UNIVERSITY OF SOUTHAMPTON

Faculty of Engineering, Science & Mathematics
School of Ocean and Earth Science

An Improved Mixed-Error Non-Equilibrium Stock-Production Model and its Application to some Brazilian Fish Stocks

by

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“I am the way, and the truth, and the life”
John 14:6

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF ENGINEERING,
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A new and more comprehensive estimation method for stock-production models is proposed, to provide more reliable stock assessment when data availability is limited. Using difference equations to implement a non-equilibrium production model, the new approach (named POEEM, for Process and Observation Errors Estimation Method) incorporates uncertainties due to both process and observation errors, employing a non-linear model fitting approach. The method has been evaluated using both simulated and real data sets, and has been applied to data from some Brazilian fish stocks. The weighting ratio between process and observation errors has proved to be a crucial factor in determining the model results, and a fully satisfactory method for selecting this ratio is still required. Sensitivity analyses conducted with the simulated data have been used to study the behaviour of the method for a range of exploitation and noise levels. Data series with low and medium levels of noise yielded consistent results irrespective of the level of exploitation, whereas very noisy data series did not provide reliable results.

For comparison, data from a previously analysed stock was also tested with POEEM and resulted in peculiar results for the stock status and management advice. Data from four demersal species caught off southeastern Brazilian coast were also analysed employing POEEM, and more conventional methods. For all of them further analyses on mapping some parameters sensitivity must be conducted in order to increased the reliability of the results. Two species have the POEEM estimated assessment trend corroborated by independent biological studies. King weakfish is apparently on the verge of a collapse, with very low levels of production and biomass. Jamaican weakfish is around its maximum sustainable yield and the exploitation level on this stock should not be intensified. For the other two species, high levels of uncertainty were responsible for contradictory outcomes. For whitemouth croaker, the balance between process and observation error could not be consistently achieved, because of high amount of observation noises. For grey triggerfish, the assessment

revealed a collapsed stock, but previous biological studies do not corroborate this scenario. Discarding onboard and fleet behaviour appear to be confusing the analysis of this data series.

In general, the new method seems to be capable of giving useful results, consistent with biological studies, when a limited amount of data is available. However, further work is needed to find a satisfactory method for fixing the weighting ratio. In order to improve the Brazilian stock assessments, both fishery and biological data must be continuously collected to maintain and update the results, and effort data needs to be collected for other fleets, and incorporated in the analysis.

DECLARATION OF AUTHORSHIP

I, Silvia Helena Bulizani Lucato declare that the thesis entitled

An Improved Mixed-Error Non-Equilibrium Stock-Production Model and its Application to some Brazilian Fish Stocks

and the work presented in it are my own.

I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- none of this work has been published before submission.

Signed:

Date: 31 March 2006

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Chapter 1

Introduction

1.1 Motivation

The overall fishery production in Brazil has increased approximately 30% in the last 10 years, especially at the beginning of the 21^{st} century when production reached just over 1,000,000 t (FAO, 2005, IBAMA, 2004). Marine aquaculture is responsible for the majority of this rise. However, marine and freshwater fisheries also show an upwards trend in their productions (IBAMA, 2004).

This phenomenon is a result of recent investment strategies in fishery and aquaculture adopted by the Brazilian government. A number of new measures with economic and social impacts have been put into practice, together with a review and amendment of current legislation. These measures range from (1) renewal of the fishing fleet, (2) a loan program for small scale fisheries and aquaculture, (3) a loan program for fishery and aquaculture development in Northern and Northeastern areas, (4) an infrastructure program to improve landing, storage, trade, and transportation facilities for fishery and aquaculture, (5) a joint venture program for foreign fleets, (6) re-enlisting professional fishers, (7) a review of environmental legislation to encourage the use of federal reservoirs for aquaculture, (8) fleet monitoring through satellite and onboard observers, (9) fuel subsidies, (10) deployment of artificial reefs, (11) literacy and further education programs for fishers, and (12) closed season insurance (SEAP, 2003).

Conversely, very little attention has been given to fundamental research in fish population and environmental dynamics, and development of sustainable fishery practices, even though effective fisheries management is dependent on the scientific understanding of the fishery resources abundance, resilience, and relationship with the environment. Brazil has acknowledged several international treaties on sustainable and responsible fishery and environmental protection (Froese and Pauly, 2005), however, most of their provisions have not been legally implemented.

Comparing global levels of fishery production, including marine and freshwater resources, with Brazilian production, the former has a lower rate of increase (FAO, 2005). In particular, marine fisheries have been largely decreasing in the last two decades (Watson and Pauly, 2001) since the vast majority of fish stocks are either fully fished, overfished, depleted or recovering (Schiermeier, 2002), particularly top predator species (Myers and Worm, 2003). There have been several claims about the crisis in the fishing sector since catch levels are at unsustainable levels (Watson and Pauly, 2001, Pauly et al., 2002).

Fishery resources are renewable but limited by the environmental capacity, since they are based on the extraction of wildlife. As a result, fishing pressure has to be controlled, otherwise it will at best increase up to the point of economic unprofitability, and at worst will result in a total stock collapse beyond replacement repair (Pope, 2002). Modern fisheries are characterised by overcapitalisation and overcapacity of the fishing fleets, which impose a high pressure in the fisheries power (Gréboval and Munro, 1999). Fleet reduction policies have been highly recommended due to the current unsustainable fishing levels specially in the developing world (Garcia and Newton, 1997). The current exploitation scale is considered to be far too intensive to be sustainable for a long term activity (Pauly et al., 2002). Despite large economic and social investments, without the living resources the sector would cease to exist. There has been a recent case of a cod stock collapse along the Canadian east coast, where social, cultural, and economic costs were enormous (Hilborn et al., 2003). Therefore, to disregard the state of the fisheries resources with respect to biological and environmental factors, when investing and legislating on fishing and aquaculture is very shortsighted.

In order to conduct either traditional single species stock assessment (Hart and Reynolds, 2002) or to apply the ecosystem based approach (Garcia et al., 2003) there is a need for the basic data of the fishery. Total catch, measures of effort, and population structure in length and/or age are among the basic data, and increases in the complexity and volume of the data are required as the chosen assessment model becomes more advanced (Hart and Reynolds, 2002). There have always been problems even in the collection of such basic data in Brazil. Lack of continuity and improper data recording for catch and effort were results of institutional instability due to changes in government policies (Lima and Dias Neto, 2002). Furthermore, catch data is recorded according to common names which might represent more than one species (Freire, 2005).

Without the basic fishery data there have been few schemes to conduct fishery assessment modelling (Magro et al., 2000, Cergole and Avila-Da-Silva, 2005). Although these modelling efforts have provided useful scientific background for a few implemented policies, they are not conducted on a regular basis, and they are mainly focused on biological studies rather than stock assessment modelling.

Effective fishery management requires data collection and analysis, frequently through quantitative biological and ecological fishery modelling. Research is fundamental for the development of management plans, for the prevention of overfishing, for recovering collapsed or overfished stocks, for the sustainable exploitation of new resources, and for establishing sustainability indicators. Stock assessment is based on mathematical and statistical concepts and approaches which have been developing for 150 years (Smith, 1994), but still has a long way to go. Although there has always been a lot of criticism on the accuracy of the results (Hilborn and Walters, 1992, Hilborn and Mangel, 1997), methodological improvements are constantly appearing (Quinn and Deriso, 1999, Haddon, 2001, Hart and Reynolds, 2002). Moreover, assessment methods are inevitably uncertain since a biological system is never so deterministic as a physical one (Schnute, 1987). The uncertainties arise from biological, ecological and technological grounds and ideally all these ought to be addressed in the assessment process in order to provide mathematical consistency, and accurate results within known confidence limits (Hilborn, 1997).

Complete coverage of landing points and reduction of the observation uncertainties are desirable features in a proper data collection system (Schnute, 1994, Sparre, 2000, Evans and Grainger, 2002). Costs of fisheries data collection are generally high and proportional to the level of detail required. Parsimony should be take in account when costs represent a constrain to achieve an efficient system.

Overfishing occurs when fish stocks are reduced below sustainable levels of replacement after natural and fishing mortality. Reduction of the catch-per-unit-effort, low spawning stock biomass, reduction of the size at first reproduction are among the signs of overfishing, i.e. the adult stock has been reduced to a level that is unable to replace, through reproduction and body growth, the portion of the population which has been taken naturally and by the fishing gears. Fluctuations of catches have been the subject of governmental and scientific attention since the middle of the nineteenth century, when the expression overfishing was firstly used (Cleghorn, 1854). Management measures, such as seasonal closure of fisheries during spawning time, establishment of minimum landing size, and total catch allowance for a species, are set to avoid overfishing.

Several methodologies are currently used to deal with uncertainties in the stock assessment modelling i.e. nonlinear approaches, maximum likelihood and Bayesian methods. Nonlinear estimation will be used as the main estimation tool to carry out stock assessment in this study, which will consider a single species stock assessment for each of the four demersal species which are responsible for a great part of the demersal fishing production in the southeastern coast of Brazil (Castro, 2000, Ávila-Da-Silva et al., 2005).The species are whitemouth croaker (*Micropogonias furnieri* (Desmarest, 1823)), king weakfish (*Macrodon ancylodon* (Bloch and Schneider, 1801)), Jamaica weakfish (*Cynoscion jamaicensis* (Vaillant and Bocourt, 1883)) and grey triggerfish (*Balistes capriscus* (Gmelin, 1789)). A stock assessment method with an appropriate mathematical basis for accurate estimation in situations when little data is available will be used.

1.2 Brazilian Fisheries

Brazilian marine fisheries together the with Uruguayan and Argentinean ones compose the FAO Southwest Atlantic Ocean major fishing area 41 (CWP, 2005). Argentinean marine fishery production has sharply increased until 1997 when it reached the maximum of just over 1,300,000 t (Figure 1.1) and has decreased since then. However, in 2004 the Argentinean marine production level was nine times the Uruguayan production and twice as much as the Brazilian one (Figure 1.1). The wide continental shelf, a rich subantarctic current, and the export of nutrients and organic matter from land to coastal waters are responsible for the great productivity in these waters. Uruguay and Argentina signed the Rio de la Plata and Its Maritime Area Treaty in 1973 allowing access to resources exploitation to Uruguay in the area between 34° S and 39°30′ S latitude. Comparatively, the Brazilian fisheries production has increased up to 750,000 t in the 1980s but dropped to current levels in the late 1980s whereas the Uruguayan marine catches have rissen considerably in the 1970s after the treaty with Argentina and have remained at the same levels since then (Figure 1.1).

Fishing is a minor sector of the Brazilian economy in comparison to other animal protein production. One of the reasons for this is the cultural preference for meat reflected in the *per capita* consumption of animal protein in kg/person/year; i.e. 6.8 of fishery products, 37.1 of beef, 12.6 of pork and 31.2 of poultry (SEAP, 2005). The fish consumption is high only in the Amazon watershed region, i.e. 30 kg/person/year (SEAP, 2005) due to the absence of agriculture there. On the other hand, Brazilian livestock production employs intensive production systems and relies on modern

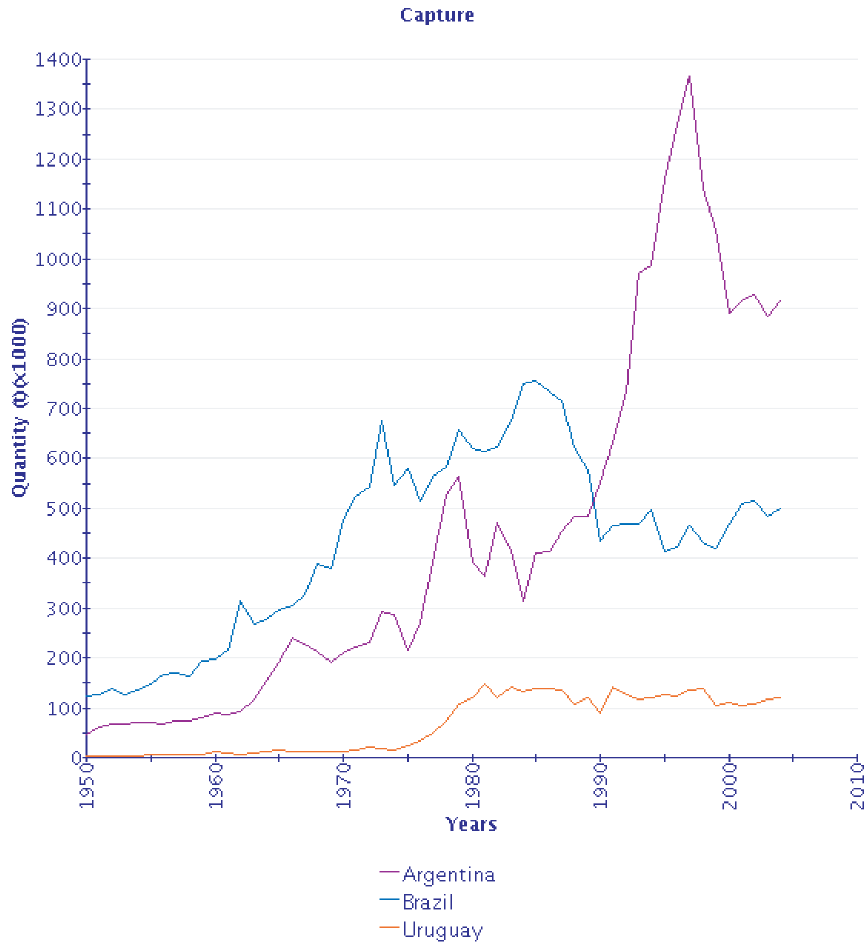

Figure 1.1: Marine fishery production for the countries in the Southwest Atlantic Ocean, i.e. FAO area 41. Data from FAO Fisheries Global Information System (CWP, 2005).

technologies resulting in highly productive crops. As a consequence of the economic importance of livestock raising this is a well regulated sector. Fisheries, on the other hand, where production is dependent on environmental factors, are neglected in terms of regulation and enforcement.

The Brazilian coastal environment has a low biological productivity compared with temperate regions since it is mostly located in the tropical and subtropical zones, without strong seasonal oceanographical variability and large scale upwelling processes (Aidar et al., 1993, Bassoi, 2005). The only exception occurs off the southern

Table 1.1: Brazilian fishery production in weight (t) and percentage (%) of the weight based, in the geopolitical regions during 2002, for various production systems, i.e. industrial, small scale, and aquaculture production. Data for both freshwater and marine ecosystems. Source IBAMA (2004)

Region	Industrial		Small Scale		Aquaculture	
	(t)	%	(t)	%	(t)	%
North	25,199.0	9.2	231,984.0	85.0	15,797.0	5.8
Northeast	13,269.0	4.7	187,675.5	65.8	84,181.0	29.5
Southeast	63,836.5	41.4	52,966.0	34.4	37,246.5	24.2
South	149,237.5	58.1	19,468.5	7.6	88,194.5	34.3
Centre-west	0.0	0.0	11,946.0	31.6	25,868.0	68.4
Total	251.542.0	25.0	504.040.0	50.0	251.287.0	25.0

coast of Brazil, where the Subtropical Convergence of the Brazil-Falklands (Malvinas) Current and continental land runoff play a fundamental role in the biological productivity of the southwestern Atlantic Ocean (Seeliger et al., 1997).

The social consequences of unsustainable fisheries are high since, on average 50% of the total production comes from small scale fishing, with a rather wide and uneven distribution between the geographical regions (Table 1.1). Therefore, ecological impacts on the natural populations, environmental changes, and social-economic consequences of the fisheries justify the need for more comprehensive research to support sustainable management in Brazil.

1.3 Aims of this Study

As a consequence of the neglect of stock assessment studies in Brazil and the urgent need to support effective management measures, this study has been designed to develop and use an appropriate stock assessment method with the available data for the target species of a bottom pair trawl fleet, aiming to

1. propose a new estimation method for stock-production models which incorporates process and observation uncertainties, using a non-equilibrium least squares framework, appropriate for situations when data availability is a constraint,

2. test the performance of the proposed method through a comprehensive sensitivity analysis, pointing out the potential advantages as well as deficiencies,

3. provide stock assessments for four marine fisheries resources from Southeastern Brazil, using the new approach. Discuss the assessment outcomes together with independent scientific knowledge and current management regulations. Provide recommendation for management measures and further studies.

1.4 Thesis Outline

This work consists of seven chapters. This chapter places the management system of the Brazilian fisheries into perspective, pointing out deficiencies and discrepancies. Whereas there is a global and wide-ranging discussion on different assessment approaches (such as, ecosystem based, singles species, multispecies, and Bayesian frameworks), in Brazil very little assessment is conducted at present. The lack of basic data, and economic and political incentives for stock assessment analysis, means that traditional fisheries resources remain poorly understood, with critical signs of overfishing. Recent government policies have stimulated the race for fish, especially offshore fishing, and there is an urgent need for decision makers to base their management plans on scientific knowledge.

Chapter 2 focuses on the theory of stock production modelling as a single species assessment methods, due to its low data requirement. Starting with an overview of the concepts and definitions of the stock production model, the chapter continues by describing different types of parameter estimation methods emphasising the nonlinear approach, as used in this study. In addition, the role of uncertainty estimations, parameter correlation, bias, and confidence interval estimation by bootstrapping is examined.

The third chapter deals with formulation of the stock production model used as a starting point for this research. Considering the importance of incorporating uncertainties in the estimation process, a stock production model which aims to allow both process and observation errors and has been previously proposed is analysed in this chapter. The data and results obtained here are compared with the previous estimation and discussed, especially with respect to perceive inconsistencies and imperfections in the previous work. This provides a general framework for the further analysis of the chapter 4 and 5.

Chapter 4 introduces a new stock production model estimation method which incorporates both observation and process uncertainties in a new approach using a nonlinear minimisation routine. Natural mortality and stock resilience are considered in the model structure. Apart from catchability, the model also attempts to provide a best estimate of the true value of current biomass and presents a short-term biomass forecast.

Chapter 5 provides the results obtained using this stock assessment method for each species and compares these with the results of others various stock assessments conducted with current methodology.

The current management actions for each of the species are discussed in Chapter 6 together with the implications of the present analyses for future management actions. The final chapter (Chapter 7) provides an overview of the scientific contributions of this thesis and recommendations for further improvements in the stock assessment of these species.

Chapter 2

Underlying Theory and Methodology

2.1 Introduction

How many fish are in the sea? What are the causes of fluctuations in the levels of fishery catches? How much fish can be caught without compromising future catch? Some of these questions have been asked since the beginning of the fishery sciences in the second half of the 19$^{\text{th}}$ century (Smith, 1994) and are still intriguing the scientists nowadays.

Substantial progress in approaches to fishery modelling has been made due to increase in the model realism. Recently, fishery models tend to be regarded as “tools for thoughts” (Schnute and Richards, 2001) so that each part of the fish stock dynamics can be approached in a systematic way, and a range of consequences can be explored. However, given the complexity of real fish populations and the fisheries based on them, models are still simplified descriptions of the reality, and an entire fishery system will hardly be representable in detail by a simple estimation model.

Fish population dynamics play a fundamental role in the management of sustainable fisheries. A particular key feature is the stock’s natural capability of renewal in the face of both changes in environmental conditions, and increases in fishing mortality caused by human operated catching gears. The finite carrying capacity of the environment is one of the driving forces of population biomass, since biomass can only increase up to a threshold where living resources become scarce. At this upper level, competition for resources will limit population replacement and net biomass increase reaches a minimal rate.

The population size decreases below the carrying capacity level when subjected to a fishery. The "room" left is filled by the so-called "surplus production". At this lower level, competition for living resources is reduced and relative abundance of these resources becomes higher, allowing faster growth and enhancement of stock biomass, and/or surplus production. Theoretically the population size can be maintained indefinitely at just below the carrying capacity level by a fishery and surplus production will always fill the difference.

This effect, so called density-dependent regulation, is widely present in animal populations. Density-dependent factors in an environment include available food, nutrients in the water, and shelter; and the buildup of metabolic wastes, among others. A particular habitat will support a maximum number of organisms of a population, known as carrying capacity (K) of the environment. As the density increases, i.e. population numbers approach the carrying capacity of an environment, competition for resources rises, and therefore, increases mortality from limited food, higher disease frequencies, among others effects. Even though fertilisation is favoured by high population densities, density dependence effects can reduce the recruitment, i.e. since competition for resources may reduce the surplus energy available for reproduction, and reproduction output will fall (Jennings et al., 2001, Myers, 2002). Density-independent factors include droughts, storms, and volcanic eruptions.

The surplus production concept is the essence of every sustainable fishery assessment from the simplest production models ((Schnute and Richards, 2002, Quinn II and Collie, 2005) for an excellent overview) to the very sophisticated dynamic pool models (see, for example (Shepherd and Pope, 2002a,b, Beddington and Kirkwood, 2005, Lorenzen, 2005)) and a crucial quantity for estimation and consideration for fisheries management purposes.

2.2 Stock Production Model

The surplus production model (Ricker, 1975, Sparre et al., 1989), generalised production model (Rivard and Bledsoe, 1978), production model (Gulland, 1983), stock production model (Shepherd, 1987), and biomass dynamic model (Hilborn and Walters, 1992) are some of the current names given to variations on the original Graham-Schaefer model (Graham, 1935, Schaefer, 1954).

The Graham-Schaefer model describes the dynamics of the stock entirely in terms of the biomass and production of the exploitable population. The data requirement, for the simplest forms, comprises only a time series of total catch and another of either total fishing effort or an abundance index. Therefore, such models are easily applicable when data availability is poor. The conceptual simplicity of the stock production models has however been blamed for leading to some non-realistic results. It has been suggested by Hilborn and Walters (1992) and Ludwig and Walters (1985) that low contrast (dynamic range) in fishing effort and stock abundance has a major influence on the results, since the data set is not very informative. Even sophisticated models and parameter estimation methods may not yield reliable results if the data set lacks information.

However, studies using age-structured models with growth and age at first capture parameters do not necessarily provide superior parameter estimation than production models (Ludwig and Walters, 1985, 1989) and these authors suggested that stock assessment with dynamic pool models should always also employ production models, since the data requirement is easily fulfilled and stock production model results serve to provide a useful comparison.

2.2.1 Model Concepts and Definitions

In a stock production model, by definition, a population is treated as one big unit of biomass without detailing its age and length structure. Recruitment and individual growth are considered as part of the population biomass enhancement process, and mortality as part of the biomass losses.

Deterministically, the ("exploitable") population biomass in the next period of time $(t+1)$ will be equal to the (exploitable) biomass during the current period of time (t) plus the positive effect of production (P) less the deleterious effect of total catch (C) according to the following equation,

$$B_{t+1} = B_t + P_t - C_t. \tag{2.1}$$

The pioneering Schaefer model (Schaefer, 1954, 1957) describes production changes in time of an exploitable population, using differential equations and a quadratic function for surplus production, in the absence of a fishery,

$$\frac{dB_t}{dt} = P_t = rB_t\left(1 - \frac{B_t}{B_{max}}\right), \tag{2.2}$$

where $\frac{dB_t}{dt}$ is the population production at certain time t, r is the intrinsic rate of the population increase, i.e. the difference of the per capita birth and death rates in the absence of density dependence, B_t is the biomass at certain time and B_{max} is the maximum biomass level, also called pristine biomass.

A second well-known production model, proposed by Fox in the 1970s (Fox, 1970, 1971, 1975), assumed a logarithmic relationship for surplus production and an exponential relationship between catch-per-unit-effort and average effort,

$$P_t = rB_t\left(1 - \frac{\ln_e B_t}{\ln_e B_{max}}\right), \tag{2.3}$$

where the terms are the same as in the Schaefer model, and $\log_e$ is the natural logarithm. The main consequence of this assumption is that the stock will never become extinct, consistent with the idea that the economical viability of the fishery will fail before biological extinction occurs. However, there is current evidence that multispecies fisheries can actually extinguish species, and the real situation may only be discovered far too late (Dulvy et al., 2003).

The third widely used production model form was proposed by Pella and Tomlinson (1969),

$$P_t = \frac{r}{p} B_t \left(1 - \left(\frac{B_t}{B_{max}}\right)^p\right), \tag{2.4}$$

where r, B_t, and B_{max} are the same terms as in the Schaefer model. They introduced a parameter p which controls the skewness of the biomass-production curve. The Schaefer model is equivalent to the Pella-Tomlinson form when $p = 1$ and the Fox model is the limit of the Pella-Tomlinson form as $p \to 0$.

The essential difference between Eq. 2.3 and Eq. 2.4 is that the former only declines gradually for $B_t > B_{max}$, whereas the latter declines very sharply and may take large negative values of production.

Quinn and Deriso (1999) presented an extensive mathematical analysis of all these previously proposed production functions, as well as some other production curves with slight theoretical variations.

2.3 Model Fitting

After selecting the model(s), i.e. equation(s), which describes the studied situation, it is necessary to move from the general form to the specific numerical form. This is called model fitting (Gilchrist, 1984).

In order to avoid a failure of an assessment model, Schnute and Richards (2001) advised some standard procedures. Firstly, the modeller should keep a skeptical view of the model produced, recognising model limitations due to assumptions about the parameter estimation. In particular, process error, measurement error, and model uncertainties have to be included in the estimation procedures. Secondly, all available information of the studied system needs to be considered in order to expand the knowledge background and include new features in the model which could help in drawing robust conclusions. Thirdly, one should follow the “classical requirements for model quality control” such as residual analysis, diagnostic checking and verification of the computer code. Finally, regulatory strategies which could be evaluated through a model should be implemented. in practice, all these aspirations are rarely achieved.

In order to fit a model to data Schaefer (1954) developed a mathematical approach which considered populations under equilibrium conditions, and so deriving a linear relationship between catch-per-unit-effort and effort for this model. To improve the accuracy of this stock production model , various functional relationships between catch-per-unit-effort and effort were introduced. Gulland (1961) proposed an equilibrium approximation relating catch-per-unit-effort with the average effort in earlier years and Fox (1970, 1971) assumed an exponential relationship between catch-per-unit-effort and average effort, corresponding to the model Eq. 2.3.

However, these methods still assume the equilibrium condition and this assumption may be of very doubtful validity and lead to results which are highly biased (Hilborn and Walters, 1992, Quinn and Deriso, 1999, Williams and Prager, 2002, Punt, 2003). In the late 1960s Pella and Tomlinson (1969) first proposed a non-equilibrium parameter estimation approach through time series fitting (Hilborn and Walters, 1992) with observation-error estimators (Polacheck et al., 1993). On that basis, a range of new procedures based on non-equilibrium parameter estimations using differential equations have since been suggested by several authors (Schnute, 1977, Fletcher, 1978, Rivard and Bledsoe, 1978, Uhler, 1979).

Difference equations, i.e. a discrete time model for production functions were introduced by Walters and Hilborn (1976) and Hilborn (1979). This approach allows growth, mortality and recruitment to be treated separately from net biomass growth and/or decline.

Although stock production models are simple conceptually and in terms of their data requirement, the mathematical procedures for model fitting may nevertheless became fairly complicated, and require the use of advanced numerical mathematics procedures

(Hilborn and Walters, 1992, Schnute and Richards, 2001). With regard to fitting a model to data, there has, of course, been a considerable improvement in parameter estimations with the advent of the computer, and methods which were previously unfeasible can now be implemented easily.

The biomass-production balance is deterministically described (in discrete time form) by Eq. 2.1. Furthermore, when one (or more) time series of abundance index from research surveys are not available, i.e. in the majority of the situations, catch-per-unit-effort (CPUE) is used as an abundance index, and assumed to be proportional to the true population abundance,

$$U_t = \frac{C_t}{E_t} = qB_t, \tag{2.5}$$

where U_t is CPUE at time t, C_t is catch at time t, E_t is effort of time t, q is the catchability coefficient and B_t is biomass of the population at a time t.

With regard to CPUE, two facts should be considered here. Firstly, the reported CPUE is actually landing-per-unit-effort ($LPUE$) (Jennings et al., 2001) since part of the catch is discarded at sea, especially undersized marketable species and the non-commercial ones, which are not landed or kept onboard for legal and economic reasons. Considering a trawl net, a substantial amount of invertebrates and fish is caught as bycatch and a great part of it is returned to the water as discards. Therefore, the reported CPUE underestimates the actual amount captured, which also varies according to the gear selectivity. For the purposes of this work, the term CPUE is, as usual, going to be used in place of landing-per-unit-effort, without however, losing sight of the difference between them.

Secondly, the proportionality between population abundance and CPUE has been broadly (Hilborn and Walters, 1992, Jennings et al., 2001) and deeply (Paloheimo and Dickie, 1964, Harley et al., 2001) discussed. In theory, the amount of fish captured by a fishing gear is proportional to the fish population abundance at a certain fishing site and time. The main relationship may however, be better represented in practice, by an exponential function (Hilborn and Walters, 1992, Harley et al., 2001), and there might exist other relationships which are poorly investigated (Harley et al., 2001) such as,

$$U_t = qB_t^{\beta}, \tag{2.6}$$

where β is the exponential term. When β equals 1, the relationship is linear and Eq. 2.5 and Eq. 2.6 are the same. This model has been widely used in a number of stock assessment models, e.g. (Shepherd, 1987, Conser, 1998, Chen and Andrew, 1998, McAllister et al., 2001, Prager, 2002). When β assumes a value different from 1 two situations can arise. First, $\beta > 1$ produces a hyperdepletion situation, i.e. the stock appears to be depleted since CPUE dropped quickly but abundance had not decreased as fast as CPUE, such as tuna stocks whose dense shoals in feeding sites are quickly fished and therefore the CPUE drops sharply. Second, $\beta < 1$ generates a hyperstability, which shows a stable CPUE even while abundance drops dramatically, for instance cod, haddock, sole and plaice (Harley et al., 2001). Biologically, the former has low depletion or extinction risk, whereas the latter is a very dangerous relationship since depletion signals might come too late for management action. Hyperstability has been the main relationship found for a variety of gadiformes and flatfish species, for a range of age and trawl nets (Harley et al., 2001) and failure to recognise this is believed to be partly responsible for historical depletion of the Northern cod in the Great Banks (Rose and Kulka, 1999).

Other factors that interfere in the proportionality between CPUE and population abundance are mostly related to environmental and technical aspects. The population abundance for a certain area and time is driven by a number of environmental and biological characteristics such as the population concentration patterns, the dynamics of the movement (or diffusive behaviour) of the stock (Hilborn and Walters, 1992) and density-dependent habitat selection (Rose and Kulka, 1999). In addition, the catch process involves a number of technical aspects related to the fishing gear such as operational characteristics of fishing gear and variability in catchability. Fishers' skills are also a fundamental factor determining the catch success. A number of aspects should therefore, really be considered when assessing the proportionality between

CPUE and abundance such as search efficiency, handling time, factors determining the effort deployed and choice of ground fishing by fisher such as the desirability of different areas because of differences of CPUE (Hilborn and Walters, 1992). However, in practice those factors are most often not considered due to difficulties in gathering this kind of information.

The assessment of fish populations most frequently therefore assumes a simple proportionality between CPUE and abundance, and a major deficiency in the models might be the assumption of linearity between those variables. However, overestimation of stock size and consequently underestimation of the fishing mortality due to random noise in the data have been experienced with more complicated nonlinear models (see (Lassen and Medley, 2001)), and the balanced of advantage is still unclear.

Despite the great range of factors affecting the proportionality of CPUE and stock biomass, the parsimony principle should be used as often as possible. For the purposes of this study, biomass will therefore be considered as linearly proportional to CPUE. The possible uncertainty of this assumption will be allowed for only as process error in the parameter estimation, in order to avoid an increase in the number of parameters to be estimated. It is recognised that if this assumption is false, the validity of the results may be compromised. However, a more complex treatment would only be possible if additional data were available to determine the true relationship, and regrettably such data are generally lacking.

2.3.1 Parameter Estimation

For stock production models the principal parameters to be estimated are, in order of importance, catchability, pristine biomass, current (or initial) biomass, and possibly, but rarely, also resilience and natural mortality.

In statistical modelling, parameters are quantities which determine model behaviour but are not directly measurable. The process of assigning numerical values for parameters is called estimation (Gilchrist, 1984). In fishery modelling, growth and mortality rates, fecundity at age and biomass in the next year are all quantities frequently treated as parameters (Hart and Reynolds, 2002).

The overall parameter estimation process involves three steps. First, one must establish the model and define the parameters to be estimated. Second, acquire data from a population and proceed with the parameter estimations according to the chosen mathematical/statistical approach. Finally, establish a criterion to judge the goodness-of-fit for any particular combination of model and parameter estimates (Hilborn and Walters, 1992). However, the best fitting results, and consequently, their estimated parameters may not necessarily provide the most accurate prediction, since the results may depend on the method chosen, and peculiarities in the historical data and model structure may also influence the results (Hilborn and Walters, 1992, Haddon, 2001). It is therefore desirable for a model (and the parameters estimated) to be testes retrospectively by cross-validation, i.e. by fitting to part of the data and testing the predictions using the remainders, and/or by testing predictions against new data if and when it becomes available.

Least Squares Method

In the current fishery modelling literature, there are three different main approaches in use for parameter estimation. First, Least Squares Estimation has been very widely used in fishery modelling since the early times, for both linear models, and currently also for nonlinear minimisations. The basic idea of least squares method is to find a set of parameters that reduces to a minimum the (squared) deviations between the observed data and the expected values obtained from the model.

The least squares method is relatively easy to use, adaptable, objective and the results may, in practice, often be close to the maximum likelihood solution, which has resulted in its wide use, from stock production models (e.g. Schaefer (1954), Conser (1998)) to virtual population analysis (e.g. Shepherd (1999), Lassen and Medley (2001)). This method does not necessarily require one to make explicit assumptions about the process and observation uncertainties. In addition, further estimations (e.g. confidence intervals) can be carried out through modern computational methods such as bootstrapping (Efron and Tibshirani, 1993).

Non-linear least squares estimation, has followed the same principle of linear estimation and has been implemented using more advanced mathematical and numerical techniques. The difference between linear and nonlinear approaches is that the latter does not necessarily, have a quadratic sum of squares surface. Thus, in order to find the minimum least squares, it is necessary to use an iterative numerical search scheme such as Newton, Simplex and Levenberg-Marquardt's methods. There has been some criticism by Hilborn and Walters (1992) with respect to the use of the nonlinear estimation method, but it is possible to easily overcome them relatively easily nowadays.

Firstly, the allegation that it is a slow method and that models with high number of parameters would take far too much time to converge to a solution can often be solved with a powerful computer widely available nowadays.

Secondly, the iteration may reaches a false (local) minimum when the local search will take any direction leading to a poorer fit. For small deviations, this can be true, but the algorithm could find better (global) minimum if larger steps were taken. To avoid and overcome this possible situation the modeller should take a series of measures such as increasing massively the number of model iterations and runs (giving the method more "room" to find the global minimum); start the estimation with different values of initial guesses to see if the model converges to the same parameter values; re-run the model with the parameter values perturbed from those previously found as an initial guess. If the model has reached the global minimum it should not give a different output.

Thirdly, initial guesses are stated to be art instead of science. There are a few procedures to help one to find initial guesses in a systematic approach. For instance, using previous knowledge, or published values, similarly to the use of priors in the Bayesian methods; try linear approximations to the model and use the values found as initial guesses; try a wide range of different starting values until a set which leads to model convergence is found.

Despite the current interest in development of alternative numerical methods based on more elaborate theories, least squares is a still robust method and is a useful starting point for the fishery data analysis. According to (Patterson et al., 2001) frequentist methods are particularly attractive because of the availability of nonparametric techniques, permitting relaxation of the error distribution assumptions, but this development is not pursued here. Moreover, the least squares approach can approximate to the maximum likelihood estimator (see below) if the error distributions are approximately normal, and either the variance is constant over the range of variables, or the proportional change in variance is known, in a weighted least-squares scheme. However, the estimates will not be maximum likelihood if the magnitude of the errors are not similar, and the changes in the variance are unknown (Lassen and Medley, 2001)

Likelihood Method

The second most used method in fishery modelling is the use of Likelihood functions, which has been applied to fishery modelling since the 1980s in the form of Maximum Likelihood Estimation.

In principle, likelihood is the probability that a set of parameters is correct given the data (Gilchrist, 1984, Haddon, 2001). During the model fitting process, given the observed data, there will be a set of parameters which is most likely to explain the data. Probability models generally look at the model and the data from the other end, i.e. describe how likely the observed data are, given the parameters, which is not usually the same thing. For some probability distributions there is no major difference, but conceptually the likelihood approach emphasises careful choice of the criteria for fitting models to data (Lassen and Medley, 2001).

In the early 1990s, there was an overconfident belief that the most rigorous works in fishery parameter estimations were being conducted by maximum likelihood estimation (see (Hilborn and Walters, 1992)). However, least squares methods are still frequently used in the analysis of fisheries data. Theoretically, using likelihood methods is better, but there are a several reasons that makes least squares more popular in practice.

Firstly, if the probability distribution for the likelihood estimation is assumed to be the normal distribution both methods become equal. Secondly, there is normally a large uncertainty involved in the specification of the error structure of the likelihood. Least squares can sometimes provide as good estimation as likelihood, just by applying some reparametrisation with the advantages of using a more straightforward procedure. Thirdly, for many parametric likelihoods (e.g. using Poisson distribution), maximum likelihood can be reformulated in terms of least squares. Finally, since numerical procedures of least squares are much simpler, they are less likely to break down than more general approaches, particularly where there are many parameters to estimate (Lassen and Medley, 2001).

Bayesian Method

Finally, but not least important, the third most used method in recent fishery model fitting is the Bayesian framework. This started being used in fishery sciences in the late 1990s following the earlier introduction of the likelihood method. The Bayesian approach is based on the conditional probability theorem and assumes a prior probability distribution for parameter values using previous knowledge or beliefs. These probabilities are then, in effect, multiplied by the likelihood of the parameters in order to estimate a posterior probability distribution. This approach explicitly quantifies the uncertainties and should be particularly useful for decision making analyses (Gelman et al., 1995, McAllister and Kirkwood, 1998). However, a non-informative prior distribution can generate misleading results (Punt and Hilborn, 1997) and the methods tend to be computationally very demanding.

Furthermore, Dennis (1996) present a wide and deep discussion on both philosophical and practical grounds, questioning the actual gains of changing frequentist statistical methods for Bayesian statistics in ecological science. According to Dennis (1996) scientific arguments may be difficult to make convincing with Bayesian reasoning.

The relationship of likelihood and Bayesian analysis lies in two points. First, the maximum likelihood definition relates to a set of parameters, i.e. when the likelihood function reaches its maximum point. Second, a Bayesian estimator uses likelihood, along with prior probabilities and a "cost" function, to define a set of parameters where the expected cost is minimised (Lassen and Medley, 2001). Unless the prior distribution are highly informative, which is unusual, the Bayesian posterior distributions are broadly centred around the maximum likelihood solution.

2.3.2 Sources of Uncertainty

Deviations between observations (data) and expected values (theory/model) are always present in any parameter estimation methods. These deviations are referred to as residuals, random noise or errors.

In fishery sciences, uncertainty is acknowledged to be the result of a lack of perfect knowledge of many factors that affect stock assessment, estimation of biological reference points and management (Restrepo, 2000). Uncertainty plays such a fundamental role in stock assessment that international policies and agreements (e.g. Anonymous (1994), FAO (1995)) have pointed out the necessity for making this information available to managers. Therefore, consideration of uncertainty must be conducted as part of the decision support process in fishery management, when assessing the current state of the resource and the resulting forecasts (Patterson et al., 2001).

Within the fishery world, there is a variety of sources of uncertainty. According to Rosenberg and Restrepo (1994) there are five types of uncertainty: (1) measurement or observation error is an uncertainty in the observed quantities such as catch or fishing effort, (2) process error is an uncertainty in the population dynamics process such as recruitment, (3) model error is an uncertainty in the specification of model parameter or model structure, (4) estimation error is an uncertainty in the imprecision of the estimated model parameter such as population production or catchability and results from any of these previous uncertainties, and (5) implementation error results from the inability to achieve a target harvest strategy exactly. Hilborn and Peterman (1996) recognised three more types of uncertainty. First, uncertainty due to future environmental conditions associated to fluctuations of the environmental state. It is advised that one should consider them in the stock assessment projections, but the probabilities associated with these changes are very difficult to estimate. Second, future social, political and economic conditions such as uncertainties resulting from changes in government subsidies, markets, and policies. There are (as far as I am aware) no assessments which routinely make projections about social and economic factors. Third, management objectives create an uncertainty resulting from the fact that management action today may cause undesirable effects in future, so the action will be changed. Although a range of types of uncertainty can always be found in population assessment, they are not usually all assessed simultaneously (Rosenberg and Restrepo, 1994).

Among all sources of error, observation or measurement and process error are the two which are most extensively discussed in the literature. Special statistical approaches have been developed to deal specifically with them and to evaluate their impact for management purposes (e.g. Chen and Paloheimo (1998), Patterson et al. (2001), de Valpine (2002)), whereas estimates of most of the other errors would be little more than guesswork. As explained by Lassen and Medley (2001) there is a fundamental difference between process and measurement errors, since the former introduces a real change in the system, whereas the latter introduces no underlying change and therefore does not affect future observations. This important difference has fundamental implications for the estimation process, and is the foremost reason to conduct studies which allow process and observation errors to be considered separately.

Building a model consists of establishing a relationship between parameters, data and uncertainty. The former relationship is based on the theory and the latter on assumptions about the error structure. In order to assess the effectiveness of the parameter estimation there are methods to evaluate the confidence in the parameter estimations. Analysing the variance of residuals has been the approach most used in least squares analysis, for example.

In addition to the examination of variance of residuals, the confidence intervals of the estimated parameters can also be calculated. One elegant and useful practical approach for calculating confidence intervals is the bootstrap method, developed by Efron and Tibshirani (1993). The residuals from the model fit are calculated as the differences between predicted values and observed values. One then generates a new data set by sampling from the residuals, with replacement, and adding a "new" residual to each predicted data point. These are then used in a new estimation, to re-fit the model, and obtain new values for the parameters. With a few hundred such estimates of the parameters one can look at the parameter distributions, variances and covariances directly, and analyse them (Hilborn and Walters, 1992).

2.3.3 Parameter Correlation and Bias

Parameter correlation is an undesirable but widely found feature in fishery models. It occurs, for example, when supposedly independent variables are actually correlated with each other, making it impossible to affirm with confidence which independent variable is causing a change in the dependent variable. For example, separating the natural mortality rate from fishing mortality in catch-at-age analysis is a hard task since they have a very high negative correlation (Hilborn and Walters, 1992).

In stock production modelling, parameter correlation is also a problem, characteristically appearing as an elongated and skewed central area of a plot of sum of squares as a function of two parameter values. This feature happens, inter alia, because the catch this year depends partly on the catch of the year before and so forth. Consequently, in a time series of catch and biomass, they are serially correlated.

Bias is also a frequent feature in fitting model to data, since the data sets are usually time series, and therefore, not entirely independent from both previous states of the fishery and random noise. The current approach to deal with this problem is to make simulations of the population, assuming the estimated parameters are correct, and analyse the bias in the output (Hilborn and Walters, 1992).

Catch data can be biased by under-reporting which could, in principle, be allowed for in the model. However, the size of this bias would have to be estimated from data, which can only be performed if the necessary data is available.

2.4 Summary and Forward Look

The evolution in mathematical model fitting approaches has opened a variety of possibilities for new improved stock production models, and further assumptions regarding error structures.

Stock production model is a data modest fisheries model that can be useful if it can be made to work satisfactorily. Nonlinear parameter estimation using difference equations has become one of the elegant methods allowing growth, mortality and recruitment to be treated separately from biomass. Simple methods are useful as a basis. If additional information is available, more complex models can also be applied and compared

In addition, the stock production model is considered to be the most suitable type of stock assessment method for the present research, as regards its data requirements. Moreover, it should be the first step in quantitative stock assessment. Furthermore, uncertainty is present in every model and will not necessarily be reduced by making models more elaborate.

The least squares method will be used for parameter estimation, since it has proved to be a useful, reasonably robust and potentially adequate simple method. Further analysis required for the validation of this method will also be conducted, using the bootstrapping method.

Chapter 3

The Conser Mixed Model

3.1 Introduction

Since the stock production model was first proposed (Graham, 1935, Schaefer, 1954), it has been widely applied to a variety of resources, including migrating fish (Goodyear and Prager, 2001, Prager, 2002), invertebrates (Polovina, 1989, Chen and Montgomery, 1999, D'Incao et al., 2002), temperate fish (Rose, 2004), and tropical fish species (Pella and Tomlinson, 1969). A range of different methods for parameter estimation have been proposed e.g. (Pella and Tomlinson, 1969, Fox, 1970, Schnute, 1977, Rivard and Bledsoe, 1978, Tsoa et al., 1985, Polacheck et al., 1993, Pella, 1993, Chen and Andrew, 1998, McAllister and Kirkwood, 1998, Meyer and Millar, 1999b, Prager, 2002, Schnute and Richards, 2002, Punt, 2003).

In practice, stock production models generally employ difference equations instead of differential equations. The formulation allows growth, mortality, and recruitment to be treated separately from biomass. Each parameter has a biological interpretation, separate from any other process. In principle, an independent parameter estimation is thus promoted (Conser, 1998) which can be conducted by using either additional data or previous studies. Despite being used in a different manner than the Bayesian framework, this is a way to incorporate prior information into the analysis. This approach avoids over-parameterisation which is commonly found when the number of independent parameters to be estimated is higher than the number of independent data sets (Shepherd, 1987).

Fitting time series difference equations with nonlinear minimisation is an elegant approach which avoids the unreliable assumption about stock equilibrium and promotes the inclusion of uncertainties, regarded as a essential features in the estimation processes (Hilborn and Peterman, 1996).

Production relationships were first written as difference equations by Walters and Hilborn (1976) and Hilborn (1979), when a multiple linear regression was proposed as the estimation method regarding catch-per-unit-effort and effort as independent variables.

A surplus production difference equation model is used as the starting point in this work. The production model was proposed by Shepherd (1987) and can be considered as one of the general class of models described by Schnute (1985). In order to estimate reliable parameters when fitting the model to available data, Shepherd (1987) treated catchability and natural mortality together with the intrinsic growth rate and pristine biomass as separate parameters. Furthermore, a re-parameterisation was presented in terms of current and pristine biomass, suggesting that reasonable ranges of two of those parameters ought to be selected to obtain a good fit.

In the Shepherd model (Shepherd, 1987), the natural mortality rate (M) can be fixed, as in more elaborate models such as virtual population analysis (Pope and Shepherd, 1985, Shepherd and Pope, 2002a). This procedure serves two different purposes. Firstly, it allows the results of stock production and age structured models to be more similar and so more easily comparable. Secondly, it clarifies the representation terms of biologically meaningful parameters and so increases the chance of obtaining convincing results, since prior estimates of natural mortality are often available from basic biological research.

Conser (1998) pointed out the lack of a formal statistical modelling for parameter estimation in Shepherd (1987) and proposed a numerical framework considering both observation and process errors, hereafter called "Conser Mixed Model (CMM)". Here the term "mixed" is used to describe a model which considers both observation and process error in the estimation procedure.

Using a composite objective function minimised by the Marquardt algorithm, Conser (1998) conducted a stock production model assessment on a sablefish stock (*Anoplopoma fimbria*) caught off the USA Pacific coast.

However, the proposed statistical framework contains some inconsistencies in the assumptions and statistical configuration which will be explained in detail in the following sections. In short, the CMM formulation of process error is not fully consistent with the biologically processes concept. Moreover, setting the same weight for process and observation errors, as in the CMM, does not guarantee a mixed model and fixing the stock resilience is not a justifiable assumption, since it has deep implications for the management actions. Further comments on these are made in the discussion of this chapter.

Therefore, the objective of this chapter is to reproduce the analysis of Conser (1998), analysing and pointing out the inconsistencies of the statistical model, and suggesting improvements. The following two sections describe the CMM and its parameter estimation method. In the section 3.4 results are analysed and structural and methodological deficiencies are exhibited and discussed.

3.2 Model background

The production dynamics is based on the basic first order difference equation (Eq. 2.1) which describes the balance between production and catch over time. The production function is the one proposed by Shepherd (1987) and is described below.

By definition, production is related to recruitment as well as to spawning stock size and are therefore expects a high variability in the process and a poor fit to any simple model (Shepherd, 1987).

Although Schaefer's logistic model (Eq. 2.2) assumes a decreasing linear relationship between net production per unit biomass and biomass itself, Shepherd (1982) suggested that a curvelinear relationship may be more appropriate. Moreover, considering a constant natural mortality and assuming a linear relationship for the net production/biomass ratio, for large stock sizes, would result in an unfeasible negative estimate of production due to recruitment (Shepherd, 1987).

A traditional stock-recruitment relationship by Beverton and Holt (1957) is therefore selected to model positive (or gross) production. The relationship has a curvelinear asymptotic shape and non-negative values. Equation (3.1) expresses the gain in biomass, i.e. that due to growth of individual fish and recruitment, in a density-dependent situation,

$$Pp_t = \frac{aB_t}{1 + \frac{B_t}{K}}, \tag{3.1}$$

where Pp_t is the positive time unit t production and has the unit of biomass; a is the parameter that represents the maximum instantaneous annual rate of positive production, i.e. the slope at the origin of the positive production curve, and its unit is yr^{-1}; K represents the stock biomass threshold up to which growth is controlled by density-dependent effects, i.e. pristine biomass.

The loss of stock biomass (i.e. the decreasing effect of natural mortality) is quantified in Eq. 3.2, where Np_t is the negative production; M is the instantaneous rate of natural mortality and its unit is yr^{-1}, and B_t is the biomass,

$$Np_t = MB_t. \tag{3.2}$$

Combining Eq. 3.1 and Eq. 3.2 gives the net surplus production, i.e. the difference between positive and negative production,

$$P_t = Pp_t - Np_t = \frac{aB_t}{1 + \frac{B_t}{K}} - MB_t. \tag{3.3}$$

The per capita production or production-biomass ratio (P_t/B_t) proposed by Shepherd (1987) is,

$$\frac{P_t}{B_t} = \frac{a}{1 + \frac{B_t}{K}} - M. \tag{3.4}$$

Here, the production biomass ratio is therefore a nonlinear function, as opposed to the Graham-Schaefer model where the relationship is assumed to be linear.

In order to complete the parameterisation, a and K are substituted by slightly more convenient parameters. Thus,

$$a = (\alpha' + 1)M, \tag{3.5}$$

or,

$$\alpha' = (a - M)/M = \alpha - 1, \tag{3.6}$$

where α' is the resilience of the stock and is dimensionless. In biological terms, resilience is equivalent to the maximum net production/biomass ratio, i.e. the maximum sustainable yield/biomass ratio, for a given natural mortality. Resilience is proportional to the slope of the biomass and production curve at the origin, and may be expected to be somewhere between 1 and 10, based on assessment for which good data are available (Shepherd, 1987).

By definition, in the absence of the fishery, the stock biomass is at its virgin stage ($B = B_{max}$), also known as pristine biomass, and therefore, the production/biomass ratio (P/B) is zero. Once the fishery has started, B_{max} is the exploitable virgin stock biomass, i.e. the portion of the virgin biomass that could have been exploited under constant exploitation patterns. The parameter K can then be expressed as,

$$K = \frac{B_{max}}{\alpha'}. \tag{3.7}$$

Thus, by substituting Eqs. 3.5 and 3.7 and into the production/biomass ratio curve (Eq. 3.4), the Shepherd model (1987) is described as,

$$P_t = \alpha' M B_t \left(\frac{1 - \frac{B_t}{B_{max}}}{1 + \frac{\alpha' B_t}{B_{max}}} \right). \tag{3.8}$$

The selection of B_{max} leads to others quantities of management interest. The biomass yielding maximum net production (B_{MSY}) is obtained by differentiating Eq. 3.8 with respect to biomass and setting $dP_t/dB_t = 0$,

$$B_{MSY} = \left(\frac{\sqrt{1+\alpha'}-1}{\alpha'}\right) B_{max}. \tag{3.9}$$

Next, maximum sustainable yield (MSY) is given by substituting Eq. 3.9 into Eq. 3.8,

$$MSY = \frac{\alpha' M}{\sqrt{1+\alpha'}} B_{MSY} \left(1 - \frac{B_{MSY}}{B_{max}}\right). \tag{3.10}$$

With these equations in place, it is now possible to estimate the parameters to best fit the actual data.

3.3 Parameter Estimations

Due to the lack of a statistical framework for the parameters estimation in Shepherd (1987), Conser (1998) proposed a nonlinear statistical parameter estimation using least squares minimisation and considering observation and process error in the objective function, i.e. the Conser Mixed Model (CMM).

The statistical model proposed by Conser (1998) first transformed exploited stock biomass, net production, and virgin biomass into indexes by multiplying them with catchability (q),

$$\begin{aligned} b_t &= qB_t \\ p_t &= qP_t \\ b_{max} &= qB_{max} \\ t &= 1, \cdots, Y. \end{aligned} \tag{3.11}$$

Then, these indexes are used to substitute biomass, production, and catch in the dynamic equation (Eq. 2.1). The process error (ϵ_t) is based on a normally distributed random variable with mean 0 and variance σ_ϵ^2, and is included as a log-normal error, multiplying predicted biomass, for reasons which were not clearly stated in Conser (1998),

$$b_t = (b_{t-1} + p_{t-1} - qC_{t-1})e^{\epsilon_t}. \tag{3.12}$$

The observation or measurement error (η_t) is taken to be a log normal error multiplying the expected index of stock biomass (b'_t), i.e.

$$\begin{aligned} b'_t &= b_t e^{\eta_t}, \qquad (3.13) \\ i.e.\ \eta_t &= \ln(b'_t - b_t), \\ t &= 1, \cdots, T. \end{aligned}$$

In other words, η_t is the natural logarithm of the difference between the true index of stock abundance and estimated biomass.

The observed catch (C'_t) is related to the true catch (C_t) by a further observation error δ_t,

$$\begin{aligned} C'_t &= C_t e^{\delta_t}, \qquad (3.14) \\ i.e.\ \delta_t &= \ln(C'_t - C_t), \\ t &= 1, \cdots, T-1. \end{aligned}$$

Both observation error terms are thus assumed to be log-normally distributed random variables, with mean 0 and variance σ^2_ϵ.

Adding the above equations (Eq. 3.12, 3.13, and 3.14) builds Conser's objective function (Eq. 3.15) which is minimised with respect to estimated biomass and catchability,

$$SS = \lambda_\epsilon \sum_{t=1}^{T-1} \epsilon_t^2 + \sum_{t=1}^{T} \eta_t^2 + \lambda_\delta \sum_{t=1}^{T-1} \delta_t^2, \tag{3.15}$$

where SS is the sum of squares, λ_ϵ and λ_δ are the weights for the process error and catch observation error, respectively, relative to the CPUE observation error. Observation error is thus represented by both η_t^2 and δ_t^2. The process error is defined as ϵ_t^2 and is related to the dynamic equation (Eq. 2.1 and Eq. 3.12).

As pointed out above, some inconsistencies have been noticed in the CMM estimation approach. Firstly, process error is fundamentally the uncertainty in the population dynamic processes such as recruitment and mortality rate fluctuations. Therefore, process error is expected to be related to the production equation (e.g. Eq. 2.2, 2.3, 2.4, and 3.8), which describes the process of incorporation and reduction of the stock biomass in relation to the carrying capacity of the environment and intrinsic growth rate. However, Conser (1998) included process error in the dynamic equation (Eq. 2.1), which comprises process and observation errors simultaneously. Process error is accounted for the presence of the production term, and observation error by both catch and biomass terms. For this reason, the dynamic equation should be considered deterministic rather than stochastic with the process error applied to the highly variable production term itself, rather than the result (the estimated biomass). As a result of Conser's process error assumption, different sources of noise are merged and likely to be confounded.

Secondly, the weight of process and measurement terms in the objective function is assumed to be equal to one which does not guaranteed to produce a model with observation and process uncertainties balanced. Actually, Conser's assumptions lead in practice, to an observation error model since the sum of process errors squared is far bigger than the sum of observation errors squared (Table 3.1 on page 40). This fact is also related to the previous inconsistency of the treatment of process error in the dynamic equation.

In general, the observation error is related to the measurement of effort and catch data, i.e. to the collected information. However, in practice the observation weight in the CMM was only attributed to CPUE, and that associated with catch was assumed to be zero, based on the inference that catch data is collected with negligible error. Therefore, ignoring observation errors from catch data results, in practical term, in a simpler objective function.

Finally, resilience was assumed to have a fixed value in the CMM and no further evaluation was carried out. Since resilience determines how conservative the assessment will be,evaluation with a range of resilience values is highly desirable but was not conducted. Fixing an arbitrary but high value for resilience is not a conservative assumption and can have dangerous consequences for fish stocks.

3.4 Model configurations

As explained in the previous section, there are several inconsistencies or imperfections in the model assumptions and the statistical configuration of the CMM which will be addressed here. These are (i) the unusual formulation of the process error; (ii) the neglecting of a weighting balance for process and observation errors in the objective function and (iii) the analysis of a range of resilience values.

To deal with these points the following procedures will be conducted. First, Conser's data will be re-analysed as a starting point of this study. This is conducted with a slightly modified objective function already assuming a process error in the production model (Eq. 3.8) and observation error weight. Second, the balance of observation and process error in the objective function will be investigated (a) by comparing models in which one of the two terms is set to zero and (b) by finding the weight ratio between observed and process error which equalises the variance of observation and process deviations. Third, the output of the stock production model is examined for a range of values of B_{max}, since the model is highly sensitive to this value and its choice influences the management approach. Finally, the model stability is tested when B_{max} and α', are no longer regarded as fixed but estimated instead.

3.4.1 Approximate Reproduction of Conser's Results

In order to avoid an undefined behaviour of the log-normal objective function due to negative arguments during minimisation, Conser's original objective function (Eq. 3.15) was modified into,

$$SS = \lambda_\rho \sum_{t=1}^{T-1} \rho_t + \lambda_\theta \sum_{t=1}^{T} \theta_t, \tag{3.16}$$

where λ_ρ and λ_θ are the relative weights for process error and observation error respectively. The process (ρ_t) and observation (θ_t) errors were formulated as follows,

$$\rho_t = \frac{(B_t - \hat{B}_t)^2}{\overline{B}_t^2}, \tag{3.17}$$

$$\theta_t = \frac{(B'_t - B_t)^2}{\overline{B'}_t^2}, \tag{3.18}$$

where B_t is the minimised value of biomass, $\overline{B}_t$ is the average of modelled biomass, $\hat{B}_t$ is the value of biomass estimated through the dinamic equation (Eq. 2.1), B'_t is the biomass index data, either from the observed time series of a research survey or CPUE data, and $\overline{B'}_t$ is the average of biomass index data. Process and observation uncertainties calculated for each year are actually the fractional deviations which approximate to log-normal errors and the sum of all deviations is comparable to the relative variance of the data.

Using CPUE and catch data series, the objective function (Eq. 3.16) was minimised with respect to the catchability and estimated biomass of each and every year. The minimisation was conducted using a nonlinear estimation routine which employs both the Quasi-Newton algorithm, and the line-search method. The quasi-Newton method evaluates, at each step, the function at different points in the parameters space in order to approximate the first-order and second-order derivatives. Then, it uses this information to follow a path towards the minimum. At each step of the main algorithm, the line-search method searches along the line containing the current point, parallel to the search direction, which is a vector determined by the main algorithm (MATLAB, 2005).

The optimisation function "fminunc", i.e. minimisation of an unconstrained multivariable function, from MATLAB V6.5 was employed. The minimisation settings were found by trial and error, in order to avoid local minima and to certify the model convergence. In addition, a wide range of initial values was tested, and the program was re-run with estimated results from previous runs, in order to ensure that a global minimum rather than a local minimum was reached.

The maximum number of iterations was set to 300,000, the maximum number of function evaluations allowed was 20,000,000 and the termination tolerance of the function value was 10^{-8}. The initial values for the nonlinear least squares optimisation were $B_1 = 220$ kton, $\alpha' = 5$, $M = 0.07$ year^{-1}, $B_{max} = 260$ kton, and $q = 1.0$.

The original data has been estimated from age 2+ at the beginning of the year and carried out previously by Crone et al. (1997) using the Stock Synthesis model and swept area estimates of stock biomass from bottom trawl surveys on the continental slope in recent years. As a result, the data series has been pre-analysed before being minimised by the proposed objective function. Catch represents reported landing plus annual estimates of discards. The instantaneous rate of natural mortality ($M = 0.07$ year^{-1}) and resilience ($\alpha' = 5$) were used from previous studies and treated as fixed parameters, and observation and measurement errors were equally weighted to one (Conser, 1998). Biomass unit, kton, stands for US kilotons and corresponds to 0.907 kt in SI unit system.

Table 3.1 presents Conser's original data set and estimated parameters, i.e. catchability, estimated biomass and pristine biomass; together with the parameter estimation, found in this study by the nonlinear estimation, i.e. catchability and estimated biomass. Model diagnosis, i.e. sum of squares, sum of observation error, and sum of process errors are also listed in the table.

In Conser's original results, the estimated biomass decreases over time by a factor of four whereas for the present study the decrease is slightly smaller, a factor of 3.6 times, for the same set of fixed parameters and initial guesses. The modified objective function is probably responsible for the slightly lower reduction in the estimated biomass in this work. The normalisation of the objective function scales the deviations, which is convenient when values with different magnitudes will be compared. Management quantities such as MSY and B_{MSY} were fairly similar for both studies (Table 3.1). According to Conser (1998) the period which the observed biomass index values were not similar to the estimated biomass values, are probably due to environmental conditions, being specially favourable during late 1970s, leading to good

Table 3.1: Conser original data and estimated results for the sablefish off the USA Pacific coast and results of the present study, where q= catchability, SS= sum of squares, $\sum \theta_t^2$= sum of all observation deviations, $\sum \rho_t^2$= sum of all process deviations, B_{MSY}= biomass at maximum sustainable yield, B_{max}= pristine biomass, MSY= maximum sustainable yield.

Year	Biomass index	Catch (kton)	Estimated Biomass (kton) Conser, 1998	present work
1971	248.66	4.428	249.77	252.58
1972	247.10	7.667	247.83	250.35
1973	242.51	6.183	242.35	245.01
1974	238.54	9.046	239.05	240.71
1975	232.12	11.113	232.54	233.83
1976	222.69	22.03	223.90	224.45
1977	202.01	8.531	201.54	204.21
1978	194.07	11.619	198.09	197.26
1979	193.80	20.14	194.44	193.69
1980	177.77	8.697	179.05	177.58
1981	182.82	11.478	181.28	178.69
1982	176.58	18.823	178.01	172.12
1983	168.47	13.629	165.38	161.67
1984	158.90	13.979	157.06	152.65
1985	146.73	16.022	146.64	142.12
1986	132.89	14.705	133.59	129.93
1987	123.78	14.291	123.21	121.19
1988	113.39	11.827	112.97	112.00
1989	105.97	11.277	105.86	105.63
1990	98.98	9.760	99.48	99.81
1991	96.89	10.284	95.69	97.55
1992	92.43	10.063	90.10	93.76
1993	84.51	8.914	82.84	88.10
1994	76.91	8.209	75.93	83.16
1995	69.06	8.479	69.48	78.41
1996	62.21	8.974	63.53	74.21
1997	56.96	8.484	58.43	70.82
		q	1.353	0.996
		SS	0.011	0.083
		$\sum \theta_t^2$	0.003	0.054
		$\sum \rho_t^2$	0.075	0.029
		K	44.537	52.000
		B_{MSY}	64.557	75.374
		B_{max}	222.687	260.000
		MSY	6.550	7.648

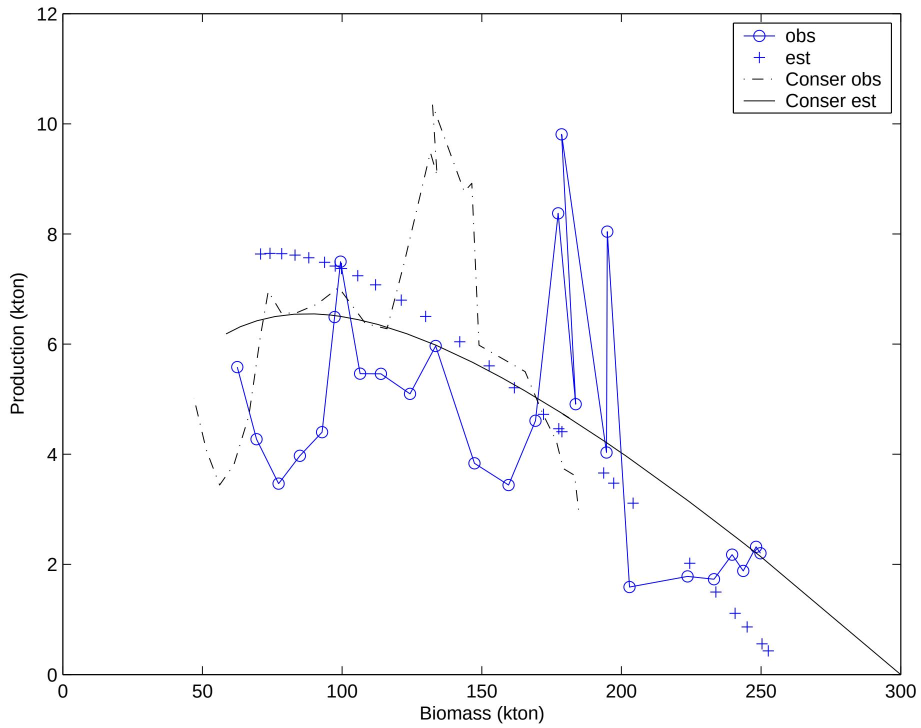

Figure 3.1: Surplus production (kton) as a function of stock biomass (kton) for sablefish, with Conser (1998) results and this study estimation, where *obs* indicates the observed values of biomass and production, and *est* indicates the estimated values of biomass and production, Conser obs indicates Conser (1998) observed results and Conser est indicates Conser (1998) estimated results. Production has been calculated from Shepherd model (Shepherd, 1987) in both studies.

recruitment, while in the early 1990s adverse conditions may lead to poor recruitment. Overall, the model results found here were satisfactorily close to Conser (1998) results although biomass values are somewhat higher but production are very similar (Figure 3.1). Management actions should seek to avoid any further increase in the catch, since the observed biomass in the last few years is already less than the biomass for the maximum sustainable yield (Figure 3.1).

The simple relationship production/biomass from stock production models cannot track transient fluctuations presented in the data, so the expected fit is considered adequate when the model curves passes through the general scattered of the data.

3.4.2 Uncertainty and Residual Analysis

Although the CMM claims to consider both observation and process errors in the minimisation function, in this study different weights for observation and process errors of the objective function have been tested. This procedure serves fundamentally three purposes: (i) to verify the behaviour of the minimisation routine when considering extreme situations such as only observation and only process error modelling; (ii) to find the right balance between process and observation deviations, quantifying a balanced variance ratio between them; (iii) to show the importance of analysing both errors together since results based on just one kind of error (process or observation) can differ greatly.

Figure 3.2 (A) shows the minimisation results for an observation error estimation only, i.e. the process error weight is null and observation error weight (λ_θ) is one. Therefore, the deviations seen by the minimisation routine relate to observation uncertainty only. The curve has a similar trend as the collected data. In addition, the dramatic reduction in the observation error term ($\sum \theta_t^2$) (Table 3.2) is reflected by a decrease of catchability (q). Since only $\sum \theta_t^2$ is minimised major deviations appear in the process error, which, however, is a null term and ignored. Both scenarios present net production, i.e. gross production less the natural mortality which may result in negative values.

The results of the process error model are shown in the Figure 3.2 (B). The estimated values for production tend to follow the model very closely presenting two curves with similar shape. In this case, the observation error weight is null and process error weight (λ_ρ) is one. Compared with Figure 3.2 (A), q value seems to be quite stable. High residuals are permitted in the null term (observation errors) as the method attempts to decrease the value of total residuals (Table 3.2). Estimated values of B_{MSY} and MSY are the same for all scenarios since they depend on assumed values (Eq. 3.9 and 3.10) which were invariable for all situations.

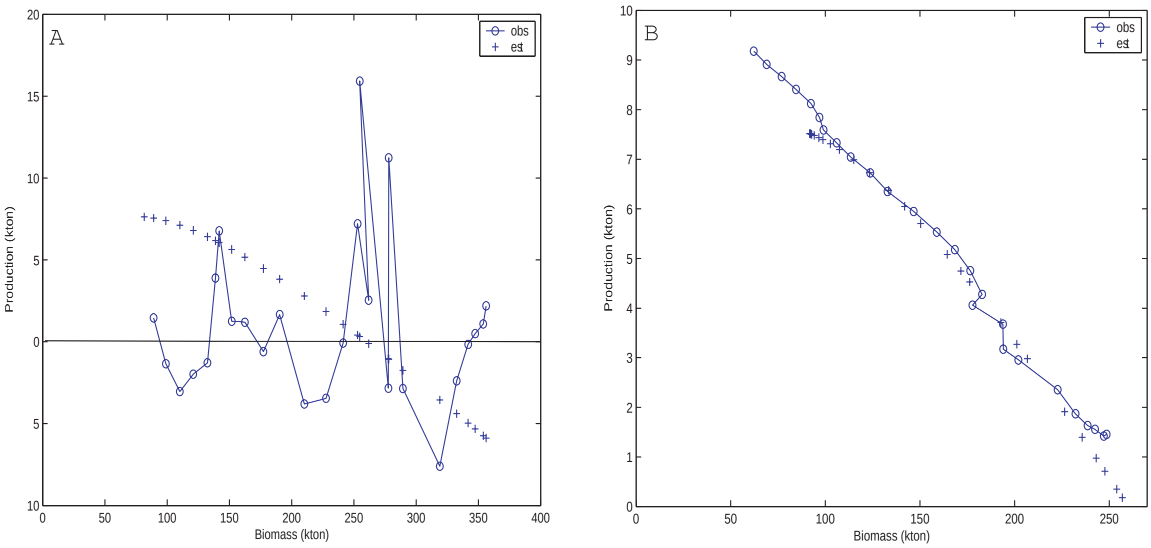

Figure 3.2: Surplus production (kton) as a function of stock biomass (kton) for sablefish. (A) Observation error model where objective function observation error weight is one and processes error weight is zero. (B) Process error model where objective function observation error weight is zero and processes error weight is one. Note that the scales differ between panels (A) and (B).

Table 3.2: Minimisation results of the observation and the process error model run separately, for the objective function *Eq.* 3.16, where mixed model means both, observation and process errors.

model type	observation model	process model	mixed model	balanced mixed model
λ_θ	1	0	1	1
$\sum \theta_t^2$	$2.634 * 10^{-10}$	0.193	0.054	0.051
λ_ρ	0	1.0	1.0	1.5
$\sum \rho_t^2$	44.982	0.003	0.029	0.032
SS	$2.634 * 10^{-10}$	0.003	0.083	0.099
q	0.698	1.000	0.996	0.995
$B_{current}$ (kton)	81.59	92.76	70.82	75.36
B_{MSY}(kton)	75.37			
MSY (kton)	7.65			

3.4.3 Weighting Consistency and Ratio

In order to find the balanced variance ratio for observation and process error, some parameters summarising the results for each pair of error weights have been calculated, and the results between models compared. Firstly, the ratio between the sum of squares of the observation error and process error, is defined as the variance ratio V (Eq. 3.19),

$$V = \frac{\sum_{t=1}^{T} \theta_t^2}{\sum_{t=1}^{T} \rho_t^2}. \tag{3.19}$$

Secondly, the ratio between the process error and observation error weights, is defined as the weight ratio W (Eq. 3.20),

$$W = \frac{\lambda_\rho}{\lambda_\theta}. \tag{3.20}$$

Figure 3.3 (A) has been generated using a range of weights for observation and process errors and the values of V and W have been calculated for each set of weights. The curve has an exponential tendency. It was assumed that observation and process errors should have the same magnitude. Consequently, it is expected that the variance ratio would be similar to the weight ratio, or $V/W \approx 1$. So, the "right" balance between V and W is achieved when the ratio V/W is equal one, which, in this case are when $\lambda_\rho = 1$ and $\lambda_\theta = 0.65$ and when $\lambda_\rho = 1.5$, $\lambda_\theta = 1$. The minimisation results for the balanced scenario are shown in the last columns of Table 3.2 and the production as a function of stock biomass for the same scenario in Figure 3.3 (B). Although catchability is equal for both balanced scenarios, the current biomass estimation is slightly bigger for $V/W \approx 1$, which predicts a stock just at its B_{MSY}. In general, the results and the figure of mixed model for $W = 1$ and $V/W \approx 1$ are very similar.

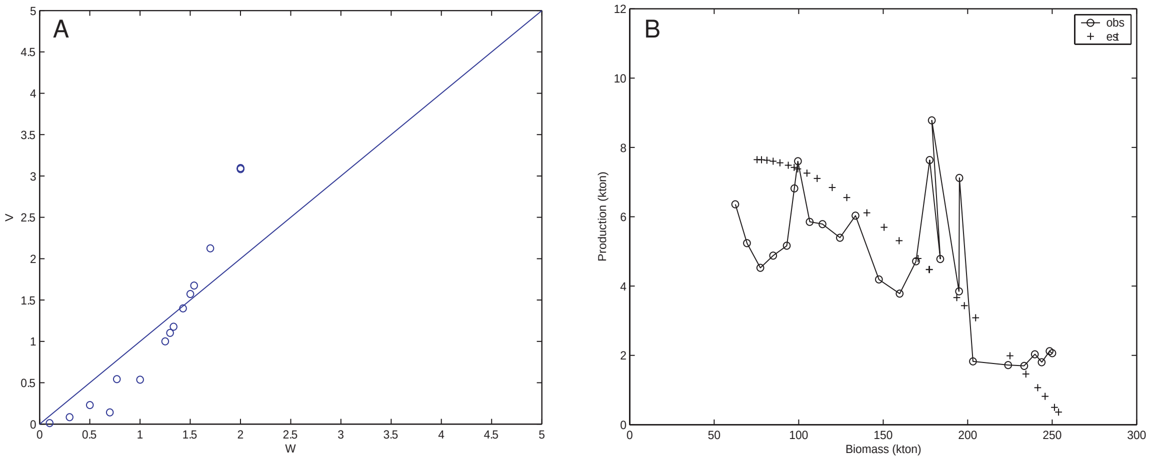

Figure 3.3: (A) Variation of variance ratio as a function of weight ratio, (B) Production (kton) as a function of stock biomass (kton) for sablefish, for $V/W \approx 1$.

3.4.4 Fixed Parameters

The biomass reduction over time is an important process in the stock production modelling especially to verify the sustainability of the fisheries. This stock production model shows a particular sensitivity to the assumed pristine biomass (B_{max}) due to the fact that the reconstruction of the biomass time series is time dependent and is calculated via the dynamic equation (Eq. 2.1). Therefore, depending on the assumed value of virgin biomass the current state of the stock could range from overexploited to underexploited. Consequently, when there is no estimate of biomass index at the beginning of the stock exploitation, it is recommended to verify a range of values for this parameter in order to observe the management consequences.

Figure 3.4 presents the variation of the different B_{max} values, calculated for the entire time series. Note that, especially for the estimation of recent biomass, the difference can be higher at the beginning of the time series.

The assumed initial value of pristine biomass has a clear influence on the estimation of the current stock biomass, and consequently, on the current stock status as seen in Table 3.3. Assuming low pristine biomass, the stock has an overexploited current biomass and high decreasing rate, whereas for high pristine biomass (300 kton) the

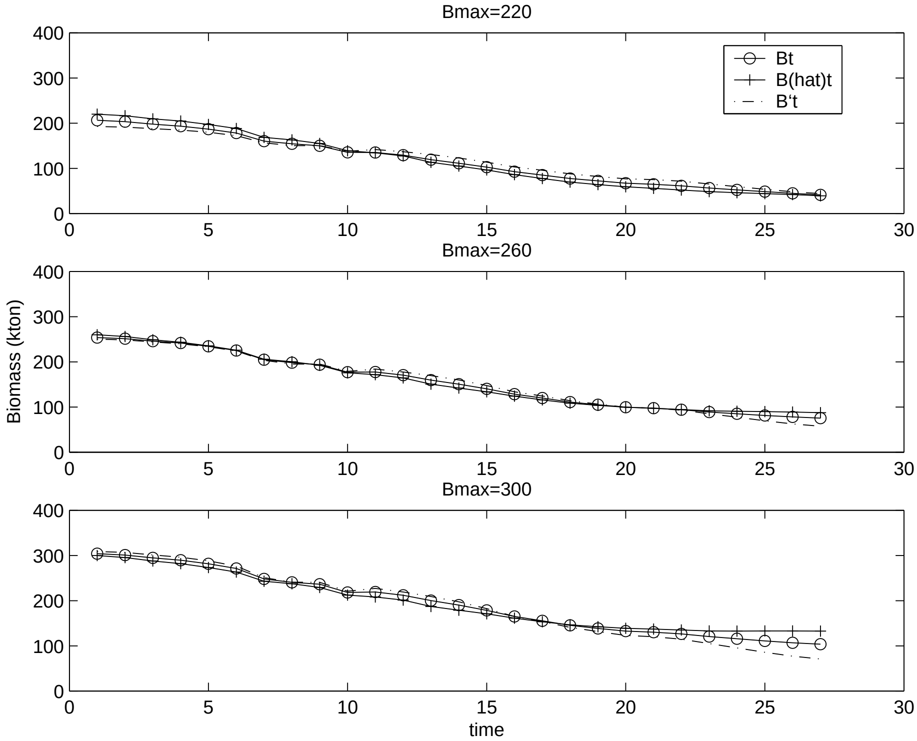

Figure 3.4: Time series of reconstructed biomass for different values of pristine biomass (B_{max}), using Eq. 3.16, where Bt is the biomass estimated by minimisation, $B(hat)t$ is the biomass calculated sequentially and $B't$ is the observed biomass, based on the index values.

Table 3.3: Estimated biomass and reduction rates for a range of initial values of pristine biomass (B_{max}), for observation and process errors model.

B_{max}(kton)	220	260	300
$B_{initial}$(kton)	206.28	253.74	303.96
$B_{current}$(kton)	41.36	75.36	103.53
$\frac{B_{initial}}{B_{current}}$	4.99	3.37	2.94
$\frac{B_{current}}{B_{MSY}}$	0.65	0.99	1.19
$\frac{B_{current}}{B_{max}}$	0.19	0.29	0.35

stock is underexploited and low biomass decreasing rate (Table 3.3). Consequently, the management quantities will be directly influenced by pristine biomass.

3.4.5 Estimation of Other Parameters

The objective function was initially set to be minimised with respect to catchability and biomass as the simplest case possible. However, it would be desirable to be able to estimate other parameters, such as pristine biomass and resilience, as well. The model sensitivity to those estimations will be examined in this section.

Estimation of Pristine Biomass (B_{max})

An estimation of three parameters simultaneously i.e. pristine biomass, catchability and biomass has been carried out. The results can be seen in Figure 3.5 (A) and Table 3.4. The values obtained for pristine biomass and the management quantities (B_{MSY} and MSY) seem to be plausible, as are the total sum of squares and sum of error components. However, the estimate of catchability was very small and the overall results are not precautionary when compared with previous minimisation, as observed in Figure 3.5 (A) where most of the observed points are under the estimated curve, i.e. observed production is lower then estimated. Letting pristine biomass be estimated brought the estimated variance ratio V closer to one.

Estimation of Resilience (α')

Resilience of the stock is the ability to take advantage of natural variation, absorbing and exploiting it, in order to avoid deleterious consequences for its survival and maintenance (Hilborn and Walters, 1992). This ability depends on a wide range of population strategies. In this natural situationthe ability to survive variations of

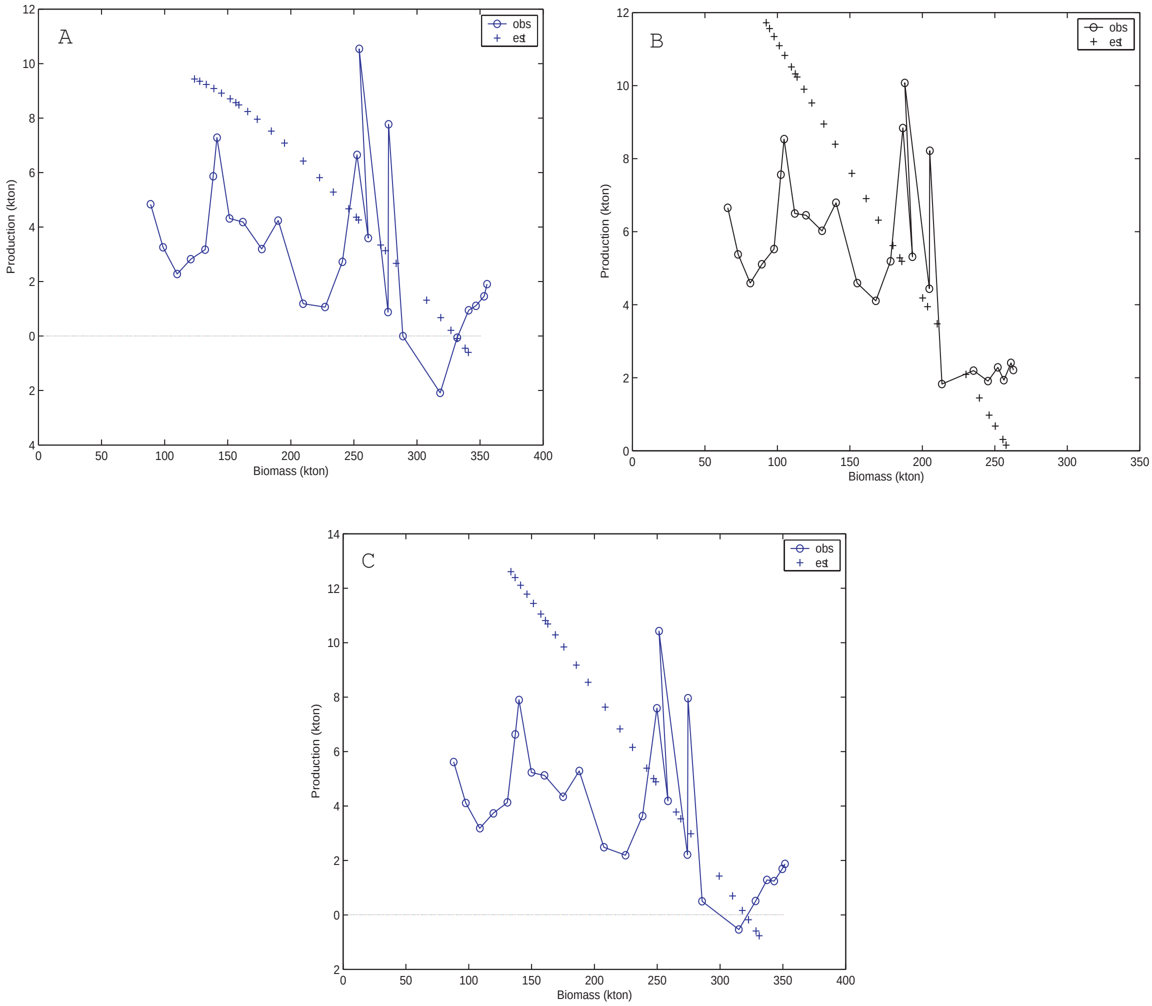

Figure 3.5: Stock production (kton) as a function of biomass (kton) for sablefish, when other parameters are estimated, see table 3.4. (A) pristine biomass (fitted value $B_{max} = 330.5$), (B) resilience (fitted value $\alpha' = 1,733$), and (C) pristine biomass and resilience (fitted value $B_{max} = 320.1$ and $\alpha' = 67.3$).

Table 3.4: Results of the model minimisation when values of pristine biomass and resilience are estimated together with catchability and biomass. Parameter units are in the text.

	B_{max}	α'	B_{max} and α'
q	0.699	0.900	0.707
B_{max}(kton)	330.51	260.00	320.10
α'	5.00	1753.00	67.27
B_{MSY}(kton)	95.81	6.06	34.56
MSY(kton)	9.72	17.35	17.57
$B_{current}$(kton)	123.70	92.30	133.57
$\frac{B_{current}}{B_{max}}$	0.37	0.36	0.42
SS	0.35	0.32	0.57
$\sum \theta_t^2$	0.18	0.15	0.31
$\sum \rho_t^2$	0.17	0.16	0.26
$\lambda\theta$	1	1	1
$\lambda\rho$	1	1	1
V	1.07	0.93	1.21
W	1.00	1.00	1.00

natural mortality is the key issue, and therefore, could be generalised as k-strategist species will have low resilience whereas r-strategist species will have a high value.

As a result, resilience is a model parameter particularly important to stocks assessment because its magnitude determines how precautionary the approach will be, considering the stock's biological response to perturbations. Therefore, the objective function (Eq. 3.16) was minimised with respect to catchability, biomass, and resilience and the sensitivity of the model was analysed.

The result of this minimisation is represented in Figure 3.5 (B) and in Table 3.4. Although the estimated catchability is similar to that of other analyses, the estimated resilience is extremely high (over 1000) and unrealistic since this would imply that the stock could never be driven to collapse. This is also reflected in the very low value of B_{MSY} (6 kton) and the MSY (over 17 kton) even though the sum of squares and sum of the error terms are reasonable.

Estimation of Both Pristine Biomass and Resilience

Finally, when both parameters, pristine biomass and resilience, were estimated by the nonlinear routine, the results were also unrealistic, although not quite as much as when resilience was estimated only (Table 3.4 and Figure 3.5 (C)). The model diagnoses values ($SS, \sum \rho_t^2, \sum \theta_t^2$) were consistent, i.e. demonstrating that the minimisation worked as it is supposed to, however the generated parameters were extremely far from any reasonable interpretation of stock dynamics and should not be considered credible.

3.5 Discussion

In this chapter a non-equilibrium stock production model expressed by difference equations has been introduced. For the model estimation routine, process and observation errors were considered and a nonlinear estimation method was employed. The population parameters natural mortality, stock resilience, and catchability, were generally set to fixed prior values but have also been treated as estimated parameters. The way these parameters affect the interpretation of the status of the exploited population was explored.

Process error was introduced in the production function as this is more consistent with the fundamental definition of process error (Rosenberg and Restrepo, 1994). The production function incorporates the population fluctuation in terms of recruitment and mortality variations, for instance. Despite the fact that process noise modelling has been applied to the dynamic equation by several authors (Walters and Hilborn, 1976, Schnute, 1977, Polacheck et al., 1993, Chen and Andrew, 1998), there are no clear biological mechanism leading to this assumption. When process error is accounted for in the dynamic equation, observation errors affecting the catch and biomass index data are also conflated into the process error, whichis an undesirable feature. The weighting of the error terms does not correspond to a clear separation between the fundamental sources of error.

For the re-implementation, the Conser model (Conser, 1998) had to be modified to avoid negative arguments during minimisation which would lead to crash of the log-normal objective function. The results generated by minimising the modified Conser objective function were consistently similar to the original work, suggesting the new objective function and minimisation algorithm are acceptable.

The use of weighted least squares minimisation is particularly advantageous due to the flexibility of the fitting procedure, demonstrating how changes in the relative weight of both sources of errors can vary the estimated results. If the data variances were known, then the approximate weights are given by $w = 1/\sigma^2$ (Lassen and Medley, 2001). In this study, process and observation error variances were unknown but were assumed to be similar (if approximately scaled), so a range of relative weight values were tested in order to find an equally balanced objective function. When only one error was admitted at one time, by setting the weight of the other term to zero, the estimation clearly "twisted" putting all the error in the other term, demonstrating that the model needs the right balancing between both errors. The relative weight applied should ideally transform the response variances to a constant value (Lassen and Medley, 2001) consistent with the known expected errors in the data and the process.

Conser (1998) pointed out the importance of assuming both errors, justifying this with the wide variation the parameters can have if just one of the uncertainties was considered. A highly variable output was identified when just one of the components of uncertainty was estimated showing the need of assuming both errors, especially since there have been several studies (Polacheck et al., 1993, Chen and Andrew, 1998, Punt, 2003) carried out considering either observation or process error, but not both.

Clearly, the weighting ratio has been proved to be crucial for the model estimation. The estimated current biomass can be bigger or smaller than B_{MSY} just by altering the weight ratio. In fact, setting the weights of observation and process errors beforehand is an indirect control of the sum of both observation errors squared and process errors squared. Neither observation error nor process error only models yield credible results. Another fundamental influence in the current biomass estimation is the setting value of pristine biomass. Under and overexploitation stock status can be reached by slightly varying the value of pristine biomass.

The process error is defined as log-normally distributed by Conser (1998) since its deviations are assumed to be dominated by recruitment fluctuations which are usually considered as log-normally distributed (Fogarty, 1993). However, there are other factors in addition to recruitment which affect the sequential evolution of biomass. Thus, considering the combined effect of these processes, it is not clear that the resultant should be log-normal.

When resilience is also estimated, the this parameters assumes unrealistic values. Therefore, resilience should probably be used as a set value but a limited range of it should also be tried. The estimation of pristine biomass seems to be more sensitive, probably because of being scaled with estimated biomass in the production function whereas resilience is just a multiplying factor, i.e. without constrain, in the same equation. Even though estimated pristine biomass are more realistic it was fairly optimistic and should be considered with caution.

The pointed out inconsistencies in Conser model assumptions, i.e. peculiar process errors formulation, neglecting the weighting balance for process and observation errors in the objective function and the lack of analysis of a range of resilience values were proved to be coherent. As a result of the inadequate process error incorporation and the fixation of certain parameters, this objective function will not be objective of further analyses since it will be proposed an improved estimation method.

3.6 Summary

The reimplementation of Conser (1998) method was successful since the present results were satisfactory close to the previous studies (Conser, 1998), even though technical reasons resulted in a slightly modified objective function.

The adjustments of weighting in the objective function lead to very different results, and must be incorporated as part of the optimisation process. Neither observation nor process error only models yielded credible results and therefore should not be preferred. The correct weighting of observation and process errors need to be found in order to obtain meaningful results.

The attempts to minimise resilience and pristine biomass together with the other two minimised parameters, catchability and estimated biomass, were not very successful. Estimation of more than the two suggested parameters should be conducted with caution and for comparison purposes.

For considering Conser (1998) objective function unsatisfactory with respect to the process error assumption and the fixed parameter further investigations are not going to be conducted. Instead a new objective function will be proposed the the following chapter.

Chapter 4

The Process and Observation Errors Estimation Model (POEEM)

4.1 Background of the Research Methodology

Estimating the status of the population via a stock production model serves two purposes, first to provide simple assessment when only incomplete information is available and second to provide a comparison with more elaborated models when data availability is not a constraint.

Stock production models have improved throughout a variety of methodological and theoretical aspects since they were first proposed. Improvements made by incorporating natural mortality, stock resilience, recruitment, and environmental variables (Shepherd, 1987, Fréon et al., 1992) and also by the use of a variety of approaches to parameter estimations (Polacheck et al., 1993, Pella, 1993, Chen and Andrew, 1998, McAllister and Kirkwood, 1998, Quinn and Deriso, 1999, Schnute and Richards, 2002) have all contributed to this.

A major recent improvement in fisheries modelling is the recognition and incorporation of uncertainties in the estimation process, since ignoring uncertainties in the available data can lead to biased predictions and has been recognised as a potential cause of stock collapse in fisheries management (Hilborn and Peterman, 1996). Therefore, in order to arrive at a reliable stock assessment different sources of uncertainty and ways to deal with these uncertainties have to be considered.

4.1.1 New Proposed Model Fitting

The incorporation of uncertainty in the estimation model varies according to the approach employed. The Bayesian framework uses data and prior knowledge, to estimate the probability of a hypothesis (Gelman et al., 1995). The use of different sources of information may be specially advantageous when data are limited and subject to a large uncertainty (Ludwig, 1996). Basically, uncertainty is included by specifying the prior probability distribution of a parameter. The prior probability is then multiplied by a likelihood estimate, generated from the analysis of the data, resulting in the posterior estimation (Gelman et al., 1995).

When employing likelihood-based methods, process errors can (in principle) be treated as parameters and consequently be estimated during model fitting (Schnute, 1994, Schnute and Richards, 1995). On the other hand, reparameterisation of the model into a state-space model, employing a Kalman filter, and the use of a likelihood estimation is a way to recognise both, observation and process errors (Pella, 1993, Schnute, 1994, Freeman and Kirkwood, 1995, de Valpine, 2002). Almost all such models are based on linear equations, and assume normally distributed errors (Millar and Meyer, 2000).

In addition, state-space models incorporating process and measurement uncertainties can also be treated by Bayesian approaches with nonlinear, non-gaussian state-space models (Meyer and Millar, 1999a, Millar and Meyer, 2000, de Valpine, 2002). However, Pella (1993) suggested the use of bootstrapping instead of Kalman filter since this method failed to estimate precise parameters when process error was admitted, in at least one case, due to the information matrix properties.

In the least squares approach, which is used in this study, uncertainty is accounted for in the objective function, during either linear or nonlinear optimisation (Gilchrist, 1984). The reliability of the estimated parameters in a stock production model may be more linked to the method used to fit to observed data than to the algebraic form of the underlying population dynamic model (Polacheck et al., 1993).

According to Chen and Andrew (1998) the most frequently employed approaches for stock production models have been *(i)* equilibrium estimators, as originally applied by Schaefer (1954), *(ii)* effort-averaging estimators presented by Fox (1975), *(iii)* process error estimators used by Walters and Hilborn (1976), Schnute (1977), and *(iv)* observation error estimators applied by Pella and Tomlinson (1969), Ludwig and Walters (1985), Ludwig et al. (1988). Clearly, the former two approaches do not explicitly incorporate any error in the estimation, resulting in highly biased results (Hilborn and Walters, 1992, Polacheck et al., 1993, Punt, 2003) and therefore, should only be used for comparison and educational purposes.

The latter two approaches incorporate either process error or observation error. Models including only the process error estimator assume that all deviations are related to the actual but unpredictable changes in population size between years, whereas catch and the abundance index are assumed to be correctly measured. A number of process error estimators have been proposed (Walters and Hilborn, 1976, Schnute, 1977, Polacheck et al., 1993), some of them using multiple regression analysis for estimation.

On the other hand, models including only the observation error estimator consider noise arising in the observed abundance index, while the population dynamic of the fish stock is assumed to be precise. The least squares method is commonly used for this kind of estimation (Hilborn and Walters, 1992, Polacheck et al., 1993, Chen and Andrew, 1998), especially when CPUE and catch data is available. It has been suggested (Hilborn and Walters, 1992, Polacheck et al., 1993) that observation error estimators are more robust than process error estimator due to the uncertainties in the error assumptions and the formulation of the dynamic models. However, the presence of process error when only observation error is considered can lead to substantial negative bias in the estimates of the variance (Punt and Butterworth, 1993). Despite the wide acceptance (FAO, 1996, Hilborn and Mangel, 1997, Chen and Andrew, 1998) that both errors are present in the real dynamics and assessment of a fish stock, they were rarely incorporated simultaneously in stock production models (Conser, 1998).

In this chapter, a new estimation method for the stock production model is proposed, which includes observation and process errors simultaneously, employing a non-linear least square approach. The new method is called Non-Equilibrium Least Squares **P**rocess and **O**bservation **E**rrors **E**stimation **M**ethod (POEEM) and will be tested through simulated data sets for assessing its robustness. First, the new method is tested on simulated data, and the reliability of the results is assessed by Monte Carlo methods. The data of Conser (1998) will then be analysed with the new method and results will be compared with the previous chapter.

4.2 New Estimation Method

Previous studies (Walters and Hilborn, 1976, Schnute, 1977, Polacheck et al., 1993, Conser, 1998) considered production error in the dynamic equation (Eq. 2.1) which comprises variation of biomass in time, balanced with production gain and catch loss. Essentially, this function conflates both errors, process error in the production, and observation error from the catch and CPUE data. Therefore, the representation of process error in this equation is not consistent with the proper definition of process error.

In the new method (POEEM), the process error is regarded truly as the uncertainty generated during the underlying population dynamics, i.e. recruitment, reproduction and mortality. In the stock production model these population dynamic aspects are related to the stock production process by,

$$P_t = \alpha' M B_t \left(\frac{1 - \dfrac{B_t}{B_{max}}}{1 + \dfrac{\alpha' B_t}{B_{max}}} \right) + \Delta P_t, \tag{4.1}$$

where P_t is production at time t, α' is the stock resilience, M is the natural mortality, B_t is the estimated biomass at time t, B_{max} is the pristine biomass, and ΔP_t is the process error. The latter is therefore estimated as,

$$\Delta P_t = Pd_t - Pm_t, \tag{4.2}$$

where Pd_t is the production calculated from the dynamic equation (Eq. 2.1) and Pm_t is the production estimated from the Shepherd model (Eq. 3.8). The process error estimate is then normalised by the mean of the calculated production ($\overline{Pd_t}$) in order to scale the deviation to the magnitude of the production,

$$\rho_t = \frac{(Pd_t - Pm_t)}{\overline{Pd_t}}. \tag{4.3}$$

The observation error term is related to the abundance index,

$$U_t = \frac{C_t}{E_t} + \Delta U_t = qB_t + \Delta U_t, \tag{4.4}$$

where U_t is CPUE at time t, C_t is catch at time t, E_t is effort at time t, q is the catchability coefficient, and B_t is biomass of the population at a time t. The observation error (ΔU_t) is described as,

$$\Delta U_t = U_t - qB_t^*, \tag{4.5}$$

and then normalised to give θ_t,

$$\begin{aligned} \theta_t &= \frac{(U_t - qB_t^*)}{\overline{U}_t}, \text{ where} \\ B_t^* &= \frac{B_t + B_{t+1}}{2}. \end{aligned} \tag{4.6}$$

B_t^* is the estimated biomass at time t, and is taken as the average of biomass between the current and the next period of time, allowing the estimation of biomass in the next period of time t, which is another small methodological enhancement since most of the studies (Polacheck et al., 1993, Chen and Andrew, 1998, Conser, 1998) are only concerned with current biomass. Here the observation error term is also normalised with the average of CPUE in order to scale the magnitude of the observation deviations. The purpose of the normalisations is to make both of the errors estimators of the same order, i.e. order of one, so that their relative sizes are comparable.

Consideration of uncertainty in indices of abundance is fundamental to estimating uncertainty in stock size using an assessment model (Patterson et al., 2001).

By combining process and observation error, an appropriated weighted objective function is expressed as

$$SS = \lambda_\rho \sum_{y=1}^{Y-1} {\rho_t}^2 + \lambda_\theta \sum_{y=1}^{Y} {\theta_t}^2, \tag{4.7}$$

where λ_ρ and λ_θ are the relative weights for process error and observation error, respectively. This objective function allows for variation of the two weights which is desirable in order to find the balanced result of observation and process errors.

Each minimisation requires a data series of catch and CPUE, so the objective function (SS) is minimised with respect to q and true biomass, using a nonlinear parameter estimation technique from MATLAB V6.5. The optimisation function "fminunc", i.e. minimisation of an unconstrained multivariable function, was employed. This function uses a Quasi-Newton Method, the most favoured gradient information method, since it builds up curvature information at each iteration to formulate a quadratic model problem (MATLAB, 2005).

In general, the maximum number of iterations was set to 300,000, the maximum number of function evaluations allowed was 20,000,000 and the termination tolerance of the function value was 10^{-8}. These values were found, by trial and error, to be necessary to ensure convergence of the method on this rather difficult minimisation problem.

4.2.1 Simulation Study

The performance of the POEEM was tested first on simulated catch, production and CPUE data series. Catch simulated data was generated by the following equations,

$$\begin{aligned} C &= LE\alpha' M B_t, \text{ where} \\ LE &\approx \frac{F}{\alpha' M}, \end{aligned} \tag{4.8}$$

where LE is the level of exploitation of each simulated population and proportional to the expected fishing mortality, α' is the stock resilience, M is the natural mortality, B_t is the biomass at time t, and F the fishing mortality. Essentially, the equation generates a population biomass, proportional to the stock resilience, which is reduced by the fisheries activity and natural mortality. A initial value of biomass is set, proportional to pristine biomass. Independent normally distributed errors with $N(0, \sigma^2)$ were used to simulate ρ_t and θ_t, respectively process and observation errors. Process error was then, added to the production curve in the Eq. 4.1 which will calculate biomass through the Eq. 2.1 also used in the CPUE estimation. Observation error was added to CPUE according to Eq. 4.4.

Low, medium and high noise levels or variance error, 0.1, 0.5, and 0.9 respectively, were assumed. The same values were assumed as low, medium and high levels of exploitation. Therefor, the model performance was analysed in a total of nine scenarios. To each scenario, the objective function was minimised with respect to q and B_t employing the unconstrained minimisation procedure described above.

4.2.2 Weighting Consistency and Residual Ratio

For the mixed model, it was assumed that observation and process uncertainties should have the same magnitude, which means,

$$\begin{aligned} R^2_\theta &= R^2_\rho, \\ \text{where } R^2_\theta &= \sum_{t=1}^{T} {\theta_t}^2, \\ \text{and } R^2_\rho &= \sum_{t=1}^{T} {\rho_t}^2, \end{aligned} \tag{4.9}$$

where R^2_θ is the sum of all observation residuals squares, i.e. the sum of the squared observation deviations. Similarly, R^2_ρ is the sum of all process residuals squared. The estimated error variance ratio, V is defined as,

$$V = \frac{\sum_{t=1}^{T} \theta_t^2}{\sum_{t=1}^{T} \rho_t^2}, \tag{4.10}$$

and this study seeks solutions where $V \approx 1$. To achieve this, the weight of each error term in the estimation model is treated as a fixed parameter and is set before the minimisation is carried out. This approach gives, some control over the variance ratio. The controlling ratio is the weight ratio W (Eq.4.11) and is defined as,

$$W = \frac{\lambda_\rho}{\lambda_\theta}. \tag{4.11}$$

Consequently, the assumption that observation and process noise have the same magnitude is equivalent to $V = W$ or $V/W = 1$.

Thus, in order to find the weighting ratio for the mixed model which comply with the initial assumption, several data series were simulated with levels of exploitation and levels of noise both taking (relative) values of $0.1, 0.5$ and 0.9. The parameters $q = 1.0$ and $M = 0.1$ were fixed for all simulations whereas $B_{initial}$, α' and B_{max} were tested over a range of values.

Table 4.1 shows the sum of observation errors squared, the sum of process errors squared, the weight of each error term, the variance ratio, and the weight ratio, for several data series with different levels of noises and exploitation, and a range of initial values for $B_{initial}$, α' and B_{max}. Observation and process error were added to each data series in equal quantity. Therefore, for the same level of noise, it was expected to find $V/W \approx 1$ when W was 1 irrespectively to the initial parameter settings assumed. However, for all the scenarios of $W = 1$, V/W was extremely big,

Table 4.1: Model residual diagnoses for simulated data set with several levels of exploitation and noise, from a a range of pristine biomass, catchability and initial biomass, where $\sum\theta^2$ is the sum of observation errors squared , $\sum\rho^2$ is the sum of process errors squared, λ_θ is he weight of the observation errors, λ_ρ is the weight of the process errors, V is the variance ratio, W is the weight ratio, and V/W is the residual ratio for simulated data series.

W=1	$\sum\theta^2$	$\sum\rho^2$	$\lambda\theta$	$\lambda\rho$	V	W	V/W
	0.373	0.006	1	1	66.752	1	66.752
	0.269	0.003	1	1	83.269	1	83.269
	0.261	0.005	1	1	56.278	1	56.278
	0.327	0.011	1	1	30.624	1	30.624
	0.275	0.003	1	1	86.592	1	86.592
	0.213	0.016	1	1	13.080	1	13.080
	0.266	0.008	1	1	35.189	1	35.189
	0.261	0.010	1	1	25.341	1	25.341
	4.691	0.418	1	1	11.215	1	11.215
	0.286	0.001	1	1	220.699	1	220.699
	0.301	0.001	1	1	276.881	1	276.881
	0.286	0.001	1	1	220.699	1	220.699
	9.309	0.038	1	1	247.876	1	247.876
	5.265	0.024	1	1	219.276	1	219.276
$V/W \approx 1$	$\sum\theta^2$	$\sum\rho^2$	$\lambda\theta$	$\lambda\rho$	V	W	V/W
	0.132	7.459	1	0.0160	0.018	0.016	1.104
	0.057	12.380	1	0.0040	0.005	0.004	1.146
	0.048	14.607	1	0.0039	0.003	0.004	0.840
	0.054	13.247	1	0.0037	0.004	0.004	1.105
	0.087	4.756	1	0.0180	0.018	0.018	1.019
	0.040	9.907	1	0.0038	0.004	0.004	1.065
	0.061	14.197	1	0.0038	0.004	0.004	1.135
	0.043	7.598	1	0.0052	0.006	0.005	1.083
	0.041	7.952	1	0.0050	0.005	0.005	1.031
	0.060	16.059	1	0.0037	0.004	0.004	1.008
	0.050	13.483	1	0.0035	0.004	0.004	1.058
	0.056	3.507	1	0.0150	0.016	0.015	1.068
	0.055	15.125	1	0.0032	0.004	0.003	1.155
	0.055	13.769	1	0.0024	0.004	0.002	1.667
$V \approx 1$	$\sum\theta^2$	$\sum\rho^2$	$\lambda\theta$	$\lambda\rho$	V	W	V/W
	0.319	0.290	1	0.0900	1.098	0.090	12.203
	0.225	0.186	1	0.1200	1.206	0.120	10.047
	0.217	0.256	1	0.1000	0.847	0.100	8.473
	0.215	0.202	1	0.1200	1.068	0.120	8.902
	0.261	0.267	1	0.1300	0.977	0.130	7.514
	0.229	0.241	1	0.1000	0.952	0.100	9.524
	0.159	0.155	1	0.2000	1.021	0.200	5.106
	0.219	0.204	1	0.1000	1.076	0.100	10.760
	0.203	0.189	1	0.1700	1.073	0.170	6.309
	0.194	0.173	1	0.2000	1.119	0.200	5.593
	0.262	0.146	1	0.0900	1.790	0.090	19.886
	0.264	0.120	1	0.1000	2.212	0.100	22.120
	0.272	0.247	1	0.0600	1.101	0.060	18.350
	0.250	0.309	1	0.0600	0.809	0.060	13.482
	8.488	6.638	1	0.0666	1.279	0.067	19.210
	8.533	4.519	1	0.0870	1.888	0.087	21.702
	0.259	0.182	1	0.0800	1.420	0.080	17.749
	4.314	3.257	1	0.1300	1.325	0.130	10.189

since production errors were far smaller than observation errors. On the other hand, when V/W was close to one, λ_ρ had to be quite small in order to have process and observation residuals balanced. Considering that, the same amount of noise has been set simultaneous for process and observation errors in each data series, it was expected to find $V \approx 1$ when $W = 1$. However, the required value of W to result in $V/W \approx 1$ was smaller than one. Thus, independently of the initial parameter settings, for simulated data with noise added with equal magnitude, estimated observation error was always bigger. Consequently, to be consistent with the assumption that process and observation errors are balanced, $V \approx 1$ will be considered as a coherent residual ratio, i.e. the sum of observation errors is similar to the sum of process errors, and the weight ratio W is chosen freely (by trial and error) to achieve this.

4.2.3 Model Consistency

The model performance was tested with different scenarios. The level of exploitation was set to 10%, 50% and 90%, to represent respectively an underexploited population, population around maximum exploitable production and an overexploited stock. For each level of exploitation, noise levels of 10%, 50% and 90% fo observation and process error were included in the data.

For each scenario, the initial parameter settings were: $B_{initial} = 180$ kton, $\alpha' = 2$, $M = 0.1$ year^{-1}, $B_{max} = 500$ kton and $q = 1.0$. The normally distributed error was added to the production model (Eq. 4.1) and to the CPUE (Eq. 4.4) and the minimisation procedure described above was used.

The results of these simulation scenarios are presented below. The frequency distribution of the catchability (q) and biomass at the next period (B_{t+1}) are shown in Figure 4.1 and Figure 4.2, respectively. The basic statistic results for the simulation diagnoses, i.e. Sum of Squares (SS) and residual ratio (V) are listed in Table 4.2.

The weight ratio (W) was determined before the simulations by trial and error using a range of values of W since it is the way to influence the variance of the observation and

Table 4.2: Basic statistic of the minimisation parameters (q and B_{t+1}) and model diagnoses (SS and V) for a range of levels of exploitation (LE) and levels of noise (LN), where min is the lowest estimated values, max is the highest estimated values and σ is the standard deviation. The "best value" of q was 1.0

catchability (q)								
LE	LN	n_{total}	$n_{analysed}$	min	max	mean	median	σ
0.1	0.1	226	213	0.90	1.16	1.03	1.02	0.06
0.1	0.5	209	81	0.97	12.40	2.62	1.49	3.04
0.5	0.1	224	221	0.81	1.23	1.05	1.06	0.10
0.5	0.5	232	174	1.01	2.96	1.82	1.72	0.41
0.9	0.1	200	196	0.93	1.18	1.05	1.05	0.05
0.9	0.5	210	157	0.76	2.13	1.26	1.24	0.28
biomass at the next period (B_{t+1})								
LE	LN	n_{total}	$n_{analysed}$	min	max	mean	median	σ
0.1	0.1	226	213	316.09	354.05	335.32	336.13	7.30
0.1	0.5	209	81	35.85	359.27	262.19	288.95	81.90
0.5	0.1	224	221	90.99	181.55	127.69	125.21	18.58
0.5	0.5	232	174	29.49	185.78	95.98	95.58	34.95
0.9	0.1	200	196	29.85	57.2	41.38	41.03	5.362
0.9	0.5	210	157	15.70	158.75	56.04	50.47	27.05
sum of squares (SS)								
LE	LN	n_{total}	$n_{analysed}$	min	max	mean	median	σ
0.1	0.1	226	213	0.086	0.53	0.24	0.23	0.07
0.1	0.5	209	81	2.26	10.91	5.78	5.25	2.10
0.5	0.1	224	221	0.092	0.47	0.23	0.22	0.064
0.5	0.5	232	174	2.21	11.39	5.71	5.55	1.61
0.1	0.9	200	196	0.085	0.74	0.26	0.25	0.094
0.9	0.5	210	157	2.03	11.81	6.11	5.92	1.94
variance ratio (V)								
LE	LN	n_{total}	$n_{analysed}$	min	max	mean	median	σ
0.1	0.1	226	213	0.61	3.81	1.88	1.75	0.74
0.1	0.5	209	81	0.32	3.95	2.22	2.32	0.95
0.5	0.1	224	221	0.38	4.20	1.37	1.21	0.65
0.5	0.5	232	174	0.33	3.92	1.49	1.25	0.81
0.1	0.9	200	196	0.25	4.25	1.59	1.41	0.77
0.9	0.5	210	157	0.33	4.00	1.90	1.67	0.90

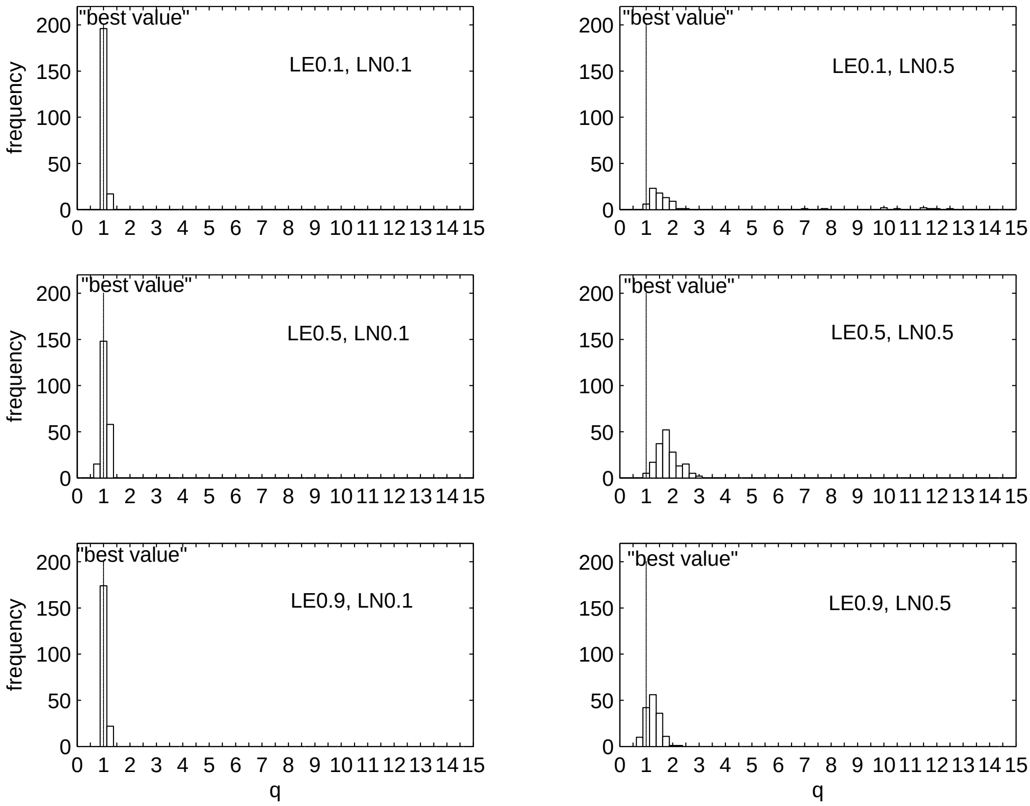

Figure 4.1: Frequency distribution of catchability (q) calculated from simulated data series with level of exploitation (LE) 0.1, 0.5 and 0.9 and levels of noise (LN) 0.1 and 0.5, where the "best value" of q was 1.0.

process errors in order to achieve the balance of the uncertainties. For each value of W, around a dozen realisations were run and the mean, median and standard deviation of V were checked. Once the variance ratio mean and median was approximately one, the value of W was employed in the optimisation of a few hundred simulated data series. The number of data series analysed for each scenario is also listed Table 4.2. The total number of simulated data series is slightly bigger then the analysed ones since results with the variance ratio (V) bigger than four and small than 0.2 were considered unbalanced and therefore have been dismissed from further analyses.

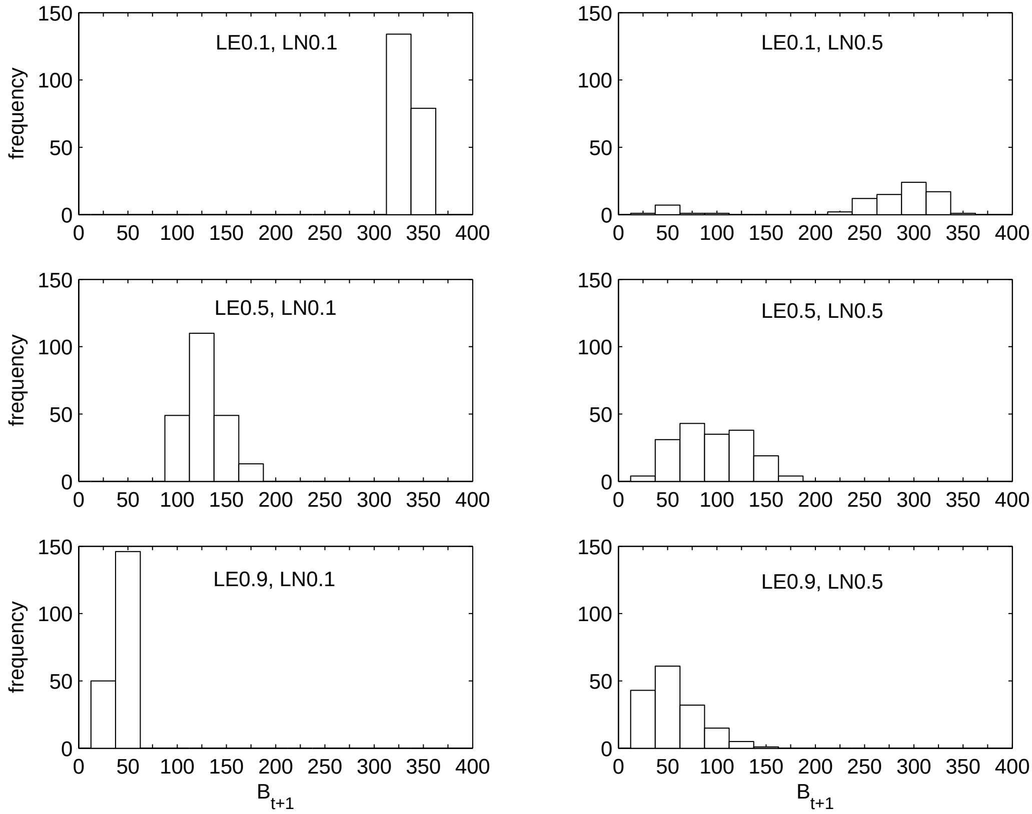

Figure 4.2: Frequency distribution of biomass at the next period (B_{t+1}) calculated from simulated data series with level of exploitation (LE) 0.1, 0.5 and 0.9 and levels of noise (LN) 0.1 and 0.5.

Noise Level of 10%

The histograms on the left of Figure 4.1 represent catchability estimated from simulated data series whose added level of noise was 10% and the exploitation rate was, from top to bottom, 10%, 50% and 90%, respectively. In order to achieve $V \approx 1$ for this level of noise, the set value of W was 0.06 for 10% of exploitation, 0.09 for 50% of exploitation and 0.12 for 90% of exploitation. Irrespectively of the level of exploitation, the modal class has a high frequency, comprises values of q within 10% of its initial value (1.0) and the dispersion is close to the modal class (Figure 4.1 and Table 4.2).

Forecast biomass for the next period (B_{t+1}) obtained through the simulated data with 10% of level of noise are shown on the left of the Figure 4.2 in the same order of the level of exploitation as q. The modal classes are also well marked for all three levels of exploitation and the data dispersion is small (Figure 4.2). As expected, the lower level of exploitation (10%) has a higher estimated biomass for the next period, decreasing substantially for higher levels of exloitation.

The sum of squares of the objective function (SS) for low levels of noise (0.1) was quite small and exhibited only a small dispersion (Table 4.2) while the variance ratio (V) has mean and median around one (Table 4.2).

Noise Level of 50%

For scenarios with a noise level of 50%, q estimated from simulated data series is represented in the histograms on the right of Figure 4.1. Levels of stock exploitation are, respectively, from top to bottom 10%, 50% and 90%. the set values of W to result in $V \approx 1$ for 50% of noise was 0.09, 0.17 and 0.17 for exploitation levels of 10, 50, and 90% respectively. Irrespectively of the level of exploitation, the modal class is not as marked and the dispersion is bigger compared with the previous level of noise (Figure 4.1). For levels of noise of 0.1 and 0.9 the modal class central point of q is 1.25 whereas for level of noise of 0.5 it is 1.75. The median estimated values of q are about 50% larger than the actual value of q (Table 4.2). Low level of exploitation and medium level of noise ($LE0.1, LN0.5$) revealed a large dispersion of the catchability estimate (Figure 4.1). It also has a higher mean and median of V than other scenarios (Table 4.2). In general, the SS were considerably higher than for lower levels of noise as expected (Table 4.2).

Noise Level of 90%

For a high level of noise, i.e. 90%, it was not generally possible to find a weight ratio (W) which would result in variance ratio (V) of approximately one for any level of exploitation. Tables 4.3 shows the basic statistics of the estimated model parameters and Table 4.4 present model diagnoses for all levels of exploitation. They point out the high dispersion of those results when high levels of noise were introduced into the simulated data. Most of the results of q and B_{t+1} are unrealistic. The variance ratio varies enormously which is incompatible with the initial assumptions and the SS is considerably higher than at lower levels of noise. Therefore, it was not possible to estimate reliable parameters with desirable precision. Median was a more meaningful statistics since the dispersion was far bigger than previous scenarios. As formerly observed the higher the level of exploitation the smaller is the dispersion.

For both tables (Tables 4.3 and 4.4) minimum and maximum values of are affected by occasional extreme results, therefore, the median gives a more reliable estimate.

Table 4.3: Basic statistics of catchability (q-top panel) and biomass at next period (B_{t+1}-lower panel), when a range of values of W was used, for simulated data with level of exploitation (LE) 0.1, 0.5 and 0.9 and levels of noise 0.9. "Best value" of q is 1.0.

q	W	n	min	max	$median$	$mean$	σ
LE 0.1	0.2	7	0.77	36665	6890.50	10022.44	13289.31
	0.27	10	0.71	36880	4.48	7349.81	12893.94
	0.3	10	1.20	44424	4.59	6202.78	14519.11
	0.32	31	0.71	91228	2.55	8911.32	20431.92
LE 0.5	0.4	20	1.23	20017	3.04	3242.41	5609.51
	0.42	10	1.06	34158	2.80	4211.72	10640.72
	0.45	8	1.08	18110	2.52	2265.88	6401.99
	0.47	10	1.94	43785	2.47	6623.46	14436.41
	0.5	12	1.00	51047	2.38	6559.79	16107.14
LE 0.9	0.48	11	0.47	14631	1.33	1458.52	4388.97
	0.5	22	0.47	51047	2.00	3867.54	12090.99
	0.52	6	0.77	2.03	1.41	1.42	0.48

B_{t+1}	W	n	min	max	$median$	$mean$	σ
LE 0.1	0.2	7	-0.25	427.02	0.08	167.42	211.00
	0.27	10	-0.26	468.91	184.01	195.26	176.47
	0.3	10	-0.11	381.14	188.55	176.05	133.35
	0.32	31	-0.10	467.99	233.71	200.05	145.86
LE 0.5	0.4	20	-0.97	140.41	74.40	59.92	55.41
	0.42	10	-0.56	147.87	84.48	70.65	64.15
	0.45	8	0.11	167.25	121.82	108.05	60.79
	0.47	10	-0.41	158.30	71.12	69.57	57.01
	0.5	12	0.03	190.82	107.94	107.50	62.62
LE 0.9	0.48	11	-0.65	242.94	71.37	80.25	72.75
	0.5	22	0.03	243.29	92.03	98.96	67.45
	0.52	6	20.96	217.14	120.05	113.00	72.36

Table 4.4: Basic statistics of sum of squares of the objective function (SS) and variance ratio(V), when a range of values of W was used, for simulated data with level of exploitation (LE) 0.1, 0.5 and 0.9 and levels of noise 0.9.

SS	W	n	min	max	$median$	$mean$	σ
LE 0.1	0.2	7	5.55	21.46	5.79	10.78	6.81
	0.27	10	7.52	28.88	15.27	15.06	6.86
	0.3	10	8.66	26.17	16.62	17.07	6.36
	0.32	31	9.11	54.98	17.59	19.02	9.29
LE 0.5	0.4	20	10.90	27.72	17.47	16.66	5.69
	0.42	10	11.03	24.53	14.21	15.83	5.14
	0.45	8	12.51	33.30	19.63	21.16	6.87
	0.47	10	11.26	24.57	17.99	17.40	4.57
	0.5	12	14.05	33.67	23.63	23.14	6.68
LE 0.9	0.48	11	10.87	27.438	21.25	19.41	5.26
	0.5	22	10.92	33.668	22.61	21.58	6.44
	0.52	6	11.601	42.261	23.12	24.32	10.36

V	W	n	min	max	$median$	$mean$	σ
LE 0.1	0.2	7	6.81E-07	160020	6.20E-06	23159.26	60354.88
	0.27	10	2.77E-07	5117	7.91	545.34	1608.61
	0.3	10	5.48E-07	264	8.98	33.35	81.41
	0.32	31	2.17E-07	4356	12.18	181.27	780.08
LE 0.5	0.4	20	3.79E-07	15.30	1.80	3.71	5.04
	0.42	10	1.82E-07	24.76	2.05	6.84	10.01
	0.45	8	2.48E-06	55.78	3.14	10.76	18.89
	0.47	10	3.73E-08	9.08	2.49	2.61	2.67
	0.5	12	2.27E-07	113.71	3.95	16.54	31.98
LE 0.9	0.48	11	2.19E-07	89.38	8.96	15.20	25.15
	0.5	22	2.27E-07	119.35	6.95	19.39	32.91
	0.52	6	1.39	18.75	4.63	6.48	6.71

4.2.4 Conser (1998) Dataset Analysis

In this section, the sablefish data set (Conser, 1998) used in the previous chapter was analysed according to the POEEM (Eq. 4.7). The results are shown in Figures 4.3, and 4.4 and Table 4.5. The latter displays the initial parameter settings and the results of the estimation for various weighting scenarios.

First, the mixed model was employed with either observation error or process error only, to verify the importance of regarding both errors in the estimation process. Figure 4.3 shows the result of the POEEM when (A) $\lambda_\theta = 1$ and $\lambda_\rho = 0$, i.e. an observation error model and (B) $\lambda_\theta = 0$ and $\lambda_\rho = 1$, i.e. a process error model. When only observation errors were considered, the model pushes all the deviations to the null term (process error) in order to decrease the sum of squares (Table 4.5) whereas for the process error only case, all deviations are accounted for in the observation error, which is the null term (Table 4.5). The data dispersion around the estimated production curve clearly reflects the value of SS in each situation (Figure 4.3) and the results of the management quantities, q and B_{t+1}, are of doubtful validity (Table 4.5). The two curves easily exemplify the bias in the results, since situation (A) shows a stock near its maximum sustainable yield levels while (B) places the stock at a fairly low level of exploitation (Figure 4.3 and Table 4.5).

It is clear that considering either process or observation errors alone in the model fitting can strongly bias the results and may lead to a wrong conclusion about the state of the stock. For the POEEM, the question is, whether the residual ratio (V/W) or the variance ratio (V) has to be approximately one in order to obtain a meaningful and realistic result. Figure 4.4 shows the results of the observed and the estimated curves, with the POEEM when (A) the errors variance ratio (V) was approximately one and (B) when the V/W was approximately one. The curves again show the stock in opposite exploitation stages, i.e. for the curve (A) the stock is still at a low level of exploitation with high biomass and increasing production, while curve (B) represents an overexploited stock which requires strict management regulation in order to recover to sustainable levels (Figure 4.4 and Table 4.5). However, the results

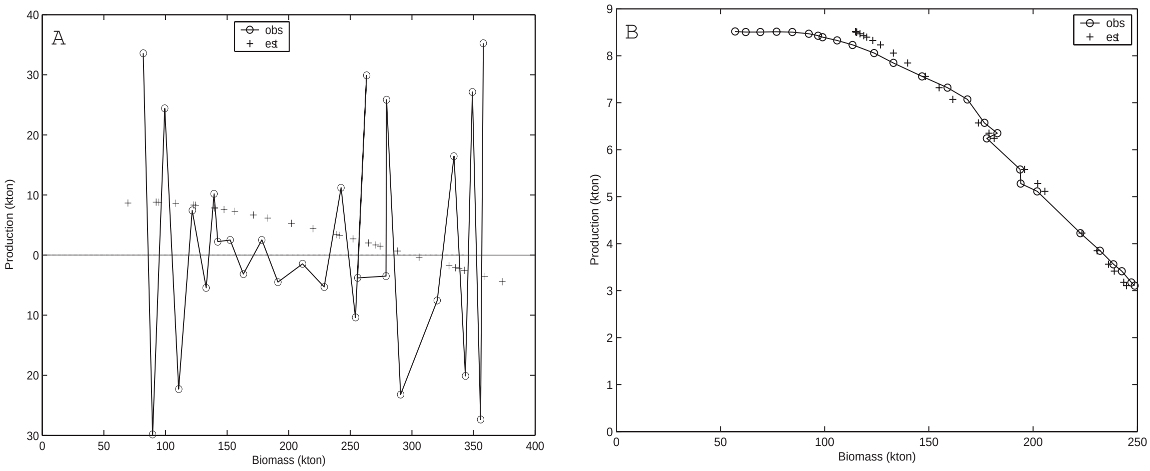

Figure 4.3: Surplus production (kton) as a function of stock biomass (kton) for sablefish employing POEEM. (A) Observation error weight is one and processes error weight is null. (B) Observation error weight is null and processes error weight is one. Note that the scales differ between panels A and B.

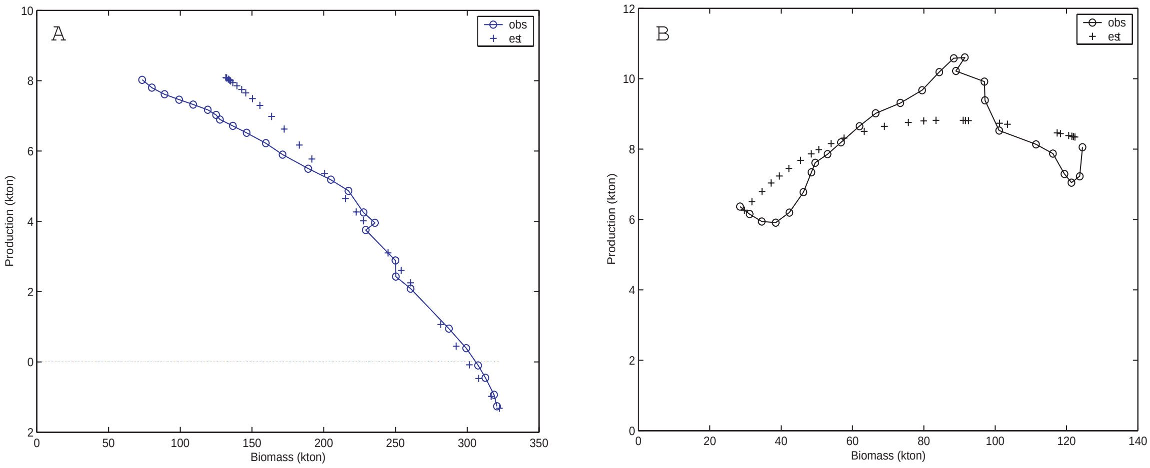

Figure 4.4: Surplus production (kton) as a function of stock biomass (kton) for sablefish employing POEEM. (A) for $V \approx 1$ and (B) for $V/W \approx 1$. Note that the scales differ between panels A and B.

Table 4.5: Initial parameter settings and results of the minimisations, of sablefish data set employing the mixed model, with different weighting settings, where 'obs only' is the model estimation which minimises observation error only, and 'proc only' is the model estimation which minimises process error only.

Parameter Settings				
	$V \approx 1$	$V/W \approx 1$	obs. only	proc only
q	1	1	1	1
B_{t+1} (kton)	220	220	220	220
α'	5	5	5	5
M year^{-1}	0.07	0.07	0.07	0.07
B_{max}(kton)	300	300	300	300
Estimated Parameters and Diagnoses				
q_{est}	0.7754	1.9981	0.6946	1.0
$B_{t+1,est}$(kton)	131.8284	29.6951	94.6498	114.8159
$\frac{B_{t+1}}{B_{max}}$	0.44	0.10	0.32	0.38
MSY (kton)	8.8243	8.8243	8.8243	8.8243
n. iterations	203	135	34	156027
SS	0.3953	0.0378	0.0011	$9.86 * 10^{-9}$
$\sum \theta_y^2$	0.3495	0.0195	0.0011	0.5537
$\sum \rho_y^2$	0.3274	0.3646	$1.86 * 10^3$	$9.86 * 10^{-9}$
$\lambda\theta$	1	1	1	0
$\lambda\rho$	0.14	0.05	0	1
V	1.0676	0.0536	$5.9 * 10^{-7}$	$5.61 * 10^7$
W	0.14	0.05	0	
V/W	7.6259	1.0716		0

of the simulations (see section 4.2.2) suggest that $V \approx 1$ should be regarded as a more reliable balance since setting $V/W \approx 1$ did not yield results consistent with the known parameters for simulated data sets. The results obtained for $V/W \approx 1$ are in this case not extreme or unfeasible, and for real data the correct values for V are unknown. This issue is discussed further below.

Goodness-of Fit Surface

The number of estimatable parameters during a model fitting is limited by the data available and their independency. One cannot achieve reliable results when too many parameters are estimated. However, the choice of the initial parameters may have a crucial influence on the model outcome, due to parameter correlations and over-parameterisation of the estimation. Therefore, it is important to analyse the per-

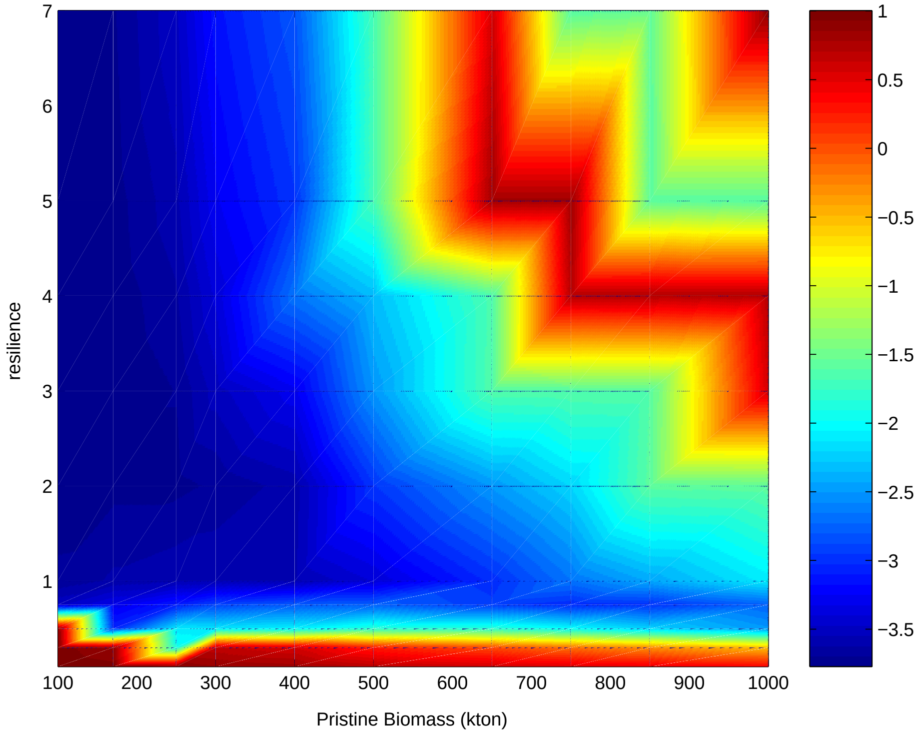

Figure 4.5: Goodness-of-fit surface of the sablefish data set fit through POEEM for a range of values of α' and B_{max}, SS is shown on a logarithmic scale.

formance of the model for a range of the parameters which are specified and not determined directly.

Here the data set used by Conser (1998) was minimised with POEEM using a range of values of resilience and pristine biomass in order to find the interval of both parameters with small sum of squares of the objective function. The set values of α' were 0.1,0.3, 0.5, 0.75, 1, 2, 3, 4, 5, 7 and the B_{max} were 100, 170, 250, 300, 400, 500, 650, 750, 850, 1000.

This procedure of parameter space mapping enables us to explore the behaviour of the model in relation to a larger number of uncertain parameters, for which direct minimisation fail.

Figure 4.5 represents the sum of squares calculated for these ranges of resilience and pristine biomass values, with SS shown on a logarithmic scale.

The dark blue region has the lowest sum of the residuals, which corresponds to α' between 1 and 7 and B_{max} between 100 and 300 (kton). The fact that the dark blue region has a curved border, i.e. "banana" shape, with the regions of larger SS reflects the correlation between both parameters. It also shows that the values of α' and B_{max} chosen for the previous analysis ($\alpha' = 5, B_{max} = 300$ kton) lie well within the region with smaller SS, but that equally good fit could be obtained for a very wide range of these parameters, which cannot therefore be determined with useful precision.

Bootstrap for Estimation of the Confidence Limits

In order to calculate the confidence intervals of the estimated model parameters, q and B_{t+1} a bootstrap method (Haddon, 2001) has been chosen.

The bootstrapping method has become popular for a number of reasons. Firstly, its principle, regarded as elegant and powerful, comprises the resampling from the empirical distribution function (i.e. the sample) rather than from the actual and unknown probability density function. Secondly, bootstrapping can be easily implemented and its name has become clearly recognisable as the resampling approach (Haddon, 2001).

In principle, bootstrapping regards the observations as a random sample from the population and any random sample from the observations are also a random sample of the investigated population. This assumption relies on independence of the observations (Lassen and Medley, 2001). In fisheries modelling, where the sequential dependence between observations is intrinsically part of the population dynamics, an alternative approach of fitted model and residuals is often used. Each observation is made up of the model estimate and the residual error. If each of the model estimates are combined with residuals drawn randomly with replacement, a new simulated data set is created (Lassen and Medley, 2001).

Bootstrapping was conducted on the Conser (1998) data for the two balanced scenarios of section 4.2.4. A confidence interval for q and B_{t+1} in each one of the balanced scenarios, $V \approx 1$ and $V/W \approx 1$ was determined (Table 4.5).

A new $CPUE$ series is generated adding normally distributed noise (N($\overline{x}, \sigma$), where $\overline{x} = 1$ and $\sigma = \sqrt{\frac{\sum \theta_t^2}{t}}$). Then, the model was recalculated using the new $CPUE$, the former catch data series, the estimated biomass and catchability, and the fixed natural mortality, resilience, and pristine biomass. Each new estimation of q and B_{t+1} was recorded, and after several hundred estimations, the results were summarised in a histogram and their confidence interval was calculated.

When the histogram approximates to the normal distribution, a parametric bootstrapping confidence intervals around the parameter can be obtained from the usual normal form,

$$CI = \hat{w} \pm z_{n-1,a/2} se, \tag{4.12}$$

where CI is the confidence interval, $\hat{w}$ is the parameter estimated, $z_{n-1,a/2}$ is the normal distribution, for n bigger than 30, value for $n-1$ degrees of freedom (n is the number of bootstrap replicates) and $a/2$ is the percentage of the confidence limit desired, and se is the standard error (Zar, 1996, Haddon, 2001).

However, if the results distribution is not symmetric the former approach will produce a biased confidence interval. Therefore, it is recommended (Haddon, 2001) to use the estimation of the percentile of the results distribution instead. The percentile is the value which lies in the percentile position, when data is ordered.

In this study, both confidence interval methods were employed on each balanced scenario with confidence limit set to 95%. Therefore, for the parametric approach, $z = 1.96$ and for the percentiles approach, a 95% bicaudal confidence interval is given by the 97.5 and 2.5 percentiles of the total number of catchability and biomass on the next period estimated.

The total number of bootstrap samples varied between scenarios, due to the time required for calculation. For $V \approx 1$, the total number of estimations conducted was 450. However 9 results failed to converge to a real number and were therefore rejected from further analysis. In this case, the 2.5 percentile was the eleventh number and

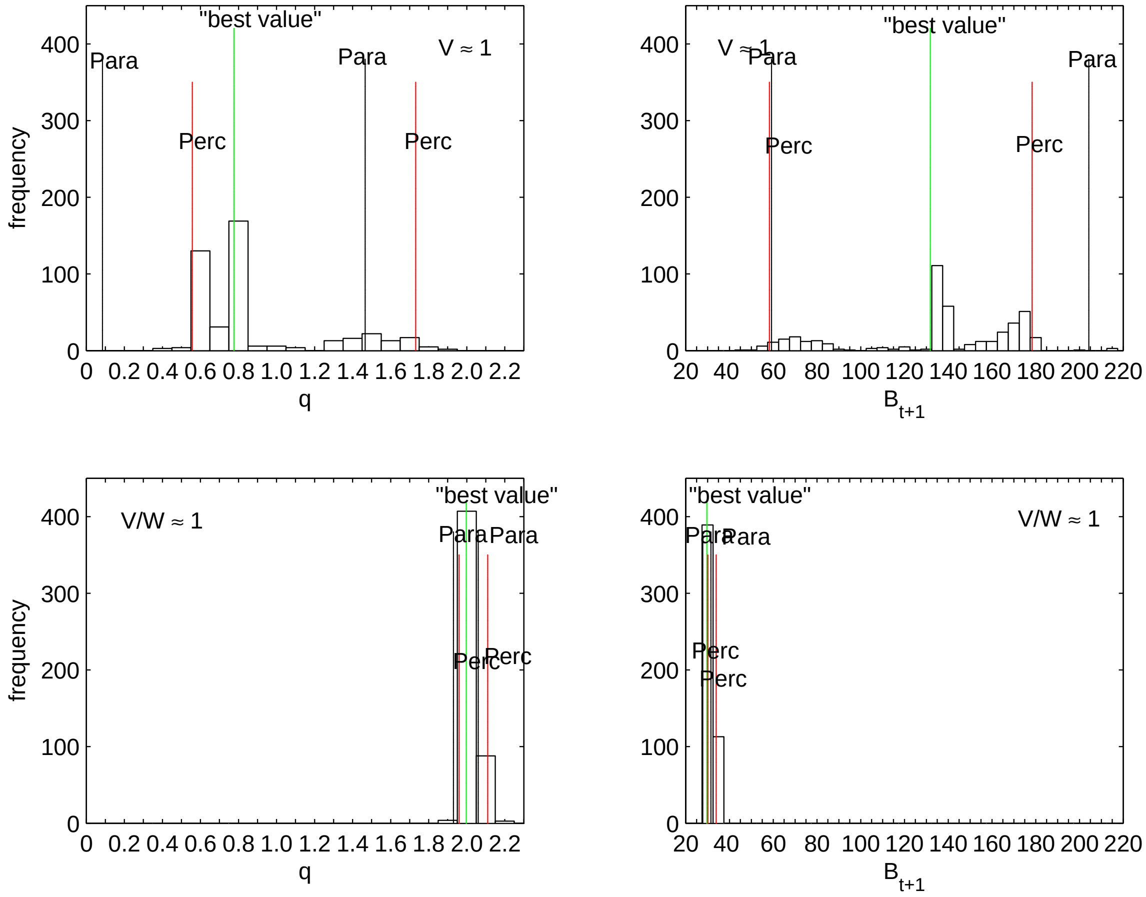

Figure 4.6: Frequency distribution of bootstrapping estimation of q (A and C) and B_{t+1} (B and D), when $V \approx 1$ (A and B) and $V/W \approx 1$, where Para is the parametric confidence interval and Perc is the percentile confidence interval.

the 97.5 was the 430^{th} result. For $V/W \approx 1$, the 2.5 percentile and the 97.5 were respectively, the 13^{th} and the 489^{th} results.

Figure 4.6 exhibits the histograms of catchability and biomass at the next period for $V \approx 1$ (A and B) and $V/W \approx 1$ (C and D) and the estimated parameter values, here named as "best value", and their 95% confidence interval calculated through the parametric methods (Para) and the percentiles ones (Perc).

For the $V \approx 1$ situation, there is a much higher dispersion of both bootstrap estimated parameters in an asymmetric distribution. Although a modal class is visible, there are several other classes with high frequency too (Figure 4.6). Consequently, the percentile confidence interval is more suitable for both estimated parameter, q and B_{t+1} (Figure 4.6).

On the other hand, the bootstrapping estimation of q and B_{t+1} for $V/W \approx 1$ is very close to the normal distribution, with a clear modal class and therefore, the parametric confidence interval is more suitable, especially for B_{t+1} (Figure 4.6).

The size of the confidence interval for each scenario is a consequence of the observation noise resultant of the model fitting. For $V \approx 1$ the $\sum \theta^2$ is about 18 times bigger than the same sum for $V/W \approx 1$, which is clearly reflected in the size of the estimated confidence intervals.

4.3 Discussion

The methodology proposed in this chapter, to simultaneously incorporate observation and process error in stock production model estimation utilising a non-linear least squares approach is, in principle, a considerable improvement on former approaches in which both errors were considered in the model fitting of stock production models (Conser, 1998). By considering the process error in the production model and the observation error in the abundance index, the new method (POEEM) treats both uncertainties separately, which is not exactly the case when process uncertainty is assumed to be in the dynamic equation (Eq. 2.1). The use of a non-linear least squares approach is advantageous for its straightforward implementation.

Moreover, considering both errors together has been proven to be essential for reliable parameter estimations. When only one of the noise terms is present, by weighting the other as null, the results were biased to extreme situations, of either underexploited stock or highly noisy. The former lead to the potentially dangerous conclusion of stock underexploitation (not likely after a long term fishing activity). In the latter, there is a lot of variability in the data not explainable by the relationship between the variables, which promotes a high risk that the data are not representative of long term average behaviour of the population (Hilborn and Walters, 1992).

With regards to weighting the objective function, the determination of the right balance has crucial management implications, since it may determine our picture of size of the current state of the stock and hence future action required. Where equal error is introduced as in the simulated data set, the conclusion drawn is that the variance ratio should be approximately one ($V \approx 1$) in order to find robust and reliable results. However, fitting the sablefish data set with the mixed model, values of q and B_{t+1} for $V \approx 1$ are close to the results of fitting observation error only or process error only which has already been shown as unrealistic. For this real data set, the true values of V is not known so, the weighting $V/W \approx 1$ should probably be pursued in order to correctly balance the POEEM objective function. This assumption is supported by the plotted results of observed and estimated biomass and production for sablefish (Figure 4.4). The result of $V/W \approx 1$ clearly display observed data scattered around the estimated curve in a credible way, without the artificially good fit as seen for $V \approx 1$.

Comparing the results of the analysis of sablefish stock with the various objective functions, the current results seems to yield two extreme scenarios, whereas the former chapter estimated an intermediate stock status.

From the simulations, two main generalisations could be drawn. Firstly, the higher the level of noise the higher the estimation dispersion within the same level of exploitation. Among various levels of exploitations, the lower the exploitation, the higher the variance. Secondly, the higher the exploitation level, the higher the values of W required to result in $V \approx 1$. High values of W mean high values of λ_ρ and consequently, low values of $\sum \rho^2$. Thus, the higher the levels of exploitation, the lower the sum of fractional deviations of the production and the higher the sum of fractional deviations of the observations.

When attributing deviations to both variables, dependent and independent, it is therefore crucial to know the ratio between the variances of these variables in order to determine them precisely. However, the likelihood surface of the variation of both parameters corresponds to a saddle point rather than a maximum (Copas, 1972). In fisheries studies, the necessity of regarding observation and process errors in the computation becomes entangled in this requirement (Schnute, 1987, Hilborn and Walters, 1992). The assumption of the variance ratio equal to one was arbitrary but relies on an educated guess, since it is not unrealistic to assume that observation noises may have the same magnitude as process noises. However, the problem of choosing the correct weighting is crucial to achieve coherent estimations, cannot be regarded as solved and further work on this issue is required.

Even though resilience and pristine biomass are fixed for the model fitting, mapping the sum of squares for a range of these parameters could serve to find more plausible values for them (i.e. giving a smaller sum of squares). This approach is desirable since resilience and pristine biomass are correlated and therefore can not be independently estimated. Furthermore this methods also serves to indicates the confidence region of the results (Shepherd, 1987).

The bootstrapping has proved to be a useful method for determining confidence limits, and allows varying the calculation for different frequency distribution of the results. The confidence intervals for the parameter estimation is specially important in fisheries assessment when preparing information for management.

Finally, the objective function optimisation needs from a few hundred to a few hundred thousand iterations to converge to an output which fulfills the tolerance setting. This is necessary to avoid local minima. However, an important consequence is that the estimation is extremely time consuming.

4.4 Summary

The results presented in this chapter highlight the fact that observation and process errors have to be properly considered in order to achieve reliable stock assessment.

Ignoring either of these errors or combining them into one error source is likely to lead to biased results which could have adverse effects on the fisheries management process.

The new approach proposed in this chapter was successfully tested with simulated and real data. It was found in this study that finding the correct weight ratio between observation and process error is crucial and non-trivial. It was expected that the relative weight applied to the observation and process errors would be inversely related to the relative size of these errors after this data had been analysed by the stock production model. This prediction corresponds to $V/W \approx 1$. However, the analysis of the simulated data showed that this prediction did not hold. Instead, for the simulated data the weighting ratio (W) to balance the objective function has to be chosen so as to result in $V \approx 1$. For real data (sablefish) however, the assumption of $V/W \approx 1$ appears to be more realistic for this particular fishery.

In addition to balancing observation and process errors the method (POEMM) incorporated bootstrapping to determine the confidence limits of the parameters q and B_{t+1}. The method was used to calculate limits for different error distributions resulting from observation variance. The higher the variance the higher the estimation dispersion and therefore wider confidence interval. However, the method is flexible to adapt to asymmetrical distributions and therefore appropriate for determining confidence intervals of the mixed model.

In summary, it was not possible to find a satisfactory automatic procedure for determining the weighting ratio between observation and process error. Therefore, there still is a need of a procedure to ensure that the estimated error variances for both process and observation errors are comparable with the expected levels for such errors, requiring future further research"

Chapter 5

Application to Brazilian Fish Stocks

5.1 Introduction

In most Brazilian fisheries, management is far from ideal. Most of the policies are based on a minimal precautionary approach of setting a minimum size at first capture, and a closed season and area to protect the spawning stock. These measures aim to assure that a reasonable portion of the stock will reproduce and therefore, allow replacement of the fish caught. Although the minimum size approach is a starting point for the fishery management, it requires that the fishing gears be selective enough to target a specific size range. Concomitantly, closures of spawning grounds and seasonal fishing bans would complement this minimal approach by allowing the replacement of biomass by fish recruitment into the population. Although those measures are applied with relative success to avoid catches of immature fish, they should really be considered alongside a combination of others measures, which would for instance aim to avoid decreasing the spawning stock biomass below the sustainable levels, in order to address the full range of possible deleterious effects of fisheries. Furthermore, enforcement of any measures is also a key issue without which,any management attempt will be frustrated and therefore, this should be given high priority.

In order to provide further support for an effective fishery management, in this chapter the stock assessment of four demersal species will be carried out using the previously proposed method. The species studied are whitemouth croaker, king weakfish, Jamaica weakfish, and grey triggerfish which are among the most important demersal fishery resources off the southeastern coat of Brazil.

In general, little information is available on the biomass of the fish stocks in Brazil. Moreover, data for further stock assessment are rarely existent and, if available, are not entirely reliable (Freire, 2005). Since little data is available for those species, a stock production model using the new proposed method is ideal to conduct the assessment of those fish stocks. An overview of the state of each species will be provided, combined with current management action. Suggestions for future studies and management recommendations based on the results of the assessments and general scientific knowledge of those species will be made.

5.2 Environmental and Ecological Background

5.2.1 History and Dynamics of the Studied Fleet

Demersal fisheries are some of the most important marine industrial fisheries in the southern and southeastern Brazilian coast and have been intensively operated for over six decades (Castro, 1998, 2000).

The pair bottom trawl fleet has been responsible for most of the demersal fish landed in this region. Thus, an evolving description of the pair bottom trawl catch and effort is important to conceive the pre-data situation and match it with current scenarios analysed here. This is also the only fleet for which a reasonably long time series of effort data is available. However, the reduced and discontinuous data availability has limited the period studied in this chapter to the last fifteen years.

When the pair bottom trawl fleet was first registered in 1944, the Santos (24°S,46° W) fleet was composed of four medium and eleven small boats (Figure 5.1). The smaller boats had an endurance for one day fishing trips only, whereas the larger ones were able to stay for several days on the fishing grounds. During the following decade, although some pair bottom trawl and otter-trawl boats expanded their fishing grounds to the southern continental shelf, they were still landing in Santos due to its proximity to trade markets. During the 1960s, government policies promoted the increase of the fleet by means of tax reductions and subsidies (Castro, 2000). In the early 1970s, decreasing shrimp catch prompted boats from other trawl fleets to diversify their catches to other bottom-dwelling fish populations (Castro, 1998). During the 1970s, some fish stocks, such as king weakfish, had already shown signs of overfishing in southern populations (Valentini et al., 1991) and the mean CPUE was 109.6 kg/hauls with a yearly effort of $14,884.6$ hauls (Castro, 2000). In the next decade, due to economic instability and rising tax, the fishing grounds were reduced and the large size boats landed their catches in the harbours of the southern region even though the main customer markets were still concentrated in southeastern states. The effort decreased by 15% and CPUE rose to 158.3 kg/haul. By the 1990s, the yearly effort was 7,689 hauls and the average CPUE was 183.0 kg/haul (Castro, 2000).

At present, there are three different pair bottom trawl fleets operating in the southern and southeastern coast of Brazil which use different landing harbours, working different fishing grounds and pursuing diverse target species. The fleet which is subject of this study lands in Santos and has been fishing between Cabo Frio (23°S) and Cabo de Santa Marta Grande (29°S) between 10 and 60 m depth (Figure 5.1). The wooden and steel boats of this fleet vary in size between 17 and 25 m (mean= 21.1 ± 2.03m), have engine powers between 188 and 406 HP (mean= 298.2 ± 49.7 HP), and an average crew size of 8.3 people (± 1.6) (Castro, 2000). This multispecies fishing fleet

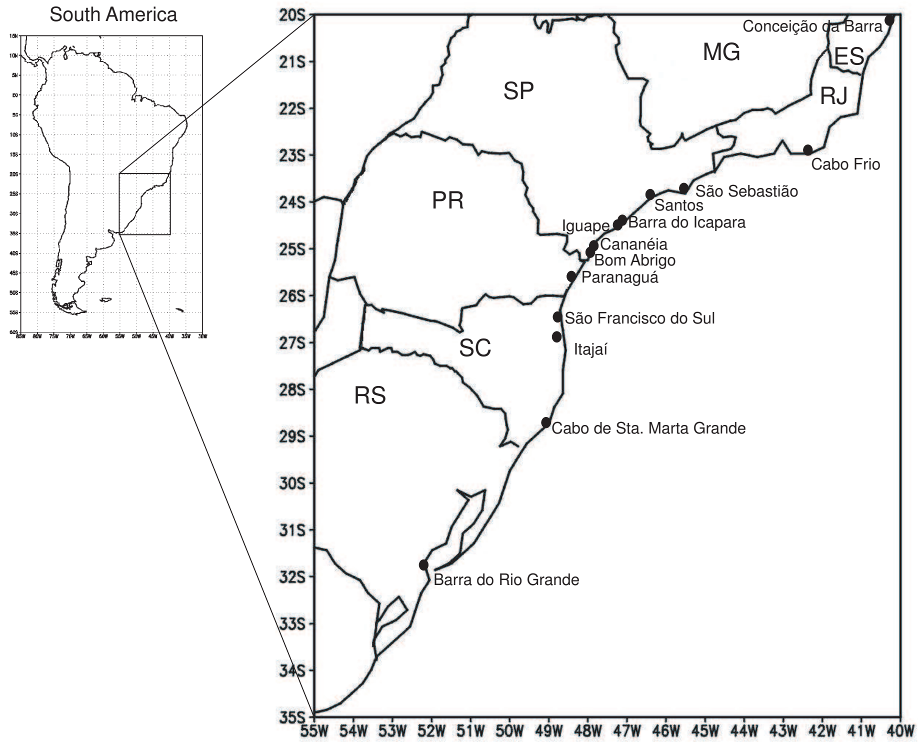

Figure 5.1: Detail of Brazilian south and southeastern coast, the pair bottom trawl fleet fishing grounds and important landmarks. Each boarded area represents a geopolitical state whose acronyms stand for RS= Rio Grande do Sul, SC= Santa Catarina, PR= Paraná, SP= São Paulo, RJ= Rio de Janeiro, ES= Espírito Santo e MG=Minas Gerais.

has currently four main target species (Figure 5.2) whitemouth croaker (*Micropogonias furnieri*), king weakfish (*Macrodon ancylodon*), Jamaica weakfish (*Cynoscion jamaicensis*) and grey triggerfish (*Balistes capriscus*) representing altogether between 60 and 70% of the demersal fish landed in Santos (Castro, 2000, Carneiro and Castro, 2005).

While these species are also caught by different fleets, the pair bottom trawl has been responsible for the majority of their catch. Figure 5.3 on page 87 displays the data analysed in this chapter, which consist of (for each species) total catch of all fleets, pair bottom trawl catch and CPUE for the pair bottom trawl. Although total catch is available from 1986, the pair bottom trawl catch and effort data is available only

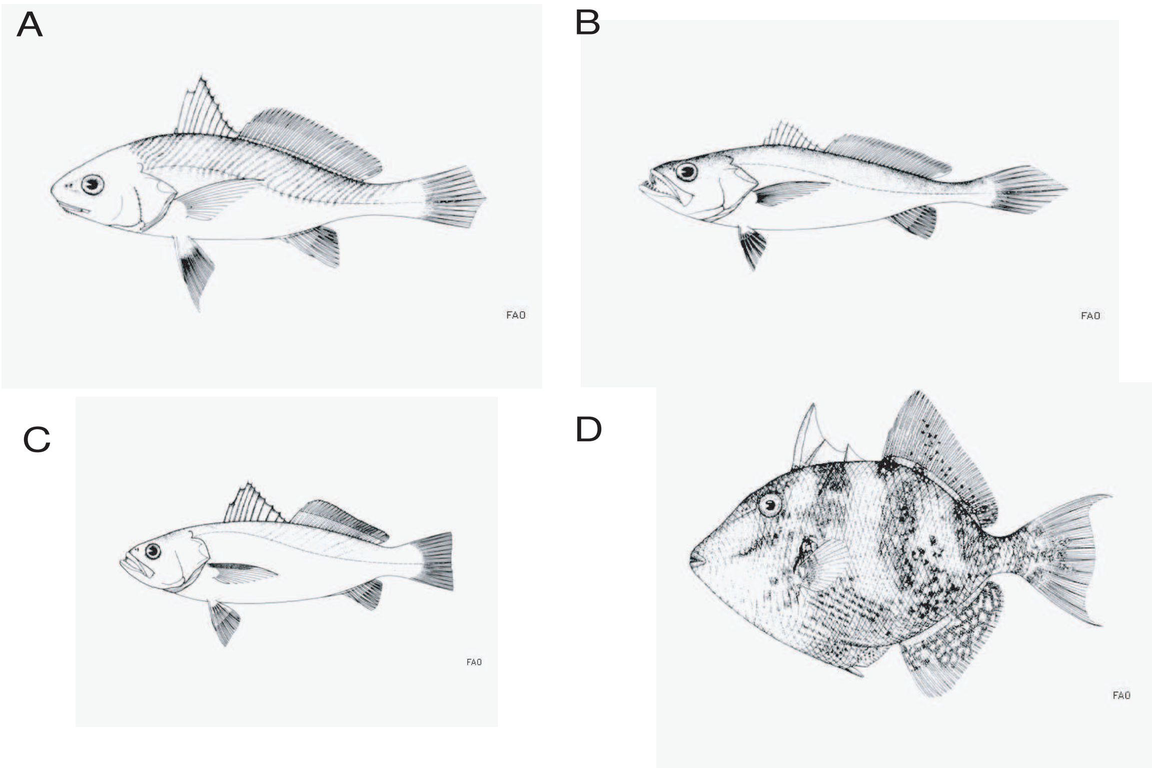

Figure 5.2: Illustration of the four studies species, (A)Whitemouth croaker after Cervigón et al. (1992), (B)King weakfish after Cervigón et al. (1992), (C)Jamaican weakfish after Cervigón et al. (1992), (D)Grey triggerfish after Schneider (1990).

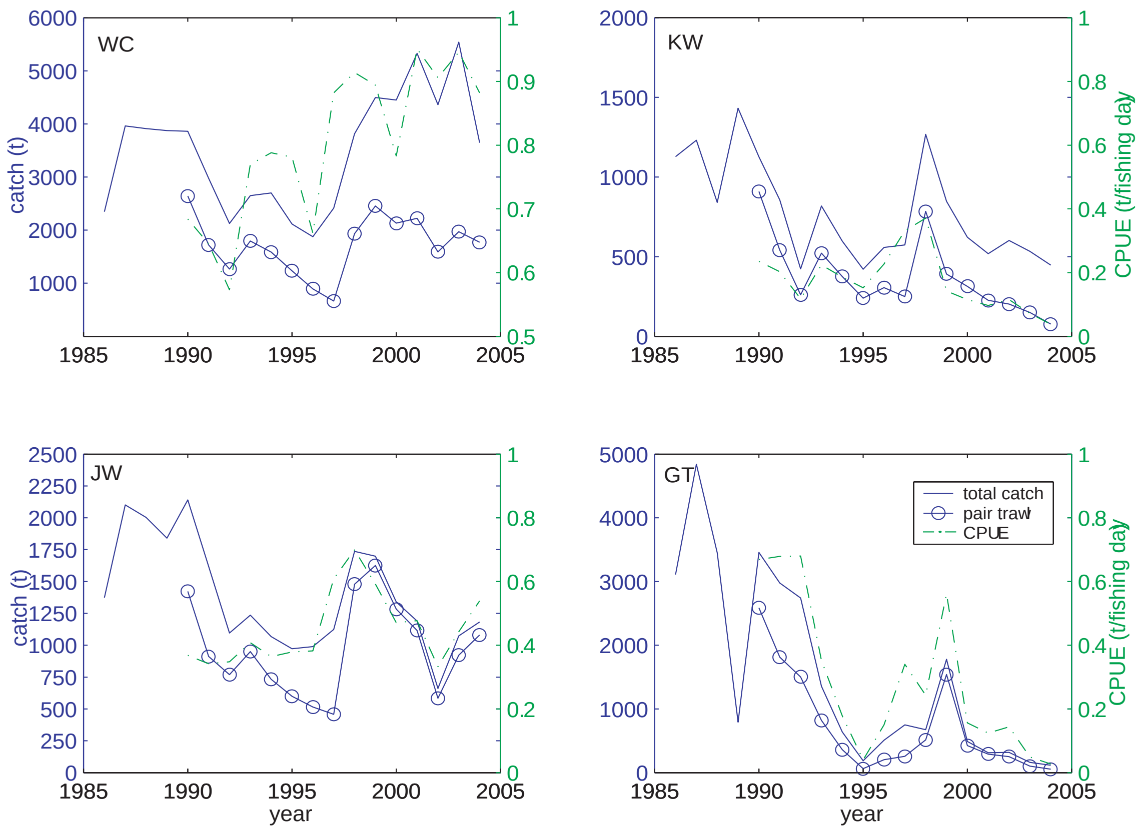

Figure 5.3: Total catch (t), pair bottom trawl catch (t), and CPUE (t/fishing days) of (A) whitemouth croaker (WC), (B) King weakfish (KW), (C) Jamaican weakfish (JW), (D) Grey triggerfish (GT) from 1986 to 2004.

from 1990 to 2004 which is the studied period here. Previous total catch data for each species contain inconsistencies and therefore, are used only to provide a reference.

As shown in Figure 5.3, the total landing of all species have fluctuated considerably up-and down. In general, from 1986 until early 1990s all species had a high catch level, decreasing considerably during the 1990s. Recovering on the catches levels happened in the late 1990s for Jamaican kingfish, king weakfish and grey triggerfish but it was again followed by a period of decline up to the present. Except for whitemouth croaker, the other species CPUE trend follow the total catch and pair trawl catch trend. The whitemouth croaker presents a fluctuation on its CPUE with relevant increase since early 1990s. This feature might present a mixture of effects, such as catch of two different stocks, which could shadow the results. Since the 1990s, several studies (Valentini et al., 1991, Castro and Castro, 1995, Castro, 1998) have suggested that the intense exploitation of those target species were leading them to overexploitation.

5.2.2 Underlying Environmental Aspects off the Southeastern Coast of Brazil

This section provides an overview of the important ecological features in the region where the stocks studied spend their life cycle. The ecosystem off the south and southeastern Brazilian coast (23°-29°S latitude) is influenced by a number of geological and oceanographic features. The region has a modest number of mangroves and estuaries to enrich the area by river runoff and to provide nursery and growing grounds. The most important mangroves are found in "Santos-Bertioga"(24° S, 46° – 47° W), in "Iguape-Cananéia-Paranaguá"(25° S, 47.5° W) and "São Francisco do Sul" (Fig. 5.1). The two major estuaries are the "Ribeira de Iguape"(25° S, 47.5° W) and the "Itajaí" river (Fig. 5.1).

The widest portion of continental shelf is near Santos with 230 km and the narrowest regions are the northern edge (Cabo Frio) with 50 km and the southern edge (Cabo de Santa Marta Grande) with 70 km. The latter is the northern limit of the Subtropical Convergence of the Brazil-Falklands (Malvinas) Current. The seafloor is composed of sand and mud with few rock features, making it largely suitable for trawling gears. The area is influenced by the South Atlantic Central Water (SACW) which is a cold and nutrient rich water mass that promotes the biological production mainly during spring and summer months (Sep-Mar). Seasonal changes in the direction of the wind, caused by the southward displacement of the South Atlantic anti-cyclonic system, leads to elevation of the upper layer of the SACW which may rise above the edge of the continental shelf. During spring and summer, the water column on the continental shelf may become highly stratified and productive because of its low temperature, low salinity, and high nutrient concentrations. Typical cold-water fauna may be present in the region during these months. Eventually, under specific local wind conditions, the SACW may reach the surface. This coastal upwelling is influenced by the bathymetric profile and the abrupt change in the coastline in Cabo Frio (Fig. 5.1) and is considered an environmental barrier to some species and a limit to their species distribution (Figueiredo, 1981, Castro, 1998, Vazzoler et al., 1999).

5.3 Data, Sampling and Analysis

5.3.1 Data and Sampling

The data set analysed in this chapter has been collected by the Fishery Institute, the fisheries research agency of São Paulo State government. The data has been gathered through interviews with fishers and skippers since 1990 in the main commercial fisheries ports in Santos. A general description of the sampling structure and current situation of the fishery activity can be found in Gasalla and Tomas (1998).

The data set comprises the total catch for each species in all fleets and the pair bottom trawl catch for each species in tonne, and the fishing effort for this fleet from 1990 to 2004 in fishing days. Fishing days is a data collected directly from in the fishers interview and a unit easily comparable with other studies. The other units available resulted from indirect observation and therefore, were not considered.

5.3.2 Stock Assessment Data Analysis

The stock assessment conducted for each species comprised two estimation approaches. Firstly, the process and observation errors estimation method (POEEM) was used with a non-linear least squares approach, i.e. non-equilibrium approach described in detail in the previous chapter. Additionally, bootstrapping was used to estimate confidence intervals for each of the parameters determined. Values of natural mortality, estimated according to Pauly (1980), from previous studies were incorporated in the assessment and the source cited. Even though Pauly's methods is generally criticised as non-realistic due to its linearised estimation these were the only estimation available. Total mortality (Z) was estimated by the linearised catch curve (Beverton and Holt, 1957, Sparre and Venema, 1997) and fishing mortality was the difference between those values.

The long history of exploitation of all species where considered when setting the value of pristine biomass and the initial values of biomass for the analysed period. In addition, those species have a wide latitudinal distribution range also considered when setting initial values.

Secondly, the traditional observation error method (Pella and Tomlinson, 1969, Ludwig and Walters, 1985, Ludwig et al., 1988, Chen and Andrew, 1998, Su and Liu, 1998) was employed, treating the dynamic equation (Eq. 2.1) as deterministic and attributing all uncertainties to the biomass and abundance index relationship (Eq. 2.5). The biomass time series is estimated by projecting the biomass at the start of the catch time series ($B_{initial}$) forward under the historic annual catches (Polacheck et al., 1993). The deviations between estimated biomass and observed biomass were minimised by the non-linear optimisation routine "solver" from Microsoft Excel, which uses the Generalized Reduced Gradient (GRG2) Algorithm (Excel, 2006). For comparative purposes three alternative stock-production models due to Schaefer (1954) (Eq. 2.2), Fox (1970) (Eq. 2.3) and Shepherd (1987) (Eq. 3.8), were also used for the production estimation. Previous studies (Hilborn and Walters, 1992, Polacheck et al., 1993) justified the use of observation error estimators, suggesting they are superior to process error estimators due to their robustness in face of the uncertainty of the error assumptions and the formulation of the dynamic models.

5.4 Whitemouth Croaker

5.4.1 Biological Aspects

Whitemouth croaker (*Micropogonias furnieri* (Desmarest, 1823)) (Figure 5.2(A)) is a bottom dwelling species widely distributed in the Americas, from the Yucatan Peninsula to Patagonia (Cervigón, 1993) and living in a wide range of salinity. Although, the species can be found down to 100 m depth, its highest abundance occurs at less than 50 m depth (Menezes and Figueiredo, 1980).

Its demersal habits are reflected in the main prey, i.e. crustaceans, polychaetes and ophiuroids (Vazzoler, 1991). Off the south and southeastern Brazilian coast, it is the most important demersal fishery resource (Valentini et al., 1991, Castro, 1998, 2000). Several studies (Vazzoler, 1971, Isaac, 1988, Vazzoler, 1991, Vazzoler et al., 1999) distinguish between two populations in this area, the southeastern one which is distributed from 23°S to 29°S and the southern one from 29°S to 33°S. However, Levy et al. (1998) found close genetic similarity between the south and southeastern population when considering 17 enzyme and one protein-encolding loci. The southeastern population is the subject of this study.

Whitemouth croaker fisheries yield has presented a downwards trend in the eighties and nineties. In the last four years, catch has substantially increased (Figure 5.3) due to a rise in catches by shrimp trawlers and sardine seiners. Although the seiners are not allowed to catch whitemouth croaker, both fleets have faced an enormous reduction of their target species and therefore turned towards alternative catches to pay the boat expenses (Castro et al., 2003, Gasalla et al., 2003, Tomas and Cordeiro, 2003).

Signs of changes in the population structure have been found in the sizes of first reproduction, growth parameters and reproduction season. The catch size composition for trawlers, seiners and liners together ranges from 140 to 710 mm with a modal class of 347 mm (Carneiro et al., 2005). The immature fish is a minor fraction of the catch since the size at first reproduction is currently 292 mm for females and 243 mm for males (Carneiro et al., 2005). These values are slightly bigger than results from the 1970s, 275 mm for females (i.e. 7 months old) and 250 mm for males (i.e. 4 months old) (Vazzoler, 1971). Although Carneiro et al. (2005) found that the catch is composed of groups from 2 to 14 years and the growth parameters are $L_\infty = 961$ mm, $k = 0.08$ year^{-1} and $t_0 = -0.99$ year, the authors believe that these parameters are overestimated when using the Bhattacharya method (Sparre and Venema, 1997), and recommended age determination from otoliths. The current age determination results differ greatly from earlier studies (Vazzoler, 1971, Isaac, 1988, Vazzoler, 1991), and it is not clear whether they are reliable.

The whitemouth croaker reproduction cycle is closely related to the estuarine waters and for this population the spawning grounds are at Bom Abrigo (Figure 5.1) (Vazzoler, 1971). Currently, spawning happens during two main periods, i.e. mid-winter and late spring (Carneiro et al., 2005). However, earlier studies (Isaac-Nahum and Vazzoler, 1983, 1987) found that the two spawning seasons happened somewhat earlier in the year, the first one during autumn and early winter and the second late winter and early spring. Despite this evidence of changes in the population structure, which are recommended to be incorporated in the fisheries modelling, in this study the available data set comprises the last fifteen years which correspond to the current period only.

The fisheries recruitment happens during summer and autumn, when a higher number of smaller fish has been found in the landings (Carneiro et al., 2005). Population parameters were estimated by Carneiro et al. (2005) according to the methods in the section 5.3.2. Natural mortality (M) was estimated to 0.22 year^{-1}, fishing mortality (F) was 0.37 year^{-1}, the exploitation rate (E) was 0.63 and the survival rate (S) was 55% (Carneiro et al., 2005).

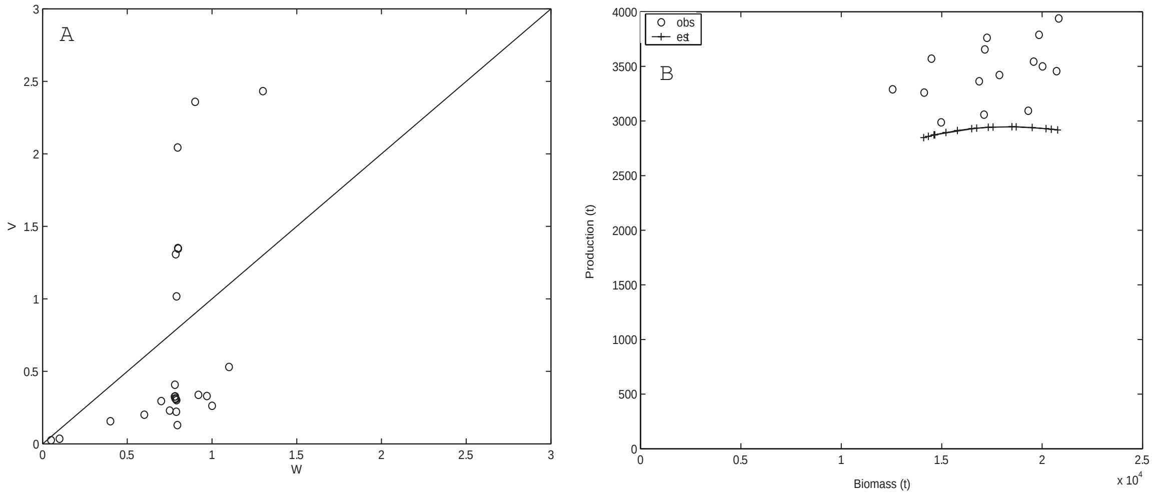

Figure 5.4: Whitemouth croaker estimated through non-equilibrium POEEM,(A) variation of variance ratio (V) as a function of weight ratio (W), and (B) biomass (t) as a function of production(t).

5.4.2 Model Results

For the mixed model stock assessment this biological background knowledge was utilised. Therefore, the initial parameter settings for whitemouth croaker were q = 0.1, $B_{initial}$ = 10000 t, $\alpha' = 2$, M = 0.22 year^{-1} and B_{max} = 50000 t.

The results of the weighting consistency test for the objective function is displayed in Figure 5.4(A). Despite the fact that $W = 0.791$ brings $V/W \approx 1$, the relationship between variance ratio (V) and weight ratio (W) is unclear and inconsistent. Similar values of W resulted in highly variable values of V and consequently finding the residual ratio close to one has just happened by chance.

Although the search for the residual ratio (V/W) has proved to be inconclusive and unpredictable, the biomass of the stock of whitemouth croaker was estimated through POEEM using the weighting balance presented in Table 5.1. Notably, the weight ratio $W = 0.791$ resulted in both, V and V/W being approximately one. The results of this calculation is shown in Figure 5.4 (B) and Table 5.1. According to the model outcome, the stock is overexploited since the estimated biomass for the next period is about 14% of the pristine biomass (B_{max}) (Table 5.1). Curiously, the observed production

Table 5.1: Results of the stock production model from different models and parameter estimation approach for whitemouth croaker.

	Observation Error			POEEM	
	Schaefer	Shepherd	Fox	$V/W \approx 1$	$W = 1$
q	$6.8 * 10^{-5}$	$6.8 * 10^{-5}$	$6.8 * 10^{-5}$	$6.6 * 10^{-05}$	$7.7 * 10^{-5}$
$B_{t+1}(t)$	12625	12821	12793	7014	7579
$B_{max}(t)$	49997	46687	45293	50000	50000
$\frac{B_{t+1}}{B_{max}}$	0.25	0.28	0.28	0.14	0.15
MSY (t)	5226	3807	3958	2947	2947
$B_{MSY}(t)$	24989	14438	16758	18301	18301
$r(year^{-1})$	0.42	1.06	2.55	0.66	0.66
SS	$3.6 * 10^7$	$3.5 * 10^7$	$3.5 * 10^7$	1.06	1.61
λ_θ				1	1
$\sum \theta_y^2$				0.60	0.33
λ_ρ				0.791	1
$\sum \rho_y^2$				0.59	1.27
V				1.02	0.26
V/W				1.29	0.26

was always higher than the estimated one (Figure 5.4), which is not satisfactory since estimated curve should go through the observed values. Further estimations of parameters confidence intervals were not conducted because of the inconsistency in the weighting balance and the unreliable estimated curve.

When whitemouth croaker stock production was analysed with observation errors only, the parameter values were q = 0.1, $\alpha' = 2$, M = 0.22 year^{-1} and $B_{max} = 50000$ t for all of the production models. The results found (Figure 5.5 and Table 5.1) were more optimistic than the POEEM model fitting. However, there are signs of overexploitation with the stock depletion ranging from 25 to 28 % of the pristine biomass (Table 5.1). Apart from the instantaneous growth rate (r) and the biomass at maximum sustainable yield (B_{MSY}), all the other results were similar between the different production equations (Table 5.1).

The sum of residuals squared (SS) are higher in the observation error only fitting than in POEEM, but the values are not comparable since the latter has a normalised objective function which reduces the residual values to close to one.

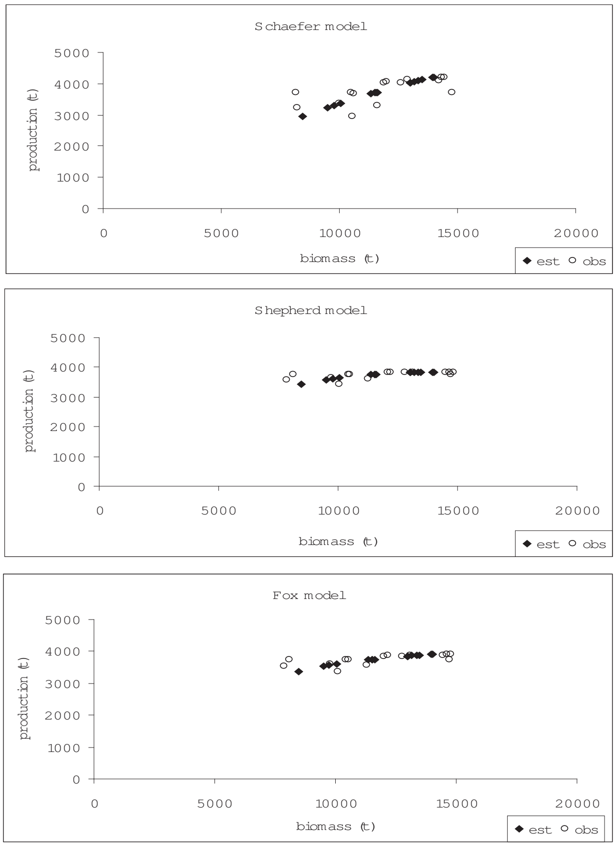

Figure 5.5: Whitemouth croaker biomass (t) as a function of production(t) for Schaefer, Shepherd and Fox production models, estimated through non-equilibrium observation error.

5.4.3 Discussion

Even though the modelling results with the whole range of production model approaches were fairly close, the conflicting weighting ratio determination reveals unreliable results that should be used only with great caution.

The overfishing status of the stock, i.e. the trend of the adjusted curves, seems to be concordant but it is not possible to employ the estimations into further reference points estimations for whitemouth croaker. A previous study (Castro, 2000) suggested that the stock is stable and the effort should not exceed levels set during that time, but this advice was not followed and the yield/biomass ratio has been increasing.

The assumed value of pristine biomass considered the long term exploitation the stock has been subject to. Lower values were chosen but resulted in current biomass lower than the current landing level. This emphasises the need of the mapping of the goodness-of-fit surface for a range of pristine biomass and resilience values.

The fact that other fleets have contributed notably to recent catches (see Figure 5.3) can have an important influence on the stock biomass for two reasons. Firstly due to the direct augmentation of the fishing effort. Secondly, sardine seiners perform a different fishing operation, which could catch part of the population that is not available on the trawlers fishing grounds. Therefore for further reliable stock assessment, it is suggested that CPUE of all of the fleets should be considered in the analysis, which at the moment was not possible due to the lack of effort data from the other fleets.

Despite the fact that the species has been exploited since the 1950s with a sharp rise recently, the yield has increased in the last four years, without a correspondent increase on the CPUE related to the pair bottom trawl. The recent boost in the catch levels can be dangerous since it is likely to bring about a faster decline of the total population biomass. According to a ecosystem based analysis (Gasalla, 2004), the decline of shark stocks seems to be one of the reasons of this increase since not only were sharks one of the whitemouth croaker main predators, but also the shark stock reduction should increase the availability of food to species like whitemouth croaker that is a key species in the community structure. This should allow an increase of biomass and hence CPUE of pair bottom trawl observed in the figure 5.3 (A). However, that could also represent a variation of catchability due to redistribution of the stock.

In addition to a more comprehensive effort data for a reliable stock assessment, a genetic studies should be conducted in order to determine the populations boundaries. Moreover, age determination would improve the reliability of the population parameters, which would be used in more elaborated models and serve for comparison purposes with this mixed model.

5.5 King Weakfish

5.5.1 Biological Aspects

King weakfish (*Macrodon ancylodon* (Bloch and Schneider, 1801)) (Figure 5.2(B)) has a wide latitudinal distribution, from Venezuela to Argentina (Menezes and Figueiredo, 1980). As a bottom dwelling species it is found down to 60 m depth, with higher abundance around 30 m, using this area to predate on fishes and shrimps (Juras and Yamaguti, 1985). The species is normally divided into two population, the southern one which occupies latitudes higher than 28° S and the southeastern one which lives between 23° and 28° S (Yamaguti, 1979, Juras and Yamaguti, 1985, Magro et al., 2000) and is the subject of study in this chapter.

The species has been very important for the demersal fishery in both amount of catch and trade value (Carneiro and Castro, 2005) and is currently considered to be overexploited. Since the 1970s, the catch of king weakfish has shown a downwards trend since the total annual catch was 3000 t early in this period, decreased to 1200 t in 1980s, reached 700 t in the 1990s (Castro and Castro, 1995, Castro, 2000, Carneiro and Castro, 2005) and has a current level of 450 t. During the 1980s there was a decrease in the effort, and an increase of the catch few years later. Therefore, Castro (2000) suggested that king weakfish had responded positively when the effort diminished. Unfortunately, the effort units used in the previous studies are not comparable with the present study, therefore only the past trend is considered. In addition, catch data prior to 1980s (Castro and Castro, 1995) include the southern and southeastern stock which might mislead deeper comparisons.

The pair bottom trawl fleet catches king weakfish between 110 mm and 460 mm of total length, with modal class of 320 mm. However, 19.1% of the catch is smaller than the size at first reproduction for both genders together, 259 mm (Carneiro and Castro, 2005), which is likely to cause recruitment overfishing. The size at first reproduction has decreased greatly during the last fifty five years (Lara, 1951, Castro, 2000), which is strong evidence of the overfishing effect in the population structure. The current estimated size at first reproduction is 290 mm for females and 239 mm for male (Carneiro and Castro, 2005).

The growth curve parameters estimated by indirect methods resulted in $L_\infty = 506.59$ mm, $k = 0.17$ year^{-1} and $t_0 = -1.91$ year (Carneiro and Castro, 2005) whereas other important estimated parameters such as natural mortality (M) was 0.22 year^{-1}, fishing mortality (F) was 0.75 year^{-1}, the exploitation rate (E) was 0.77 and the survival rate (S) was 38%. These population parameters were estimated by Carneiro and Castro (2005) according to the methods in the section 5.3.2. The maximum sampled length corresponded to an age of 13 years (Carneiro and Castro, 2005). However old fish are rarely found in the landings which is another evidence of the heavy exploitation of the species (Castro, 2000). In general, older females produce a higher amount of eggs which seems to results in more successful offspring (Palumbi, 2004). For this reason this females should be targeted os a fundamental source of biomass replacement.

Spawning seems to happen all year around, with a stronger peak in late spring and summer at Barra do Icapara and Bom Abrigo (25°S). Recruitment of one-year-old fish happens during spring (Carneiro and Castro, 2005).

5.5.2 Model Results

In order to set the minimisation parameters in the POEEM, the above background knowledge and the long term stock exploitation was taken into account. Thus, for king weakfish initial parameter settings q = 0.01, $B_{initial} = 5000$ t, $\alpha' = 1$, M = 0.22 year^{-1} and $B_{max} = 50000$ t were used.

These settings led to the mixed model weighting consistency analysis shown in Figure 5.6(A). The residual ratio was reasonably coherent therefore, the weight ratio for $V/W \approx 1$ was $W = 0.09$ and $w = 0.2$ for $V \approx 1$ (Figure 5.6).

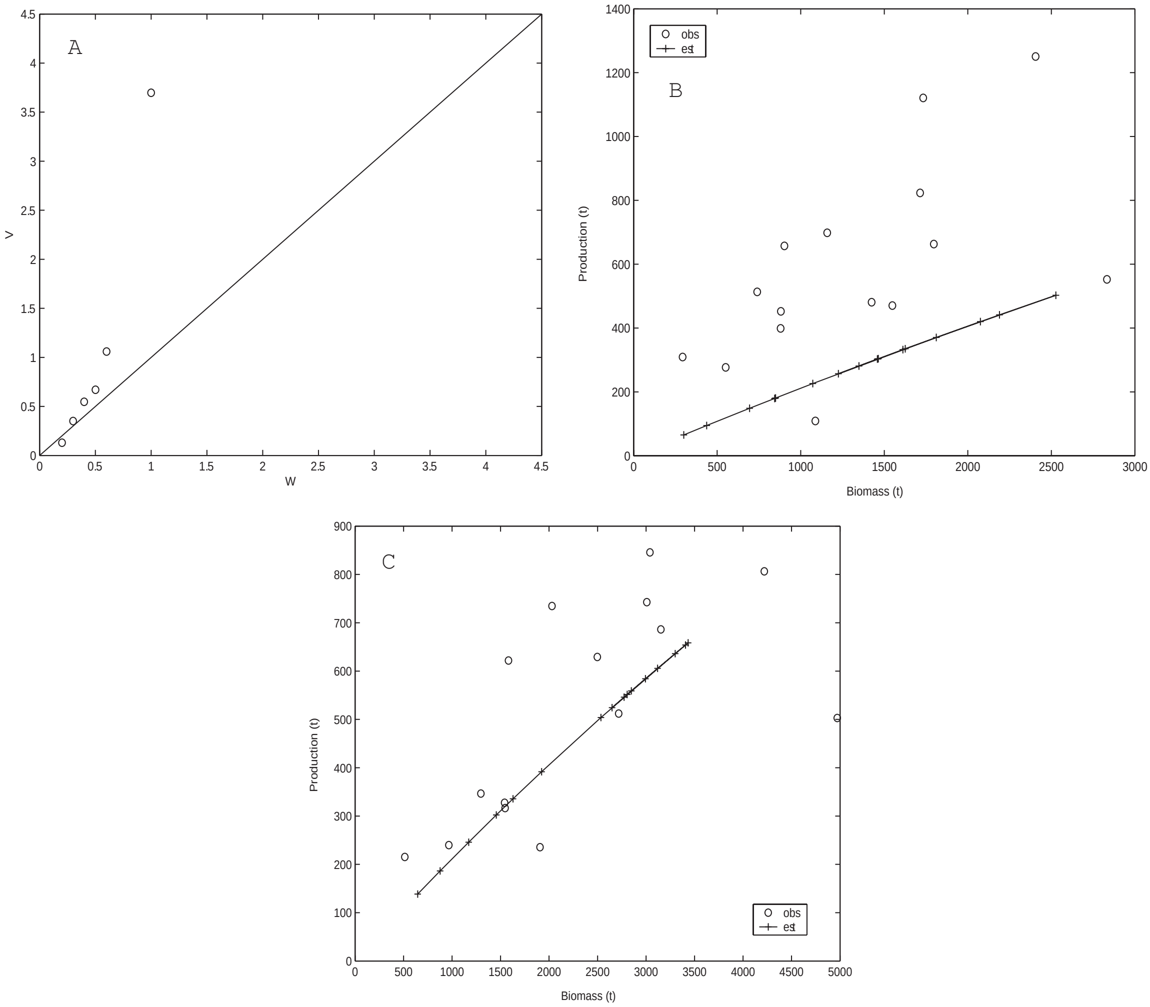

Figure 5.6: King weakfish estimated through non-equilibrium POEEM,(A) variation of variance ratio (V) as a function of weight ratio (W), (B) biomass (t) as a function of production (t), for $V/W \approx 1$, and (C)biomass (t) as a function of production (t), for $V \approx 1$.

Table 5.2: Results of the stock production model from different models and parameter estimation approach for King weakfish.

	Observation Error			POEEM		
	Schaefer	Shepherd	Fox	$V/W \approx 1$	$W = 1$	$V = 1$
q	$1.3 * 10^{-4}$	$1.3 * 10^{-4}$	$1.3 * 10^{-4}$	$1.3 * 10^{-04}$	$7.1 * 10^{-5}$	$7.5 * 10^{-5}$
$B_{t+1}(t)$	441.3	236.6	264.3	300.1	800.3	645.9
$B_{max}(t)$	2580	4474	2652	50000	50000	50000
$\frac{B_{t+1}}{B_{max}}$	0.171	0.053	0.100	0.006	0.016	0.013
MSY (t)	743	593	720	1887	1887	1887
$B_{MSY}(t)$	1290	785	981	20711	20711	20711
$r(year^{-1})$	1.15	4.32	5.82	0.44	0.44	0.44
SS	$1.8 * 10^6$	$2.6 * 10^6$	$2.0 * 10^6$	1.19	1.88	1.62
λ_θ				1	1	1
$\sum \theta_y^2$				0.58	1.78	1.42
λ_ρ				0.09	1	0.20
$\sum \rho_y^2$				6.82	0.11	0.99
V				0.08	16.79	1.43
V/W				0.94	16.79	7.15

The results of the stock production model estimation for king weakfish using POEEM are given in Figure 5.6 (B and C) and Table 5.2. As expected, the stock is found to be on the verge of collapse, having a current estimated biomass of only 0.6 % of the pristine biomass and nearly 70 time smaller than the biomass at maximum sustainable yield (MSY), for $V/W \approx 1$ (Table 5.2). The observed biomass and production exhibit a high dispersion around the estimated data series (Figure 5.6) producing a high sum of squares (Table 5.2). Estimation for $V \approx 1$ scenario present a slightly higher production than to $V/W \approx 1$, but the stock is also around the collapse (Figure 5.6).

When the weight ratio (W) was equal one, the $\sum \theta^2$ was bigger than the $\sum \rho^2$, feature found for both, the sablefish data analysis and the simulations, in the previous chapter.

The confidence interval for catchability and forecast biomass for the next year was just conducted for $V/W \approx 1$ scenario using the bootstrapping approach. So, for illustration purposes both methods, parametric and percentile confidence interval, were calculated for both parameters. The former is recommended when the data distribution is close to the normal curve. The latter is suggested for asymmetrical

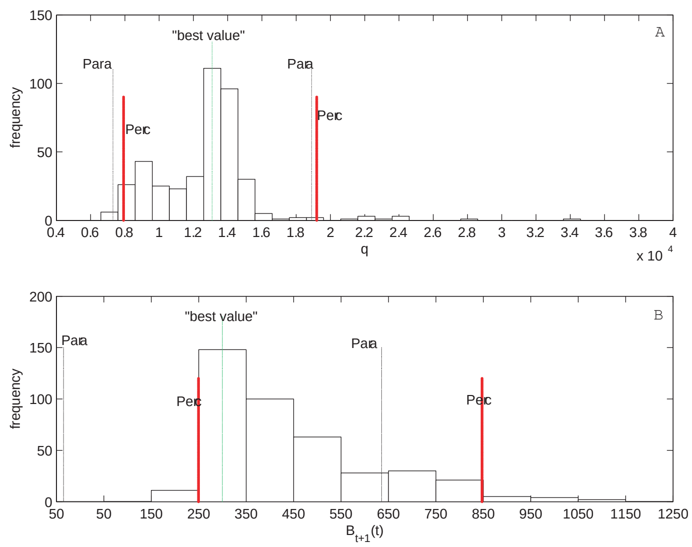

Figure 5.7: Frequency distribution of bootstrapping estimation of catchability (A) and biomass at next year (B) for king weakfish stock from POEEM minimisations, where Para is the parametric confidence interval and Perc is the percentile confidence interval.

parameter distribution. The value of σ used for this estimations was 0.19. Details of these estimation method are presented in section 4.2.4.

From a total of 546 estimation, 412 were used in this analysis since most of them resulted in either no real number or the V/W ratio was bigger than 4 or smaller than 0.2.

Despite the fact that distribution of catchability estimated from bootstrapping is irregular, both confidence intervals, parametric and percentile, have similar limits. The "best value" is located on the modal class and at the middle of the confidence range (Figure 5.7(A)). The fact that the lower limit of q is twice as small as the upper limit, will have a direct influence on the estimation of management quantities. For instance, inferring stock biomass using the CPUE and catchability relationship (Eq. 2.5) and taking the q confidence interval as reference will result in upper biomass interval twice as big as the lower one.

Values of forecast biomass for the next year are asymmetrically distributed and therefore, the percentile estimation for the confidence interval is more coherent than the

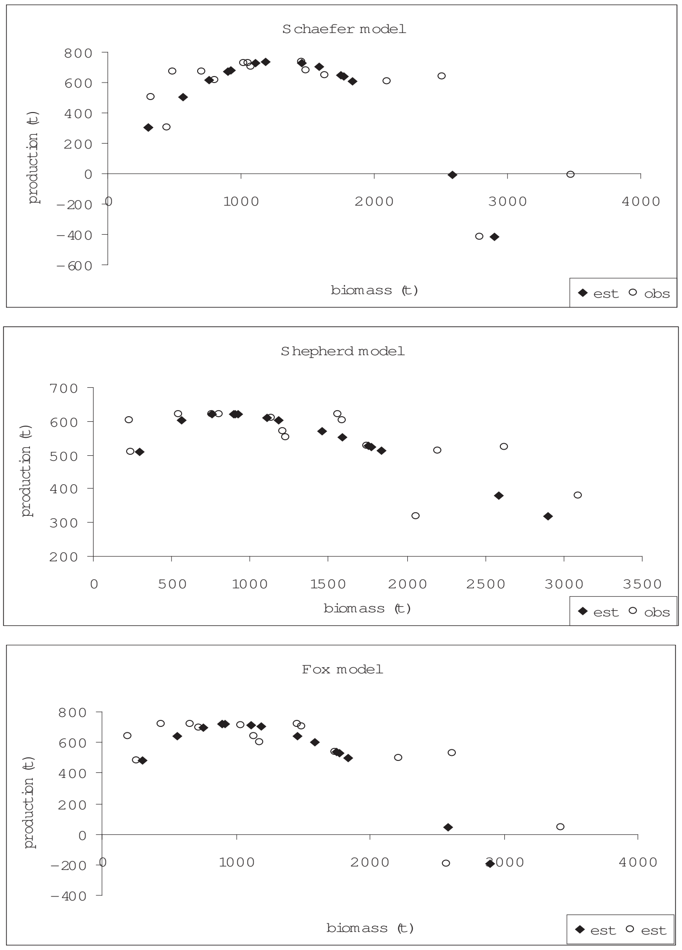

Figure 5.8: King weakfish biomass (t) as a function of production(t) for Schaefer, Shepherd and Fox production models, estimated through non-equilibrium observation error.

parametric method. The upper limit is more than three times bigger than the lower limit which will greatly influences the management measures. This wide dispersion of the results is caused by the high observation standard deviation from the model fitting (Figure 5.7(B)).

For the observation errors only analysis, the parameter settings for all production models were q = 0.01, $\alpha' = 1$, M = 0.22 year^{-1} and $B_{max} = 50000$ t. Figure 5.8 and Table 5.2 display the results for the stock production model estimation in these scenarios. All production model estimations agreed with the current overexploited status of the population, just varying the intensity of the overexploitation. The Shepherd model, has the smallest forecast biomass and the lowest percentage of the pristine stock. The Schaefer model provides the most optimistic scenario. Catchability and sum of squares were similar for all models (Table 5.2).

More importantly, all estimation approaches have resulted in estimated biomass at next year with similar magnitude of the current level of total catch ($\approx 450t$) which is unrealistic and must not be considered into further studies. Therefore, the need of mapping the space of a range of pristine biomass and resilience proves to be compulsory to further inferences.

5.5.3 Discussion

Since POEEM allows for both types of uncertainties in model fitting, its results are regarded as more reliable. Previous results for natural mortality were incorporated into the POEEM model fitting. King weakfish exhibits a fairly low level of production and a stock on the verge of collapse for both weighting circumstances. The detection of the long term reduction of the size at first reproduction corroborates this diagnosis.

The heavy exploitation with recruitment and spawning stock overfishing, are the reasons for this critical situation, probably rooted in the high trade value and customer appreciation.

The long term exploitation the king weakfish stock has been subject to was considered when assuming pristine biomass, specially when lower values of pristine biomass resulted in unrealistic current biomass, i.e. lower than the current landing levels. Therefore, the need of the mapping a range of pristine biomass and resilience values through the goodness-of fit surface is a crucial complementary analysis that must be conduct in order to produce reliable results. Even though the the observation error only analysis may look more realistic they do not consider the process error component which is an important part of the uncertainty.

Although the confidence intervals for catchability and biomass at next year were quite wide, it is desirable to work with a range of possible values due to natural and measurable uncertainties in the stock assessment procedure. However, the initial values of pristine biomass and resilience must be mapped in terms of the sum of squares before further conclusion can be drawn on parameters estimations.

Effective recovery measures for this species should comprise a set of policies focused on protection of the spawning grounds and season, and an increase the size at first capture. The latter is a specially difficult measure since strict enforcement is crucial for the full accomplishment of it and that is one of the poorest aspects of the Brazilian fisheries management.

5.6 Jamaican weakfish

5.6.1 Biological Aspects

The Jamaican weakfish (*Cynoscion jamaicensis* (Vaillant and Bocourt, 1883)) (Figure 5.2(C)) is distributed from Panama to Argentina, from shallow waters down to 100 m depth (Menezes and Figueiredo, 1980), but limited to waters warmer than 17° C (Figueiredo, 1981). Fish and shrimp are the main prey of this demersal species (Magro et al., 2000). It has been exploited since the 1960s, but the effort has increased recently, as the abundance of this resource is believed to have been reduced (Castro, 2000, Castro et al., 2005b).

This study will focused on the southeastern stock of Jamaican weakfish whose separation was supported by morphological and meristic aspects (Spach and Yamaguti, 1989a,b,c). The catch of this resource had had a descending trend since the mid 1980s for 10 years. In the late 1990s, its catch increased dramatically but still did not reach the high 1980s levels. Another drop in the early 2000s and a small increase in the last two years (Figure 5.3) has been noticed as a consequence of the shrimp trawlers, seiners and gill net boats redirecting their effort to bottom dwelling resources, i.e. rising total effort (Castro et al., 2005b). The current scenarios do not conform to the Castro (2000) interpretation of a stock in equilibrium, since there was a drop in the

CPUE from the 1980s (112.35 kg/hauls) to the 1990s (99.70 kg/haul) which suggests that this resource must not be a subjected to a further rise in effort.

Jamaican weakfish catch size ranged from 110 to 365 mm with modal length of 230 mm, which are 3 and 4 year-old fish. Considering that its size at first reproduction is about 193 mm, the species is not likely to have suffered severe recruitment overfishing compared to the previous resource. The smallest fish are one-year-old and their recruitment has happened during autumn and winter (Castro et al., 2005b). A growth study using indirect methods found fish from 2 to 8 years old in the catch and further parameters were $L_\infty = 390$ mm, $k = 0.2$ year^{-1} and $t_0 = -0.88$ year (Castro et al., 2005b). Comparison with studies from the 1960s to the late 1980s have given similar results (Castro et al., 2005b).

Natural mortality (M) was 0.54 year^{-1}, fishing mortality (F) to be 0.70 year^{-1}, the exploitation rate (E) 0.76 and the survival rate (S) was 29% (Castro et al., 2005b), estimated by Castro et al. (2005b) according to the methods in the section 5.3.2. The spawning season seems to have two strong peaks, one in late spring and the other during summer, throughout most of the population distribution area. Recruitment of one-year-old fish happens during spring (Castro et al., 2005b). Higher catches take place during late spring and summer when the species is concentrated in shallow water due to the penetration of the SACW into the continental shelf off the southeastern coast, whereas the catch is lower during winter in this region (Castro et al., 2005b).

5.6.2 Model Results

The mixed model fitting incorporated results from Jamaican weakfish previous studies in selecting the initial parameter settings. These were q = 0.1, $B_{initial} = 7000$ t, $\alpha' = 2$, M = 0.54 year^{-1} and $B_{max} = 30000$ t.

The weighting consistency analysis for the POEEM objective function was satisfactory reached in this case. In order to reliably have $V/W \approx 1$, the weight ratio used was $W = 0.3$ and for $V \approx 1$ W was 0.6 (Figure 5.9(A)).

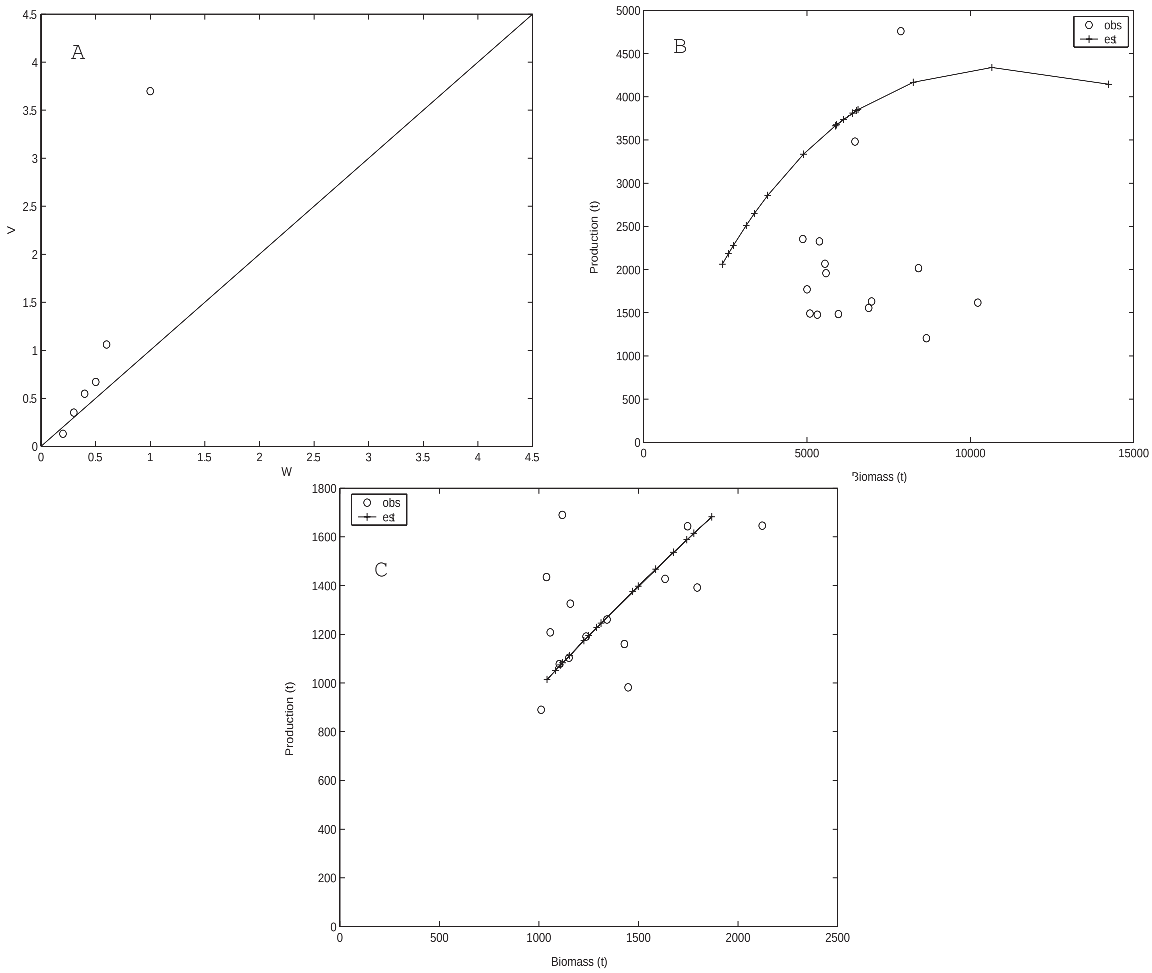

Figure 5.9: Jamaican weakfish estimated through non-equilibrium POEEM,(A)variation of variance ratio (V) as a function of weight ratio (W), (B)biomass (t) as a function of production (t), for residual ratio approximately one ($V/W \approx 1$), and (C)biomass (t) as a function of production (t), for variance ratio approximately one ($V \approx 1$).

Table 5.3: Results of the stock production model from different models and parameter estimation approach for Jamaican weakfish.

	Observation Error			POEEM		
	Schaefer	Shepherd	Fox	$V/W \approx 1$	$W = 1$	$V \approx 1$
q	$3.2 * 10^{-4}$	$3.2 * 10^{-4}$	$3.2 * 10^{-4}$	$6.8 * 10^{-5}$	$6.2 * 10^{-5}$	$3.3 * 10^{-4}$
B_{t+1} (t)	1379.1	1594.0	1563.5	14236.0	1567.0	1742.8
B_{max} (t)	27853	5022	3971	30000	30000	30000
$\frac{B_{t+1}}{B_{max}}$	0.050	0.317	0.394	0.475	0.052	0.058
MSY (t)	6558	1307	1336	4341	4341	4341
$B_{MSY}(t)$	13926	1260	1469	10981	10981	10981
$r(year^{-1})$	0.94	4.61	7.58	1.62	1.62	1.62
SS	$2.80 * 10^6$	$1.50 * 10^6$	$1.54 * 10^6$	4.39	6.48	0.36
λ_θ				1	1	1
$\sum \theta_y^2$				2.16	5.10	0.23
λ_ρ				0.3	1	0.6
$\sum \rho_y^2$				7.42	1.38	0.22
V				0.29	3.70	1.06
V/W				0.97	13.70	1.8

The Jamaican weakfish stock biomass and production relationship is shown in Figure 5.9 (B and C) and further results are found in Table 5.3. For both weighting balance the stock has apparently a recovering status, varying the current levels of recovering. While for $V/W \approx 1$ the stock is already at MSY levels, for $V \approx 1$ it is still on overexploitation levels but on the recovering trend (Figure 5.9). Most of the POEEM estimated values of production are bigger than the observed ones when $V/W \approx 1$ (Figure 5.9 (B)). When the model was minimised with $W = 1$, i.e. equal weight for observation and measurement errors, the sum of observed errors squared was smaller than in all other scenarios for this species (Table 5.3).

The uncertainty about the "real" weighting balance has consequences in further analysis, since considering distinct population status would wider the range of possible outcomes without increasing the results reliability. So, due to the uncertainty about the most suitable weighting balance, the confidence interval was only estimated, for $V/W \approx 1$ for illustration purposes, since further investigation on a reliable method to determine the balance must be conducted. The value of σ used in the confidence intervals estimation was 0.1. The number of resampling used in the bootstrapping

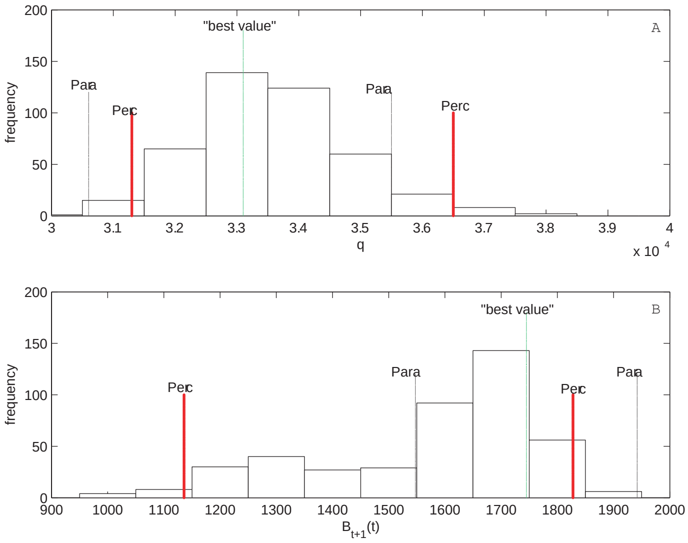

Figure 5.10: Frequency distribution of bootstrapping estimation of q (A) and B_{t+1} (B) for Jamaican weakfish stock from POEEM minimisations, where Para is the parametric confidence interval and Perc is the percentile confidence interval.

estimation was 435 out of 444 in total because 9 of them failed to converge to a real number result.

The distribution of catchability estimations were close to the normal curve with low data dispersion, reflecting the small value of sigma (Figure 5.10 (A)). Both confidence intervals, parametric and percentile, presented similar limits but the parametric one is more desirable since it is statistically more a robust method. The result considered the "best value" is placed in the modal class, i.e. around the middle of the confidence range. The smaller confidence interval will also narrow the estimation of other management quantities.

The forecast biomass for the next year shows a distribution skewed to large biomass the right which requires the percentile confidence interval since these are more consistent (Figure 5.10 (B)) than the parametric one. The forecast biomass exhibits a wide dispersion and therefore, these estimates would yield wider management scenarios.

The observation error only estimator had the following initial parameter settings for all production models, q = 0.1, $\alpha' = 2$, M = 0.54 year^{-1} and $B_{max} = 30000$ t. Results

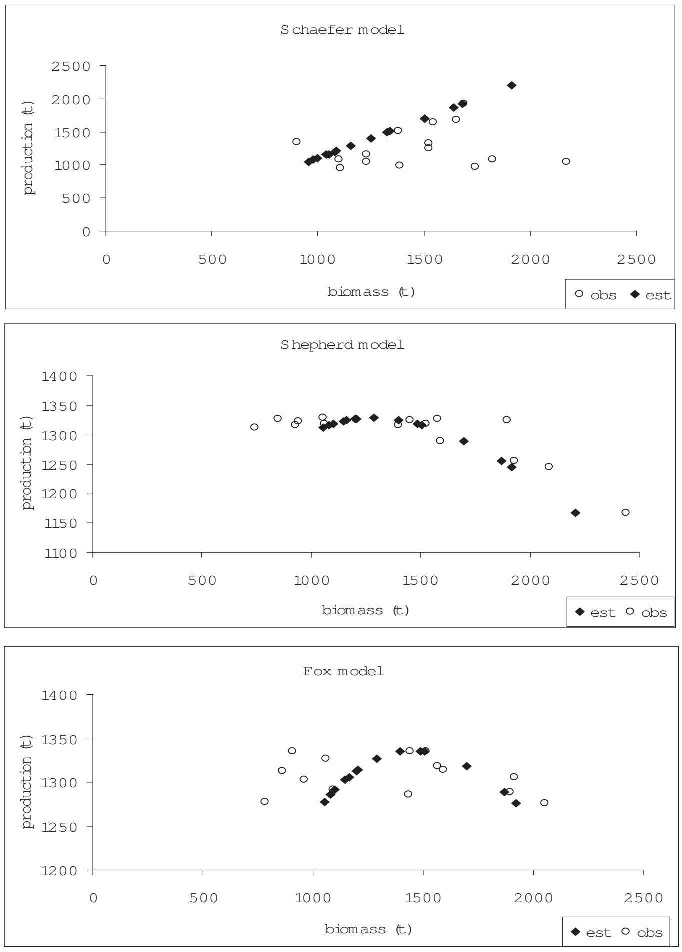

Figure 5.11: Jamaican weakfish biomass (t) as a function of production(t) for Schaefer, Shepherd and Fox production models, estimated through non-equilibrium observation error.

of this model fitting approach within all production curves are shown in Figure 5.11 and Table 5.3. Each production method indicates a different status for the population. The Schaefer model predicts an overfished stock, whose biomass in the next year is just 5% of the pristine biomass (Table 5.3). The Shepherd and Fox models predict a healthy stock where its forecast biomass is bigger than the B_{MSY} and the depletion rate ranges between 32 and 40%.

The conflicting results among the models possibly occurs because this stock has a low level of exploitation. The simulation conclusions suggested that lower levels of exploitation can result wider range of results. Highly exploited populations do not present such variable results (see king weakfish analysis). However, all estimation approaches yielded similar levels of estimated biomass at next year.

Besides, the essential need of mapping a range of B_{max} and α' values added to the lack of reliability in the estimated quantities. Unless further investigations on this ground were carried out the estimations should not be considered.

5.6.3 Discussion

The POEEM results show that Jamaican weakfish stock is depleted but recovering and should not be subject of further effort. The diverging findings for the observation only estimator and the mixed model, associated to the weighting balance uncertainty indicate that further testing on several values of pristine biomass and resilience would be useful.

In order to produce realistic current biomass, assumed values of pristine biomass took into account the long term fisheries exploitation the stock of Jamaican weakfish has been subject to. Lower values of pristine biomass yielded current biomass lower than the current landing levels. It therefore, reinforce the essential requirement of the mapping the goodness-of fit surface through a range of pristine biomass and resilience values, specially when the past catch history has a high level of uncertainties which just increase the level of noise and is very uninformative.

There are two pieces of evidence that corroborate with POEEM suggestions on the current state of the stock. Firstly, there has been no considerable changes in the size at first reproduction in the last 30 years (Magro et al., 2000, Castro et al., 2005b). Secondly, the fisher seem to target mature fish, i.e. there has been no alarming signs of exploitation of juveniles, which is desirable to preserve the sustainability of the fisheries.

The fleet seems to take advantage of the seasonal migration of this species, and increase the catch during summer, when Jamaican weakfish is found in the shallower waters to avoid the SACW. During winter, the species seem to migrate to other regions (Rossi Wongtschowski and Paes, 1994, Rocha and Rossi Wongtschowski, 1998), and as a result the catch is reduced. Therefore, the species seasonal migration is a natural protection against overexploitation, since its "disappearance" during winter is reflected in the catch. The seasonal closure of shrimp trawling has a positive effect on this species, as it reduces its catch by this fleet and especially since this is their spawning season. If the closure would be extended to the pair bottom trawl there should be a considerable enhancement of the stocks for all species.

5.7 Grey Triggerfish

5.7.1 Biological Aspects

Grey triggerfish (*Balistes capriscus* Gmelin, 1789) (Figure 5.2(D)) is distributed in the western Atlantic from Nova Scotia to Argentina and in eastern Atlantic from the Mediterranean to Angola (Robins and Ray, 1986). Triggerfish can be classified as demersal-pelagic species according to its feeding habits and behaviour. It predates on invertebrates with and without hard shells (Magro et al., 2000), such as crustaceans, gastropods, cephalopods, polychaetes and fish (Bernardes, 1988). The species has been found as prey of epipelagic fish (Zavala Camin and Lemos, 1997) and also is associated with floating Sargassum (Aiken, 1983).

Its broad distribution may imply the existence of several populations but no studies on this matter for the Brazilian coast have been published so far. For the purpose of this thesis, the triggerfish landings from the Santos fishery port will be analysed. These landings have been mainly caught between Santos and Bom Abrigo (Castro, 2000). The species has been exploited since 1967 as bycatch, but from the 1980s on its catches has increased and started to be commercialised as a separate fishery due to the decline of the other main resources, transforming the species into one of the pair bottom trawl target species (Castro, 2000, Castro et al., 2005a). The landings of triggerfish have been fluctuating enormously since late 1980s with dramatic reductions in late 1980s, mid 1990s and currently (Figure 5.3). In addition, the species is exploited by line fishing in northern areas (Castro et al., 2005a). Castro (2000) suggested that the wide fluctuation in triggerfish catches implies a necessity for more detailed studies.

Triggerfish catch size from trawls ranges from 140 mm to 410 mm fork length, with most fish bigger than 200 mm fork length, which corresponds to mature fish (Castro et al., 2005a). Indirect growth and age methods found fish in the catch with age varying from 2 to 9 year-old, but it is believed that younger fish are discarded onboard (Castro et al., 2005a). In the 1980s, 16% of the fish landed was immature (Bernardes, 1988). Further growth parameters were estimated as $L_\infty = 531$ mm, $k = 0.18$ year^{-1} and $t_0 = -0.23$ year (Castro et al., 2005a).

Spawning takes place in late spring and summer at the outer part of the continental shelf (Zavala Camin and Lemos, 1997, Bernardes and Dias, 2000). Current natural mortality (M) was estimated as 0.21 year^{-1}, fishing mortality (F) 1.76 year^{-1}, the exploitation rate (E) 0.89 and the survival rate (S) was 14%. The latter is 23% higher now than in the middle 1980s whereas total mortality is 16% higher for the same period (Castro et al., 2005a). Population parameters were estimated by Castro et al. (2005a) according to the methods in the section 5.3.2.

5.7.2 Model Results

The POEEM model fitting incorporated the initial parameter settings from previous studies. For grey triggerfish these settings were q = 0.1, $B_{initial} = 5000$ t, $\alpha' = 2$, M = 0.21 year^{-1} and $B_{max} = 30000$ t.

The determination of the weighting consistency for the mixed model objective function was coherent for $V/W \approx 1$ whereas for $V \approx 1$ it was not possible to find even though the number of decimal places of W were increased (Figure 5.12 (A)). The values of weight ratio (W) that reliably reached $V/W \approx 1$ was 0.11 (Table 5.4) for grey triggerfish. It was not possible to find a value of W which would result in $V \approx 1$,

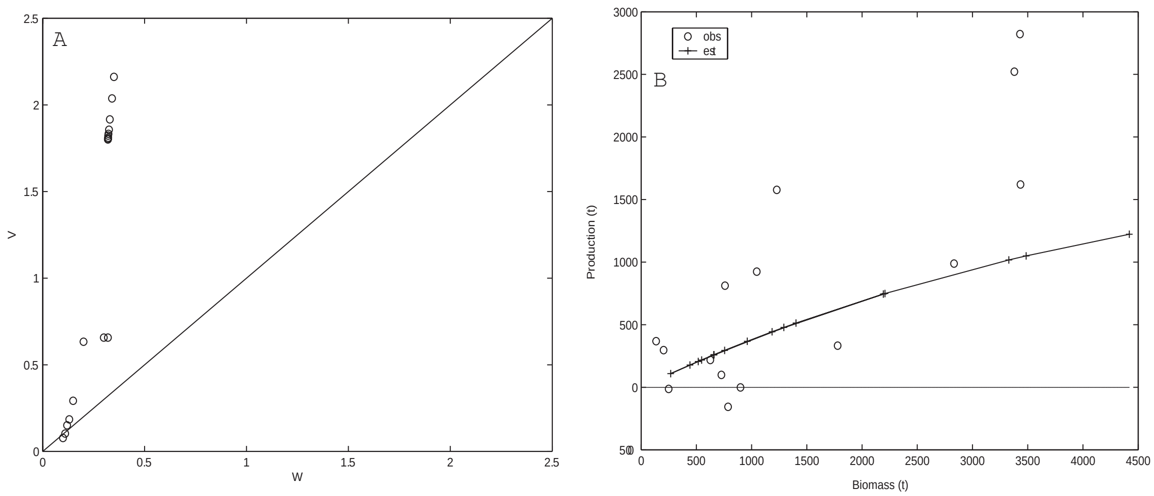

Figure 5.12: Grey triggerfish estimated through nonlinear POEEM,(A) variation of variance ratio (V) as a function of weight ratio (W), and (B) biomass (t) as a function of production (t), for residual ratio approximately one ($V/W \approx 1$)

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Table 5.4: Results of the stock production model from different models and parameter estimation approach for Grey triggerfish.

	Observation Error			POEEM	
	Schaefer	Shepherd	Fox	$V/W \approx 1$	$W = 1$
q	$5.3 * 10^{-5}$	$5.3 * 10^{-5}$	$5.3 * 10^{-5}$	$2.0 * 10^{-4}$	$1.3 * 10^{-4}$
B_{t+1} (t)	538.6	174.8	354.5	516.7	822.0
$B_{max}(t)$	11184	9486	10511	30000	30000
$\frac{B_{t+1}}{B_{max}}$	0.048	0.018	0.034	0.017	0.027
MSY (t)	463	732	668	1688	1688
$B_{MSY}(t)$	5592	2165	3889	10981	10981
$r(year^{-1})$	0.17	1.43	1.60	0.63	0.63
SS	$1.43 * 10^{8}$	$1.39 * 10^{8}$	$1.41 * 10^{8}$	2.50	3.77
λ_θ				1	1
$\sum \theta_y^2$				1.21	3.56
λ_ρ				0.11	1
$\sum \rho_y^2$				11.73	0.21
V				0.10	16.78
V/W				0.94	16.78

since the stock the level of noise is to high, and therefore only results of $V/W \approx 1$ will to be shown here.

Figure 5.12(B) displays triggerfish production as a function of stock biomass and the minimisation outcome are listed in Table 5.4. The stock has apparently collapsed and the forecast biomass is only about 1.7 % of the pristine biomass (Table 5.4). Observed biomass and production present a wide dispersion including negative production (Figure 5.12), which may indicate a high level of noise in the data set. Model minimisation for $W = 1$ resulted in sum of observation errors squared being larger than the sum of process errors squared (Table 5.4), which has been a constant feature in the model optimisation through POEEM.

The bootstrapping confidence interval for q and B_{t+1} was estimated with a $\sigma = 0.28$, originated from the $\sum \theta_y^2$ of the POEEM results. The number of resampling values used for the confidence interval estimation was 428 out of a total of 483, due to two features. First, the inability of convergence to a real number and second due to V/W ratio being bigger than 4 or smaller than 0.2 as in the section 4.2.3.

Both parameter distributions were wide mirroring the high value of σ. Due to its proximity with the gaussian curve (Figure 5.13) the parametric confidence interval can be consistently used. The "best value" is in the modal class as expected (Figure 5.13). Due to the large dispersion of the biomass at the next year (Figure 5.13(B)) the management action should be carefully planned.

The initial parameter settings for the Schaefer, Shepherd and Fox production model fitted by the observation error only estimator were q = 0.1, $\alpha' = 2$, M = 0.21 year^{-1} and B_{max} = 30000 t. These production models predict that the stock is overexploited and very close to collapse (Figure 5.14 on page 116 and Table 5.4). Although variable, the predicted biomass for the next year is less than 5% of the original pristine biomass (Table 5.4). The Schaefer model gave the most optimistic scenario but the deviations between the models were large (Table 5.4).

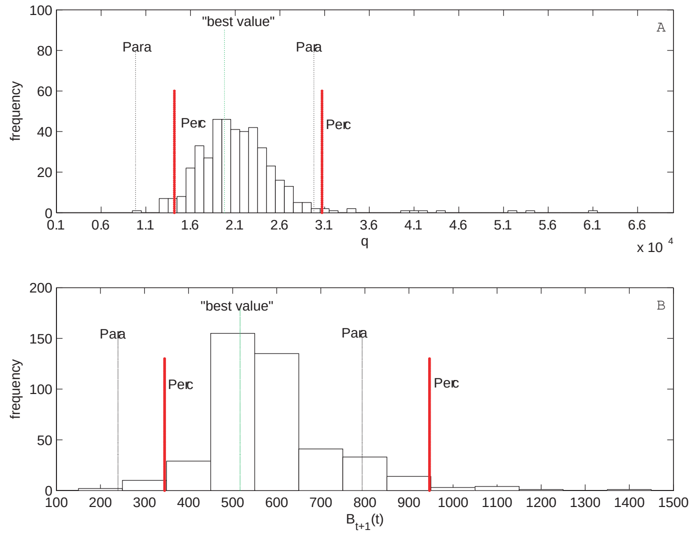

Figure 5.13: Frequency distribution of bootstrapping estimation of q (A) and B_{t+1} (B) for Grey triggerfish stock from POEEM minimisations, where Para is the parametric confidence interval and Perc is the percentile confidence interval.

The observation error estimate tend, in this case of high level of stock exploitation, to corroborate the trend of the POEEM, but results of the former should not be given much weight because of the high uncertainty associated with these results (Table 5.4). Moreover a range of pristine biomass and resilience must be tested to verify the reliability of the chosen initial values. The great influence of this parameters in the stock estimation outcome demand this procedure.

5.7.3 Discussion

Stock production model analysis employing POEEM minimisation for triggerfish stock revealed a collapsed stock, resulting from a downward catch trend with significant fluctuations during the analysed period. Those results should be used with caution due to the lack of knowledge about the population boundaries, migration patterns and recruitment. Further studies on age and growth aspects should greatly contribute to understand changes in the population structure. These aspects are fundamental and ought to be considered in the stock assessment either to provide model

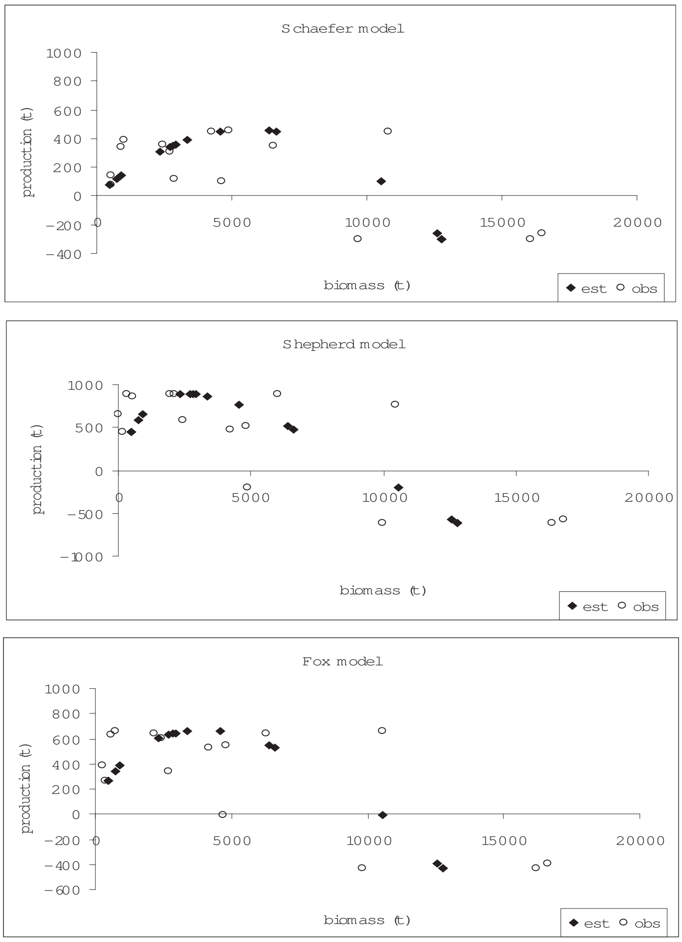

Figure 5.14: Grey triggerfish biomass (t) as a function of production(t) for Schaefer, Shepherd and Fox production models, estimated through nonlinear observation error.

parameters or as a guidance for the parameter settings. The need for additional information about this stock becomes clear from the fact that current results (Castro et al., 2005a) of size at first reproduction and catch size structure do not reflect this level of concern about the state of the stock. Furthermore, if the stock biomass is really at this low level, the surrounding populations of triggerfish could probably move to occupy the empty niche and balance this population size.

Even though the assumed value of pristine biomass considered the long term fisheries exploitation the grey triggerfish has been subject to, unrealistic results were not avoided. The complementary mapping the goodness-of fit surface through a range of pristine biomass and resilience values is therefore crucial, specially when the stock is subject to several pressures and the available data is not informative.

There are two events playing a crucial role in the triggerfish assessment results. Firstly, the discarding of small individuals onboard, which has already been documented (Castro et al., 2005a) is biasing the capture. This problem, well known in the fisheries literature, renders the use of landings data inappropriate since distortions in the recorded catch lead to biases in stock size and fishing mortality rate estimation (Patterson, 1998).

Moreover, the causes and magnitude of discarding are so variable and unpredictable that incorporating them into the model estimation may not lead to more realistic results. Conversely, independent fishery data analysis may offer a way to characterise the uncertainty associated with the systematic bias in catch misreport and incorporate this results into the stock assessment. In addition, management actions will be unpredictable where misreporting and discarding are present, since the uncertainty is extremely difficult to characterise and may crucially influence medium- or long-term forecasts (Patterson et al., 2001).

Secondly, the species has become one of the fleet's target species due to the decline in the catch of more profitable resources. Rising catches of the former target species can redirect skippers, i.e. effort, back to them in detriment of triggerfish catch, which due to its feeding and behaviour habits occupies a different niche. Therefore, the fact that its catch has decreased does not necessarily reflected a shrinkage in the stock abundance but it may be a process uncertainty related to multispecies catches and fleet dynamics.

Thus, the stock abundance and catch relationship will have the already accounted observation error and the process error associated to it. This process noise is not only driven by ecological factor of species distribution, but also by skipper choices. Both uncertainty can not be accounted together to this relationship since there is no way to separate them. Moreover, incorporation of fleet dynamics and its trade aspects can only be added if those movements follow a predictable pattern which is rarely the case.

5.8 Fish Stock Management in Brazil

Stock management comprises a set of actions that aims to maintain fishery activity which is economically viable, on a sustainable and long-term level. These actions are rooted in three important aspects. Firstly, actions ought to be legally bounded by official policies, based on the best scientific knowledge available and on international agreements and principles. Secondly, promoting widespread, constant and unconditional enforcement, not only in terms of making the policies known to the involved public but also to put them into action. In general, for proper fisheries management the effort employed in the policy making process is just a small part, since without an effective enforcement the policies are just an inadequate set of regulations. Finally, the measures have to be monitored in order to regularly assess their effectiveness and adequacy in relation to the current situation.

In this section, the current Brazilian legislation affecting the four species analysed here and the fleets involved in their fisheries will the examined in relation to the model findings. The set of policies presented here were put into place by the Brazilian federal government, which is the only administrative body allowed to legislate over fisheries resources.

5.8.1 Current Legislation

With respect to the species studied, there are two direct policies in place (i) establishing the minimum landing size for all four species and (ii) classifying king weakfish and whitemouth croaker as overexploited which requires a management plan to be put into practice until 2009 for both of them. Two indirect policies also have an effect on the four species studied here. These are two closure seasons, one for seabob and the other for pink shrimps trawling, which have a positive effect on those four species in form of reduction of effort leading to their exploitation.

The current minimum landing size policy is suitable for triggerfish, but it sets a size which is rather too small size for the other three species studied here. The existing knowledge about these species (Carneiro et al., 2005, Castro et al., 2005b) should be sufficient to change the current policy. However, more importantly, effective measures should evaluate the actual fishing gear selectivity since the current policy dates from 1983 and technological innovations introduced in the last 22 years have most probably changed the selectivity of those gears. Furthermore nursery grounds should be protected to avoid the species being caught before reaching maturity. This is more desirable than allowing escapement from the net, since this can still damage the fish. Both measures should help to prevent recruitment overfishing.

Considering that nursery grounds generally support a number of species, there might well be an overlap of area and time among fish stocks, making this an effective measure to protect the whole community. The shrimp fisheries closed seasons might also contribute to this matter, especially that for the seabob which takes place in late spring and early summer when king weakfish, Jamaican weakfish and whitemouth croaker have their recruitment. Therefore this seasonal closure should be extended to the pair bottom trawl as well. Triggerfish would need a specific policy to avoid its catch during late spring and summer since its reproduction takes place at the outer part of the continental shelf.

The management plans required for king weakfish and whitemouth croaker should follow FAO instructions (FAO, 1995, 1996, Cochrane, 2002) setting a comprehensive and robust set of measures.

In terms of direct fleet control measures, there are two possibilities concerning fishing effort control and one possibility concerning avoidance of recruitment overfishing. Firstly, the fishing effort controls set a maximum number of boats in the fleet, which was established in 1997 for trawlers and seiners when the number of boats was just "frozen". Secondly, it legislates the gear dimensions and mesh size for trawlers and gillnets. The third fleet measure prohibits trawling on the shallowest strip of sea, limited from one side by the average tide levels and on the other by 2 to 5 nautical miles depending on the region. This measure protects the nursery grounds which are mainly inshore.

5.8.2 Enforcement and Monitoring

Even policies prepared with very accurate scientific knowledge are not useful if they are not implemented effectively. Furthermore, it is fundamental for a proper maintenance of the regulations to constantly monitor and evaluate those measures, since the fisheries are dynamic and highly variable systems.

Enforcement off the Brazilian coast and at the fisheries port is a herculean task, because of the size of the area and the number of people involved, Too few enforcers have to control too many fishers and businesses. This unsatisfactory situation can make use of new technology to monitor and enforce the law. Furthermore, education is needed to make the policies known and respected. However, the enforcement must be much more emphasised and strengthened by the government, if it expects some return from the effort employed in the policy making and more importantly if it wants to fulfill its duty of environment protection.

5.9 General Discussion and Recommendations

The similarity of results between the observation error only estimator and POEEM seems to depend on the level of exploitation of the stocks, i.e. for fairly heavily exploited populations the results were similar, but for lower levels of exploitation, the different models predicted a variety of scenarios. Conceptually, POEEM is more consistent with the actual circumstances, due to its underlying proposed properties should be preferred. Even though there has been some support for observation error only methods, this kind of model fitting (Chen and Andrew, 1998), incorporation of both, observation and process error, is the most recommended analysis (Rosenberg and Restrepo, 1994, Hilborn and Peterman, 1996, Meyer and Millar, 1999a, Millar and Meyer, 2000).

Evaluating a range of initial values for pristine biomass and resilience serves to guide the choice of a credible parameter settings which would also correspond to a lower sum of squares. This parameter space mapping proved to be harder then expected and therefore was not conducted here as comprehensive as expected. Since they are not estimated by the model, it is crucial that all four species have further determination using a range of α' and B_{max} to increase the reliability on the final optimisation outcome. In addition, to validate the estimation each pair of α' and B_{max} must be weighting balanced, which is a high time consuming task because of the high number of iterations the optimisation routine needs to reach conversion. Moreover, the lack of a clear determination for the weighting ratio just increase the possible range of outcomes.

With regard to the **whitemouth croaker** stock, it was not possible to draw any firm quantitative conclusions about its status from the POEEM estimation. The levels of noise in this species data set is very high and, as observed in the simulations of the previous chapter (4.2.3), the results are not consistent with the model assumptions. However, the population status of overexploitation should be seriously considered, since the trend of the stock production curves were concordant which should be a sign for highly exploited populations. In addition, a previous study (Castro, 2000) suggested not to increase the fishing effort, which has not been followed. More comprehensive catch and effort data are necessary for more conclusive stock production model analyses. Further population aspects, such as population determination through population genetic studies, age and growth studies through direct methods could be investigated. As an immediate management measure, the minimum landing size should be increased to 292 mm, which is the mean length where 50% of the population have reached maturity (L_{50}) (Carneiro et al., 2005) and the

Bom Abrigo area should be closed during, at least, one of their reproduction peaks, winter and later spring.

King weakfish presented a low level of production and a collapsed stock caused mainly by recruitment and spawning stock overfishing. Even though there is a strong need of further investigation in the pristine biomass and resilience space mapping, this trend should be considered for further management actions, since the decrease of the size at first reproduction corroborates this diagnoses. For an effective management and recovery plan, the king weakfish spawning grounds, e.g. at Bom Abrigo, should be closed during late spring and summer. In addition, the size at first capture must be increased in accordance with Carneiro and Castro (2005) and it must be effectively enforced.

The POEEM results revealed that the **Jamaican weakfish** stock is on a recovering status, probably result of the population biological and ecological strategies described in the section 5.6. Even considering the need of further estimations on the initial parameter settings, if the fishery effort can be held at the current levels no further actions, other them monitoring the stock, need to be taken. Management actions affecting the previous species will have a positive impact on this species, since they share habits and habitat. This is specially advantageous since the main fleet uses a multispecies gear with reduced selectivity making it virtually impossible to formulate species selective policies.

Grey triggerfish stock was revealed as being collapsed using the POEEM. Further investigation in the pristine biomass and resilience mapping are also essential for this species. This result should be used with caution due to the lack of knowledge of fundamental species dynamic aspects, and since if the species populations become so low, other populations of triggerfish could occupy the empty niche and replenish the population size. However, in order to increase the model accuracy of POEEM more reliable fishery data is necessary. The main sources of model uncertainty comes from the unknown amount of discarding onboard. Monitoring and decreasing this practice would not only improve the model accuracy but also benefit the stock itself. Furthermore, the discarding of triggerfish is subject to increase if the other three species are caught at economically viable levels. The amount of triggerfish landed therefore reflects its economical value as much as stock abundance. Biomass estimation from scientific surveys is ideal data for further independent analyses, since the fleet dynamics may be misleading with respect to stock abundance. Despite the uncertainty about the status of this stock catches should be prohibited during summer, i.e. its spawning season, as a precautionary measure. In the mean time, more precise data needs to be gathered in order to provide improved predictions.

The general need of increase in the minimum lading size could be met by a change in the mesh size, considering the technological innovations contribute to vary the gear selectivity and update scientific advice must be seek by the policy makers.

The Bom Abrigo region (25° S) is part of biologically rich system of coastal lagoon and estuary. So, it plays a vital role in the life cycle of whitemouth croaker, Jamaican weakfish and king weakfish, and it should be seriously considered as part of a marine protected area, or at least, for a seasonal closure for any fishing gear. Considering that shrimp trawlers are not allow to operate during part of the year, this measure should be extended to all trawlers, especially during spring and summer when reproduction and recruitment are taking place for those three species.

Finally, small improvements in the catch should not be considered as indicating a stock recovery, but as natural environment fluctuation. All four species have long life cycles since several year classes are present in the catch. Consequently, actual changes and improvement in the stock biomass are only consistent when they persist for few generations. Monitoring those stock biomass changes through CPUE and/or research surveys are essential to the success of management plans.

5.10 Summary

The results of this chapter suggest that in order to increase the reliability of the model estimations and confidence intervals for all four species there is a crucial need to evaluate a range of pristine biomass and resilience as an usual practice for this model.

Reliable data is always required for a meaningful modelling of fish stocks. For all species studied the outcome trend of POEEM gave a reasonably idea of the current stock status. For king weakfish and Jamaican weakfish stocks the trend was supported by comparison with conventional models and historical data in these two extreme cases. While the former stock has important signs of collapsed the latter seems to be at around sustainable levels but effort must not be increased.

For whitemouth croaker, the available data was very noisy, leading a meaningless analysis of the stock, even with the advanced methods of POEEM, i.e. separating process and observation errors.

Triggerfish data is also difficult to analyse since the effects of discarded juveniles seems to play an important role in the catch-landing proportion, interfering adversely in the assessment results. Furthermore, commercial (marketing) aspects are playing an important part in this fishery due to interaction with the other three species.

Based on the model findings, fishery management measures can be recommended for the four species. These include seasonal closures of spawning grounds (for king weakfish), increasing the size at first capture (for king and Jamaican weakfishes), and improving gear selectivity (for king weakfish and triggerfish). In general, the Bom Abrigo region (25° S) should be considered as part of marine protected area, or at least be closed for fishing activities during the shrimp closure season, due to its importance in the species life cycle.

For the two species with low data quality, whitemouth croaker and triggerfish, more detailed and accurate monitoring, and further biological studies are recommended.

Finally, monitoring of management measures and stock biomass changes are essential to the success of management plans. Improvements in the catch must be consistent for several generations, in order to be considered an effect of the measures instead of a naturally environmental variation.

Chapter 6

Conclusions

This final chapter presents an overview of the scientific contributions of this study. Several stock production models have been investigated in this study and a number of conclusions have been drawn in the preceding chapters. Stock production models are particularly useful when limited amount of data is available, i.e. a situation faced in large number of important fisheries worldwide. In addition, less data demanding models allow data collection resources to be used allocated with parsimonious to more demanding areas, such as recruitment, which is always desirable.

A new stock production model and fitting method has been developed, with the aim of improving the reliability of the results. For the first time, both process and observation error were explicitly included in a non-equilibrium stock production model and minimised using a weighted least squares methods.

The sensitivity of the new model and method, POEEM, were tested with both simulated data and real fishery data. The latter also served for comparison with previous studies.

POEEM was first evaluated with sablefish stock, since the species stock production has been previously assessed through a similar method and it would serve for comparison purposes. This data set has been already estimated using a biomass-based model. Further, POEEM was used to analyse four demersal species which have been exploited during six decades but little data was available until recently and stock assessment has been conducted sparsely.

6.1 Process and Observation Errors Estimation Model-POEEM

In principle, the new model and fitting approach, POEEM, has two fundamental advantages. First, it allows for the simultaneous incorporation of observation and process error and the employment of a non-equilibrium least squares framework for the optimisation. The inclusion of process uncertainty in the production model rather than in the dynamic equation, as traditionally conducted, is in agreement with the general understanding about the origin of process noise. Practically, it fulfilled published recommendations of allowing for both types of errors in the model fitting process, since both are known to be significant and of comparable magnitude.

Second, while the current POEEM formulation as presented here uses the Shepherd stock production model to quantify the stock biomass dynamics, any other production model, e.g. classical Schaefer and Fox, can be used instead. This can be useful for comparison among production models and using other fitting methods. However, the Shepherd model has the advantage of using difference equations which treat growth, mortality and recruitment explicitly, i.e. as biologically meaningful parameters.

In practice, I encountered unexpected difficulty in deciding on the weighting ratio (the relative weights on process and observation errors). Moreover the results were very sensitive to this ratio, with a strong tendency to switch between observation error type and process error type results, for small changes of the weight ratio.

The simulation results were sensitive to the various levels of exploitation and levels of noise applied to the population. The use of simulated fishery data proved to be a useful method for testing the POEEM in a range of situations. It was found that the parameter confidence interval estimations were coherent for different scenarios and a suitable complementary estimation. However, high levels of noise exacerbated the switch between observation error type and process error type. As a result of this, it was not possible to use the intended fitting procedure, i.e. fitting catchability and terminal biomass automatically, and explaining the parameters space by mapping the minimised sum of squares surface with respect to other parameters such as resilience and pristine biomass, with adequate confidence in the results.

It is known from previews studies (Polacheck et al., 1993, Punt and Hilborn, 1997, Patterson et al., 2001, Punt, 2003) that finding reliable interpretations of the limited data sets characteristically available for stock production modelling is difficult. Contrary to expectations, the additional realism of the model used here, allowing for both of the known major sources of errors explicitly, and allowing for non-equilibrium nature of the data sets, has not made the problem more tractable.

The method limitation in terms of number of estimated parameters can be overcome by the space mapping of more parameters, especially pristine biomass and resilience. This evaluations proved to be always necessary and must not be neglected.

6.2 Future Directions

The use of simulated data revealed an unexpected and still unexplained difficulty in balancing between observation and process errors. When an equal amount of each error was introduced in the simulated data series, the amount of observation noise was expect to be similar to the amount of process noise in the fitted results. However, for all simulation scenarios and all five analysed species, it was found that when the weight ratio (W) was equal to one, i.e. observation and process error had the same weight, the estimated sum of observation errors squared was much bigger than the sum of process error squared. Further investigation should be conducted to identify the reason of this, and so find a reliable way to set the ratio between observation and process error.

Although difficulties were encountered, the present outcome trend for king weakfish and Jamaican weakfish should be considered as indicative of state of the stock since they are confirmed by other biological evidences.

King weakfish appears to be a collapsed stock caused mainly by recruitment and spawning stock overfishing. The decrease in the size at first reproduction corroborates this diagnoses.

The Jamaican weakfish stock appears to be around its maximum sustainable yield which is corroborated by other population dynamics aspects. Management actions related to the previous two species will have a positive effect on this species as well since they have similar life strategies.

High levels of uncertainty seems to be responsible for unreliable results of the other two species. Whitemouth croaker due to the lack of more comprehensive CPUE data and the grey triggerfish because of discarding and fleet dynamics.

Whitemouth croaker stock could not be properly analysed due to the high level of noise in the data. Further catch and effort data from all fleets catching this species are necessary. Genetical population determination might help to determine the population boundaries and improve population assessment results.

The grey triggerfish stock is apparently collapsed according to the analysis with POEEM. However, this result is not backed up by other population dynamics aspects. A lot more studies on the population dynamics must be conducted to elucidate key issues in life cycle of triggerfish. Measures to protect the species should comprise catch prohibition during summer, i.e. their reproduction season, since triggerfish spawning takes place at outer part of the continental shelf.

Constant monitoring management measures and stock biomass changes are essential for the success of management plans. Improvements in the catch must be traced along a few generations, in order to be considered an effect of the measures instead of environmental natural variation.

The conceptual problem of incorporating process and observation uncertainties in the model fitting proved to be more difficult and time consuming than expected. The results are therefore, not as comprehensive as originally expected. Although, the method still looks promising, it needs further evaluations and development with both simulated data and real and reliable data sets such as that analysed by Polacheck et al. (1993).

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