scope to investigate the performance of alternative management procedures using multiple (biological, economic, and social) objectives. Moreover, ecosystem dimensions (e.g. species interactions) and spatial elements are not accounted for in my case studies, and

the latter may be particularly important to consider in the future as seasonality in the spatial distribution of the resource and fishing intensity are relevant in the assessment of short-lived species (Seijo 2005).

In this chapter I have focused on fisheries targeting short-lived species. In the next Chapter (Chapter 4), a similar input-based MP based on bioeconomic reference points is developed for a fishery targeting long-lived species, using the Patagonian toothfish fishery around the island of South Georgia as an example, and the performance of such a MP is tested in comparison to the current MP. The outcomes of both Chapter 3 and Chapter 4 are used as basis for exploring and comparing different bioeconomic behavior under multiple uncertainties in Chapter 5 and Chapter 6.

Chapter 4. Economically optimal management strategies for long-lived species: A case study for South Georgia toothfish (*Dissostichus eleginoides*) fishery

Abstract

This chapter aims to identify the economically optimal harvesting policy which would maximise the net present value of the sum of future annual profits from the longline fishery targeting Patagonian Toothfish (*Dissostichus eleginoides*) around the island of South Georgia, and to compare it to the current biologically-focused management policy. A highly complex integrated Bayesian age-structured stock assessment model currently being used to assess the stock and the management of this species by the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR) was translated into a simple surplus production model to replicate the stock dynamics of this species, preserving the known biological information while maintaining model simplicity. A simulation-based management strategy evaluation (MSE) demonstrated that optimum long-term profitability at a discount rate of 2% would be achieved at a biomass of 59% of initial biomass, which is higher than the target biomass of 50% incorporated into the current management procedure, and at a reduction in effort of approximately 19%. A number of potential effort reduction strategies are investigated, several of which would achieve better conservation objectives and higher future profits from the fishery than those predicted using the current management.

4.1 Introduction

Patagonian toothfish, *Dissostichus eleginoides*, is a large demersal, long lived fish distributed widely in shelf and shelf-slope waters around Sub-Antarctic islands and both

east and west coasts of South America. There are assumed to be 5-6 stocks in the Antarctic (SC-CAMLR 2007) and probably 2-3 on the east and west coasts of South America (Payne et al. 2005). It is fished in deep water (600m – 2000m) using bottom longlines (CCAMLR 2000).

Globally the resource has been experiencing high levels of exploitation due to high international demand for what is considered to be luxury seafood in the USA, Japan and the EU (Catarci 2004). The global catches of Patagonian toothfish peaked in the mid-1990s, with a declared catch of around 40,000 tonnes from 1994-1996, and an additional illegal, unreported and unregulated (IUU) catch in Antarctic waters estimated to be between 30,000 and 40,000 tonnes (Agnew 2000; SC-CAMLR 2008). Catches of both regulated and IUU fishing have declined since then, and for 2008 were estimated to be 24,000 tonnes including about 1,000 tonnes of IUU catch (SC-CAMLR 2008).

The stock of Patagonian toothfish around the island of South Georgia is managed by the Government of South Georgia and the South Sandwich Islands (GSGSSI), an Overseas Territory of the UK, which manages fishing and other activities within the South Georgia Maritime Zone (SGMZ). The stock falls within the area of application of the Convention for the Conservation of Antarctic Marine Living Resources, and along with other Antarctic resources is subject to management advice from the Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR). Management measures are implemented by GSGSSI to be consistent with, or to be more rigorous than, those agreed by CCAMLR. The fishery has been operating since 1985 but with some variability in the fleets and management systems implemented over this period. For a more detailed exposition of the history of this fishery see Chapter 2 and Agnew (2004).

CCAMLR has defined specific harvest control rules (HCRs) for toothfish species exploited in the convention zone. These HCRs are designed to avoid significant impacts on recruitment and to ensure that removal of this top predator is consistent with obligations to maintain a functioning ecosystem. CCAMLR tends to consider the decision rule to represent an implicit limit reference point of spawning stock biomass (SSB) at

20% of its median unexploited level, and target reference point of SSB at 50% of its median unexploited level. TACs are set within these bounds, and are divided between a number of licensed vessels. Both GSGSSI and CCAMLR management objectives have been focused heavily on biological/ecological sustainability, driven by both organisations' primary objective of ecosystem conservation. As a result, the current management target and reference points, as set out above, were set solely on the basis of biological perspectives. No consideration has yet been given to the long-term economic aspects of the fishery.

In this chapter an alternative set of potential management procedures (MPs) with economic objectives are explored, and these MPs are compared, based on both economic and biological performance criteria, with the current management objectives. This is the first attempt to apply bioeconomic modelling to the Patagonian toothfish fishery at South Georgia and to Antarctic marine living resources in general. This chapter is organised as follows: Section 4.1 contains objectives of the chapter and data used. Section 4.2 provides details of methods in modelling toothfish biomass and harvest, as well as methods for management strategy evaluation. Section 4.3 reports the main results. Discussions and conclusions of the Chapter are detailed in Section 4.4. Note that an overview and history of the Patagonian toothfish fishery in South Georgia is given in Chapter 2.

4.1.1 Objectives

The objectives of this chapter are 1) to identify the long-term economically optimal fishing conditions; and 2) to determine a suitable management procedure designed to achieve the economically optimal conditions over a time-frame dictated by the current management objectives for this stock that is robust to the biological and economic uncertainties in the system.

It will simulate the whole process of the management of this fishery from stock assessment and the setting of the relevant TAC/effort level, implementation error and bias in either the harvest taken or the effort set, to the dynamics of the stock given the

management actions. There are already pre-existing management objectives for this stock as defined by CCAMLR but there are also potential economic objectives to consider. In this chapter multiple objective criteria are used when evaluating the performance of each strategy.

4.1.2 Data

Catch and effort data for this fishery were obtained from the CCAMLR secretariat. These data are available on a haul-by-haul and 1 degree square aggregation level, but for the purposes of this work, the catch data were used only as yearly biomass removals and the effort data simply as the total number of hooks set over the year.

Cost data were obtained from a sample vessel operator with three vessels. Because it was not possible to obtain the cost information from all participants, I used the cost information from the sample operator, assuming that those three vessels' cost structure represents the cost structure for the entire fleet, although there is an indication that the cost structure varies substantially among fishing nations (based on an observer; pers. comm.). The detail of how the cost uncertainty was dealt with is given in the Methods.

For reasons of confidentiality, the detailed cost information is not summarised here. The variable costs include salaries, charter fee, fuel, repair & maintenance, spares & consumables, bait, observer costs and other miscellaneous operational costs. Fixed costs include licence fees, insurance and port/agent charges. Depreciation costs of fixed capitals for vessels and gears are not available so they were excluded from my analysis.

The landing prices were estimated from a combination of published prices from INFOFISH and informal industry contacts. The average landing prices for headed and gutted fish before 1998/1999 season were less than US\$4000 per tonne, but the price increased substantially in the following years, and the average price over the past 3 years (Table 4-1) was approximately US\$14,000-14,500 per tonne. The price of toothfish in live weight, p , was estimated at around \$9,100 per tonne based on the prices of various parts of the fish and their proportions:

$$p = p^{HG} \mu^{HG} + p^{CO} \mu^{CO} + p^{CH} \mu^{CH} = \text{US\$ } 9,131 \text{ per tonne}$$

where p^{HG} , p^{CO} , p^{CH} are the ex-vessel prices of headed gutted fish, collar of the fish, and cheek of the fish, respectively and proportion (or conversion factor) of the each part $\mu^{HG}=0.565$, $\mu^{CO}=0.127$, $\mu^{CH}=0.007$.

Table 4-1: Estimated ex-vessel price of Patagonian tootofish. All prices are first landed prices of headed and gutted fish. The ex-vessel prices for collar and cheek of the fish in 2007/08 season were estimated at around \$7,000 per tonnes.

Year	Price* (US\$/t)	Year	Price* (US\$/t)
2001/02	\$7,000 - \$7,500	2007/08	\$14,500
2000/01	\$8,400	2006/07	\$11,000 - \$14,000
1999/00	\$10,500	2005/06	\$14,000 - \$17,500
1998/9	\$3,500 - \$4,000	2004/05	\$8,500 - \$10,500
1997/8	\$4,000 - \$3,500	2003/04	\$8,500 - \$10,500
1996/7	\$4,000	2002/03	\$8,500 - \$10,500

4.2 Methods

4.2.1 Developing a bioeconomic operating model

A bioeconomic operating model was constructed to 1) estimate bioeconomic optimum, and 2) to examine how the current management targets set by CCAMLR, based on the biological target and limit reference points, differ from the economic optimum. I use the term operating model (OM) because not only are the biomass dynamic population model and the production function parameters used to estimate economically optimal harvesting conditions, I also subsequently use them as the basis for a full simulation model of the population and fishery. The OM is type 2 (see 2.3.4 for classification) as the biomass dynamic model is derived directly from the assessment model and I assume the assessment model is "true."

4.2.1.1 Population dynamics

The Patagonian toothfish fishery at South Georgia is managed according to the principles of the CCAMLR. A complex, integrated Bayesian age-structured (Beverton-Holt) stock assessment with 35 age classes is used to assess toothfish stock status and to set catch limits (Hillary et al. 2006) as per the CCAMLR decision rules for finfish fisheries (SC-CAMLR 2006). Dynamic optimisation in the Beverton-Holt model quickly becomes complex, including a stock-recruitment relationship makes it almost incomprehensible from the dynamic viewpoint (Clark 1990). To simplify the problem of estimating optimal conditions as well as to simulate the whole fishery system, I reduced the age-structured model to a more tractable surplus production/biomass dynamic model. This kind of approach has been applied in a stock assessment context for a range of other species (McAllister et al. 2001), particularly when the information on life history is available but catch at lengths and growth information are partially lacking (such as shark and some tuna species), but not for a 'translation' from an age-structured model to a biomass dynamic model. This translation approach was initially developed in collaboration for the EU FP6 COBECOS ("Cost and benefits of fisheries control strategies") project, which aims to simulate legal and illegal fishing at South Georgia through bioeconomic modelling using a simplified biomass dynamic model, and CCAMLR management rules. It is worth reflecting that the major potential information loss incurred by this translation work is selectivity. Although a longline gear is selective, the over-riding driver of selectivity is the depth of fishing (Hillary et al, 2006), which is strictly controlled and has not changed for over a decade (Agnew, 2004). Assuming no future changes in depth regulations, the lack of ability to model selectivity is considered unlikely to affect the analysis and I test this assertion later in the validation section 4.2.1.4.

The model is the standard Schaefer model, dictating the change in biomass, X_t , over time:

$$X_{t+1} = X_t + rX_t(1 - X_t/K) - Y_t \quad (4-1)$$

where r and K are the intrinsic rate of increase and carrying capacity parameters, respectively, and Y_t is the total harvest taken from the stock at period, t , by both the legal

and illegal fleets.

4.2.1.2 Estimating intrinsic growth rate

The r parameter was estimated by solving the Euler-Lotka equation given in Chapter 3 equation 3-23. The life-history parameters—age at maturity, natural mortality, and stock-recruit parameters were obtained from the results from CCAMLR stock assessment (SC-CAMLR 2007). These life history parameters have distributions with known mean and variance. I used a Monte Carlo approach to obtain a sample of values for r , to account for the uncertainty in this key parameter, given uncertainty in the life history parameters that define r . From these samples I calculated a median value ($r=0.12$) and 95% confidence interval of r of 0.09- 0.17. The reasons for estimating r in this manner are as follows: Firstly, the stock of toothfish at South Georgia has experienced a gradual “fish-down” dynamic, without any periods of decline followed by growth. This makes the sensible estimation of both r and K from the assessment-derived biomass trend and the catch biomass infeasible. The analogy would be with trying to estimate such parameters given “one-way trip” abundance trend data (Hilborn and Walters 1992). Secondly, the intention is to use the model as a simplified form of the current management procedure while preserving the information on the key life-history characteristics in the biomass dynamic model as they are in the fully age-structured model.

Table 4-2: Biological parameter values for *Dissostichus eleginoides* in Subarea 48.3 (SC-CAMLR 2006). SD=standard deviation, BH=Beverton-Holt, SSB= spawning stock biomass.

Component	Parameter	Value	Component	Parameter	Value
Natural mortality	M	0.13	SR relationship steepness	Z	0.75
Von Bertalanffy growth parameters	k	0.067	Recruitment SD	σ_R	0.6
	$T0$	-1.49	BH parameters	a	472.3
	$L\infty$	152.8		b	1.243e-4
Maturity 0%		Age 0-6	Virgin SSB(tonnes)	SSB_0	88125
50%		Age 11			
75%		Age 17			
100%		Age 23			

4.2.1.3 Estimating carrying capacity

Catches prior to 1985, when the deep water longline fishery was initiated, were extremely small, limited to research and some bottom trawl by-catches of juveniles over the shelf. The main adult population, which lives deeper than 600m, was not impacted by the earlier bottom trawl fisheries on the shelf (Agnew, 2004). Thus carrying capacity, K for toothfish is assumed to be equal to the biomass level in 1985. The recent (2007) exploitable biomass is estimated to be 55% of K (CV = 0.102) (SC-CAMLR 2007). A paired Monte Carlo approach was used to obtain a distribution of plausible values of K for given values of r , which gives the current toothfish biomass equal to 55% of K . This was done by using a numerical equation solver to estimate K – for a given sample value of r - that gives $X_{2007} = 0.55 * K$ for a range of potential X_{2007} values based on CV, given the population dynamics in Eq. (3-1). The median and 95% confidence interval for K is 109,225 (89,579-126,961) tonnes, respectively. The resulting historical biomass dynamics (and their uncertainty) can be seen in Figure 4-1.

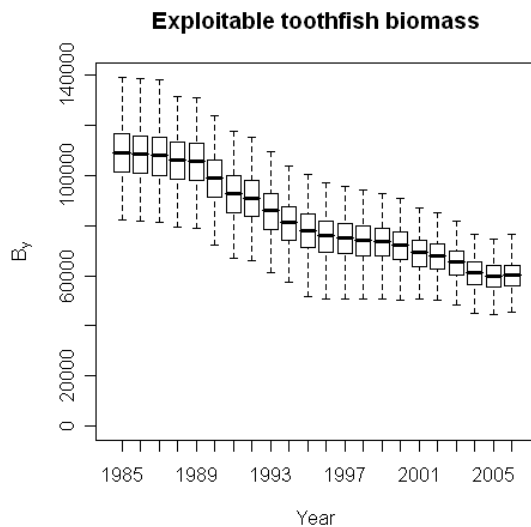


Figure 4-1: Box and whisker plot of historical biomass of South Georgia toothfish, from 1985 to 2007, and the population was assumed to be at carrying capacity, K , in 1985.

4.2.1.4 Validation of the model as a management tool

In collaborative work for the previously mentioned COBECOS project, code was developed to calculate the TAC given the CCAMLR management decision rules (SC-

CAMLR 2007) using the Schaefer model as outlined above. In order to validate whether this simpler model developed here (reduced model) performs well as a management tool for the South Georgia toothfish fishery, I compared the catch limit or Total Allocable Catch (TAC) predicted by the reduced model and the catch limit predicted by the age-structured Bayesian assessment model of CCAMLR.

TACs are set by CCAMLR according to a constant catch rule:

1. Find the constant catch for which the probability of spawning biomass dropping below 20% of the unfished median spawning biomass during a projection period of one generation time (35 years) is equal to 0.1;
2. Find the constant catch that generates a median spawning population biomass equal to 50% of the median un-fished spawning biomass after a projection period of 35 years;
3. Choose as a TAC the maximum harvest level that satisfies the two conditions above.

A simple comparison showed that the TAC predicted using the reduced model, given stock size in 2006, was 3,478 tonnes, while the TAC set by CCAMLR for this stock in 2006 was 3,554 tonnes (SC-CAMLR 2007). This equates to a difference of around 2% between predictions of the full stock assessment model and the reduced model. The reduced model should therefore provide sufficiently robust results for the analysis of short- and long-run bioeconomic equilibria. Note that TAC is the minimum value that satisfies the two conditions of the CCAMLR harvest control rules, and only one value is obtained so no variance estimates are possible.

4.2.1.5 Production function

I developed a simple economic model of production which describes a harvest of toothfish in South Georgia by the legal fishing fleet in relation to its historical stock biomass and aggregated fishing effort by legal fleet. Catch by the illegal fleet was excluded as there is no known illegal activities in the area at present and also because my

primary interest is to estimate the catchability coefficient of the legal fleet.

The harvest level of the legal fleet, Y in period t is given by the following Cobb-Douglas production function (Cobb and Douglas, 1928):

$$Y_t = Y(E_t, X_t) = q E_t^\alpha X_t^\beta \quad (4-2)$$

where q is the catchability coefficient, and E_t is the aggregated fishing effort by fleet in period t . The term α is the effort output elasticity and β is the stock output elasticity.

The estimating equation for the production function can be expressed in logarithmic form:

$$\ln Y_t = \ln q + \alpha \ln E_t + \beta \ln X_t + u_t \quad (4-3)$$

Here, u_t is assumed to be a normally distributed error term. The time series data on catch and effort from the legal fleet are available since 1984/85 season, but there was a major change in the CPUE (Figure 4-2) due to the shift from a summer fishery to a winter fishery and an associated requirement for night-time setting of longlines, both were introduced gradually from around 1995/96 season and completed by 1997 (Agnew, 2004). The assumption of constant catchability cannot be justified because of this technological change in the study period. For these reasons, I decided to use a subset of time series data between 1997/98 and 2007/08 ($n=11$).

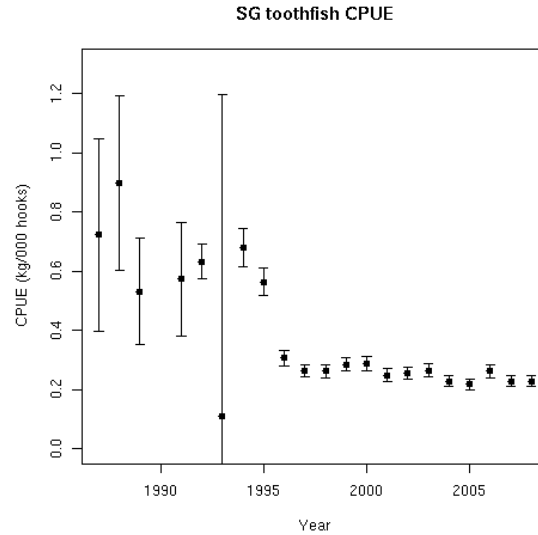


Figure 4-2: Standardized CPUE for toothfish longline fishery in South Georgia (SC-CAMLR 2006)

The number of hooks deployed each year was used as an aggregated effort index. A potential econometric issue arise is that the number of hooks deployed is determined endogenously by individual fishing agents, hence the effort variable is probably endogenous and consequently OLS estimators may be biased. Using lagged values of the number of hooks as an instrumental variable, a two-stage least squares regression (2SLS) was carried out to test if the model estimates are consistent. The null hypothesis is that the parameters are consistent. If we reject the null hypothesis, one or both of the estimators is inconsistent. The Hausman test statistics of 0.01, which follows a chi-square distribution (p-value = 0.943) indicates that the parameter estimates from the full model were consistent.

The standard Schaefer production function is a special case of equation (4-2) where $\alpha = \beta = 1$. A stock output elasticity, β of less than one is commonly found for fisheries on schooling stocks, such as Norwegian spring spawning herring (Bjørndal 1987) and juvenile cod (Eide et al., 2003). Although toothfish may aggregate around particular features (such as sub-sea canyons) observational evidence is that they are not a schooling species (Yau et al. 2001). The South Georgia stock assessment implicitly assumes β to be

equal to one (SC-CAMLR 2007), so one must naturally make the same assumption in estimating the production function parameters using such stock assessment data. It is worth noting that alternative work to look for a hyper-stability in CPUE (similar to assuming $\beta < 1$) detected no such effect for this stock (SC-CAMLR 2005), confirming this assumption.

I have carried out OLS regression fixing $\beta = 1$, and assuming that the toothfish are uniformly distributed (Model A). I compare this model to the standard Schaefer model where $\alpha = \beta = 1$ (Model B). The estimated parameters are given in the Results.

4.2.1.6 Model selection

Even though a distribution of stock biomass values is derived, I use the median historical biomass for the purposes of determining which production function is the most suitable. Based on the parameter estimate results, both models have a similar goodness of fit. To choose between Models A and B, a likelihood ratio test was carried out to assess the significance of the improvement from a simpler model to the more complex model. For a simpler Model B and a more complex Model A and for the two associated maximum likelihood estimates, $\hat{\theta}_1$ and $\hat{\theta}_2$, with (normal) likelihood $L(\theta)$, then the following statistic will be a Chi-squared random variable with degrees of freedom equal to the extra number of parameters in Model B:

$$-2 \times \ln(L(\hat{\theta}_1)/L(\hat{\theta}_2)) \quad (4-4)$$

The null hypothesis is that Model B is better than Model A. The results of Chi-square test and autocorrelation function (ACF) is given in the Results.

4.2.1.7 Optimisation

Optimal policies were based on the usual criterion of maximising the discounted sum of net present value of annual profit from the fishery. Discounted annual profit was calculated according to:

$$\pi = \sum_{t=0}^{\infty} \rho^t \pi(X_t, Y_t) \quad (4-5)$$

where $\rho = 1/(1+\delta)$ is the discrete discount factor and δ is the annual discount rate. The objective function can be written as:

$$\text{maximise } \pi = \sum_{t=0}^{\infty} \rho^t \pi(X_t, Y_t) \quad (4-6)$$

$$\text{Subject to: } X_{t+1} - X_t = F(X_t) - Y_t$$

$$X_0 \text{ given}$$

$$X_t, Y_t \geq 0$$

Profit is defined as follows:

$$\pi(X_t, h_t) = p q E_t X_t - c_v E_t - nv c_f \quad (4-7)$$

In the above equation c_f and c_v are the fixed and variable costs and nv is the number of vessels in the fleet. An explicit solution for the steady-state optimal values of stock X^* , harvest Y^* and effort E^* was obtained following the equations detailed in Conrad (1999).

4.2.1.8 Dealing with uncertainty in economic parameters

The key uncertainty in economic parameters in this case is in the cost c , as the available data are cost data for a subsample of operators. I accounted for this uncertainty by allowing the cost to have a uniform distribution $\pm 15\%$ of the actual subsample cost value and I assumed no correlation between cost and the other parameters r , K and q . Although the price of toothfish has been relatively stable since 2005, I also accounted for the price uncertainty by allowing the price to have uniform distribution of $\pm 10\%$. The results of steady-state optimal effort, harvest and biomass are given in the Results.

It could be argued that there is no specific precautionary element in the objective function. If this was a serious concern perhaps a more appropriate estimator for the optimal effort would be some lower percentile (e.g. 25thile). That way, the higher the uncertainty in

the key variables the lower the estimate of effort would be, as per the precautionary principle. However, the primary motivation of including the uncertainty in the uniform distribution was to assess the resultant variation in the key derived management quantities and the robustness of the conclusions about optimal levels to this variation.

4.2.2 Management Strategy Evaluation

In the previous section the calculation of optimal effort implicitly assumed an infinite time-horizon. In this section the MSE approach is employed to look at ways of reducing effort over a finite time-horizon to the optimal levels of effort calculated in the preceding section, while not adversely affecting the profitability of the fishery over the management period (35 years) for this stock. The MSE approach has been applied frequently in a more general fisheries modelling context (Butterworth and Punt 1999; Punt and Smith 1999; Campbell 2005) and provides a framework for both identifying robust management procedures but also sensibly comparing alternative procedures in the presence of multiple management objectives and system uncertainties. The FLR framework (Kell et al. 2007) is a generic, open-source framework for the construction of fisheries management simulations in the R statistical language (<http://www.r-project.org/>) and was used to construct the bioeconomic operating models used in the following and previous analyses.

The aim is to simulate the whole process of the management of this fishery from observation, stock assessment and the setting of the relevant TAC/effort level, implementation error and bias in either the harvest taken or the effort set, to the dynamics of the stock given the management actions. There are already pre-existing management objectives for this stock as defined by CCAMLR but there are also potential economic objectives to consider. In this chapter multiple objective criteria are considered when evaluating the performance of each strategy. A management time-horizon of 35 years is selected, since this is the time-horizon over which the CCAMLR rules are designed to operate.

4.2.2.1 CCAMLR Management Procedure

To determine a sustainable harvest level every year, CCAMLR has adopted an approach in which a single annual catch is calculated, conditional on the effect of this catch on the projected stock dynamics given the CCAMLR harvest control rules. In the simulations, the stock assessment process is treated as a random mis-estimation of stock biomass in the given assessment year, with a known coefficient of variation (CV) which is assumed to be 0.1. Based on the results from the stock assessment, the TAC for that year is calculated according to the CCAMLR harvest control rule. Using the historic time-series of TAC and actual catch taken it was possible to parameterise a simple implementation error model where the historic bias and variation dictate future levels of implementation error. The observed harvest level has been slightly (about 3%) lower in the past 11 years than the corresponding TAC level, thus an implementation bias factor (= 0.97) and the associated error (CV=0.017) were used. This whole process was simulated for 35 years into the future from 2007.

4.2.2.2 Immediate Effort Reduction

The effort level is set constant at median E^* with discount rate between 1 and 4%. In this scenario, the effort reduction takes place immediately from 15.2 million hooks per year (2007) to median E^* , 11.6-13.6 million hooks per year, depending on the discount rate used. The comparison of the performance of this effort reduction strategy and current CCAMLR management is given in the Results.

4.2.2.3 Constructing gradual effort reduction schedules

In addition to the immediate effort reduction regime, gradual effort reduction regimes were explored to determine a suitable management path designed to achieve the economically optimal conditions over a time-frame dictated by CCAMLR.

There are many potential effort reduction paths that can be imagined over a 35 year period, but rather than trying to find the unique optimal path, which exists in theory as noted in Clark (1976), for practical reasons only two functional forms are considered: (a) a simple piecewise linear reduction in current to optimal steady-state effort over a given

time horizon, and (b) a non-linear 'decay'-type reduction to optimal effort levels. For the piecewise linear effort reduction scheme future effort can be expressed as follows:

$$\text{If } t < t^*, \quad E_t = E^* + (t-1)*(E^* - E_{2007})/(t^* - 1) \quad (4-8)$$

$$\text{Otherwise,} \quad E_t = E^*$$

For the non-linear reduction scheme future effort is defined as:

$$E_t = E^* + (E_{2007} - E^*) * \left(\frac{1}{1 + \nu} \right)^{t-1} \quad (4-9)$$

Here E^* is the optimal effort level, t^* , is the year when the effort reaches E^* , E_{2007} is the initial effort level in the 2007 fishing season, and ν is the reduction rate which can be interpreted as the year-to-year proportional reduction in the difference between current and optimal effort. The relevant parameters of each reduction scheme were estimated in two ways:

- a. Estimated as the values which maximise the median sum of the discounted annual profits over the 35 year simulation, subject to the constraint that at the end of the 35 years the effort must be equal to the optimal effort, E^* .
- b. Estimated as the values which yield a median sum of the discounted annual profits *equal* to those obtained under the CCAMLR management scenario, subject to the same constraint as above.

The main reason for these two criteria is that one knows (a) which reduction-scheme parameters yield the most profitable reduction path given the time frame, and (b) which reduction parameters result in a path at least as profitable as the current management while still reducing the effort levels to the long-term optimum. No account was taken of potential adjustment costs to the industry, since reducing the effort (number of hooks in this case) is unlikely to cause fleet size reduction. The effort reduction path was

calculated using the median steady-state effort at 2% discount rate.

4.2.2.4 Choice of discount rate

Recognising that the estimates of optimal effort, harvest, and biomass are sensitive to the choice of discount rates, choosing an appropriate rate is difficult. Higher discount rate increases the optimal rate of exploitation of a renewable resource and increase risks of extinction (Clark 1973b, 1976). In the USA, estimates of the discount rate have ranged between 2% and 5%, and the choice of discount rate will vary depending on countries/culture and point in time (Conrad 1999). Given that 1) society views the Antarctic as an ecosystem sanctuary, with high conservation priority, 2) both CCAMLR and GSGSSI have strong conservation objectives, and 3) applying higher discount rates to a slow-growth species may increase extinction risks, I selected a relatively low discount rate (2%) as the base-case assumption for the full simulation evaluation. It should also be noted that the key qualitative conclusions are robust up to a 4% discount rate.

4.2.2.5 Performance indices

In evaluating the performance of each management procedures, four performance indicators were used: 1) sum of discounted profits over 35 years at 2% discount rate; 2) probability that the median final stock size is greater than 50% of the initial stock size; 3) probability of stock size dropping below 20% of K at any time over the 35 years projection period; and 4) final year CPUE (tonnes/1000 hooks).

4.3 Results

4.3.1 Parameter estimates

The results of production function parameter estimates for the South Georgia toothfish fishery are given in Table 4-3.

Table 4-3: Estimate of production function parameters for the South Georgia toothfish fishery, 1997/98 and 2007/08 (n=11). Y_t = harvest, E_t = effort, X_t = biomass at time t . Standard error in parentheses. *** indicate the p-value less than 0.000, and ** less than 0.01

<u>Model A</u>		
$\ln Y_t = -13.21 + 1.08 \ln E_t + \ln X_t$	$(R^2=0.96, \bar{R}^2=0.95, df=9)$	
(0.73)*** (0.08)***		
<u>Model B (Schaefer)</u>		
$\ln Y_t = -12.42 + \ln E_t + \ln X_t$	$(R^2 = 0.95, \bar{R}^2 = 0.95, df=10)$	
(0.02)***		

The Chi-squared test for testing the null hypothesis, Model B is better than Model A, indicated that the probability of the null hypothesis being true is less than 0.029, so I rejected the null hypothesis. Thus, from a likelihood perspective, Model A is significantly better than Model B at predicting the levels of harvest by the legal longline fleet. Because the value of the parameter ($\alpha=1.08$) in Model A is very similar to one, I tested if it is significantly larger than one. The p-value (one-tailed) was 0.155, thus I concluded that there is no statistical evidence that α is larger than one. ANOVA (Table 4-4) confirmed that there is no evidence that Model A is better than Model B. For simplicity, I concluded that Model B is the most appropriate model. In order to detect the presence of autocorrelation in the residuals from the selected regression model, an autocorrelation function (ACF) was calculated as well as a simple linear equation fitted to the residual at time $t+1$ against the residual at t . The results from both ACF (Figure 4-3) and the t-statistics and p-value (0.821) indicate that there is no first order autocorrelation in the residuals.

Table 4-4: Analysis of Variance (ANOVA) table for model selections. RSS= residual sum of squares, SS=sum of squares

	Residual DF	RSS	DF	SS	F value	Pr(>F)
Model A	10	0.03826				
Model B	9	0.03388	1	0.00438	1.1645	0.3086

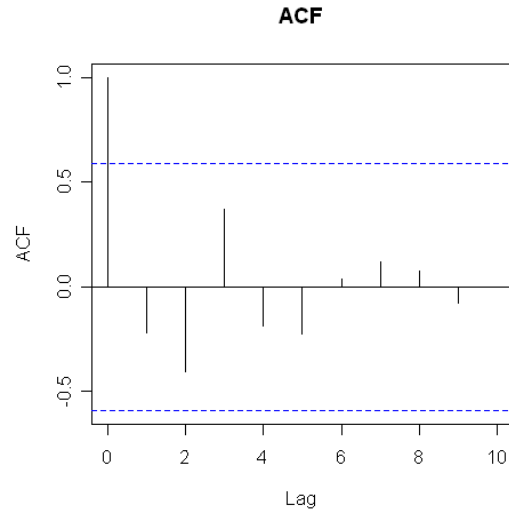


Figure 4-3: Autocorrelation function (ACF)

I used the median historical biomass to determine the best form for the production function, but having decided to use Model B, the production function parameters could be estimated using not only the median stock biomass but also each possible sample value of the stock biomass. For the given selected production function, I estimated the q parameter for each sample of the historical biomass to obtain a Monte Carlo sample of r , K and q which could be used in the economic analysis, thus accounting for parameter covariance. Figure 4-4 displays a plot of the observed and predicted harvest of toothfish over time, as predicted by the production function relating to Model B. The plot of observed versus predicted harvest is also given in Figure 4-4.

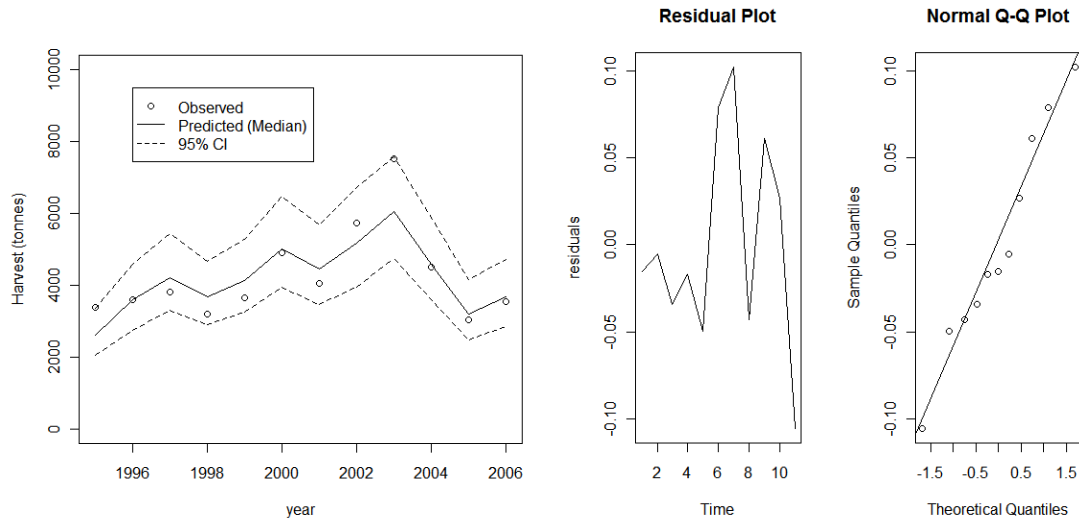


Figure 4-4: Left: Observed and predicted harvest as predicted by Monte Carlos samples of the parameters from Model B and the toothfish biomass (tonnes) over time. Right: Residual plots for Model B.

4.3.2 Optimal conditions and sensitivity analysis

The median optimal steady-state equilibrium harvest (Y^*) and biomass (X^*) are estimated at 3,134 - 3,270 tonnes per year, and 59,544 - 66,644 tonnes, respectively, depending largely on the choice of discount rates (Table 4-5). As one would expect, an increasing discount rate resulted in higher estimates of optimal effort and resultant yield, with lower optimal levels of stock biomass.

The estimates of E^* , Y^* , and X^* were roughly normally distributed, with no difference between the median and mean values, suggesting the estimates are consistent. The current CCAMLR target biomass point ($K/2$ = around 54,000) is about 8-20% lower than the median X^* with any of the discount rates considered (Table 4-5). This indicates that any further reduction in stock biomass is likely to lead to economic inefficiency due to the higher harvesting costs associated with smaller stock sizes, which results in the loss of resource rent or future profits. I will test this later in a management strategy evaluation.

Table 4-5: Optimal steady-state conditions for the Patagonian toothfish fishery in South Georgia when taking into account the variability in the values of key parameters and uncertainty in cost per unit effort and price. Steady-state biomass (X^*), effort (E^*) and harvest (Y^*)

Discount Rate	0.01			0.02		
	Median	95% CI		Median	95% CI	
X^* (tonnes)	66,692	54,792	78,468	64,190	53,163	75,170
E^* (1000 hooks)	11,661	9,861	13,262	12,292	10,577	13,857
Y^* (tonnes)	3,143	2,644	3,590	3,197	2,699	3,641
Potential Rent (US\$ million)	10.0	5.7	14.9	9.9	5.5	14.8
Discount Rate	0.03			0.04		
	Median	95% CI		Median	95% CI	
X^* (tonnes)	61,702	51,302	71,458	59,459	50,299	69,007
E^* (1000 hooks)	12,956	11,169	14,465	13,585	11,907	14,957
Y^* (tonnes)	3,236	2,732	3,689	3,266	2,747	3,713
Potential Rent (US\$ million)	9.5	5.5	15.3	9.2	5.0	14.1

Harvests for 2007 and 2008 were around 3,600 and 3,900 tonnes, respectively, which are at the edge of (2007) and outside (2008) the upper 95% confidence interval (CI) for the optimal harvest calculated in the bioeconomic analysis (Table 4-5). When higher discount rates are used, higher levels of Y^* are predicted. The current effort level of 15.2 million hooks (total annual effort of 10 participating vessels in 2007 fishing season) is also greater than the median optimal steady-state effort levels with any of the discount rates considered, and closed to the upper 95% CI of 14.9 million hooks under the 4% discount rate scenario. This suggests that, under the current price and cost structure, the sum of net present value of profits from the fishery can be maximised by reducing the current fishing effort. A continuation of the current effort at 2007 level is predicted to decrease the stock biomass below the steady-state optimal biomass X^* , so while a reduction in effort will decrease the short-term harvest levels this lower effort should maintain stock biomass at X^* level. The potential discounted annual profit at the steady-state is estimated at US\$9.2 to 10.0 million per year.

The optimal effort levels estimated across all discount rates fall well within the historical levels of effort (Agnew 2004). Since such historical changes have been accommodated with no apparent loss of profitability, it is reasonable to assume that the suggested ranges of effort reduction can be implemented in practice without major adjustment costs.

4.3.3 Current vs. immediate effort reduction

The performance of CCAMLR MP was compared to an alternative MP where the effort is reduced immediately to the median optimal steady-state level at 1-4% discount rates. Under the CCAMLR MP, the biomass of toothfish is projected to decline to around 56,400 tonnes at the end of the 35 year projection period.

The annual harvest gradually declines to around 3,200 tonnes while the effort increases gradually (Figure 4-5), indicating a decline in CPUE. In the last few years of the projection period, both effort and harvest are reduced sharply because the probability of the population being below the limit reference point becomes greater as the biomass level approaches to 50% of K . On the contrary, the harvest under the immediate effort reduction MP, except for the 4% discount rate scenario, gradually increases while maintaining the constant effort levels of 12-13 million hooks per year, suggesting an increase in CPUE. The biomass levels under the effort reduction scenarios gradually increase (in the case of 4% discount rate, biomass level is maintained around initial level) and stabilise at X^* – the steady-state equilibrium biomass.

Gross annual profits (no discount) for the immediate effort reduction MP are initially lower than those observed with the CCAMLR MP, but they eventually exceed the gross annual profits of CCAMLR MP at around 14-17 years into the future (Figure 4-5). In terms of the sum of the net present value (NPV) of annual profits at a 2% discount rate over the 35 years projection period, the CCAMLR MP actually yields more total net profits (\$245.9 million) than the immediate effort reduction MP (\$229.2 million). This is driven by the size of the initial effort reduction and the low growth rate of the stock: the economic losses associated with the initial rapid reduction in harvest outweigh the future economic gains from stock growth within the 35 year projection period.

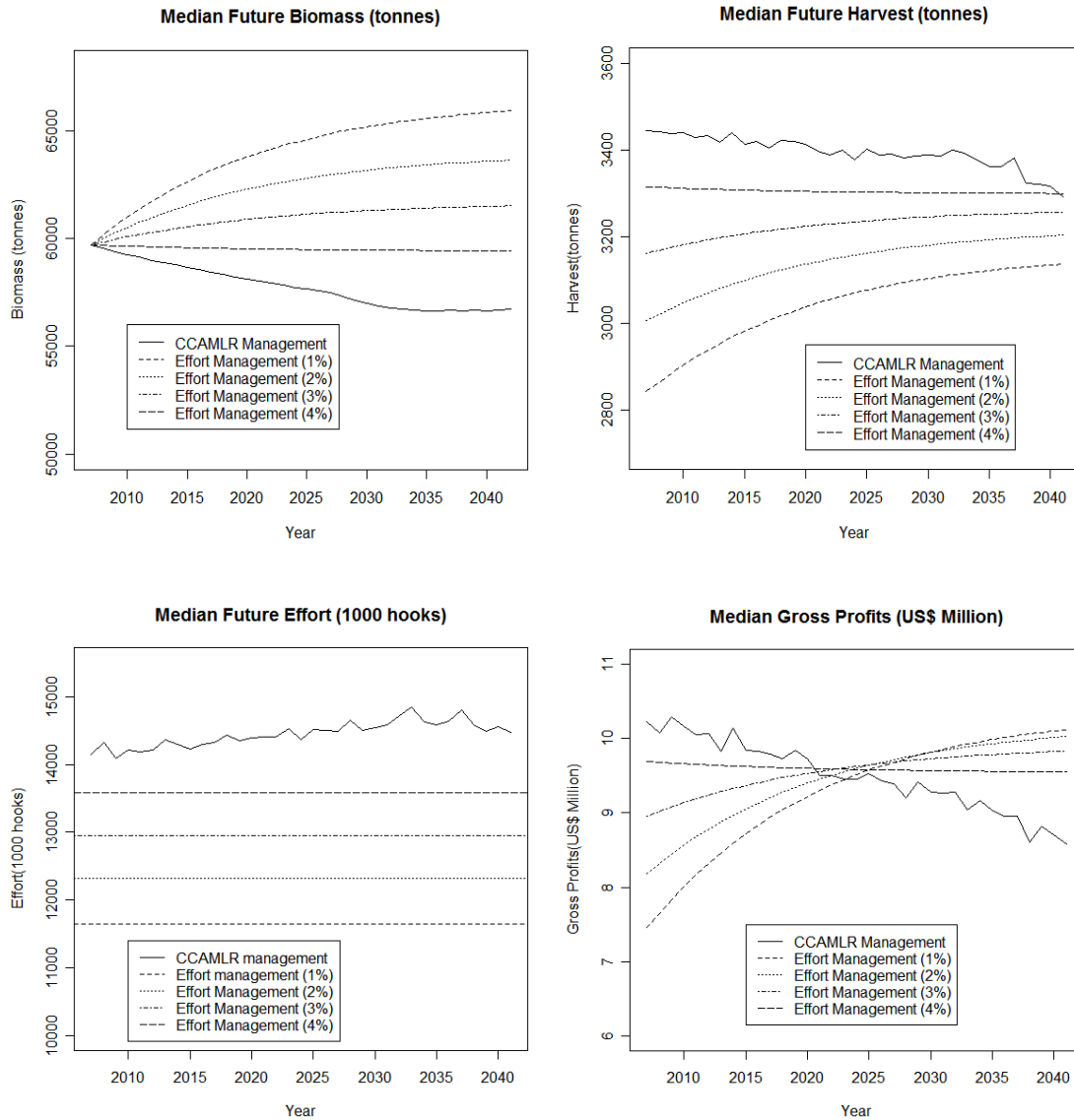


Figure 4-5: Thirty five year projection of median future toothfish biomass, harvest, and gross profits (no discount) under the CCAMLR management procedure and the reduced-effort management procedure.

The effort reduction MP will eventually generate higher discounted annual profits (Figure 4-6) but a longer time than 35 years is required to compensate for the initial economic losses. Clark (1976) established the existence of an optimal path from the current to the optimal effort level. In my case the optimal path is clearly not an immediate reduction in effort to the optimal steady-state level. It is, however, difficult to convince stakeholders to cut down the harvest/effort if a long time is required to appreciate the future economic

gains. To avoid/minimise such initial losses, gradual effort reduction schedules are investigated (results are presented in 4.4.4) and the result of performance of such MPs is given in section 4.4.5.

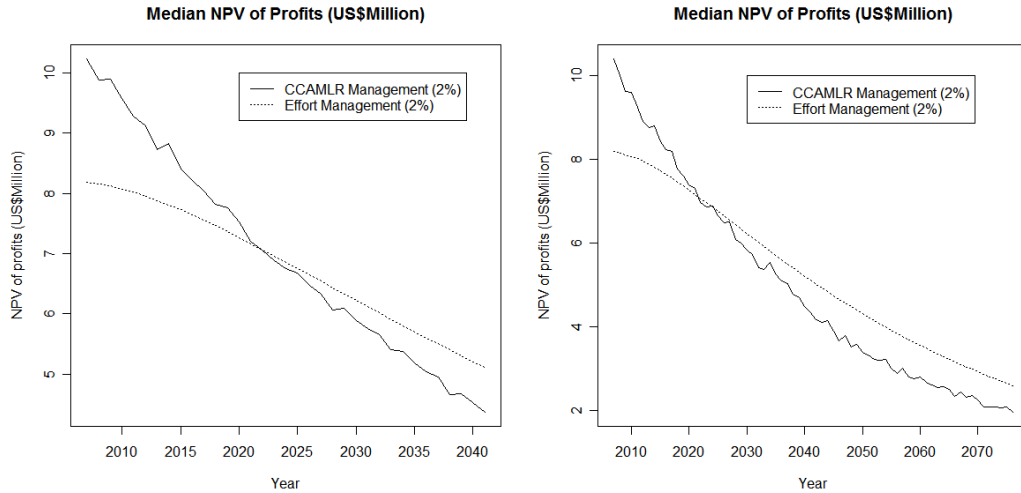


Figure 4-6: Median net present value (NPV) of profits at 2% discount rate under the CCAMLR management regime and the reduced-effort management regime. 35 year projection (left) and 70 year projection (right).

4.3.4 Gradual effort reduction scheme

It was found that the most economical effort reduction path at which one reaches steady-state equilibrium effort, E^* is 35 years from the present for the linear effort reduction model—the maximum year permitted. For the non-linear effort reduction scheme the decay rate of 0.075 was considered most economical. The year at which an effort reduction regime will generate a sum of discounted annual profits as high as those obtained under the current management is projected at 5.66 year for the linear model, and reduction rate of 0.538 is required under the non-linear model. The possible reduction schedules are given in Figure 4-7.

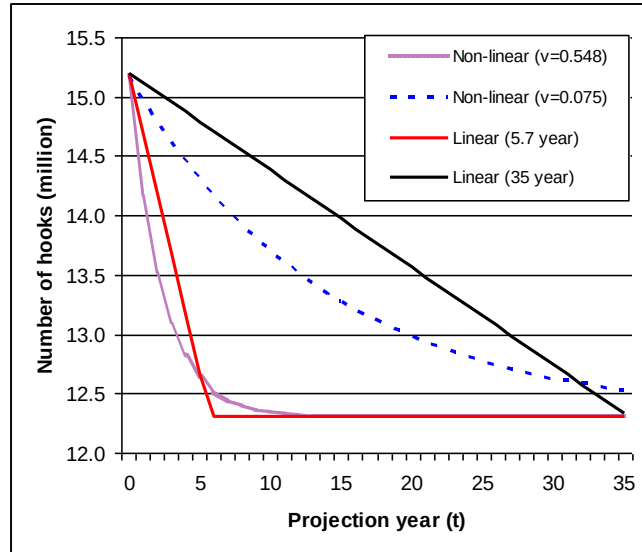


Figure 4-7: Possible effort reduction paths. v = reduction rate

4.3.5 Performance of all MPs

The performance of the current and alternative MPs is summarised in Table 4-6. For all reduced effort-based MPs the biological performance in terms of one of the CCAMLR stock biomass objectives was significantly better than the CCAMLR MP (Table 4-6). More specifically, the probability that after 35 years, the stock size is greater than 50% of the initial stock size was between 0.96 and 0.997 under the reduced effort-based MP, while it was 0.5 under the CCAMLR MP. The probability of stock biomass dropping below 20% of K at any time over the 35 years of the future projection was maintained at 0 under all scenarios, thus meeting the CCAMLR objectives in all cases.

With respect to the sum of discounted annual profits over 35 years, except for the immediate effort reduction MP, both linear and non-linear gradual effort reduction MPs yield higher total discounted profits (up to an additional \$35 million) than the CCAMLR MP. This indicates that as long as the effort reduction takes place gradually, the economic losses from the initial reduced harvest can likely be avoided. When comparing the two gradual effort reduction MPs, over the 35 years time-horizon, the linear scheme performed better in terms of economic performance but gave a marginally higher risk of depleting the stock below target levels than the non-linear reduction scheme. This is not

surprising as the non-linear scheme by definition requires an initially stronger decrease in effort than the linear scheme. This larger decrease in harvest combined with discounting means that the stock biomass and catch rates are not increasing fast enough to counteract the reduction in revenue due to lower harvests and discounting. This is also the reason why the immediate effort reduction MP performs poorer in terms of the sum of discounted annual profits than the current CCAMLR management over the 35 year management period.

Table 4-6: Performance of current and alternative management procedures. $p(X_{2042} > K/2)$ is the probability that the median final stock size is greater than 50% of the initial stock size (K), $p(X_t < K/5)$ is the probability of stock size dropping below 20% of K during projection period

Management	Effort Reduction Path	Sum of NPV profits at 2% discount rate in 35 years (\$ millions)	$p(X_{2042} > K/2)$	$p(X_t < K/5)$	Final year CPUE (t/000 hooks)
CCAMLR	NA	245.9	50.0 %	0 %	0.22
	Immediate	229.2	99.7 %	0 %	0.26
	Linear (5.66yrs)	245.9	99.7 %	0 %	0.26
Effort	Linear (35 yrs)	282.3	96.5 %	0 %	0.25
Control	Nonlinear($v=0.538$)	245.9	99.7 %	0 %	0.25
	Nonlinear($v=0.075$)	272.4	98.0 %	0 %	0.24

In terms of the CPUE (tonnes/1000 hooks) after 35 years, slightly improved CPUE levels (0.24-0.26) are predicted for the effort reduction management regime compared to the CCAMLR MP. The CPUE under CCAMLR MP after 35 years is about 10% less than the observed CPUE of 0.24-0.25 tonnes/1000 hooks in 2008. This demonstrates that the continuation of the current CCAMLR harvesting policy would result in the reduction of future CPUE, while a reduced effort policy would at least maintain the current level of CPUE. Even higher CPUE is possible with rapid effort reduction. The median estimates of future biomass and CPUE over time for all six scenarios are given in Figure 4-8.

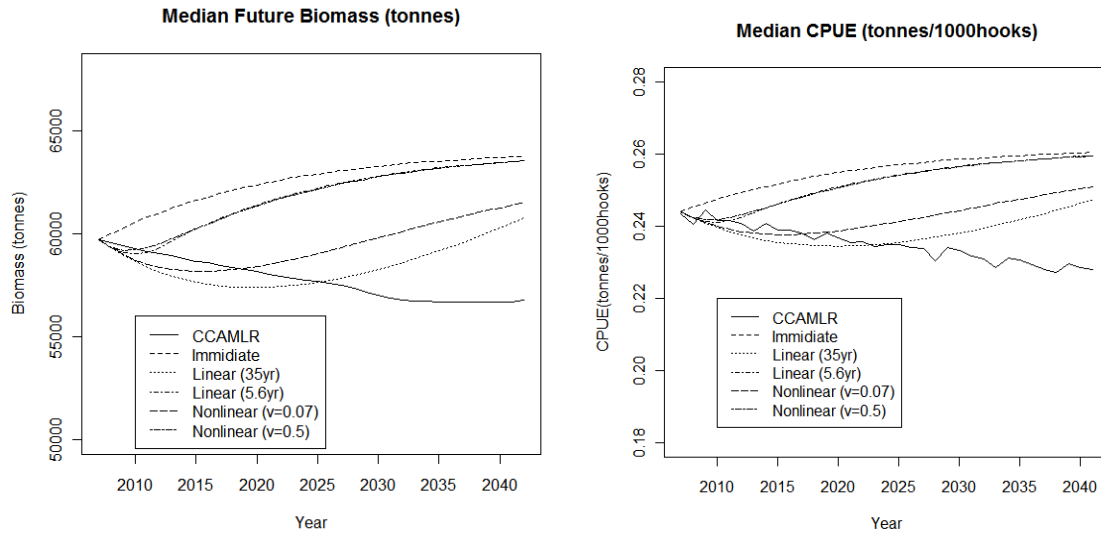


Figure 4-8: Predicted median biomass, and CPUE over 35 years period. v =reduction rate

For the purpose of evaluating the long-term performance of the current CCAMLR management procedure, a 70 year projection (2-generation time) was also carried out. The projection (Figure 4-9) suggests that, if the current harvesting control rules are maintained, there is a substantial probability that the stock will decline further, so jeopardizing the management objectives, even though the median trajectory indicates that a reasonable rate of recovery would be expected. The confidence interval initially becomes narrower as the biomass approaches to 50% of K . This is because the harvest and biomass are approaching to the equilibrium levels at which the uncertainty in a surplus production model is presumably the smallest, because the uncertainty in biomass estimates comes from r and K in Eq.(4-1). However, the confidence interval becomes progressively wider and negatively skewed after this point. This is likely due to a combination effect of 1) biomass becoming far away from the equilibrium level, and 2) a significant proportion of biomass estimates going below 20% resulting in the reduction of TAC levels as dictated by the second condition of CCAMLR harvest control rule, and consequently the median biomass level increases. However, some trajectories of the biomass level drop so low that the reduction of TAC does not help the stock to recover, hence a negative skew is projected.

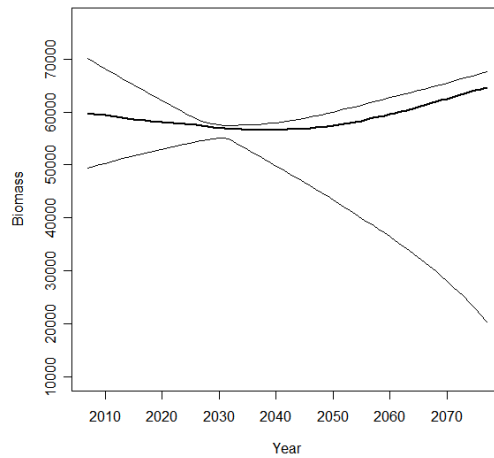


Figure 4-9: Probabilistic projections of spawning stock biomass for Patagonian toothfish in South Georgia: 5th percentile, median, and 95th percentile of the distribution, assuming the current CCAMLR management procedure continues for 70 years.

4.4 Discussion

In this chapter, economically optimal harvesting strategies were identified for the fishery for Patagonian toothfish around the island of South Georgia and the performance of effort-based management procedures with bioeconomic consideration were compared with the current management procedure.

The complex age-structured population estimates coming from the stock assessment, along with the key life-history characteristics, were translated into a simpler biomass-dynamic surplus production model while accounting for the uncertainty in the population and production function parameters. It was found that while the stock biomass in 2007 was close to the steady-state optimum, both effort and catch were higher than the steady-state optimum levels. For instance, current effort (2007) is actually close to being outside of the optimal effort's confidence interval even at a 4% discount rate, and levels of catch are currently between 250-400 tonnes above the steady-state optimum. The target stock biomass set by CCAMLR is around 54,000 tonnes (50% of K), and it is expected that levels of effort and catch at their current levels will further decrease the current stock

biomass towards this target level. However, the simulation results demonstrate that bringing the stock below the economically optimal level would decrease the profitability of the fishery as higher effort is required to take similar levels of catch. Thus, to maintain the long-term economic sustainability of the fishery would require a gradual reduction in harvest of around 12-20% (400-600 tonnes), and this would imply maintenance of the current biomass level rather than a continued decline in this level to the CCAMLR target of around 54,000 tonnes.

While most empirical examples of bioeconomic models in fisheries account for some levels of measurement errors in the key parameters, few studies has incorporated variance/covariance of each key parameters simultaneously. This analysis consistently accounts for the uncertainty in stock biomass, harvesting and in the economic parameters themselves. The clear advantage in such an approach is that it permits us not only to assess whether current exploitation levels are significantly higher or lower with respect to the economic optimum, but also allow us to assess the robustness of the conclusions.

Application of the MSE approach for the CCAMLR management procedure was previously not possible because of the complexity of the model used for stock assessment and management of toothfish by CCAMLR. Translating this complex model into a simple biomass dynamic model allowed for the simulation of the future outcomes of the current and alternative management procedures. The simulation results presented here provide an economic justification for a gradual reduction of current effort, and also demonstrate the benefits of using multiple objectives.

In a wider context, the results in this chapter add weight to what has become an almost accepted principle: the biomass that produces the largest discounted economic profits from fishing (X_{MEY}) is greater than the biomass that maximise the sustainable yield (X_{MSY}), as repeatedly demonstrated in the fishery literature (Clark 1990; Grafton et al. 2007; Maravelias et al. 2010). This increasing wealth of evidence implies more economics-based approach will perform better, in terms of both economics and conservation, than MSY.

Chapter 5. Simulating the behaviour of bioeconomic systems under multiple uncertainties: biological components

Abstract

This chapter investigates the implications of neglecting key life history uncertainties and the biological components of structural uncertainties in the estimation of bioeconomic target reference points (TRPs) and their resultant policy performance, using the three case study fisheries presented in the previous chapters. I constructed a set of age-structured bioeconomic estimation models involving alternative hypotheses about both parameter values and the structural form of the population dynamics. The study found that the relative importance of different types of uncertainty for equilibrium conditions differs among fisheries targeting species with different life-history traits; the estimates were sensitive to the stock-recruitment variability *only* for the species/scenarios with low steepness values (short-lived, fast-growing species), while the specification of the underlying population models had much stronger impacts on the estimates of equilibrium conditions for the long-lived Patagonian toothfish. The study also found that a fixed effort strategy, based on a target effort level from an age-structured bioeconomic estimation model which incorporated the complex population dynamics actually used for the assessment of Patagonian toothfish, failed to meet the conservation objective for the stock when the uncertainty in steepness was not accounted for, while the fixed effort strategy, based on a target effort level from the simpler Schaefer bioeconomic estimation model, performed much better in meeting the conservation objective, although the latter resulted in much lower total discounted profits over 35 years management time-frame. The assumptions made about stock structure also had significant impacts on the economic outcomes. The results demonstrated a clear potential trade off between economic returns and conservation goals.

5.1 Introduction

There is a growing recognition of the uncertainties and risks in fisheries management, triggered by some failures in the management of well-studied stocks in the end of the 20th century (see Chapter 2). Since then considerable progress has been made and estimates of uncertainty have become an integral component of the scientific advice given to decision makers. While observation and process errors have been studied fairly extensively in the fisheries literature in relation to parameter estimation and stock assessment (Kirkwood and Smith 1996), structural uncertainty is rarely explicitly studied, with limited exceptions (Kirkwood and Smith 1996; Kuikka et al. 1999; Patterson 1999; Hammond and O'Brien 2001; McAllister and Kirchner 2002; Michielsens and McAllister 2004). McAllister and Kirchner (2002) list five common structural uncertainties in stock assessment: the form of the stock-recruitment relationship; assumptions about catchability; stock structure; selectivity; and model error structure. Charles (1998) provides a broader set of examples of structural uncertainties in fisheries models. They are: the fundamental quantities such as the number of species interacting in the fishery system, or the number of fishing vessels that will take part in a new fishery; spatial complexity (e.g. stock concentrations, migration patterns); species interactions; fish-environmental interactions; technical changes; management objectives; fishers' objectives; fisher's response to regulations; and institutional arrangements.

Ludwig and Walters (1985) compared the optimal fishing effort derived from a surplus production model with Ricker stock-recruitment relationship to one from Deriso's age-structured model, and concluded that the simpler production model generally gives as good or better estimates for the optimal effort. More recently, the issue of structural uncertainty in bioeconomic modelling was addressed by Moxnes (2005) who used empirical and simulated data for the estimation of the surplus production model and compared the resulting optimal solution and economic output with those of an age-structured model, using the example of the Northeast Arctic cod fishery in the Barents Sea. He concluded that a simple aggregated model and a more complex cohort model yield quite similar policy recommendations. However, this conclusion was challenged by

Tahvonen (2008), who argued that the optimal harvest was restricted to being specified as a function of aggregate biomass in Moxnes' age-structured model, and this suboptimal specification may have removed some essential differences between the two approaches. Using an approach which does not rely on any suboptimal solutions for the age-structured model, he concluded that the deviations between the biomass and age-structured approaches are most significant in the presence of multiple steady states. He also noted that there is insufficient analysis of the role of the population age-structure information in economic optimisation studies (Tahvonen 2008).

Structural uncertainty is the hardest uncertainty to account for in a fishery model, because there is generally little information to formulate and distinguish between competing underlying assumptions (Caddy and Mahon 1995; FAO 2001). Consequently, few studies have developed formal probabilistic methods to account for structural uncertainties (Punt and Hilborn 1997; McAllister and Kirchner 2002). The use of quantitative decision analysis has been advocated by several authors as a way to incorporate wider ranges of uncertainties explicitly into fisheries management (Hilborn and Peterman 1995; Punt and Hilborn 1997; Patterson 1999; McAllister and Kirchner 2002). Decision analysis is a structured, formalised method that enables analysts to rank proposed actions by quantitatively taking into account the effects of probabilities of uncertain events and the desirability of the potential outcomes (Hilborn and Peterman 1995), and was originally developed in the business world for investment decisions (Raiffa 1968). A benefit of decision analysis is that it can include various structural forms of models as alternative hypotheses (Peterman 2004). However, one must not only choose which alternative models are legitimate and necessary for inclusion, but also assign a probability to each model, and such choices may influence the rank order of actions, which in turn leads to considerably different predictions (Peterman 2004).

Another approach that has been increasingly used for the assessment of multiple uncertainties in fisheries management is the comprehensive simulation of sources of uncertainties using the "management strategy evaluation (MSE)" (see Chapter 2). One of the earliest and most influential applications of this approach was by the Scientific

Committee of the International Whaling Commission (Kirkwood and Smith 1996; Cooke 1999), where robustness of the management strategy for baleen whales was examined relative to a much wider range of uncertainties than is normally considered, including incorrect assumptions about the true dynamics of the stock (Kirkwood and Smith 1996).

Although the MSE approach can be used for assessing the impacts of structural uncertainties in bioeconomic modelling, to the best of my knowledge it has not, to date, been applied for such a purpose. In fact, few studies have applied the MSE approach to investigating the economic aspects of fisheries management. One notable exception is Sainsbury (1991), who investigated the performance in terms of economic returns of management regimes for tropical multispecies fisheries in North-Western Australia under different assumptions about the structure of multi-species communities. More recently, Dichmont et al. (2006a, b, c) investigated factors affecting the performance of management procedures for the Australian northern prawn fishery, by taking into account how assumptions regarding spatial structure and stock assessment models (simple catch-rate regression, biomass dynamic and delay-difference models) impact performance in terms of both conservation and economic criteria, although they did not carry out economic optimisation. Dichmont et al. (2008) extended their analysis to include an economically-based objective (MEY) and compared the performance of MEY-based management to that of MSY-based management for the Northern prawn fishery, taking into account the uncertainties associated with the values of the biological parameters and the catchability coefficient used to convert from fishing effort to fishing mortality, but structural uncertainty was not explicitly included in the calculation of MEY in their analysis. There is much scope to expand the application of the MSE to investigate the relative importance of a wide range of uncertainties for the robustness of the economically-based advice derived from bioeconomic fishery models, including structural uncertainty.

5.1.1 Objectives

The inferences of most bioeconomic fisheries models are sensitive to subjective assumptions, and one can generally be more confident in results that are robust to alternative plausible assumptions. Recognising this, I used the case study fisheries presented in Chapters 3 and 4 as an opportunity for exploring and comparing the implications of multiple uncertainties with respect to the reliability of the estimates from bioeconomic fisheries models and for their utility in providing robust economically-based management advice (in the form of bioeconomic target reference points), with a primary emphasis on the role of life history and on structural uncertainties reflecting a lack of knowledge about the nature of the fishery system.

This chapter aims to answer to the following broad questions:

- What is the relative importance of different types of uncertainties for the reliability of bioeconomic models for the case study species? Is a certain type of uncertainty more important than others in terms of providing robust bioeconomic target reference points (TRPs)?
- Does the relative importance of uncertainties differ between a fishery targeting short-lived species and one targeting long-lived species?
- Does a fixed effort strategy based on a steady-state effort (E^*) estimated from a simple (biomass dynamic) bioeconomic estimation model as a target perform better than one based on E^* from a more complex age-structured bioeconomic estimation model in the face of multiple uncertainties, even assuming that the age-structured model is the correct form?

To meet these objectives, this and the next chapter develop a set of bioeconomic estimation models that include the key uncertainties and alternative scenarios of model structure. This chapter focuses on biological components of key uncertainties. As

described in Chapter 2, the underlying population model forms in an OM can be different from those in an estimation model, which provides estimates of target reference points (TRPs; such as MEY or MSY). In this chapter, estimation models with varying complexity in population model forms are developed, while age-structured OMs are used to simulate future stock sizes, catches, and discounted profits, and to calculate performance statistics. The aim is not to find a management procedure that is robust to structural uncertainties (as my models do not include assessment procedures), but rather to focus on exploring the implications of having imperfect information about the underlying structures of the population dynamics and life history parameters in estimating bioeconomic TRPs, and the resultant performance of simple effort-based strategies.

Section 5.2 introduces the types of uncertainties to be included in the bioeconomic estimation models. Section 5.3 gives details on how to construct a generic age-structured bioeconomic operating model, defining alternative model scenarios, and methods of performance testing. The results and discussion are in sections 5.4 and 5.5.

5.2 Range of uncertainties considered

The range of uncertainties and underlying assumptions of the models for each case study are discussed below. In practice, however, it is not easy to categorize the types of uncertainties because many of these error types are interdependent, and the total uncertainty cannot always be decomposed into its constituent types (Kell et al. 2007).

While it is not possible to test all plausible sources of uncertainties, I selected the key assumptions about the structural forms of the models developed in Chapter 3 and Chapter 4. Because the impacts of uncertainty can vary between species with different life histories, of particular interest is the investigation of the interaction between life history parameters and other sources of uncertainty. For instance, environmental fluctuations may not be a big issue for a long-lived species, while it would be a considerable issue for

a short-lived species. Similarly, the misspecification of population dynamics might not be a serious issue for a short-lived species, while it could be potentially large for a long-lived species.

5.2.1 Parametric uncertainties and process errors

The key life history parameters in fisheries models are: the stock-recruitment (S - R) relationship; the size of the virgin stock biomass and recruitment (B_0 , R_0); natural mortality (M); and maturity & growth relationships. Because these parameters are correlated with one another, it was decided to focus on the uncertainties associated with the S - R relationship. Two major sources of uncertainties associated with the S - R relationship are: the value of the steepness parameter (z); and the standard deviation of the stock-recruitment relationship due to random fluctuations (σ_R). Uncertainties associated with M and the size of B_0 or R_0 are indirectly accounted for in the steepness parameter to some degree.

Growth parameters can also influence estimates of gear selectivity (Ricker 1969; Lucena and O'Brien 2001), because the gear selectivity curve (e.g. selectivity at age) is generally derived from an assumed growth and maturity curve, and vice versa. Knowledge of the size selectivity of commercial gears is crucial to the management of fish populations because it allows the identification of the sizes of a target species that are most susceptible to the fishing gear (Millar 1992). An imprecise gear selectivity estimate in turn can lead to over or under-estimation of the harvest levels of the target species. This could have a significant impact on model results, particularly for fisheries targeting long-lived species with a large number of age-classes and caught by highly selective gears, such as the Patagonian toothfish longline fishery. Thus, gear selectivity parameters were also considered among key sources of uncertainty for the bioeconomic estimation models for the Patagonian toothfish fishery around South Georgia.

5.2.2 Structural uncertainties

5.2.2.1 Underlying population model

In Chapter 3, a simple biomass dynamic model was used to describe the population dynamics of Pacific saury. This model has been used for the annual assessment of the stock, as the data needed to determine the stock-recruitment relationship are not yet available. If the true system is age-structured, and the conclusions from a simplified bioeconomic estimation model are biased because the model does not reflect the true population dynamics, what are the implications?

Similarly, a simple biomass dynamic model was used for the South Georgia toothfish fishery in Chapter 4 to estimate an economically optimal harvest level and associated effort, as well as in predicting the outcomes of the current versus an effort-based management procedure. This raises the question as to whether the optimal conditions from a simple model and a more complex model are similar. I investigate the conditions under which conclusions from a simple biomass dynamic model closely approximate the optimal conditions estimated from a complex age-structured model. My speculation is that the characteristics of the toothfish life history (long-lived, slow to mature), its relatively low level of annual mature biomass variability, as well as the gear selectivity play important roles in determining the optimal levels of effort and associated harvest. The factors I explore are therefore:

- (1) Life history of the target species;
- (2) Gear selectivity;
- (3) The interaction of (1) & (2); and
- (4) Stock-recruit variability.

While the factors (1) and (2) are quite intuitive, the investigation of the interaction between the life history traits and gear selectivity is unique in that its bioeconomic implications have rarely been discussed in the literature. In the case of the South Georgia toothfish fishery, the age at 50% maturity and the age at 50% selectivity are very similar, both around age 12 (Figure 5-1). My speculation is that when a fishery is 1) targeting long-lived species; and 2) the gear selectivity coincides with the size at maturity, a simple biomass dynamic model closely approximates the optimal conditions estimated with an

age-structured model. This hypothesis is tested in a simulation framework. Subsequently, constant effort management procedures are developed, based on the results from both age-structured and biomass dynamic bioeconomic estimation models, and the performance of the fixed effort strategy based on different estimation models is evaluated through simulation. This allows us to identify which model is superior in producing fixed-effort based management advice that meets both conservation and economic objectives.

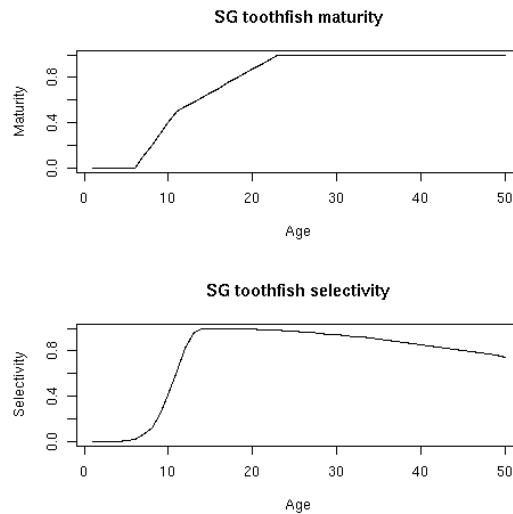


Figure 5-1: Maturity at age, and gear selectivity of the South Georgia toothfish fishery

5.2.2.2 Uncertainties in stock structure

The form of the stock-recruitment relationship is poorly understood for the winter stock of Japanese common squid, and therefore the two sub-stocks were treated as a single population in a bioeconomic model in Chapter 3. What is the implication of treating multiple stocks as a single stock in bioeconomic modelling? Would the fixed effort strategy using a multi-stock estimation model perform better than the single-stock model developed in Chapter 3, as it would better capture the true underlying stock structure?

While intuition tells us that detailed models should be better than simple ones because they more accurately represent “reality”, research has shown that simple models can often perform better (Ludwig and Walters 1985; Kirkwood and Smith 1996; Punt and Smith 1999; Parma 2002) because they require fewer parameters to be estimated, and

frequently the uncertainty surrounding the estimation of some of these parameters only reduces the ability of the models to produce useful information (Ludwig and Walters 1985; Bonfil 2005; Butterworth et al. 2010). Dichmont (2006) tested whether the input-control management procedure for the Northern prawn fishery using a multi-stock assessment model performs better than the single-stock model, and found little evidence for improved performance in terms of leaving the spawning stock size close to B_{MSY} . In her study, the input-control management procedures were based on E_{MSY} derived from three alternative stock assessment methods. Interestingly, she found that the management procedures based on the Deriso delay-difference method, used for the current assessments of the resources, performed better than an alternative stock assessment method based on a biomass dynamic model in terms of maintaining the spawning biomass below the target level. This suggests that a simpler model does not always perform better as a management tool. The impacts of structural uncertainties should be tested more rigorously than is currently the norm in relation to the characteristics of the fish and fisheries.

In this chapter a bioeconomic estimation model with multi-stock structure (as opposed to the single stock model developed in Chapter 3) is constructed for the Japanese common squid angling fishery to obtain the estimates of equilibrium effort (E^*). Then the performance of a constant effort strategy based on mean E^* from the multi-stock estimation model is compared to the performance of a constant effort strategy based on mean E^* from the single-stock estimation model developed in Chapter 3.

Other sources of uncertainties that may have potential impacts are the form of variation (e.g. auto-correlated vs. random variability), spatial complexity and species interactions, but such an evaluation is beyond the scope of the present study. The uncertainties considered in Chapter 5 are summarised in Table 5-1.

Table 5-1: List of uncertainties assessed for each of the case studies

Case studies	Life history	Uncertainties and types of errors (in brackets)				
		Random fluctuation	Steepness	Gear selectivity	Population model	Stock structure
		(process)	(estimate)	(estimate /model)	(model)	(model)
Pacific saury	Short-lived	✓	✓		✓	
Common squid	Short-lived	✓	✓			✓
Patagonian toothfish	Long-lived	✓	✓	✓	✓	

5.3 Methods

The Methods section consists of the following steps:

1. Constructing a generic age-structured bioeconomic operating model (OM), capable of specifying the population dynamics for different species with contrasting life histories, and different economic characteristics;
2. Adapting the generic OM to include the relevant factors for each case study;
3. Defining a set of model scenarios in the estimation models which includes alternative plausible parameter values and model structures for each stock.
4. Re-estimating the bioeconomic TRPs in the form of equilibrium effort E^* and harvest Y^* , using the estimation models with varying complexity. Based on these estimates the management actions (target input/output) are set at a fixed (constant) level.
5. Based on the results from step 4, selecting the scenarios in which the estimates of mean E^* were very different from the baseline, due to the different assumptions made about underlying model structure.
6. Carrying out performance evaluations for the selected fixed input/output strategies, assuming the more complex estimation model is the correct one.

A core set of estimation model specifications is listed below, although I define the model

scenarios in more detail in later sections.

Table 5-2: A core set of model scenarios in the estimation models. Base indicates the base model specification in the previous chapters; “Alternative” indicates alternative specifications in this Chapter.

Species		Population model	Number of stocks
Patagonian toothfish	Baseline	Schaefer	single stock
	Alternative	Beverton-Holt	single stock
Pacific saury	Baseline	Schaefer	single stock
	Alternative	Beverton-Holt	single stock
Japanese common squid	Baseline	Beverton-Holt	single stock
	Alternative	Beverton-Holt	multiple stock

5.3.1 Developing the age-structured population models

The population model in the OM for all three fisheries is age-structured (type 1 and 2 OMs, according to the classification in Kell et al., 2007. See 2.3.4). It is similar to the population model used in the OM developed in Chapter 3 to evaluate the performance of adaptive management procedures for the two Japanese fisheries, where the biological component includes up to 2 age classes, 4 seasons, and Beverton-Holt stock-recruitment relationship. The major differences in the biological model are: 1) seasonality was removed, as it was not my main interest; 2) the model enables one to specify multiple age-classes to be able to accommodate the population dynamics of both long and short-lived species, and 3) gear selectivity parameters were included. This operating model described below is generic and can easily be adapted to include the relevant factors for the three case study species.

5.3.1.1 Population model

From age 2 to one year prior to reaching the maximum age class A ($A-1$), the number of animals can be written as:

$$N_{t,j} = N_{t-1,j-1} \left(1 - \psi_{t-1,j-1}\right) e^{-M_{t-1,j-1}} \quad (5-1)$$

where $\psi_{t,j}$ is the exploitation rate at time t , age j , $M_{t,j}$ is the natural mortality at time t , age j . For age $j=A$, the number of animals is:

$$N_{t,j} = N_{t-1,j-1} \left(1 - \psi_{t-1,j-1}\right) e^{-M_{t-1,j-1}} + N_{t-1,j} \left(1 - \psi_{t-1,j}\right) e^{-M_{t-1,j}} \quad (5-2)$$

5.3.1.2 Stock-recruitment relationship

The number of recruits can be expressed as the following Beverton-Holt stock-recruitment relationship:

$$N_{t,1} = \frac{aSSB_{t-1}}{1 + bSSB_{t-1}} e^{\varepsilon_R} \quad (5-3)$$

where a and b are Beverton-Holt stock-recruitment parameters, SSB is the spawning stock biomass, and ε_R is the normally distributed error term with mean zero and standard deviation σ_R . SSB at year y can be expressed as:

$$SSB_t = \sum_{j=1}^A N_{t,j} m_j w_j \quad (5-4)$$

where m_j is the maturity at age j , w_j is the weight at age j .

5.3.1.3 Exploitation rate

The exploitation rate, $\psi_{t,j}$ can be defined as:

$$\psi_{t,j} = \kappa_{t,j} \times qE_t \quad (5-5)$$

where $\kappa_{t,j}$ is the gear selectivity function, q is the catchability coefficient, and E_t is the fishing effort at year y . The catch biomass at year y is expressed as:

$$Y_t = \sum_{j=1}^A N_{t,j} w_j \psi_{t,l} \quad (5-6)$$

This can be also written as:

$$Y_t = q E_t X_t \quad (5-7)$$

where X_t is the exploitable biomass at time t , the portion of a stock's biomass that is available to the fishing gear. This can be also expressed as:

$$X_t = \sum_{j=1}^A N_{t,j} w_j \kappa_{t,j} \quad (5-8)$$

5.3.1.4 Patagonian toothfish

The population dynamics of the Patagonian toothfish *D. eleginoides* around the island of South Georgia (CCAMLR Subarea 48.3) was based on Hillary et al. (2006). They used a CASAL population model, which is a combined sex, single-area, and three season model with an age-structured, Beverton-Holt stock-recruitment relationship. Seasonality was removed from this model. The biological parameter values and gear selectivity parameter values were taken from the report from the CCAMLR stock assessment (SC-CAMLR 2007). In calculating the selectivity at age, I repeated the procedure described in SC-CAMLR 2007, which was expressed as a double-normal curve with the following form:

$$s(j) = 2^{-\frac{(j-s_{\max})^2}{sl}} \quad \text{if } j < s_{\max}$$

$$s(j) = 2^{-\frac{(j-s_{\max})^2}{sr}} \quad \text{if } j \geq s_{\max} \quad (5-9)$$

where $s(l)$ is the selectivity at age j , s_{max} is the age at maximum selection, sl is the left-hand decay term, sr is the right-hand decay term. The biological parameter values and gear selectivity parameter values are given in Table 4-2 in Chapter 4, and Table 5-3.

Table 5-3: Gear selectivity parameters

Component	Parameter	Value
Age at maximum selection	s_{max}	13.7335
Left-hand decay term	sl	3.31394
Right-hand decay term	sr	56.007

Re-estimation of production function parameter for Patagonian toothfish

In Chapter 4, generation of the production function parameters for the South Georgia Patagonian toothfish fishery was based on the biomass estimates from the Schaefer model, originally translated from an age-structured CASAL model. Because the “stock biomass” can differ from the “exploitable biomass” in an age-structured model, the production function parameters were re-estimated using the reported effort (number of hooks), legal catch (tonnes) and the “exploitable biomass” estimated from the age-structured population model described in equations (5-1)-(5-2) during the period 1997-2007. The estimation method was the same as in Chapter 4.

5.3.1.5 Pacific saury

The information on life history parameters (M , K and r , weight-at-age, and maturity at age) was obtained from Ueno et al. (2006). Although the parameters values for carrying capacity (K) and intrinsic growth rate (r) were derived from an age-aggregated Schaefer model, it is possible to disaggregate them into age-specific parameters. To do so, I first estimated the spawner biomass per recruit ($SBPR$) given M , weight-at-age, and maturity-at-age as follows:

$$SBPR = \sum_{j=0}^A N_j w_j m_j \quad (5-10)$$

$$= \frac{SSB_0}{R_0} \quad (5-11)$$

where A is the maximum age, m_j is the maturity at age j , w_j is the weight at age j . SSB_0 is the virgin spawning biomass, and R_0 is the virgin recruitment. I then estimated the parameter a , one of the Beverton-Holt stock recruitment parameters, by solving the Euler-Lotka equation given in Chapter 3, equation (3-26). The steepness (z) was then estimated by solving the equations $a = 4z/(SBPR(1-z))$ and (5-11) simultaneously. The size of SSB_0 was assumed equal to the value for K . The resulting parameters are summarised in Table 5-4.

Table 5-4: Biological parameter values for *C. saira* around Japan

Component	Parameter	Value	Component	Parameter	Value
Virgin SSB (tonnes)	SSB_0 (K)	8.15 million	SR relationship steepness	Z	0.245
Maturity 50%		Age 0	Recruitment SD	σ_R	0.29
100%		Age 1	BH parameters	a	19517
Natural mortality	M	0.665		b	3.66e-08

5.3.1.6 Japanese common squid

The generic operating model was modified to account for multi-stock structure for *Todarodes pacificus*. Because the S - R relationship for the winter stock of this species is unknown, I “borrowed” the information on S - R parameters from the autumn stock to derive the indicative S - R parameters for the winter stock, using the method described in chapter 3, based on the assumptions that the two stocks have the same Beverton-Holt relationship and the same steepness values.

The standard deviation of the S - R relationship for the two stocks combined was expressed as:

$$\sigma_{Rtotal} = \sqrt{\sigma_{Rw}^2 + \sigma_{Ra}^2 + 2\rho\sigma_{Rw}\sigma_{Ra}} \quad (5-12)$$

Where σ_{Rw} and σ_{Ra} is the standard deviation of the S - R relationship for the winter stock and autumn stock, respectively. The correlation term, ρ , was included to account for the covariance between the two stocks in response to environmental variation, because if

multiple stocks share common environments, they should show similar responses to environmental variation. If $\rho = 0$ the stock-recruitment (S - R) variability between the two stocks is independent, while $\rho = 1$ indicates the S - R variability of one stock coincides with the S - R variability of the other stock. Numerous studies have documented positive covariance among stocks in particular variables, with the magnitude depending on the spatial distance between the stocks. Examples include Pacific herring (*Clupea pallasii*), Baltic salmon (*Salmo salar*) and numerous other marine, anadromous and freshwater species (Myers et al. 1997b; Peterman 2004).

Biological parameter values for *T. pacificus* are given in Table 5-5. For simplification, S - R variability for the winter stock (σ_{Rw}) was assumed to be the same as that of the autumn stock (σ_{Ra}), reported by Ueno et al.(2006). The total S - R variability for the two stocks combined (σ_{Rtotal}) depends on the correlation factor: 0.34 ($\rho=0$), 0.41 ($\rho=0.5$), and 0.46 ($\rho=0.9$). In general, the higher the correlation, the larger the combined standard deviation in equation 5-12 (DeGroot and Schervish 2002). Note that the S - R variability in Chapter 3 was set to 0.25-0.3, and correlation between two stocks was implicitly assumed to be 1, as the two stocks were treated as a single stock.

Table 5-5: Biological parameter values for *Todarodes pacificus* around Japan

Component	Parameter	Value	Component	Parameter	Value
Virgin SSB combined(tonnes)	SSB_0 (K)	3.8 million	SR relationship steepness	Z	0.516
Autumn stock	SSB_0A	2.1 million	BH parameters	a	7.76
Winter stock	SSB_0W	1.7 million	Autumn stock	b_A	0.079
Maturity 50%		Age 0	Winter stock	b_W	0.097
100%		Age 1	Natural mortality	M	0.6

Because the available data on harvest of common squid by the coastal angling fleet (10-30GT class) were aggregated, with no information on how much of each stock makes up the catches, it was not possible to estimate the production function parameters for each

stock separately. Based on the information that the winter-stock is mainly caught by coastal angling fleet (Mori and Nagasawa 2006), an assumption was made that between 50% and 90% of the 10-30GT fleet's effort is allocated to harvest the winter stock. Note that in Chapter 3, the effort allocation of the fleet between the two stocks was implicitly assumed fifty-fifty in the combined stock model. I selected effort allocation to the winter-stock to be 50%, 70%, and 90% in the multi-stock model in order to test the sensitivity of the results to different effort allocations. The allocations were assumed fixed over the projection period.

5.3.2 Estimation model scenarios

5.3.2.1 Patagonian toothfish fishery

Nine qualitatively different scenarios were considered with respect to model structure and the S - R parameters used to fit the model. Scenario A1 is the baseline scenario where I fitted an age-structured model of a single population with a Beverton-Holt stock-recruitment relationship, using the values of steepness (0.75) and standard deviation of SR relationship, σ_R (0.6), as reported in SC-CAMLR (2007). Scenarios A2-6 used the same population model, but considered a higher value of σ_R (0.9), as well as both lower and higher values of steepness (0.65 and 0.85), while maintaining other parameter values at the baseline scenario. The reported steepness parameters for *D. eleginoides* in similar locations range between 0.75 (CCAMLR Subarea 58.6-7) and 0.8 (Subarea 58.5.2) with values used for sensitivity analysis between 0.7 and 0.9. In Chapter 4, the uncertainty in the steepness parameter between 0.65 and 0.85 was included when translating the age-structured parameters into a Schaefer model. A value of steepness lower than 0.65 was considered unrealistic for this long-lived demersal fish and therefore the value 0.65 was used as a lower bound of the steepness for this species.

Scenarios A7-9 were designed to capture the impacts of gear selectivity parameters, and their interaction with the life history parameters of Patagonian toothfish. Scenario A7 used the baseline population model, but the value of one of the three gear selectivity

parameters - age at maximum selection (s_{max}) was assumed lower (age 10) than the baseline (age 13.7), while holding all the other parameters constant. A lower s_{max} indicates that the gear is able to catch younger fish, which results in changes in the composition of mature fish caught by the fishing gear (Figure 5-2). Scenario A8 assumes higher (age 16) s_{max} than the baseline. Scenario A9 is the special case where the gear selectivity curve is exactly the same as the maturity curve. In this case, the exploitable stock biomass coincides with the *SSB*—the same assumption as Schaefer model. This scenario was included to test whether a simple biomass dynamic model closely approximates the optimal strategies with an age-structured model when the gear selectivity coincides with maturity. Under this scenario, the age at maximum selection (s_{max}) is 23. Scenario SF is the Schaefer model used in Chapter 4, and is included for comparison. A summary of all scenarios considered for simulation is given in Table 5-6.

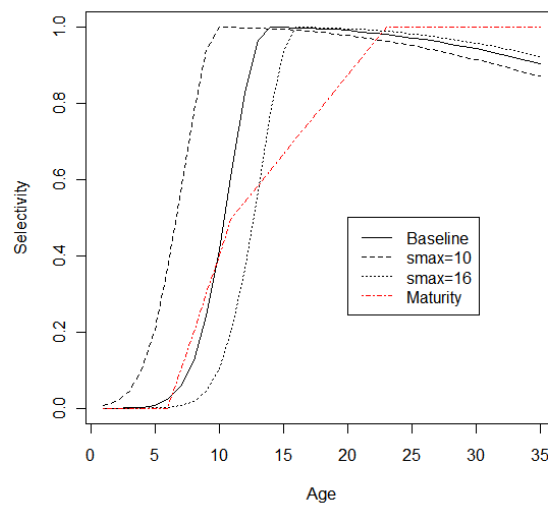


Figure 5-2: Interaction between gear selectivity and maturity

Table 5-6: A list of model scenarios for the South Georgian Patagonian toothfish fishery. SDR = standard deviation of the stock recruitment curve, z = Beverton-Holt steepness parameter, σ_R = standard deviation of SR relationship, s_{max} = age at maximum selection

Scenario	Description	Patagonian toothfish		
		σ_R	Steepness	s_{max}
Age-structured 1 (A1)	Baseline. Parameters in Table 5-1	0.6	0.75	13.7
Age-structured 2 (A2)	Higher SDR	0.9	0.75	13.7
Age-structured 3 (A3)	Lower z	0.6	0.65	13.7
Age-structured 4 (A4)	Lower z & higher SDR	0.9	0.65	13.7
Age-structured 5 (A5)	Higher z	0.6	0.85	13.7
Age-structured 6 (A6)	Higher z & higher SDR	0.9	0.85	13.7
Age-structured 7 (A7)	Low s_{max}	0.6	0.75	10
Age-structured 8 (A8)	High s_{max}	0.6	0.75	16
Age-structured 9 (A9)	Selectivity = maturity	0.6	0.75	23*
Schaefer (SF)	Developed in Chapter 4			

* Note that the selectivity curve was adjusted to match the maturity curve.

5.3.2.2 Pacific saury stick-held dip net fishery

Six scenarios were considered with respect to model structure and parameters for the Pacific saury stick-held dip net fishery. Scenario A1 is the baseline scenario where I fit an age-structured model of a single population with Beverton-Holt stock-recruitment relationship, using the values of steepness z (0.24) and σ_R (0.3), that were derived indirectly from reported Schaefer biological parameters by Ueno et al. (2006), as described in Chapter 3. Scenario A2-6 used the same population model, but considered a higher value of σ_R (0.6), as well as higher values of steepness (0.3 and 0.4), while maintaining other parameter values as in the baseline scenario. Steepness lower than the baseline was not considered because a steepness less than 0.2 is not possible if the population is to survive under the presence of fishing, and the available meta-analysis on steepness (Myers et al. 1999; Rose et al. 2001) shows that the average steepness value for small, rapidly maturing, short-lived fishes is 0.55, and the lowest value (20th percentile) reported among a similar group of fishes was around 0.34 (Pacific sardine, *Sardinops sagax*). Thus, I used the steepness value for the baseline scenario as a lower limit. Scenario SF is the Schaefer model used in Chapter 3, and included for comparison. A summary of all scenarios considered for simulation is given in Table 5-7.

Table 5-7: A list of model scenarios for the Pacific saury stick held dip net fishery. SDSR = standard deviation of the stock recruitment curve, z = Beverton-Holt steepness parameter, σ_R = standard deviation of SR relationship

Scenario	Description	σ_R	Steepness
Age-structured 1 (A1)	Baseline. Parameters in Table 5-1	0.3	0.25
Age-structured 2 (A2)	Higher SDSR	0.6	0.25
Age-structured 3 (A3)	Higher z	0.3	0.30
Age-structured 4 (A4)	Higher z & higher SDSR	0.6	0.30
Age-structured 5 (A5)	Maximum z	0.3	0.40
Age-structured 6 (A6)	Maximum z & higher SDSR	0.6	0.40
Schaefer (SF)	Developed in Chapter 3		

5.3.2.3 Japanese common squid coastal angling fishery

Nine scenarios were considered with respect to the multi-stock structure of Japanese common squid (M1-9). Scenario C1 is the combined (single) stock model used in Chapter 3, and included for comparison. A summary of scenarios considered for common squid is given in Table 5-8.

Table 5-8: The list of model scenarios for the coastal Japanese common squid angling fishery. ρ = correlation factor of the two stocks, $C(Et)$ = cost assumption relative to effort

Scenario	Description	Winter stock share	ρ
Multi-stock 1 (M1)	Baseline (50% winter stock)	0.5	0
Multi-stock 2 (M2)	50% winter stock. Higher ρ	0.5	0.5
Multi-stock 3 (M3)	50% winter stock. Higher ρ	0.5	0.9
Multi-stock 4 (M4)	70% winter stock	0.7	0
Multi-stock 5 (M5)	70% winter stock. Higher ρ	0.7	0.5
Multi-stock 6 (M6)	70% winter stock. Higher ρ	0.7	0.9
Multi-stock 7 (M7)	90% winter stock	0.9	0
Multi-stock 8 (M8)	90% winter stock. Higher ρ	0.9	0.5
Multi-stock 9 (M9)	90% winter stock. Higher ρ	0.9	0.9
Combined stock (C1)	Developed in Chapter 3	0.5	1

5.3.3 Dynamic optimisation of the bioeconomic models

The dynamic optimisation problem for the Beverton-Holt model is vastly more complex than the Schaefer model (Clark 1990), and an analytical solution is not possible for my case study models, where multiple cohorts, gradual gear selectivity (as opposed to knife-edge selectivity) and stock-recruitment relationships are incorporated. Thus, the approach

taken here is to use a simulation model, projecting forward the annual profit from the fishery subject to the stock dynamics, and to identify the harvest strategy which would maximise the projected sum of discounted annual profit.

The objective function can be written as:

$$\text{Maximise sum of NPV } \pi = \sum_{t=1}^T \left(\frac{1}{1+\delta} \right)^t (pY_t - cE_t) \quad (5-13)$$

subject to the population dynamics described above. The same values for the economic parameters (p and c) and associated uncertainties in Chapter 3 and Chapter 4 were used for optimisation. A simulation time frame (T) of 500 years for toothfish (14 generations) and 100 years for both saury and common squid (50-100 generations) was used to ensure that the stock reached the steady-state equilibrium. A discount rate of 4%, commonly used in the economic assessment of fisheries in Japan (FRA, per. comm.), was assumed for the Japanese common squid fishery and the Pacific saury fishery, as in Chapter 3. Higher discount rates correspond to smaller resource stocks in standard bioeconomic models (Clark 1990; Conrad 1995). Populations with low productive capacities can be driven to extinction under high discount rates (Clark 1973a). Based on the long-lived nature of the toothfish, and the strong wish of both CCAMLR and the South Georgia government to harvest the stock sustainably, a conservative 2% discount rate was selected for the Patagonian toothfish fishery (see Chapter 4 for the effects of discount rates) as the baseline scenario.

5.3.4 Performance-testing simulations

5.3.4.1 Selection of model scenarios

Simulating the performance of the entire set of management procedures based on all the scenarios above is time consuming and unnecessary. Instead I carried out the dynamic optimisation for all scenarios and then selected a “base-case” set of specifications and a set of scenarios for sensitivity tests in order to evaluate the effect of uncertainties on the

robustness of management procedures. This is common practice in MSE (Punt and Smith 1999). The scenarios selected for full evaluation were those in which the estimates of mean E^* were very different from the baseline, due to the different assumptions made about underlying model structure.

The list of selected model scenarios is given in Table 5-9. Since no differences were found in the management advice (both in terms of E^* and Y^*) derived from the two structurally different models for the Pacific saury fishery, the full MSE was only done for the Patagonian toothfish fishery and the Japanese common squid coastal angling fishery. For the Patagonian toothfish, three constant-effort strategies (based on mean E^*) were selected for evaluation, of which two were based on age-structured estimation models (A1, A3) and one was based on the Schaefer model (SF). In addition, three constant-catch strategies (based on mean Y^*) using the same estimation models were also evaluated in order to test the relative robustness of the output-based management procedures. For common squid, I chose scenarios M7-9 for full evaluation. These multi-stock estimation models provided new estimates of E^* . The HCR is the constant effort based on the new estimates of mean E^* , as well as the previous estimate of mean E^* derived from C1 (combined stock model developed in Chapter 3). These fixed effort strategies were tested using a multi-stock OM.

Table 5-9: The list of model scenarios for full simulation

	Estimation model	HCRs	OM
Chapter 4: Patagonian toothfish	Schaefer (SF)	Constant effort based on mean E^*	Schaefer (SF)
This chapter	Beverton-Holt (A1, A3)* and Schaefer (SF)	Constant effort based on mean E^* and constant harvest based on mean Y^*	Beverton-Holt (A1)
Chapter 3: Japanese common squid	Beverton-Holt, combined-stock (C1)	Constant and adaptive effort, based on mean E^*	Beverton-Holt, combined stock (C1)
This chapter	C1 and M7- 9	Constant effort based on mean E^*	Beverton-Holt, multi-stock (M7-9)

*A1 = baseline age-structured model (Beverton-Holt steepness parameter, $z= 0.75$), A3 = age-structured model with lower steepness ($z=0.65$), SF= Schaefer baseline model used in Chapter 4.

C1 = combined stock baseline model developed in Chapter 3

M7-9 = multi-stock models, 90% effort allocation, correlation =0 (M7), 0.5 (M8), and 0.9 (M9).

5.3.4.2 Monte Carlo runs

The *SSB* for the case study species, as well as the net present value of annual profits from the fisheries, were projected into the future from 2004 to 2014 (10 years) with 4% discount rate for the common squid fishery, and from 2007 to 2042 (35 years) with 2% discount rate for the Patagonian toothfish fishery under the management scenarios described above. A 35-year projection period was selected for toothfish because it is the management time frame set by CCAMLR. Since common squid is a short-lived species which lives up to 1 year, a shorter 10-year projection period was selected. A thousand Monte Carlo trials were undertaken in the simulation for each scenario.

5.3.4.3 Performance indices

Similar conservation-related and economic-related performance measures used in Chapter 3 and 4 were considered. For the Patagonian toothfish fishery, there was generally a very small probability of the spawning stock size dropping below 20% of the virgin stock size at any time over the 35 year projection period, given the effort range considered, based on the results of Chapter 4. The conservation measure therefore focuses on the final year *SSB* depletion; the probability that the median final stock size is greater than 50% of the initial stock size (as required to meet CCAMLR's objective). The economic measure was the sum of discounted annual profits over 35 years at 2% discount rate.

For the Japanese common squid angling fishery, a higher fishing pressure on the winter stock than on the autumn stock is expected from the multi-stock model scenarios, since a higher share (50-90%) of effort was allocated to the winter stock. Thus, the conservation related indices focus on the status of the winter stock in the final year. Two conservation-related performance indices were considered; the probability that, after 10 years of management, the *SSB* for the winter-stock in the final year 1) had dropped below 20% of the SSB_0 for the winter stock, 2) was equal or larger than 50% of SSB_0 for the winter stock. Economically-based measures were 1) the sum of discounted annual profits at a 4% discount rate over a 10 year period; and 2) the probability that the annual discounted

profit was negative (out of 1000 Monte Carlo runs). Since the forms of stock structure may affect the profitability of each participant, the sum of discounted profits over 10 years divided by the number of operators was also included as a performance measure.

5.4 Results

5.4.1 Parameter estimates

Production function parameter estimates

The catchability coefficient, q estimated from the age-structured model for the Patagonian toothfish fishery, was 4.185×10^{-6} (log-scale SE of 0.02667) with a residual standard error of 0.08844. The q estimated from the stock dynamics model in Chapter 4 was 4.037×10^{-6} , which equates approximately to 3.7% difference between the two. This validates the reasonable accuracy of the translation work from an age-structured CASAL model to a Schaefer production model in Chapter 4. The production function explains 89.4% of variability in harvest. The results from both the ACF (Figure 5-3) and the t-statistics and p-value (0.125) indicate that there is no first order autocorrelation in the residuals.

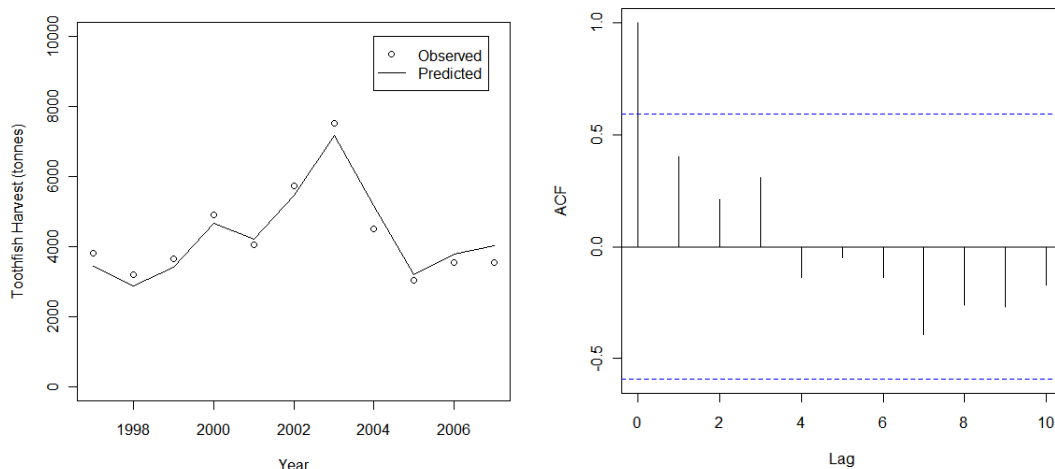


Figure 5-3: Observed vs predicted harvest of Patagonian toothfish from the age-structured model (left) and autocorrelation function (AFC, right).

5.4.2 Estimates of optimal conditions under different assumptions

The estimates of mean steady-state effort (E^*) and associated harvest (Y^*) under different assumptions of population dynamics and stock-recruitment parameters for the Patagonian toothfish fishery, as well as the Pacific saury fishery are given in Table 5-10. The following section explains in detail how each factor affected the estimates of E^* and Y^* .

Table 5-10: Mean values of steady-state effort (E^*) and harvest (Y^*) for the Patagonian toothfish fishery around South Georgia (2% discount rate) and the Pacific saury stick-held dip net fishery around Japan (4% discount rate) with different assumptions concerning stock-recruit uncertainty, steepness, and gear selectivity. See tables Table 5-6 and Table 5-7 for the description of the scenarios. Depletion = the ratio of steady-state SSB relative to the virgin SSB (SSB^*/SSB_0).

Scenario	Patagonian toothfish			Pacific saury		
	E^*	Y^*	Depletion	E^*	Y^*	Depletion
	(000 hooks)	(tonnes)		(operators)	(tonnes)	
A1	16,498	3,587	0.49	43.1	82,478	0.93
A2	16,298	3,564	0.49	36.2	69,113	0.93
A3	14,565	3,216	0.50	42.0	83,345	0.96
A4	14,635	3,221	0.50	40.1	79,592	0.96
A5	17,984	4,010	0.47	41.7	83,826	0.97
A6	17,858	3,992	0.47	40.7	81,985	0.97
A7	14,324	3,557	0.41			
A8	16,273	3,314	0.57			
A9	16,128	3,262	0.55			
SF	12,271	3,190	0.59	43.5	81,717	0.91

5.4.2.1 Effects of the values of steepness and stock-recruit variability (σ_R)

The impacts of the stock-recruitment variability (the values of σ_R) on the mean values of E^* and Y^* for the South Georgian Patagonian toothfish fishery were negligible, given that the difference in the results between a higher value and lower value of σ_R were only 1-2%, with no evidence of statistical significance. With a lower steepness (0.65) case, however, the 95% confidence interval for Y^* became much wider with a higher σ_R scenario (Figure 5-4 and Table 5-10).

On the contrary, the values of steepness significantly affected the estimates of E^* and Y^*

for the Pacific saury fishery: their mean values were significantly lower (approximately 10-12%, 10%, respectively) when the steepness value was lower (0.65), while they were higher (9-10%, 12%, respectively) when the value of steepness was higher (0.85; Figure 5-4 and Table 5-10). This makes sense from a biological perspective, since a lower steepness, such as is characteristic of the saury compared to the toothfish, generally indicates the stock is more vulnerable to recruitment overfishing, and a more conservative harvest strategy is required.

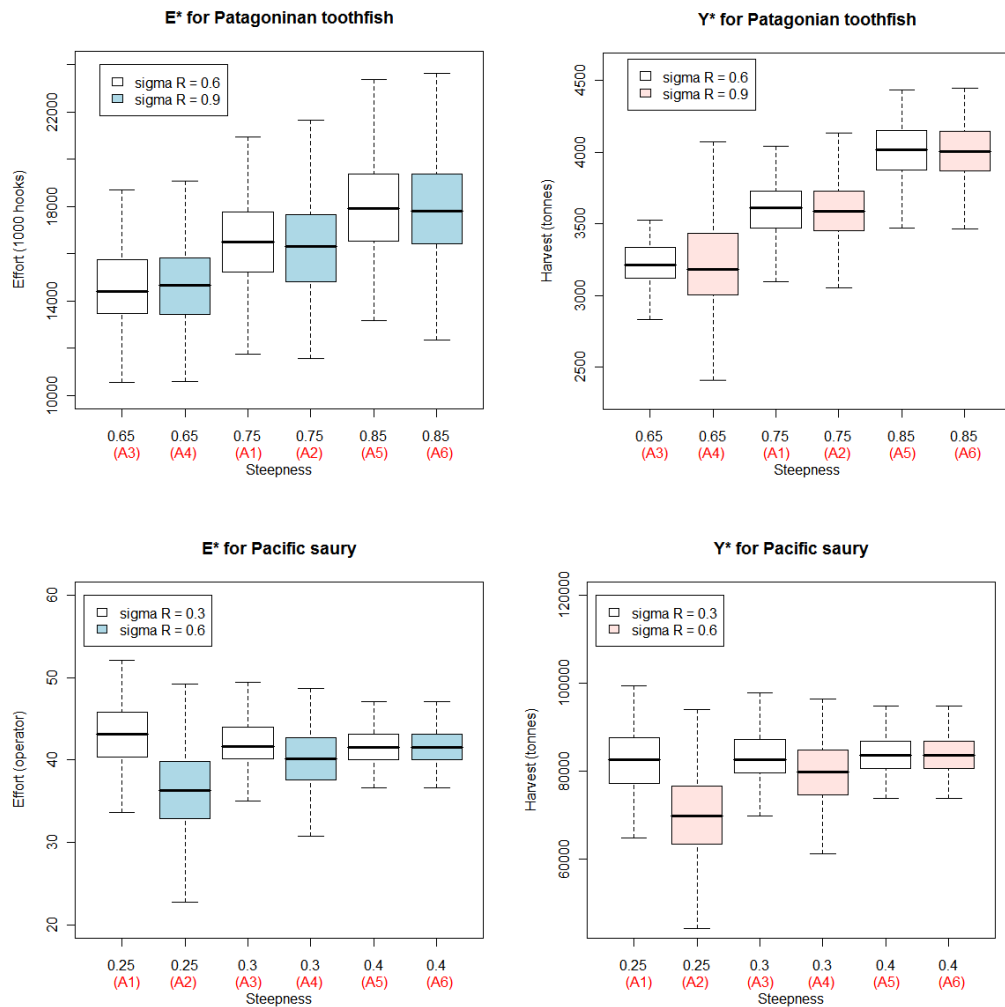


Figure 5-4: Comparative plots of the distribution of steady-state effort (E^*) and harvest (Y^*) for the Patagonian toothfish fishery (top) and the Japanese pacific saury stick-held dip net fishery (100-200GT fleet) (bottom) with different values of the standard deviation of S-R relationship (σ_R).

Unlike the Patagonian toothfish case, the values of σ_R had significant effects on both the mean values and the distribution of E^* and Y^* for the Pacific saury fishery, particularly when the steepness value was lower (0.25, baseline scenario). The mean E^* and corresponding mean Y^* under a higher σ_R (0.6) were approximately 16 %, 3%, and 2% lower than the lower σ_R (0.3) case when steepness value was 0.25, 0.3, and 0.4, respectively (Figure 5-4 and Table 5-10). The impacts of higher σ_R became almost negligible under a steepness value of 0.4. This, together with the results from the Patagonian toothfish fishery above, imply that the estimates of E^* and Y^* were sensitive to the stock-recruitment variability *only* for species with low steepness values, the typically life history characteristics of small pelagic species.

Under all scenarios, higher steepness values resulted in a tighter 95% confidence interval. This also indicates that the errors associated with the stock-recruitment variability on the estimates of E^* and Y^* were reduced with higher steepness values, which is consistent with the previous results.

5.4.2.2 Age-structured versus age-aggregated model

I first compared the values of E^* and Y^* derived from the Schaefer model (SF) developed in Chapter 4 for the Patagonian toothfish fishery to those from the age-structured models, with different gear selectivity assumptions in order to test the initial hypothesis that the interaction between gear selectivity and maturity is the key to comparability of age-structured and Schaefer model results.

The estimates of E^* derived from the age-structured models were found to be consistently larger (approximately 16.7-34.4% higher on average) than that from the SF model, regardless of the gear selectivity assumptions. On the contrary, the discrepancy in the Y^* estimates between the two models was much smaller (Figure 5-5). For instance, under the scenario A9, where the maturity and gear selectivity are coincident, the difference in mean Y^* estimates was reduced to 2% between the age-structured model (3,262 tonnes) and SF model (3,190 tonnes). Although a t-test with unequal variances

(Welch's t-test) confirmed that their mean values were statistically different ($df=249$, $t=167$, $p\text{-value}= 2.2e-16$), the distributions of Y^* under the scenario A9 are within the distribution ranges of those in SF (Figure 5-5). The estimate of Y^* under A9 was also very similar to the estimates of Y^* under the low steepness scenarios (A3 = 3,216 tonnes, and A4=3,221 tonnes), where the difference in mean Y^* between the Schaefer and age-structured models was reduced to less than 1% (Table 5-10).

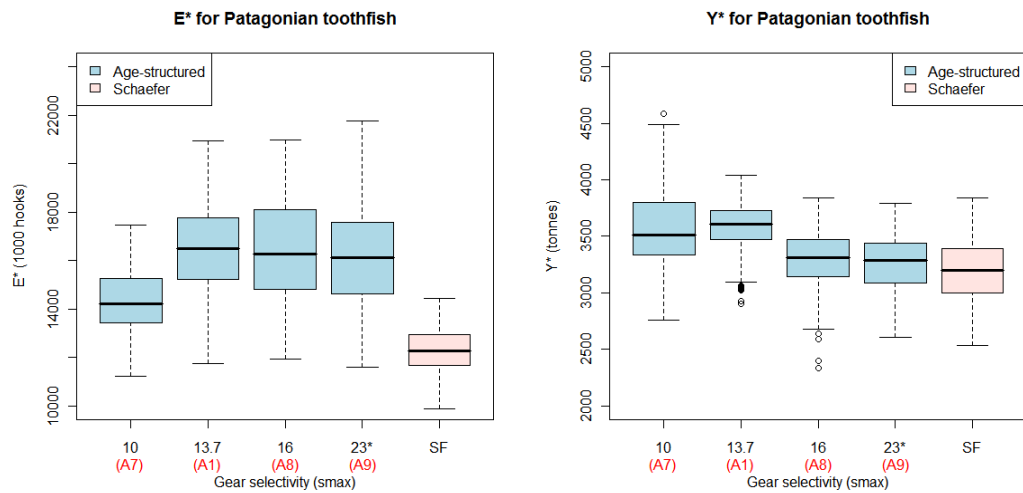


Figure 5-5: Comparative plots of steady-state effort (E^*), and associated harvest (Y^*) under different gear selectivity assumptions in age-structured bioeconomic models (blue) and Schaefer (pink) bioeconomic model for the Patagonian toothfish longline fishery. Steepness $z=0.75$, standard deviation of S - R relationship (σ_R)=0.6.

The large discrepancy in the estimates of E^* between SF and the age-structured models, in comparison to the smaller discrepancy in the estimates of Y^* , could be explained as follows. The Patagonian toothfish fishery around the island of South Georgia is considered to be a young fishery, where the fishery has been operational for approximately 25 years — less than one generation time (35 years) of the toothfish. The current population consists of older and larger fish, while a much lower proportion of older and larger fish would remain in the long-time future population. For example, the mean weight in the exploitable stock of the toothfish population over the history of the fishery (1985-2008) was 28.0 kg, while that of the population at equilibrium (e.g. 500 years into the future) was estimated in the model at 18 kg. This “contraction” in both age

structure and mean weight over time for fish populations is common after many years of fishery exploitation (Yemane et al. 2008; Cope and Punt 2009). Given the young nature of the fishery this contraction has not yet occurred on a scale comparable to that which occurs in the exploited equilibrium state. The stock in its current age structure can support higher catches than the stock at exploited equilibrium, for the same level of effort. The age-structured optimisation model is initialised at deterministic equilibrium and projected forward 500 years to search for the present level of effort which would maximise the total discounted profits over time, to remove historical effects and ensure sustainability. However, due to the changes in the population mean weight, the optimal effort is estimated at a much higher level (but not as large for optimal harvest) when moving from the biomass dynamic to the age-structured optimisation model. Such a drastic change in mean weight is unlikely to be an issue for short-lived species and/or an already developed fishery operating for many fish generations. This suggests that effort-based management advice (i.e. E^*) derived from a bioeconomic model for a young/developing fishery targeting long-lived species can be unreliable or misleading, and a harvest-based policy (i.e. based on Y^*) may be more appropriate for such a case. This speculation is tested in the following MSE section 5.4.3.

In contrast to the toothfish case study, the estimates of both E^* and Y^* derived from the age-structured model (A1: baseline scenario) for the Pacific saury fishery were very similar to those derived from the Schaefer model, with the difference in mean value up to only 0.9%. Welch's t-test suggests inconclusive evidence that mean values of E^* were different (df=401, $t=-1.9$, p-value=0.06), and found no evidence that mean Y^* values were different (df=401, $t=1.4$, p-value=0.15). This means that the estimates of E^* and Y^* for the Pacific saury fishery are quite robust to the structural uncertainties we tested for in the underlying population dynamics (Figure 5-6).

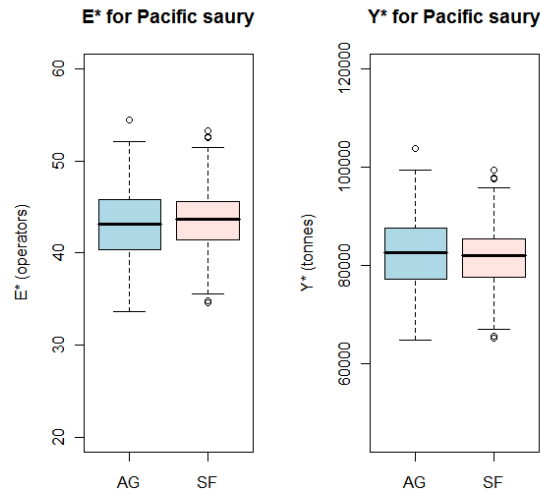


Figure 5-6: Comparative plots of steady-state effort (E^*), and associated harvest (Y^*) between the baseline age-structured model (blue) and the Schaefer (pink) bioeconomic models for the Pacific saury stick-held dip net fishery around Japan

5.4.2.3 Effects of gear selectivity

The gear selectivity parameter s_{max} (age at maximum selection) corresponds to the depth of fishing operations (e.g. a lower s_{max} corresponds to a shallower depth in general) for the toothfish fishery, and variation in this parameter resulted in a significant change in the optimal conditions (Table 5-10, Figure 5-5). In general, the larger the s_{max} value, the larger the equilibrium spawning stock biomass (SSB^*) and the smaller the exploitable stock biomass (X^*) available for the fishing gear (Table 5-11). Under A9, where gear selectivity coincides with maturity – the implicit assumption of the Schaefer model - the median values of SSB^* and X^* were equal. However, the discrepancy between the SSB^* and X^* became progressively larger as the value of s_{max} decreased (Table 5-11), in other words, as the selectivity curve departed far from the maturity curve (Figure 5-2). The higher X^* meant the biomass available for the fishing gear was more abundant, which directly affected CPUE. The lowest s_{max} scenario (A7) predicted the highest X^* , with the highest Y^*/E^* ratio (or CPUE), resulting the highest annual discounted profits. This suggests that it is more profitable to target younger fish at shallower depth as it requires less fishing effort to harvest given a larger exploitable stock biomass, resulting from a higher growth rate relative to the mortality rate at younger ages. This higher yield and

increased targeting of the younger immature fish decreases the *SSB*. However, this does not offset the advantage of the increase in exploitable biomass and CPUE, as the decrease in *SSB* was not enough to impact recruitment. In practice, however, various conservation measures are in place to prohibit altering the depth of fishing operation for Patagonian toothfish, and such a change is unlikely to be approved for licensed vessels.

As noted earlier, the estimate of median Y^* was the closest to that of the Schaefer model (2% difference) under A9, where gear selectivity was assumed exactly equal to the maturity.

Table 5-11: The median values of equilibrium spawning stock biomass (SSB^*), exploitable biomass (X^*), and discounted annual profit (US\$ million) under different values of s_{max} (age at maximum selection). Unit= 1000 tonnes

Scenario	Spawning stock biomass (SSB^*)	Exploitable biomass (X^*)	Discounted profit (R^*) (US\$ million)
A7 ($s_{max}=10$)	36.5	57.7	11.8
A1 ($s_{max}=13.7$)	42.8	52.2	9.8
A8 ($s_{max}=16$)	49.7	48.1	7.1
A9 ($s_{max}=23$)*	48.1	48.1	4.6

*gear selectivity is exactly equal to the maturity

5.4.2.4 Effects of treating multi-stocks as a single stock

Treating two sub-stocks as a single stock in a bioeconomic modeling implicitly assumes that the effort is allocated equally to each sub-stock. In the multi-stock models, effort allocation to the winter stock is assumed 50% (M1-3), 70% (M4-6), and 90% (M7-9) to reflect alternative plausible assumptions of true effort allocation. The estimates of E^* and Y^* for the Japanese common squid multi-stock model for the 10-30GT class fleet are in Table 5-12. The estimates of both E^* and Y^* became progressively smaller and the interval became narrower as the share of the effort allocation of the fleet to the winter stock increased (Figure 5-7). A larger allocation of effort to the winter stock implies a larger fishing pressure on the winter stock by this fleet. As total effort allocation increased the winter stock became depleted and this would eventually reduce profitability of the fleet. For the autumn stock, lower effort is sub-optimal because historically the autumn stock biomass is larger than the winter stock biomass, and it is more profitable to

employ more effort given the larger biomass and growth. During the optimisation process, the search algorithm tried to find the effort level which balanced the marginal returns from the two stocks, and the depletion effect for the winter stock eventually dominated this search and a reduced total effort estimate, relative to the combined stock model, was the result.

For this reason, compared to the combined stock model, estimates of mean E^* and Y^* from the multi-stock model scenarios were generally smaller, except for M1-3, which assumes 50% effort allocated to the winter stock. This is counter intuitive as the effort allocation assumption was the same as the combined stock model. One possible reason is that the larger S - R variability (values of σ_R) under the multi-stock models (0.34-0.46) compared to those of the combined stock model (0.25-0.3) have increased the errors, which in turn positively biased the mean value of E^* . A closer look at the distributions of E^* and Y^* (Figure 5-7) suggest that larger values of ρ made the 25th and 75th quantile range wider. This is due to the increase in the total variability in the S - R relationship as a result of increases in the value of ρ , the correlation factor between the population dynamics of the two stocks. This effect is the most prominent when the effort allocation between the two stocks are equal, but less severe when the effort is predominantly allocated to the winter stock, since a bad recruitment for the autumn stock has less impact on the overall profitability of the fleet. Such complexity makes the straightforward interpretation of the impacts of ρ difficult.

The median values of E^* and Y^* for all scenarios remained zero (or near zero), suggesting that fishery closure is optimal more than 50% of the time, regardless of the assumptions of underlying population structure. Mean values are highly biased due to large errors, and the fixed harvest control rule based on the mean E^* may perform poorly, particularly when stock structure was ignored and resulting mean E^* estimate was large. This will be tested in the performance evaluation section (5.4.3).

Table 5-12: Mean values of E^* and Y^* for the Japanese common squid angling fishery.
 ρ =correlation in S-R variation between the two stocks

Scenario	Effort allocated to the winter-stock	E^* (operators)			Y^* (000 tonnes)		
		$\rho=0$	$\rho=0.5$	$\rho=0.9$	$\rho=0$	$\rho=0.5$	$\rho=0.9$
C1	50%	1,291-1,480			179-273		
M1-3	50%	1,475	1,736	1,909	124	145	159
M4-6	70%	779	1,216	1,103	63	98	89
M7-9	90%	456	574	529	35	44	41

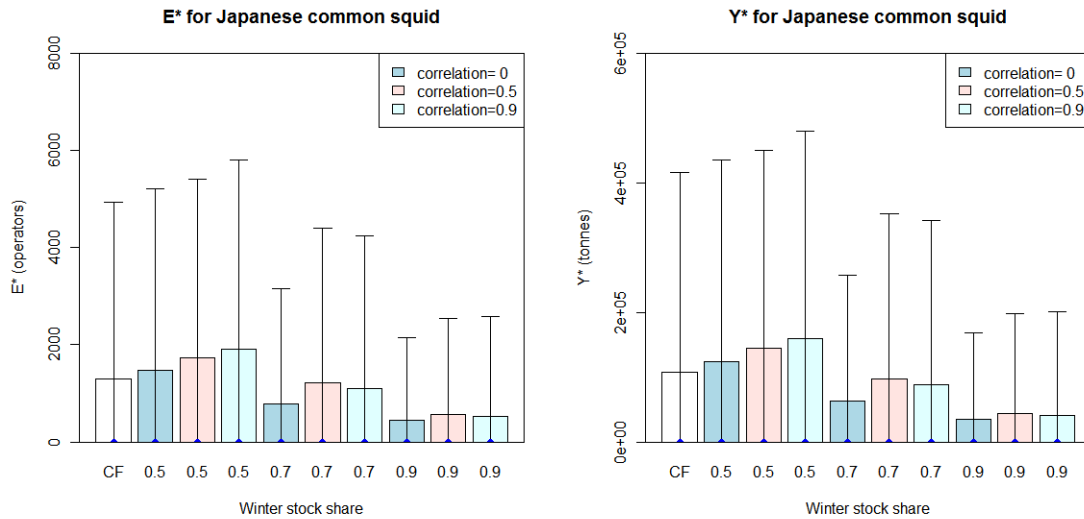


Figure 5-7: Distributions of E^* and Y^* estimates under different assumptions of effort allocation to the winter stock, and the correlation of S-R variability between the two stocks for the Japanese common squid. Mean values are the height of the bars, and blue dots are medians. The whisker lines show the upper and lower 90th percentiles.

5.4.3 Performance evaluations

For all effort-based strategies, the target effort levels were set at the mean steady-state effort derived from the bioeconomic estimation models, and maintained constant over the projection period. Similarly, the target catch level was maintained constant at the mean steady-state harvest derived from the bioeconomic estimation models.

5.4.3.1 Patagonian toothfish fishery

Three constant effort-based strategies, two based on an age-structured bioeconomic estimation model: A1 (baseline, 16.5 million hooks/year) and A3 (lower steepness, 14.6

million hooks/year), and one based on the Schaefer model (SF: 12.3 million hooks/year), were compared in terms of *SSB* and the sum of annual discounted profits at 2% discount rate over a 35 year projection. The true population model was taken as the age-structured model (A1) in each case. Constant catch-based strategies estimated using the same bioeconomic estimation models (A1=3,587 tonnes, A3=3,216 tonnes, SF=3,190 tonnes) were also evaluated in order to test the relative robustness of the output-based TRPs relative to effort-based ones.

Under the A1-based constant effort strategy, the median *SSB* trajectory started to fall below 50% of the initial size (SSB_0) around 30 years into the future. The probability that the median final stock size was greater than 50% of the initial stock size at the end of 35 year projection was estimated at 0.44. This means that the A1-based constant effort strategy failed to meet the CCAMLR conservation objectives, which requires this probability to be 0.5 or greater. Conversely, the median *SSB* trajectory under the A3 and SF-based constant effort strategies were maintained above 50% SSB_0 over the entire projection period (0.64 for A3 and 0.84 for SF), thus meeting the conservation objectives of CCAMLR.

In terms of the sum of annual discounted profits, the A1-based constant effort strategy yielded about 13.6% higher total discounted annual profits (US\$559 million) than the SF-based constant effort strategy (US\$492 million), and 6% higher than the A3-based constant effort strategy (US\$527 million) over the 35-year projection period. This is due to the large initial economic returns associated with higher effort levels (Figure 5-8, left). However, this economic advantage diminished in the later years as the stock depletion progressed.

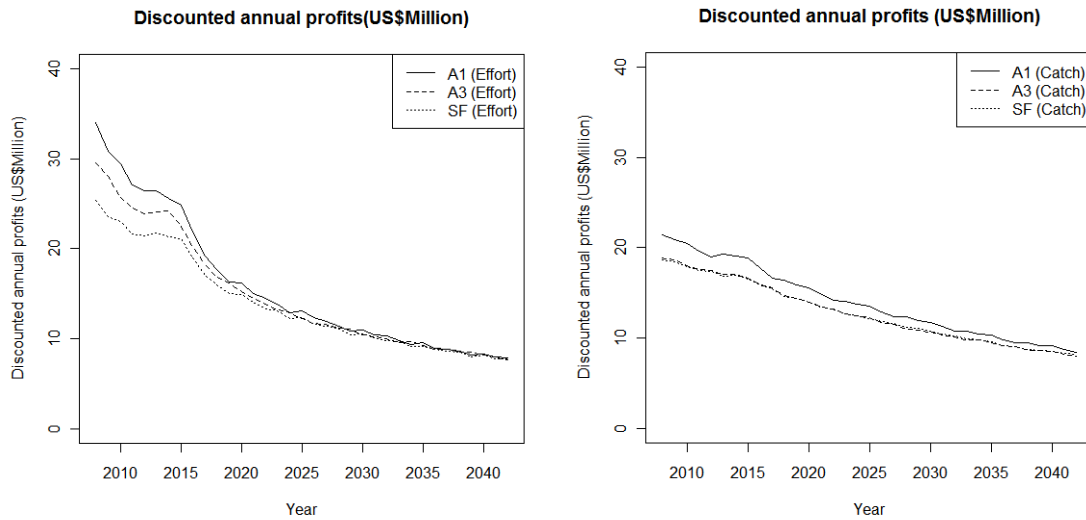


Figure 5-8: 35 years projection of median annual discounted profits (2% discount rate) from the Patagonian toothfish longline fishery under constant effort MPs (left) and constant catch MPs (right) under Scenario A1, A3, and SF.

The comparison of the outcomes between A1 and A3 leads to the general conclusion that constant effort-based strategies using an age-structured bioeconomic estimation model which ignore the uncertainty in steepness can lead to an unwanted stock depletion (e.g. below the target set by CCAMLR). Despite the simplistic assumption about the population dynamics, the SF-based constant effort strategy developed in Chapter 4, where multiple uncertainties in stock variance, costs, and price were accounted for, performed the best among the three scenarios on the conservation measures, but performed the worst on the economic measures. The result demonstrates that there is a clear trade off between the total economic returns and the depletion of the stock.

Under the constant catch-based strategies, the probability that the median final stock size was greater than 50% of the initial stock size after 35 years was estimated at 0.65 (A1), 0.81(A3), and 0.82 (SF)—all meeting the CCAMLR’s conservation objectives. This provides evidence for the relative advantage of using catch-based management advice from an age-structured bioeconomic model, as opposed to effort-based advice, for a young/developing fishery targeting long-lived species, as Y^* estimates were more robust to the uncertainties in the stock dynamics. The A1-based constant catch strategy yielded about 9% higher total discounted annual profits (US\$489 million) than that of the A3 and

SF-based constant catch strategies (both US\$446 million) over a 35-year projection period. These values were generally smaller than those from the effort-based strategies due to the smaller annual returns in the first quarter of the projection years (Figure 5-8), as a result of lower yields.

5.4.3.2 Common squid coastal angling fishery

Effects of stock structure

The combined stock scenario (C1: baseline) assumes that the effort of the 10-30GT class fleet is allocated evenly to the two stocks (50%), while the multi-stock scenarios (M7-9) assumed 90% effort allocation to the winter stock. Under these scenarios, smaller constant effort levels (456 to 574 operators) were estimated than the C1-based target effort level (1,291 operators). The true stock structure was assumed multi-stock with 90% effort allocated to the winter stock (M7-9) for each evaluation. Scenario M1 (50% allocation) similar to the single stock model assumption is also included for comparison.

Despite the higher exploitation rate for the winter-stock under the multi-stock models, there was no apparent significant differences in conservation indices for SSB_w between the constant effort strategy based on the multi-stock TRP and the combined stock TRP, suggesting that the effect in terms of stock conservation was minimal, given the exploitation rates considered. On the other hand, the different assumptions of effort allocation resulted in a considerable difference between the constant effort strategy based on the combined stock TRP and the multi-stock TRP. For instance, when the true effort split is fifty-fifty (M1), the constant effort strategy based on the combined stock TRP yields more than 8 times higher discounted profits over 10 years than those from multi-stock TRP, while negative discounted profits were predicted when the true effort was disproportionately allocated to the winter stock (Table 5-13).

In contrast, the constant effort strategy based on multi-stock TRPs yielded positive discounted profits for all scenarios, although the profits were generally smaller for the scenarios with disproportionate effort assumptions (M7-9), because it is more profitable

to allocate higher effort to exploit the autumn stock given the relatively larger abundance of the autumn stock. The effort strategies based on combined stock TRPs perform well in terms of generating higher discounted profits when the true effort allocation is fifty-fifty. However, if the true effort is predominantly allocated to the winter stock (as in M7-9), but the management authority fails to take into account such disproportional effort allocation in the estimation model, the management action will be based on an overly optimistic level of optimal effort, which then results in poor economic performance, as evident by the high probabilities of negative future profits for the fishing industry and individual operators.

Table 5-13: Performance statistics for the Japanese common squid angling fishery based on a 10 year projection of stock biomass and discounted profits at 4% discount rate. *SSBw0*, and *SSBw.final* corresponds to the spawning stock biomass for the winter-stock at the initial year and the final year of the projection, respectively

Assumptions			Conservation Indices		Economic Indices		
Estimation model	Constant effort level	OM	Prob. of <i>SSBw.final</i> < 20% <i>SSBw0</i>	Prob. of <i>SSBw.final</i> ≥ 50% <i>SSBw0</i>	Sum of dis. profits in 10 years, median value (Billion yen)	Sum of dis. profits per operator (Million yen)	Prob. of annual dis. profits being negative*
C1	1,291	M1	0.001	0.88	81.8	6.7	0.37
		M7	0.005	0.90	-2.8	-2.3	0.46
		M8	0.002	0.89	-5.9	-4.8	0.47
		M9	0	0.88	-5.6	-4.6	0.47
M7	456	M1	0.001	0.89	10.2	22.3	0.37
		M7	0.001	0.91	5.0	11.0	0.46
		M8	0.003	0.88	4.6	10.0	0.46
		M9	0.001	0.90	5.7	12.4	0.46
M8	574	M1	0.001	0.89	9.9	17.3	0.36
		M7	0.002	0.91	4.0	6.9	0.46
		M8	0	0.90	3.2	5.5	0.46
		M9	0.002	0.90	4.5	7.8	0.44
M9	529	M1	0	0.90	10.4	19.7	0.35
		M7	0.002	0.91	4.4	8.3	0.46
		M8	0.003	0.9	4.5	8.5	0.45
		M9	0	0.89	3.4	6.5	0.46

*Excluding the initial year.

** The effort allocation and correlation assumptions of M3 are the closest to the assumptions of C1.

In terms of the probability that the annual discounted profits were negative, no improvement was found under the multi-stock-based effort strategies. Perhaps, this is because of the relatively high S - R variability ($\sigma_{R \text{ total}} = 0.34\text{-}0.46$) was assumed in the OMs.

5.5 Discussion

In this chapter, I expanded the application of the MSE - a rigorous approach to accounting for multiple uncertainties - to investigate the relative importance of a wide range of uncertainties for the robustness of the effort-based harvesting policies based on bioeconomic TRPs for the case study fisheries. I focused primarily on structural uncertainties with respect to the form of the population dynamics and stock structure, by constructing age-structured bioeconomic estimation models, capable of specifying structurally different forms of population dynamics for different species with contrasting life histories and stock structures. The primary lessons learned and suggestions for future research are summarised as follows:

i) Uncertainties in the form of the population dynamics

Biomass dynamic models, such as the Schaefer or Fox model, have been used extensively in the bioeconomic modelling of fisheries. While such simple models clearly have their advantages, the consequences of imposing their simplified assumptions on bioeconomic models have not been discussed adequately. With respect to the question of whether a simple biomass dynamic model can closely approximate the optimal strategies estimated with an age-structured model, this study yielded mixed results. The equilibrium effort estimates with age-structured models for the Patagonian toothfish fishery were significantly higher than those with a biomass dynamic model, particularly when uncertainty in steepness was not accounted for, but the difference in terms of optimal harvest was negligible under the scenarios in which either 1) uncertainty in steepness was accounted for, or 2) gear selectivity was assumed equal to maturity – the assumption closest to the Schaefer model’s underlying assumptions.

In contrast, no evidence of differences in equilibrium effort levels under an age-structured model compared to a biomass dynamic model was found for the Pacific saury fishery. This fishery uses a non-selective gear, and fishing does not take place during the period when new recruits have just entered the population or are not large enough to be marketable. Thus, it was implicitly assumed in the age-structured model that the fishing gear takes only the mature population. In other words, gear-selectivity was assumed to be the same as maturity, which is the same assumption as the Schaefer model. Although it is too early to draw conclusions, the interaction between the gear selectivity and maturity appears to be the key to the comparability of age-structured and Schaefer model results. For the future, it would be particularly interesting to carry out a further case study using a fully developed fishery targeting a long-lived species, so that we could remove the effects of age-structure “contraction” and decreases in mean weight, which would allow us to assess more clearly the interaction between the gear selectivity and maturity. A general lesson learned is that the interactions between life history and fisheries parameters can significantly affect the behaviour of bioeconomic models, and ignoring such characteristics and interactions could potentially result in misleading policy recommendations. The robustness of the bioeconomic models to simultaneous multiple uncertainties needs to be tested more rigorously in relation to the characteristics of the fish and fisheries.

Previous studies have shown that increasing the apparent realism of the underlying dynamics of the population model would not necessarily improve performance (Ludwig and Walters 1985; Kirkwood and Smith 1996; Punt and Smith 1999; Parma 2002). Because the aim of this chapter was to assess the implications of bioeconomic estimation models with varying complexity in relation to the estimates of TRPs and the resultant effort-based strategies, a full MSE (including MPs that include stock assessment process) for the purpose of identifying robust strategies under multiple uncertainties was not developed, although it would be interesting to carry out a full MSE in the future. Such an extension would allow us to add weight to the previous studies which have explored whether a simpler MP improves or at least maintains performance, relative to a more complicated or realistic one. Nevertheless, comparing the management outcomes of

simpler versus complex bioeconomic estimation models is useful to understand the potential impacts of neglecting the true population dynamics in general bioeconomic modelling, and trade-offs between the biological conservation and economic returns from effort-based strategies. In the case of the toothfish fishery, the constant effort strategy based on a simple Schaefer bioeconomic TRP was found to be preferable to the one based on an age-structured bioeconomic TRP in conservation terms, even though the latter resulted in higher total discounted profits over 35 years. These results were largely consistent with the findings from the above examples, although this is the first clear demonstration of the trade-off between economic returns and conservation goals, using alternative model hypotheses in an MSE framework.

ii) Uncertainty in stock structure

Few serious attempts have been made to consider spatial structure or stock structure in operating models (Butterworth and Punt 1999), and to my knowledge the studies on whale stocks by the IWC (IWC 1994), the Australian Northern prawn stock by Dichmont (2006), the Atlantic bluefin tuna stock by Kell and Fromentin (2007), and the Australian rock lobster by Punt and Hobday (2009) are the only fisheries examples where OMs were specifically designed to examine the implications of stock-structure uncertainty. In all cases, the economic performance was not considered. This study found that the assumptions made about stock structure not only resulted in different bioeconomic target reference points (generally, smaller equilibrium effort from the multi-stock models) but also different economic outcomes, although little evidence of differences in conservation-related outcomes was found. The divergence between the economic performance of the multi-stock and single-stock model was the largest when the true effort was predominantly allocated to the winter stock, and the variation of the two stocks was assumed to be highly correlated (scenario M9). These results suggest that disregarding the stock structure and disproportional effort allocation in the estimation model leads to a management recommendation based on an overly optimistic estimate of the optimal level of effort, which then results in poor economic performance.

The current analysis could be extended to investigate an efficient distribution of effort over the two stocks, so that the overall profitability of the fleet could be maximised. The optimal policy for multiple stocks has been studied in the broader bioeconomic modelling context, i.e. for moose (*Alces alces*) management (Skonhøft and Olaussen 2005), but few examples exist for fisheries. Another interesting research avenue would be to modify the adaptive effort management scheme developed in Chapter 3 to incorporate the information on multi-stock structure and their correlated variability, so that knowledge about the abundance of the autumn stock at the beginning of the fishing season could be used to predict the subsequent abundance of the winter-stock, and a more efficient effort distribution could occur.

This chapter has evaluated the effect of a few key biological uncertainties on the outcomes of MSEs for the three case study species. I have demonstrated both the usefulness of this approach and the importance of considering structural uncertainty in MSEs. The next chapter focuses on the economic components of structural uncertainty.

Chapter 6. Simulating the behaviour of bioeconomic systems under multiple uncertainties: economics components

Abstract

This chapter explores the implications of simplified assumptions made about cost and price in the estimation of bioeconomic target reference points (TRPs) and policy performance, using the Japanese common squid coastal angling fishery as an example. I have, for the first time, included economic components of structural uncertainty into the fisheries MSE framework, and demonstrated that the outcomes of neglecting such economic structural uncertainties were staggering for this fishery, where most operators are often on the verge of profitability. The presence of a downward-sloping demand curve seems to improve the robustness of bioeconomic TRPs estimates by suppressing large effort and catch levels in order to maintain the highest prices even at high stock abundance, which in turn results in tight confidence intervals around the estimated mean optimal effort levels. Including robustness tests for economic assumptions into MSEs is an important step forward, and this case study demonstrates that economic uncertainties have the potential to outweigh biological uncertainties in determining the performance of management procedures.

6.1 Introduction

Previous investigations of structural uncertainties tended to focus on biological aspects alone (Kirkwood and Smith 1996; Kuikka et al. 1999; Patterson 1999; Hammond and O'Brien 2001; McAllister and Kirchner 2002; Michielsens and McAllister 2004), and little work has been done to investigate the economic components of structural uncertainty. Charles (1998; 2008) wrote that structural uncertainty differs in a very practical economic and financial sense from simple random fluctuation. One can insure

against random fluctuations for which the probabilities of occurrence are known, but this is much more difficult in the face of basic ignorance about the system. Given the lack of economic considerations in most MSE work to date, and the difficulties in addressing structural uncertainty with standard modeling approaches (e.g. stochastic bioeconomic modelling), it is not surprising that studies that explicitly account for economic structural uncertainty are absent from the literature. In this chapter, a limited set of key economic structural uncertainties in the case study fisheries are explored, and the sensitivity of the model to different assumptions concerning the economic structure of the model is evaluated. I investigate the effect of different assumptions concerning the economic structure of the fisher on the estimates of bioeconomic target reference points (TRPs). Subsequently, I evaluate the performance of the management procedures based on the bioeconomic TRPs obtained under different assumptions, as well as the current TAC-based management procedure, using a MSE framework.

Section 6.2 provides the types of uncertainties to be included in the bioeconomic operating models. Section 6.3 describes the methods used in constructing bioeconomic operating models, defining alternative model scenarios, and methods of performance testing. The results and discussion are in Section 6.4 and Section 6.5.

6.2 Uncertainties considered

6.2.1 Uncertainties in the cost specification

For all three case study fisheries in the previous chapters, the Cobb-Douglas production function parameters were empirically estimated using historical biomass, catch and effort data. Effort output elasticities larger than one were estimated for the two Japanese fisheries (although they were not significantly different from one), indicating that the resulting cost function may be a decreasing function of effort.

Because it was not possible to obtain the cost data needed to determine the cost structure with respect to effort from boat owners, a constant proportional cost $C(E_t)$ assumption

was used in maximising the future profits from the fisheries in Chapters 3 and 4. In this chapter, two hypothetical specifications for C are included in the bioeconomic optimisation models for the Japanese common squid angling fishery to explore the effects of different cost specifications on optimal resource use. The first specification assumes increasing average and marginal costs of effort due to, for instance, congestion of fishing grounds as the number of fishing boat increases (Lewis 1981). This specification was considered for the common squid fishery, because the mean equilibrium effort suggested by the bioeconomic model in Chapter 3 exceeds the recent level (2004) in this fishery by approximately 40%, and crowding of fishing grounds may occur with increased effort. The second specification assumes decreasing average and marginal costs of effort, resulting from e.g. economies of scale in effort supply or from gains in efficiency due to information sharing as the number of fishing vessels increases (Lewis 1981). Empirical evidence exists for decreasing cost functions, for example in the North Sea herring fishery (Bjørndal 1987). Several authors in their theoretical studies have argued that “cyclical” harvesting (pulse fishing), rather than steady state harvesting, may be optimal in situations with convex (or increasing) returns to harvesting (Lewis and Schmalensee 1979; Lewis 1981; Liski et al. 2000; Kitti et al. 2002). The results in Chapter 3 suggest that there is no steady state and cyclical fishing may be optimal for this fishery. However, the purpose of this Chapter is to investigate the limitations and biases of standard bioeconomic analyses, and therefore the assessment of the cost structure is my primary focus.

6.2.2 Uncertainties in the demand function

An assumption of constant price is common in fisheries bioeconomic models (Nøstbakken and Conrad 2007). Moreover, prices are generally assumed to be invariant with the quantity landed (Dichmont et al. 2010). Although I incorporated uncertainties in price due to random fluctuation in three case studies, the price was assumed independent of the landed quantity of the stocks, except for the Pacific saury case study. While this is a reasonable assumption for the Patagonian toothfish, given that the fishery is supplying a relatively small proportion of the total supply of a species to the global market, it might be invalid for Japanese common squid as they are mainly supplied locally. In Chapter 3, I

found the invariant assumption of squid price with the quantity supplied reasonable because the ex-vessel price (real price) in 2004 was approximately the same as the median ex-vessel price of common squid in the whole data period (1985 -2004). However, a strong negative correlation between the price of squid and quantity landed was observed for the data prior to the early 1990s, although the relationship became weak and statistically insignificant in more recent years, which coincided with the increase in substitutes (i.e. cheap imports and alternative squid species). This means that the independent price assumption can be both valid and invalid, depending on which data period is included in the analysis of the supply-demand relationship.

To demonstrate the danger of making a subjective assumption about the supply-demand relationship, in this chapter I derived a downward sloping demand function for Japanese common squid using the data period of 1991-2004 (the same as in Chapter 3), assuming that the relationship was significant, and incorporated this relationship in the bioeconomic optimisation model, then contrasted the results with the previous model. Furthermore, I re-evaluated the performance of the annual TAC-based strategy for common squid, as well as the constant effort strategy, under the assumption of a significant downward-sloping demand, because the economically-related performance measures are sensitive to this assumption, and the inclusion of this assumption is likely to alter the management outcomes.

A core set of model scenarios is listed in Table 6-1, although I define the model scenarios in more detail in the later section.

Table 6-1: A core set of model scenarios. Base indicates the base model specification in the previous chapters; Alt indicates alternative specifications in this Chapter.

Species		Biological model	Number of stocks	Cost relative to effort size	Price relative to harvest quantity
Japanese common squid	Base	Beverton-Holt	single stock	constant	constant
	Alt1	Beverton-Holt	single stock	varying	constant
	Alt2	Beverton-Holt	single stock	constant	negative function

6.3 Methods

The population dynamics, stock-recruitment relationship, and exploitation rates for the Japanese common squid fishery are described in equations from (5-1) to (5-8) in Chapter 5.

6.3.1 Alternative specifications of the economic models

6.3.1.1 Introducing different cost specifications

In addition to the constant cost specification used in Chapter 3 and 5, where $C(E) = cE$, an additional hypothetical specification for $C(E)$, similar to Lewis (1981), was introduced to simulate the future profits from the Japanese coastal angling fishery.

$$C(E) = cE + \nu E^2 \quad c > 0 \quad (6-1)$$

where c is the unit cost of harvesting, ν is a factor altering the cost trend in relation to effort, where cost increases when $\nu > 0$, and decreases when $\nu < 0$. The resulting net returns equation corresponding to the cost specification is:

$$\pi(E_t, X_t) = pY_t - cE_t - \nu E_t^2 \quad (6-2)$$

The interpretation of the factor ν is totally dependent on the level of E . I selected arbitrary numbers to investigate the theoretical effects on the estimates of optimal effort. For the increasing cost specification, the cost increase factor ν was set at between 100 yen and 500 yen (roughly US\$1-5). For the decreasing cost scenario, the factor ν was set at between -100 yen and -500 yen. This ensures the cost increase and decrease scenarios as defined in equation (6-1) are symmetrical. The small values of ν were chosen due to the extreme sensitivity of the results to changes in economic parameters based on the results of Chapter 3.

6.3.1.2 Specifying a supply-demand relationship for squid

The effect of a downward-sloping demand curve for common squid was also included. Data on the ex-vessel price of squid and landed quantities from 1991 to 2004 were fitted to the same inverse demand function as was described for Pacific saury in Chapter 3. Parameter estimates are given in the Results section. Although the estimates were not statistically significant, their values and the residual standard errors were used to describe the price-quantity relationship for squid.

6.3.2 Estimation model scenarios

The baseline scenario is the constant cost specification (C1), and two scenarios with different cost specifications (C2-C3), and additional scenario with demand specification (C4) were considered. In the previous Chapters, random variability in cost and price (mean values $\pm 15\%$) were included. However, such large variability may mask the impacts of cost specifications. As an alternative, a smaller variability (mean values $\pm 5\%$) in mean cost (c) and price were included for the comparison among C1-3, since the true mean cost for all participants and true price in a given year cannot be known accurately. For C4, the residual variance around the fitted inverse demand function was used to define a stochastic relationship between quantity supplied and squid price.

Table 6-2: The list of model scenarios for the coastal Japanese common squid angling fishery. ρ = correlation factor of the two stocks, $C(Et)$ = cost assumption relative to effort

Scenario	Description	Winter stock share	ρ	$C(Et)$
Combined stock (C1)	Developed in Chapter 3	0.5	1	constant
Combined stock (C2)	CS model with increasing cost	0.5	1	increasing
Combined stock (C3)	CS model with decreasing cost	0.5	1	decreasing
Combined stock (C4)	CS model with demand function	0.5	1	constant

6.3.3 Dynamic optimisation of the bioeconomic models

The basic method of dynamic optimisation is described in section (5.3.3), although the constant cost specification was replaced by the cost trend functions specified in equations

(6-1), as well as a downward-sloping demand specification during optimisation for the selected scenarios.

6.3.4 Performance-testing simulations

A summary of model scenarios for simulation testing is given in Table 6-3. Monte Carlo runs, and the performance indices used are the same as Chapter 5.

Table 6-3: The list of model scenarios for full simulation.

Japanese common squid case study	Estimation model	HCRs	OM (simulation model)
Chapter 3	Beverton-Holt, combined-stock (C1)	Constant and adaptive effort, based on mean E^*	Beverton-Holt, combined stock (C1)
This Chapter	C2- 3	Constant effort based on mean E^* (and TAC)	C2-3
	C1 and C4	Constant effort based on mean E^* (and TAC)	C4

C1 = combined stock baseline model developed in Chapter 3

C2 = combined stock model with increasing cost (cost increase factor $v=300$)

C3 = combined stock model with decreasing cost (cost decrease factor $v=-300$)

C4 = combined stock model with downward-sloping demand function

Of particular interest is the re-evaluation of the annual TAC-based strategy for common squid under the different assumptions concerning demand and cost specifications, because the economic-related performance measures are sensitive to those assumptions. The TAC-based strategy with a relatively high exploitation rate may perform poorly due to saturation of the market when a downward sloping demand is accounted for, while it may perform well if the true cost is a decreasing function of effort.

6.4 Results

6.4.1 Parameter estimates

Inverse demand function parameter estimates

The estimated inverse demand function parameters for Japanese common squid are given in Table 6-4. The parameter n was not statistically significant. The large standard error and the observed versus predicted price (Figure 6-1) suggest a poor fit of the model to the data. However, this scenario is investigated for heuristic purposes to illustrate the potential effects of a downward-sloping demand function on the management advice, and so the poor fit is not of particular concern to us.

Table 6-4: Inverse demand function parameters (a and n) for Japanese common squid. σ_p = standard deviation of the residual standard error from the fitted model, df =degree of freedom,

Inverse demand parameters	Pr ($> t $)=p-value			
	Estimates	t-value	d.f.	Pr($> t $)
a	66190	7.12	12	1.21e-05
n	2.72	1.91	12	0.179
σ_p	58.4			

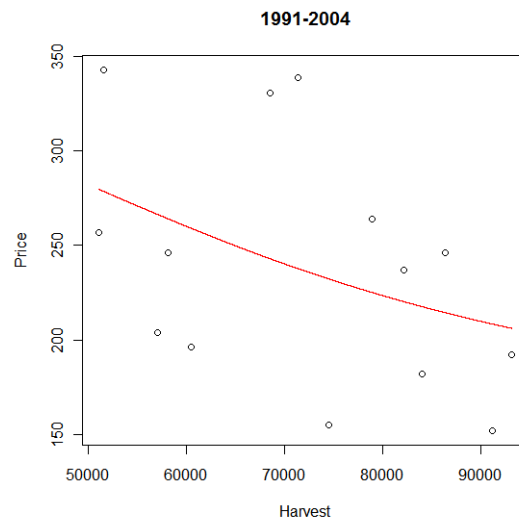


Figure 6-1: Observed versus fitted inverse demand curve for Japanese common squid. Ex-vessel price data for period 1991-2004 were used.

6.4.2 Estimates of optimal effort under different assumptions

6.4.2.1 Effects of the cost specification

The estimates of E^* were extremely sensitive to cost increases at any values of v . For instance, if one assumes an increasing cost of $v = 300$ yen, the resulting E^* in terms of mean value was 239 operators - nearly half of the mean E^* under the constant cost assumption scenario (Table 6-5). The difference in the average unit harvesting cost between the two scenarios was 0.3% (approximately 66,900 yen or roughly US\$660).

Similarly the estimates of E^* were extremely sensitive to cost decreases (Table 6-5). For instance, setting the cost decreasing factor v at -300 yen resulted in a 6-fold increase in the mean E^* . The effects appear to be non-linear (Figure 6-2). At a cost decreasing factor of -500 yen, the discrepancy between the mean and median value of E^* was reduced to approximately 12%, due to the reduced frequency of zero effort trajectory (about 35 runs out of 250). A general conclusion is that the estimates of E^* for the Japanese common squid coastal angling fleet are highly sensitive to the cost changes, and there is no consistent estimator, with significant discrepancies between the mean and median (Figure 6-2). This is consistent with the results from Chapter 3, where the estimates of E^* were highly sensitive to random changes in costs around the mean value, and the median values were zero. Perhaps this is because most operators of the fleet are on the verge of profitability, as evident by the observed frequent occurrence of negative profits (see Chapter 2 for a detail of the expenditure and revenue survey data), as well as a continuous declining trend in the number of operators since 1985.

Table 6-5: Mean values of E^* the Japanese common squid angling fishery under different cost specifications. v = cost trend factor. Price and cost median values $\pm 5\%$ was used as a baseline

v	Mean E^*	Median E^*	Total cost change as % of baseline	unit cost change as % of baseline
-500 yen	8,474	9,652	92%	-23.5%
-400 yen	6,163	8,139	89%	-12.5%
-300 yen	3,329	0	82%	-4.7%
-200 yen	1,567	0	63%	-1.4%
-100 yen	842	0	34%	-0.4%
0 (Baseline)	547	0	0%	0.0%
100 yen	444	0	-22%	0.2%
200 yen	297	0	-81%	0.3%
300 yen	239	0	-125%	0.3%
400 yen	216	0	-149%	0.4%
500 yen	198	0	-171%	0.4%

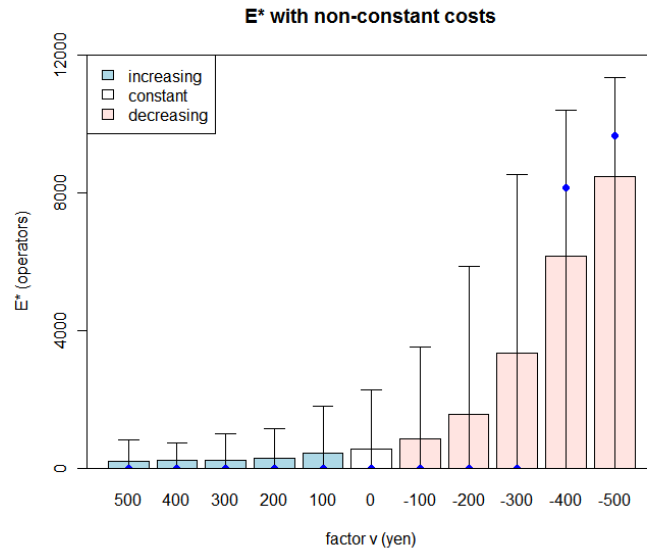


Figure 6-2: Distributions of E^* estimates under different values of the cost decreasing/increasing factor v (yen) with non-constant cost specification relative to effort. Mean values are the height of the bars, and blue dots are medians. The whisker lines show the upper and lower 90th percentiles.

6.4.2.1 Effects of the demand specification

The distribution of E^* for 10-30GT class operators of the Japanese common squid angling fishery when a demand function is included in the model is given in Figure 6-3. Unlike the assumption of squid price being independent of the quantity landed made in Chapter 3, which resulted in a bi-modal distribution of E^* , effort is roughly normally distributed with much narrower confidence intervals of between 217 and 437 operators, despite the large cost variation ($\pm 15\%$ around mean). The mean E^* (344 operators) is less than one third of the estimate under the constant cost assumption (1,226 operators), and is approximately 40% of the observed effort level in 2004. With a downward-sloping demand specification, it is not economical to oversupply the squid in the market even when the environmental conditions are favourable, and this is probably why the estimates of optimal effort are much smaller than the constant price case.

A roughly normal distribution of the predicted optimal effort (Table 6-3) suggests that the errors attributed to the random year to year fluctuations in stock size and cost variables are reduced, with the difference between the mean and median value of E^* merely 0.5%. The experience from the Pacific saury fishery model with the similar demand function in Chapter 3 also suggests that a consistent estimator is obtainable under a downward-sloping demand specification, even when the stock abundance and costs exhibit random fluctuations. Therefore, it can be concluded that the major impact of including a downward-sloping demand in a bioeconomic optimisation results is that it not only yields more conservative estimates of E^* , but reduces errors, which makes it possible to obtain a consistent estimator under fluctuating systems.

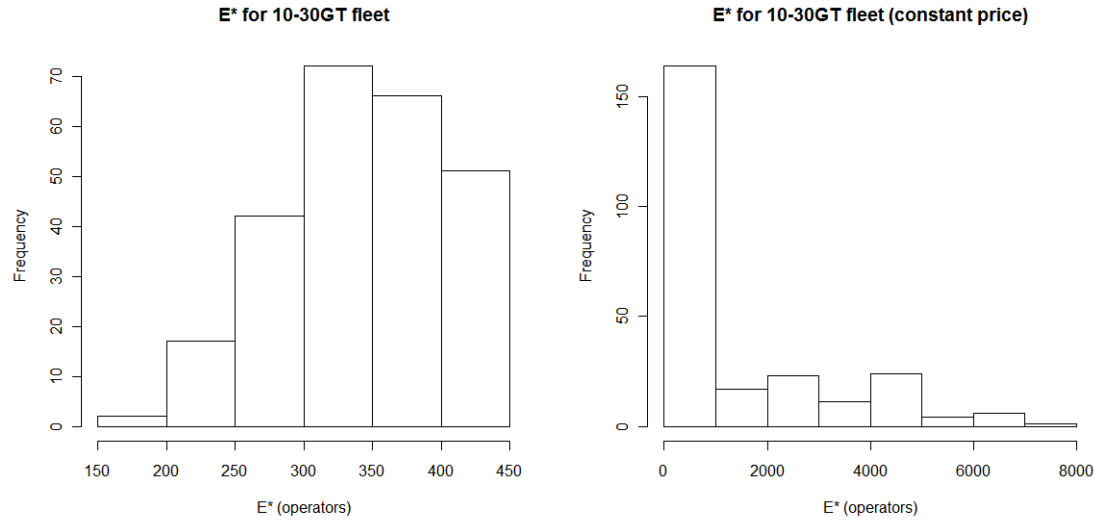


Figure 6-3: Distribution of steady-state effort E^* for 10-30GT fleet of coastal angling fishery for Japanese common squid, when downward-sloping demand is included in the model (left), and the one without demand function(right) with constant price at 2004 level. Stock-recruitment variability $\sigma_R = 0.3$, cost variability with mean $\pm 15\%$ was assumed for both cases.

6.4.3 Performance evaluations

6.4.3.1 Effects of the cost specification

A comparison was made between the constant effort- based and TAC-based strategy ($F_{\text{target}} = 0.3$ and 0.5). The true cost function was assumed non-constant relative to effort, with the cost trend factor v at ± 300 yen. Three levels of constant effort (C1: 547 operators; C2: 239 operators and C3: 3,329 operators) were used.

Under the assumption that the true cost function was a decreasing function of effort, the C3-based constant effort strategy, which incorporated a decreasing cost function in the estimation model, yield a much higher (180% to 330%) sum of discounted profits over a 10 year projection period than those under the TAC-based strategies, and 12 fold larger than C1-based constant effort strategy, which assumes a constant cost relative to effort. This was not surprising because the C3-based constant effort strategy employed a large number of operators (hence, a higher harvest rate than TAC and C1-based strategies) and the harvesting cost per operator became progressively lower as the number of participants

increased.

Table 6-6: Performance statistics for the Japanese common squid angling fishery based on a 10 year projection of stock biomass and discounted profits at 4% discount rate. *SSB_{w0}*, and *SSB_{w,final}* corresponds to the spawning stock biomass for the winter-stock at the initial year and the final year of the projection, respectively

Management Scenario	Conservation Indices		Economic Indices		
	Prob. of <i>SSB_{w,final}</i> < 20% <i>SSB_{w0}</i>	Prob. of <i>SSB_{w,final}</i> ≥ 50% <i>SSB_{w0}</i>	Sum of dis. profits in 10 years, median value (Billion yen)	Prob. of annual dis. profits being negative*	Sum of dis. profits per operator (Million yen)
True system is assumed to have an increasing cost ($v = 300$) function relative to effort					
TAC (F=0.3)	0	0.99	20.4	0.30	17.0
TAC (F=0.5)	0	0.98	32.1	0.31	16.0
Constant effort (C1)	0	0.99	5.5	0.27	10.1
Constant effort (C2)	0	0.99	-2.5	0.27	-10.5
True system is assumed to have a decreasing cost ($v = -300$) function relative to effort					
TAC (F=0.3)	0	0.99	29.8	0.25	23.6
TAC (F=0.5)	0	0.99	54.5	0.23	26.0
Constant effort (C1)	0	0.99	8.0	0.25	14.6
Constant effort (C3)	0	0.99	101	0.22	30.4

*Excluding the initial year.

In contrast, under the assumption that the true cost function was an increasing function of effort, the performance of the constant effort strategies, both C1 and C2-based, was worse than TAC-based strategies in terms of the sum of discounted profits, although they performed marginally better in maintaining the lower probability of negative annual profits. The relatively good performance of the TAC-based strategy was somewhat counter intuitive. The possible reason is that the relative economic gain from a higher harvest rate outweighed the losses from cost increases due to crowding as the number of participants increased over a 10-year projection period. Unlike the cost decreasing case, no improvement was found from the baseline model (C1) to the alternative model (C2), which incorporated the true cost structure. In fact the economic performance of the C2-based strategy was much worse than that of the C1-based strategy, projecting a negative sum of future profits over 10 years. Under the cost increasing assumption upon which the C2-based constant effort strategy was based, the estimate of mean E^* was biased

downwards, due to the high frequency of zero effort trajectories. Perhaps using such a biased estimator caused the poor performance of the constant effort-based strategy.

6.4.3.2 Effects of the demand specification

Assuming that the true relationship between the price of squid and quantity landed was negative (downward- sloping demand), the performance of the constant effort-based strategies (C1 and C4) as well as the current TAC-based strategies were re-evaluated (Table 6-7). The constant effort strategy based on the baseline scenario (C1) was more than 3 times higher (1,291 operators) than that of C4 (344 operators) and this strategy performed poorly in economic indices; the total returns over the 10 years projection period were negative, with a 74% probability of annual discounted profits being negative. These results are not surprising as the future revenues in C1 were assumed to be directly proportional to the harvest of common squid, and driving the squid price down through oversupply was not accounted for, while in fact this was occurring. The TAC-based strategies (both $F=0.3$ and 0.5) performed poorly also, with a 65-75% probability of the annual return from the fishery being negative. The C4-based constant effort strategy, which is approximately 40% of the effort level in 2004, was the only one where positive total discounted profits were projected, and the risk of negative annual profit was maintained at a relatively low level (12.5%). These results confirm that misspecification of the demand function significantly alters the performance of effort-based strategies derived from bioeconomic models. In terms of conservation indices, all scenarios performed equally well, with no significant difference in outcomes across scenarios.

Table 6-7: Performance statistics for the Japanese common squid angling fishery based on a 10 year projection of stock biomass and discounted profits at 4% discount rate. The true model is assumed to have a downward sloping demand. *SSBw0*, and *SSBw.final* corresponds to the spawning stock biomass for the winter-stock at the initial year and the final year of the projection, respectively

Management Scenario	Conservation Indices		Economic Indices	
	Prob. of <i>SSBw.final</i> < 20% <i>SSBw0</i>	Prob. Of <i>SSBw.final</i> ≥ 50% <i>SSBw0</i>	Sum of dis. profits in 10 years, median value (Billion yen)	Prob. of annual dis. profits being negative*
TAC (F=0.3)	0	0.98	-41	0.65
TAC (F=0.5)	0	0.98	-84	0.75
Constant effort (C1)	0	0.99	-47	0.74
Constant effort (C4)	0	0.99	16.3	0.13

*Excluding the initial year.

6.5 Discussion

The assumption that cost and price are constant still dominates bioeconomic fisheries models. In this study, I have demonstrated the consequences of making such assumptions in a MSE framework, by introducing trends in the cost function, and a downward-sloping demand function estimated empirically from the available data. Although the assumptions made were rather arbitrary, the major aim was to demonstrate the risks of disregarding the true structures of demand and cost relative to effort. The outcomes of neglecting these structural uncertainties were staggering for this particular example. In fact negative annual profits for the sampled fleet operators have been reported on average about 40% of the time between 1985 and 2000 (see Chapter 2). Other economic indicators, such as the declining price of squid, and decreasing number of operators, all suggest that most operators in this case study fishery are only on the verge of profitability. Perhaps a high likelihood of negative profits is a major contributing factor to the extreme sensitivity to the changes in operating costs in the bioeconomic model for this fishery. It would be interesting to further expand the analysis of economic structural uncertainties to a highly profitable fishery, such as the Patagonian toothfish fishery, and compare the results. Since the estimates of E^* and Y^* for the toothfish fishery were

found to be robust to cost variability up to $\pm 15\%$ around mean value and price variability up to $\pm 10\%$ in Chapter 4, the impacts of economic structural uncertainties might be smaller, compared to the Japanese common squid case study.

I have demonstrated that including a downward-sloping demand function in bioeconomic models not only resulted in significantly lower optimal effort estimates, but also altered the distribution of the estimates to be roughly normal. The implication is that such a demand curve helps in stabilising such fluctuating systems in the optimisation process and a consistent estimate becomes possible. This is an important aspect when operationalising a bioeconomic TRP-based control measure for fluctuating stocks. When available demand-supply data exhibit inconsistent trends over different time periods, the consequences of alternative plausible assumptions should be tested routinely. An interesting future research avenue would be to apply formal quantitative decision analysis and assign probabilities to plausible model hypotheses being true and/or expert opinions about the supply-demand structure in the OMs to see if such additional information helps to minimise unintended outcomes from the bioeconomic management procedures for short-lived, fluctuating stocks.

I have for the first time included economic components of structural uncertainty into a fisheries MSE, and have demonstrated that the effect of these economic uncertainties can be substantial, potentially dwarfing the effects of biological uncertainties. This makes it imperative that future research considers both biological and economic structural uncertainties, and that management advice emanating from MSEs is fully grounded in testing of relevant alternate model structures.

Chapter 7. General Discussion

7.1 Summary

This thesis had the following three objectives: (1) To estimate bioeconomic target reference points (TRPs) for selected case study fisheries to illustrate the relative robustness of bioeconomic models for different life histories; (2) To develop bioeconomic operating models (OMs) to test the performance of alternative management procedures based on the bioeconomic TRPs, compared to the existing harvest control rules derived from traditional biologically-based TRPs; and (3) To extend the bioeconomic OMs to explore the limitations of standard bioeconomic analyses; to determine whether simple bioeconomic models are capable of summarising the dynamics of a complex system and to what degree of accuracy; and to explore the implications of my findings for the development of efficient management systems for fisheries.

To fulfill these objectives, a two-step approach was taken: First, a framework for bioeconomic MSEs was developed for short-lived species, using the examples of the fisheries for Pacific saury *Cololabis saira* and Japanese common squid *Todarodes pacificus* off the coast of Japan (Chapter 3), as well as for long-lived species, using the example of the Patagonian toothfish (*Dissostichus eleginoides*) fishery around the island of South Georgia (Chapter 4). My main motivation was to test the performance of alternative effort-based harvest strategies based on bioeconomic TRPs for the case study species using multiple performance criteria, compared to the existing harvest control measures derived from more traditional biologically-based target and limit RPs. Another important motivation was to illustrate the relative robustness of bioeconomic model results to the contrasting life history characteristics of the target species. I then used these case studies fisheries as an opportunity for exploring and comparing the implications of multiple uncertainties and to investigate the effects of simplifying assumptions concerning both the biological (Chapter 5) and economic (Chapter 6) parts of the

bioeconomic models.

The fisheries for Pacific saury and Japanese common squid off the coast of Japan are currently managed by a total allowable catch (TAC) system based on maximum sustainable yield (MSY) – oriented target and limited reference points (RPs), which makes implicit assumptions concerning the deterministic and stable nature of harvested populations. However, short-lived pelagic stocks do not fulfil such assumptions, and adopting constant harvesting policies based on MSY may be impracticable, potentially leading to economic inefficiencies or resource depletion. In Chapter 3, I developed a set of adaptive input control strategies, as opposed to traditional fixed input/output strategies, for the stocks of Japanese common squid and Pacific saury, aiming to identify adaptive strategies which make the fisheries more profitable and maintain the sustainability of the resources. It was found that for both fisheries, fixed and adaptive input-based management procedures (MPs) with bioeconomic objective were superior to the current TAC-based MP in terms of achieving higher economic profits, while maintaining or improving (in the case of Pacific saury) the probability of keeping the stock at sustainable levels. The adaptive MPs were found to be preferable to the fixed input control for both fisheries, as they were capable of generating higher economic profits (in the case of the Japanese common squid fishery) and minimising the economic losses from the fisheries, while maintaining the precautionary principle.

In Chapter 4, a similar bioeconomic MSE framework was developed to investigate the relative advantages of an input control measure based on a bioeconomic TRP for a long-lived species, the Patagonian toothfish, versus the current TAC-based measures set by the Conservation of Antarctic Marine Living Resources (CCAMLR). A highly complex age-structured stock assessment model currently being used by the CCAMLR was translated into a simple surplus production model to replicate the stock dynamics of this species, preserving the known biological information while maintaining model simplicity. This enabled me to simulate the future outcomes of the current versus effort-based management procedures. It was found that the 2007 effort level is actually close to being outside of the optimal effort's confidence interval even at a 4% discount rate, and levels

of catch are currently between 250-400 tonnes above the steady-state optimum. The simulation results demonstrate that bringing the stock below the economically optimal level would not only decrease the profitability of the fishery, but also decreases the probability of meeting the conservation objectives.

Chapter 5 and Chapter 6 used the above case studies as an opportunity to explore the role of life history and the interaction between the life history characteristics and fisheries variables for the robustness of parameter estimates from bioeconomic models, as well as the implications of neglecting uncertainties and the “reality” of the fishery system in the estimation of bioeconomic TRPs. This was done by constructing a set of bioeconomic estimation models involving alternative hypotheses about parameter values as well as the structural forms of the dynamics of the population and the economic system. The study found that the effects of uncertainties in key parameter estimates from bioeconomic fisheries models vary among fisheries targeting species with different life history traits. The study also found that the effect of economic structural uncertainties could be substantial for the Japanese common squid fishery, where most operators are on the verge of profitability.

7.2 Scientific Contribution

As mentioned in Chapter 1 and Chapter 2, there is general lack of economic considerations in the existing MSEs (Dichmont et al. 2008; Holland and Herrera 2009), as well as a lack of real world experience in the actual implementation of bioeconomic TRPs in a management context (Dichmont et al. 2010). My thesis was intended to fill these gaps.

Understanding the limitations and biases in parameter estimates from bioeconomic fisheries model is an important aspect when operationalising bioeconomic TRPs. In this thesis, I have illustrated how economics can be explicitly integrated within the MSE framework, and demonstrated the usefulness of this flexible approach as a rigorous tool

for the evaluation of the effect of multiple uncertainties on key parameter estimates from bioeconomic fisheries models, as well as highlighting the merits of including economics in MSE in general.

There are four major scientific contributions from this study: 1) development of a methodology for feedback control rules which adapt to population and economic changes over time for short-lived species; 2) development and evaluation of gradual effort reduction strategies useful for the practical implementation of bioeconomic TRPs for long-lived species; 3) illustration of the role of life history (including maturity and selectivity), and biological structural uncertainties in the robustness of bioeconomic TRPs, as well as the performance of policies based on them; 4) assessment of the implications of economic components of structural uncertainties in parameter estimates from bioeconomic models.

7.2.1 Adaptive management with bioeconomic considerations

One of the major contributions of Chapter 3 was the development of an adaptive or feedback control rule, with bioeconomic considerations. The existing studies of adaptive management in the fisheries economics literature tend to focus on economic evaluations of the history of a fishery by comparing the actual harvest pattern over a period with the optimal pattern (Grafton et al. 2000; Sandal and Steinshamn 2001a; 2001c; McDonald et al. 2002; Arnason et al. 2004), and few applications exist that compare actual management with management using a feedback rule with bioeconomic considerations. The adaptive scheme developed for the coastal angling fleet for Japanese common squid is a model-based method, where new knowledge is gained over time and the models are updated and management decisions are adapted accordingly, while the scheme developed for the Pacific saury is an empirical approach, where the control action is decided based on the results from a pre-season survey, and predicted and observed changes in prices and costs. These are similar to the existing adaptive output-based management practice for the South African pelagic fisheries (De Oliveira and Butterworth 2004), and to some extent the Falkland island squid fishery (Basson et al. 1996), but the major difference is the explicit inclusion of economics.

A novel feature of the adaptive scheme proposed was the development of a feedback rule, where in-season adjustment in effort levels was based on the detected changes in stock abundance and the catchability coefficient - a key parameter for a stock assessment, often assumed to be constant over time despite the evidence to the contrary (Ricker 1975; Arreguín-Sánchez 1996). Annual catchability variation has not been taken into account in the existing examples of adaptive management for fisheries resources. Higher catchability means that fish are easier to catch on average given the same level of inputs. This scheme might permit resource managers to set a more aggressive harvesting strategy when environmental conditions are favourable, and also enables them to make the necessary adjustments when environmental and economic conditions change. Thus, higher profitability can be expected from the fishing operation under such a scheme, while maintaining the precautionary principle. The results in Chapter 3 demonstrate that this approach is possible, and is potentially useful for other stocks with similar biology and especially for fisheries that are borderline profitable.

7.2.2 Gradual effort reduction strategies

One of the key features of the framework developed in Chapter 4 is the evaluation of gradual effort reduction strategies, where the effort is reduced gradually to the optimal equilibrium level within a management time-frame of 35 years as dictated by CCAMLR, so that sudden reduction in the levels of effort and associated harvest can be avoided. This is an important consideration for implementing bioeconomic TRPs in practice, because a drastic harvest/effort reduction can result in short-term economic losses and such a control measure is unlikely to be supported by the fishing industry. The performance of the gradual effort reduction MPs were found to be superior to the current TAC-based MP in terms of both the probability of keeping the final stock size above 50% of the initial stock size, and generating higher total discounted profits over 35 years. The simulation results provide an economic justification for a gradual reduction of current effort to the economically optimal steady-state level, and also demonstrate the conservation benefits of including economically-based objectives, as the economic strategies outperformed the current management approach in terms of the sustainability performance criteria.

7.2.3 Roles of life history and biological structural uncertainties on the robustness of bioeconomic TRPs and policy performance

Past studies of uncertainties in bioeconomic parameter estimates have focused on the comparison between deterministic and stochastic results (see section 2.1.7), or the uncertainties related to random effects and parameters, and less attention was paid to structural uncertainties (Nøstbakken and Conrad 2007). For instance, biomass dynamic models, such as the Schaefer or Fox model, have been used extensively in the bioeconomic modelling of fisheries, but the consequences of imposing their simplified assumptions about the population dynamics onto bioeconomic models have not been discussed adequately (Tahvonen 2008). Moreover, little work has been done to investigate in detail how differences in the life history characteristics of the fish or the interaction between these characteristics and fisheries variables affect the robustness of bioeconomic parameter estimates.

One of the key findings from Chapter 5 was that the estimates of equilibrium effort and harvest were sensitive to the stock-recruitment variability *only* for the species or scenarios with low steepness values – one of the more typical life-history characteristics of small pelagic species. On the other hand, the specification of the underlying population models (maturity, fishery selectivity and so on) had much stronger impacts on the estimates of equilibrium effort and harvest for the long-lived Patagonian toothfish, while such an impact was found to be negligible for the short-lived Pacific saury. This confirms that the relative importance of different types of uncertainty on equilibrium conditions differs among fisheries targeting species with different life-history traits. Interaction between the gear selectivity and maturity parameters appeared to be key to the comparability of age-structured and biomass dynamic model results and I recommended that there was a need to gather more empirical examples to test this hypothesis.

Another major contribution from Chapter 5 is the simulation of the future performance of a constant effort-based control policy comparing the less complex (Schaefer) with complex (Beverton-Holt) bioeconomic estimation models. In the case of the Patagonian toothfish fishery, the fixed effort strategy based on the age-structured bioeconomic TRP,

which incorporated the complex population dynamics actually used for the assessment of Patagonian toothfish around South Georgia, failed to meet the conservation objective for the stock set by CCAMLR when the uncertainty in steepness was not accounted for, while the fixed effort strategy based on a simpler Schaefer bioeconomic TRP performed much better in meeting the conservation objective, although the latter resulted in much lower total discounted profits over 35 years. This is the first clear demonstration of the trade-off between economic returns and conservation goals, using alternative model hypotheses in an MSE framework.

The last contribution from Chapter 5 is the demonstration of the economic implications of misspecifying the stock structure. Few serious attempts have been made to consider spatial structure or stock structure in operating models (Butterworth and Punt 1999), with limited examples where OM's were specifically designed to examine the implications of stock-structure uncertainty (IWC 1994; Dichmont 2006; Kell and Fromentin 2007; Punt and Hobday 2009). In these available examples, the economic performance was not considered. I used the Japanese common squid case study as an opportunity to assess the economic implications of the misspecification of stock structure, and found that the assumptions made about stock structure not only resulted in different estimates for the bioeconomic TRPs (generally, smaller equilibrium levels of effort from the multi-stock models) but also different economic outcomes, although little evidence of differences in conservation-related outcomes was found. If the true effort is predominantly allocated to the winter stock, but the management authority fails to take into account such disproportional effort allocation in the estimation model, the management action will be based on an overly optimistic level of optimal effort, which then results in poorer economic performance.

7.2.4 Implications of economic structural uncertainties

The previous investigations of structural uncertainties mentioned above which used the MSE approach, as well as formal decision analysis (Kirkwood and Smith 1996; Kuikka et al. 1999; Patterson 1999; Hammond and O'Brien 2001; McAllister and Kirchner 2002; Michielsens and McAllister 2004), tended to focus on the biological aspects of structural

uncertainty alone. The assumption that the prices and costs are constant still dominates standard bioeconomic fishery modelling, although such assumptions are rarely, if ever, true in the real world and the implications of making such a simplified assumption for a real fishery has not been investigated adequately. In Chapter 6, I have, for the first time, included economic components of structural uncertainty into a fisheries MSE framework, and have demonstrated that the effect of these economic uncertainties can be substantial, potentially dwarfing the effects of biological uncertainties. This makes it imperative that future research considers both biological and economic structural uncertainties, and that management advice emanating from MSEs is fully grounded in testing of relevant alternate model structures.

7.4.5 Implications of my findings

Lastly, combining the work mentioned above enabled me to comment on the following two questions related to the limitations and potential of implementing bioeconomic TRPs for a real fishery.

Is it possible or practical to identify “optimal” conditions for fluctuating stocks?

The experiences of the Japanese common squid fishery case study provide a classic example of the ever-present management issue of estimating the “optimal” level of fishing effort for fluctuating stocks: the estimated equilibrium effort trajectory was highly volatile with no consistent estimates, made evident by the large discrepancy between the mean and median values. The difficulties in identifying the optimal levels for short-lived species was recently reported in Dichmont et al. (2010) using the Australian Northern prawn fishery as an example. They argued that implementing MEY as a management target in practice is difficult because different assumptions concerning constraints, prices and costs result in differing estimates of MEY and its associated effort trajectories, so that management based on MEY as a target will require the ongoing revision of the target, and is even less likely to be successful without stakeholder participation in the definition of the problem, including the assumptions used. The findings from the Japanese common squid fishery case study in Chapter 3 were largely consistent with their observations. This almost tempts me to conclude, like them, that estimating the “optimal” level of fishing

effort or catch for fluctuating stocks is difficult and impractical. However, this thesis found that a consistent estimator is obtainable under a downward-sloping demand specification, even when the stock abundance and costs exhibit random fluctuations (see Chapter 3 for the Pacific saury case study, where such a demand curve was empirically estimated, and Chapter 6 for the Japanese common squid fishery, where alternative forms of demand function were investigated for heuristic purposes). The presence of a downward-sloping demand curve seems to improve the robustness of bioeconomic TRP estimates by suppressing large effort and catch estimates in order to maintain the highest prices even at high stock abundance, which in turn result in tight confidence intervals around the estimated mean.

This leads to a general conclusion that the use of bioeconomic TRPs may be inappropriate for fisheries that meet the following conditions: i) fisheries that exhibit considerable fluctuations in abundance; and ii) whose profitability is low or borderline, as this makes the results of bioeconomic models naturally sensitive to the changes in economic variables; and iii) no clear negative relationship between the quantity landed and price of the fish.

This work does not cover enough possible fishery examples to provide a general set of responses of bioeconomic model results to certain types of uncertainty, with uncertainties associated with economic variables and their structural forms adding to the already complicated biological uncertainties. It is hoped that, as time goes by, more work is done and a broad enough set of examples exists to create such a general understanding. This will enable scientists to develop a set of proxies for bioeconomic TRPs based on the characteristics of fisheries through meta-analysis, as opposed to a single default proxy (e.g. $1.2B_{MSY}$ is used as a proxy for B_{MEY} in Australia). In the meantime, it is perhaps better to make educated guesses about potentially applicable strategies, based on the currently available set of examples, and use the MSE approach to evaluate the most appropriate one for the system under consideration.

Are bioeconomic TRPs more precautionary than their biological counterparts?

Throughout this study, I used bioeconomic operating models as a tool not only to test the robustness of the estimates from the models, but also to determine whether management procedures based on bioeconomic TRPs perform better than more biologically-oriented management procedures in the face of multiple uncertainties. Although bioeconomic TRPs are generally considered more conservative (Defeo and Seijo 1999; Grafton et al. 2007), their performance has rarely been tested.

The Patagonian toothfish fishery case study demonstrates the conservation benefits of using bioeconomic TRP-based management, as the economically-oriented strategies outperformed the current management approach in terms of both economic and sustainability performance criteria, although caution needs to be taken to properly account for the uncertainty in steepness parameter when using an age-structured bioeconomic model. This shows an encouraging potential for the successful implementation of bioeconomic TRP-based management for long-lived species. Although the difficulty in estimating consistent bioeconomic TRPs limits the potential for implementing them for short-lived species, the adaptive management framework developed for the Pacific saury fishery demonstrated both the conservation and economic benefits of using bioeconomic TRPs-based adaptive management. Testing the future performance of bioeconomic TPRs has proved useful to validate the effectiveness of their use as a management target for a real fishery.

7.3 Areas for further research

In the present study, the types of uncertainties considered were limited to key parametric uncertainties in the stock-recruitment relationship and gear selectivity, observation and process errors, and structural uncertainties with respect to the specification of the relevant population models (age structured versus biomass dynamic, stock structure and connectedness), cost specifications, and the demand function. I also focussed on a limited set of case studies to illustrate my points, for which the data were not always of the best

quality and availability, particularly the economic data.

Based on the results of the common squid case study, the failure to incorporate the information on the nature of the supply-demand relationship and the structure of cost relative to effort can be potentially very important. When more detailed data on price, landed quantity, and the costs of operation become available it is important to test the sensitivity of existing model results to assumptions concerning price and cost. For example, among my case studies the treatment of the price of Patagonian toothfish as independent of the landed quantity, as well as the constant cost assumption, require further investigation. There is a clear need for accurate economic data for the case study fisheries, which is true for fisheries in general. Lack of cost data seems to be a fundamental constraint to integrating economics into MSEs. For example, the Commission for the Conservation of Southern Bluefin Tuna (CCSBT) is currently developing a new MSE framework to limit the catch for the stock of Southern bluefin tuna *Thunnus maccoyii*, but the economically-related performance criteria have not yet been considered due to the lack of cost data (CCSBT per. comm.). Given that an understanding of these economic relationships has a substantial impact on the predicted economic outcomes, more institutional effort should be directed towards establishing a mechanism to collect reliable economic data through e.g. strengthening stakeholder involvement and industry collaboration in deciding management objectives.

There is often a strong possibility of temporal autocorrelation in recruitment. Punt (1997) wrote that ignoring the consequences of autocorrelation in the recruitment anomalies can lead to overly optimistic appraisals of the ability of management procedures to achieve conservation objectives. In this study, the form of recruitment variability was assumed random because no apparent autocorrelation was detected in the available time-series data for the Patagonian toothfish fishery, and no such data were available for the fisheries for Pacific saury and Japanese common squid. However, it was interesting to see the sensitivity of the bioeconomic MSE to the form of recruitment variation (autocorrelated versus random) for the case study fisheries. In addition, the form of the stock-recruitment relationship for the winter-stock of Japanese common squid was assumed to be the same

as that of autumn stock. Although this is a plausible assumption, it would be useful to investigate the sensitivity of the results to such an assumption of environmentally driven correlation. A wider implication of properly incorporating environmentally driven correlation, as well as ecosystem dimensions (e.g. population and/or species interactions), is that it allows us to assess the impacts of other drivers (e.g. global climate change) on the fish stocks, rather than fishing alone. The joint effects of overexploitation and climate-driven declines in productivity have contributed to the collapse of Atlantic cod in the North Sea (Beaugrand et al. 2003), and in Canada (Myers et al. 1997a). Ecosystem-based models capable of integrating multiple drivers across trophic levels are becoming increasingly popular as a tool to assess the risks of future stock collapse under different climate scenarios (Lindegren et al. 2010) or to investigate the impacts of both climate and fishing on marine ecosystems (Smith et al. 2007; Travers et al. 2007; Fulton 2010). So called “big picture models” of the whole ecosystem have been used mainly to explore or evaluate hypotheses and one proposed future research priority is to evaluate the minimum level of realism needed when providing management advice (Kell et al. 2007). An intriguing research avenue would be to use the MSE approach to evaluate the benefits of adding complexity into the practical management models and how far one can go with the data we have towards a set of minimum realistic models.

Another major limitation of the study was the exclusion of spatial elements in the case studies. Spatial elements may be particularly important to consider in the future, since seasonality in the spatial distribution of the resource and fishing intensity are relevant in the assessment of short-lived species (Seijo 2005). Moreover, the study did not consider social aspects - one of the key management objectives for many fishing nations. Mardle et al. (2002) found that the main objectives of fisheries management are generally similar throughout the world and include resource conservation, food production, economic wealth, and employment and incomes for fishers. Thus there is further scope to investigate the performance of alternative strategies using multiple (biological, economic, and social) objectives. The technique of multiple-criteria decision-making (MCDM), a subset of multi-objective programming, has been applied to general natural resource management (e.g. forestry, agriculture) to find solutions under multiple objectives, but its

applications to fisheries management have been quite limited compared to other natural resource management (Mardle and Pascoe 1999; Leung 2006; Kjærsgaard 2007). There has been some examples of MSEs that have incorporated social objectives (Mapstone et al. 2008; McDonald et al. 2008), but more are needed.

Another interesting research avenue would be to extend the study on the Patagonian toothfishery in South Georgia to carry out an MSE using a fully age-structured OM, and use the Shaefer-based MP developed in Chapter 4 as a management model, although at this point, it was not possible due to the computational difficulties. This would allow us to investigate whether the simple MP is capable of producing robust management advice compared to the current complex MP. If we can show that the simpler MP performs better, it will add weight to the results from previous studies that have shown that increasing the apparent realism of the underlying dynamics of the population model does not necessarily improve performance (Ludwig and Walters 1985; Kirkwood and Smith 1996; Punt and Smith 1999; Parma 2002). Furthermore, a simpler MP has the potential to reduce the management costs.

In this study, all three case study fisheries are single-species fisheries largely due to the limited availability of cost data from participating fleets. However, many world fisheries are multi-species, and bioeconomic modelling for multi-species fisheries faces additional challenges. For instance, fisheries bioeconomic models typically use an aggregated production function (e.g. Cobb-Douglas), which generally links the physical quantity of outputs and specific combinations of the physical quantity of inputs used in the production process. These models assume that separate components of effort can be consistently aggregated into a composite index, and also assume a single production process (joint in inputs production) for multispecies fisheries. These assumptions, however, have rarely been tested and are rarely true in practice. Based on a survey of firm-level production technology studies, Jensen (2002) noted that most empirical studies suggested disaggregated modelling was appropriate (hence, did not support the Cobb-Douglas form). If the underlying assumption of the aggregated production function is incorrect, the results from bioeconomic models could be biased because the model would

underestimate the “true” fishing effort due to input substitutions (e.g. fishing location) and result in the underestimation of fishing mortality. Moreover, fishers may alter the combinations of species caught by changing when, where and how they fish in response to fisheries regulations (e.g. area closures) and enforcement, or economic conditions. This situation, called “effort creep”, occurs as operators in an input-controlled fishery substitute unregulated fishing inputs for regulated inputs, and has been reported for several mixed fisheries with input control, such as the Australian northern prawn fishery (Elliston and Cao 2004) and the Dutch beam trawl fishery (Hoff and Frost 2008). In most dynamic bioeconomic models, however, fleet dynamics are represented in a crude or *ad hoc* manner and relatively few empirical examples (Holland and Sutinen 1999; Holland 2000; Elliston and Cao 2006) exist that model individual vessels’ behaviour or location choices explicitly. Recently, considerable work has been directed towards understanding vessel movement in the fisheries literature (Branch et al. 2006; Little and McDonald 2007; Rijnsdorp and Poos 2007; Poos et al. 2009; Venables et al. 2009) and “fleet-dynamic models” which simulate the spatial and temporal effort allocation and the movement of individual vessel are becoming prevalent, although relatively few MSEs have incorporated fleet dynamics so far (Fulton and Smith 2007; Venables et al. 2009).

There are numerous uncertainties that may affect the bioeconomic assessment of fisheries. Although it is not possible to capture all aspects of uncertainty in a bioeconomic model, the MSE approach can be used to identify the consequences of the major uncertainties for management performance, and prioritize further research. Punt (2006) noted that one feature of an MSE that has perhaps not been used as extensively as might have been expected is the ability to comment on the “value of research” to reduce uncertainty in achieving management goals. The simulation evaluation work presented in this thesis, and in particular the survey-based MP tested for Pacific saury, which looked at the impacts of survey precision, demonstrates how an MSE can be used to identify which factors are more likely to impact the robustness of estimates, and to provide a basis for resource managers to prioritise future research needs. Given that fishery-independent surveys and research in general are costly, it is worth investigating further the usefulness of economic MSEs from the administrative perspective, in order to support the

development of cost effective research plans.

In order to promote the implementation of MEY as a target for a real fishery, perhaps it is time for us to move from a simple illustration of the “expected” value of optimal effort based on deterministic methods (Nøstbakken and Conrad 2007) to stochastic approaches that provide a probability distribution of the estimates of bioeconomic RPs, so that scientists can provide more information to decision makers on the precision of their estimates and the risks attributed to uncertainties. Routinely testing the sensitivity of the results from bioeconomic models against a set of plausible assumptions would be another step towards gaining credibility among stakeholders, and towards the successful implementation of economically-oriented harvest strategies, that hold a potential to achieve both conservation and economic objectives.

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