Modelling Dominance Shifts of Anchovy and Sardine with a Frame–Based Approach: Sensitivity to the Underlying Sardine Population Dynamics

by

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Abstract

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Small pelagic populations in upwelling systems are characterised by oscillation between states of alternating dominance. The size of the small pelagic fishery make it a key fishery for the South African Department of Agriculture, Forestry and Fisheries' plan to implement an Ecosystems Approach to Fisheries. It has been shown that sardine and anchovy populations in the southern Benguela have alternated dominance during the past 50 years, and a frame based model that explores the usefulness of frames within a marine ecosystem by modelling sardine/anchovy dominance shifts in the southern Benguela has been developed in a previous study. The existing model contains a sardine population sub–model without age structure and the inclusion of age–structure allows age–related dynamics to be incorporated in the model design.

In this mini–dissertation, an age–structured sardine population is implemented in the frame based model by using the sardine assessment model from the joint sardine/anchovy Operational Management Procedure, OMP–02. Methods for incorporating biological processes — such as the hypothesised school trap phenomena — that were present in the existing frame based model into the OMP–02 equations are developed, critically analysed and tested.

A wide range of model tests and a sensitivity analysis are successfully utilised to interpret model outputs, quantify model sensitivities and identify design flaws. A series of comparative tests indicate that the modelled sardine population is more responsive to fishing pressure after the implementation of the OMP–02 equations and decreased average recovery rates from low biomass levels were noted. The inter–annual variability of the modelled sardine catch is sensitive to the natural mortality parameters, and the majority of model output metrics are sensitive to the values of the stock–recruit relationship parameters.

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Nomenclature

Acronyms

FBM	Frame Based Model
OMP	Operational Management Procedure
TAC	Total Allowable Catch
TAB	Total Allowable Bycatch
HS	Hockey-Stick
SR	Stock-Recruit
DS	Double Sloped
BH	Beverton Holt
ESI	Environmental Suitability Index
OAT	One At a Time
EAF	Ecosystem Approach to Fisheries

Variables

symbol	**description**
μ	arithmetic mean
σ^2	standard deviation
$N_{y,a}$	the number of sardine aged a at the beginning of year y (in billions)
$C_{y,a}$	is the mass of sardine of age a caught in year y
$\overline{w}_a$	the mean mass at age (in grams) of adult sardine from the November surveys
$\overline{w}_{ac}$	the mean mass of sardine associated with the catch $C_{y,a}$ (in grams)
B_y	the sardine biomass from the November survey in year y
$B_{AM-high}$	the level above which sardine are classified as high by the AutoManager
B_{AM-low}	the level below which sardine are classified as low by the AutoManager
M_{ju}	the natural mortality of juvenile sardine
M_{ad}	the natural mortality of adult sardine
ε_y	the standardized sardine recruitment residual
σ_r	the standard deviation of the sardine recruitment residuals
ω_y	a random sample drawn from the standard normal distribution

symbol	**description**
a_1	base recruitment level (billions) when the ESI favours sardine
a_2	base recruitment level (billions) when the ESI favours anchovy
b_1, b_2	biomass values (kilotons) of the SR curve inflection points
V_{IA}	the measure of interannual variability in the sardine directed TACs

Terms of Reference

This project began in 2009 when a previous MSc (Applied Marine Science) student, Michael Smith, explored the usefulness of a frame–based model (FBM) to simulate anchovy/sardine regime shifts in the southern Benguela marine ecosystem. The MA–RE BASICS program subsequently provided funding for the modification of the original FBM to include age structure in the underlying sardine population model.

Specific constraints were placed on the project by the project supervisor:

- the FBM would only consider the west coast situation (i.e. prior to the eastward shift of sardine),
- no statistical fitting of parameters to real world data was to be performed,
- the sardine population equations were to be sourced from the OMP–02 assessment model and
- the FBM was, insofar as possible, to be kept identical to the version implemented by Smith, to aid comparison of model outputs.

The specific objectives identified for the part of the project documented in this thesis, were:

- implementation of an age–structured sardine population model within the FBM,
- implementation of sardine fishing in accordance with fishing dynamics as implemented in OMP–02 and
- a sensitivity analysis of the final FBM.

Chapter 1

Introduction

1.1 Project Background

In eastern boundary upwelling systems, sardine and anchovy populations are characterized by alternating dominance patterns called “regime shifts”. Regime shifts occur naturally due to “bottom-up” climate variability but may also be induced by “top-down” fishing pressure, as appears to be the case in the northern Benguela (Cury and Shannon, 2004). Regime shifts appear to occur roughly simultaneously in all four major upwelling systems (Lluch-Belda et al., 1992) and the global synchronicity of these events is possibly due to climate variability “teleconnections” (Klyashtorin, 1997). Regime shifts complicate fisheries management because they are masked by inter-annual variability and may therefore be hard to detect (Hutchings et al., 2011) — this makes it difficult to plan for the medium–term future.

A frame–based model (FBM) that investigates the long term population trends of sardine and anchovy under various management strategies in the southern Benguela was developed (Smith and Jarre, 2011) and first and second generation prototypes were created using rapid application development. The purpose of Smith’s study was to provide a proof–of–concept for the application of the frame–based modelling approach to marine ecosystems. This study aims to further explore the potential usefulness of a diagnostic FBM in fisheries management by refining a key aspect of the second generation prototype namely the sardine population model. The sardine population model implemented by Smith had no age–structure and it was suggested by him that it be replaced with an age–structured one which would allow for age–specific fishing and natural mortalities. The sardine population model used by the Operational Management Procedure (OMP) approach for stock assessment purposes (de Oliveira, 2002) was identified as a suitable candidate for this study. The FBM is useful in this context because it is well suited to weakly defined state transition probabilities — such as aperiodic dominance shifts — and it models the environment and the sardine/anchovy populations stochastically whilst allowing the exploration of various medium–term fishing strategies.

1.2 Structure of This Thesis

The spatial distribution of sardine extends along nearly 4 000 km of coastline, from southern Angola to KwaZulu–Natal. This study models the sardine population in the southern Benguela region, which extends south of the Orange River to about East London (Jarre et al., 1998). Whilst this "southern" stock has recently experienced a relative shift in biomass, with larger biomass levels being recorded eastward of Cape Agulhas, spatial distribution is not explicitly included in the model design. This project does, however, focus on the situation where the bulk of sardine was found west of Cape Agulhas, ca. 1950-2000. Furthermore, whilst information on the age–structure from the sardine stock surveys has recently become more noisy, this model uses the parameters from OMP–02 when the information on the age–structure was still relatively clear.

The outputs of the FBM using the age–structured sardine population equations are compared with the outputs of the FBM without age–structure. The difficulty of drawing conclusions from this step is evident (because so much has changed in the model design), yet these difficulties are highlighted and analysed throughout the text in an effort to compare the high level model outputs from the two versions of the FBM, and a sensitivity analysis provides useful information during this process.

This mini–dissertation consists of four chapters:

Chapter 2 - General Introduction, Literature Review and Methodology

The ecological background related to the research question is presented here. Work previously done by others is also presented in a literature review. In this chapter the *modi operandi* are described. Reasons for sardine model refinement are discussed and a perspective is provided on the anticipated changes to the model.

Chapter 3 - Model Design and Implementation

The revised design of the model is presented in this chapter and the equations implementing the sardine population submodel are discussed. Relevant implementation details are also documented here.

Chapter 4 - Testing and Analysis / Modelling Results

This chapter consists of two components. The first component performs general model tests to gain confidence in the model outputs. The second component presents the results of the sensitivity analysis, and compares the results to those of the simple model.

Chapter 5 - Interpretation of Results, Discussion and Conclusion

The results from the model world are interpreted in terms of the real world in this chapter. Insights gained and recommendations for future work are also given here.

Chapter 2

Context and Methods

The forage fish species in the Southern Benguela consist of sardine, anchovy, juvenile Cape horse mackerel, round herring, lanternfish and others. They form the basis of the South African small pelagics fishery and population levels are therefore of interest. The two cornerstone species of the fishery are sardine (*Sardinops sagax*) and anchovy (*Engraulis encrasicolus*). This review covers literature in the fields of sardine biology, population modelling of sardine, frame–based modelling techniques and the population modelling techniques currently used by fisheries management procedures.

2.1 Biological Background

When constructing an exploratory population model with incomplete knowledge of the spatio–temporal behaviour of the population, the available biological knowledge can be useful when making decisions about the model design. Therefore, a review of four important biological aspects of sardine populations is now presented.

2.1.1 Distribution

Sardine are epipelagic fishes that occur in dense shoals extending from southern Angola to KwaZulu-Natal. The spatial distribution of the shoals is heterogeneous and there appear to be two separate stocks: one north of the Lüderitz upwelling cell and one to the south of the Orange River mouth in the region known as the southern Benguela. The majority of the southern Benguela stock has recently been observed to shift eastwards towards the south coast (Coetzee et al., 2008), for unknown reasons.

Hydroacoustic surveys to estimate sardine abundance are conducted biannually: a survey in November measures the spawner biomass and a survey during May/June provides recruitment estimates. The measurements clearly indicate an age–specific distribution pattern, with recruits found on the west coast and mature sardines concentrated over the Agulhas Bank, but also known to occur on the west and south coasts. Armstrong et al. (1987) analysed data from predator diets, commercial catches and research cruises and concluded that the majority of juvenile sardine were caught off the west coast. They also found the majority of intermediate-sized fish ($14 - 20$ cm standard length) on the Agulhas Bank. During winter, dense shoals of sardine are known to occur inshore off the KwaZulu-Natal coast during what is known as the "sardine run", but this is most likely a different stock (Fréon et al., 2010).

2.1.2 Reproduction

The majority of sardine spawning takes place on the Agulhas bank (Hampton, 1992), but is also known to occur on the west coast (Hutchings et al., 2002). Davies (1957) found that sardine spawning may occur throughout the year but that the main season extends from September to February. More recently, Hutchings et al. (2002) noted that the spawning season peaks during autumn and spring on "either side" of the main anchovy spawning season. Whilst studying reproduction of sardine in the northern Benguela, Le Clus (1979) found that sardine have the potential to spawn more than once during the season and that sardine from larger length classes had a higher spawning potential than those from smaller length classes. Furthermore, van der Lingen et al. (2006a) found that the reproductive parameters of sardine in the southern Benguela are strongly suggestive of density dependence. This has implications when modelling the stock–recruitment relationship: it means that recruitment is not only an instantaneous function of the current population size, but also that the slope of the stock–recruit curve itself is likely a function of the population size.

In a review of clupeoid reproductive strategies across the globe, Shin et al. (1998) noted that in 10 of the 12 upwelling systems the spawning and nursery grounds overlapped. This is only partially true for the Southern Benguela — here the sardine spawners migrate from the nursery grounds near St Helena Bay to an area east of Cape Point on the western Agulhas Bank (Hutchings et al., 2002) where it seems that the warmer Agulhas current provides more favourable conditions for icthyoplanktonic survival (de Oliveira, 2002). Studies in upwelling systems in general have also suggested that warmer conditions are more favourable to sardine larval survival (e.g. Yañez et al., 1998; Borges et al., 2003; van der Lingen et al., 2006b).

2.1.3 Growth and Age

Sardines are a relatively short–lived and fast growing species (van der Lingen, 1999). From the spawning area on the Agulhas Bank, eggs and larvae are transported along the coast to the food–rich nursery near St Helena Bay — assisted by a north flowing frontal jet (Fowler and Boyd, 1998; Shelton and

Hutchings, 1982). Here juvenile sardine can occur in mixed shoals with anchovy on the northern part of the west coast and first become available to the fishery as recruits during March/April (Beckley and van der Lingen, 1999). During a study of commercial catch data for sardine caught in the southern Benguela during the period 1965–1967, Baird (1970) recorded the maximum age of a specimen as six years.

An important aspect of small pelagic populations is the “school trap” phenomenon: the tendency of juveniles from a relatively small population of a certain species to school with shoals of other, more abundant species (Cury et al., 2000). The feeding behaviour of the shoal will likely be dictated by the dominant species and, in the case of juvenile sardine schooling with adult anchovy, will result in adverse feeding conditions for sardine which in turn will likely result in reduced growth rates.

2.1.4 Feeding

Sardine are omnivorous microphagist filter feeders that obtain the bulk of their energy from small zooplankton (van Der Lingen, 2002). This is in contrast with anchovy who are selective biters feeding primarily on mesozooplankton (James, 1988). This disparity between anchovy and sardine feeding habits has been noted in other upwelling systems (Konchina, 1991) and results suggest that sardine prefer conditions favourable to the production of smaller foods, lower down on the food chain, than do anchovy. van Der Lingen (2002) notes that “virtually all prey items ingested by sardine were less than 1.2 mm maximum dimension” and that this size–based prey partitioning is likely to contribute to observed anchovy/sardine dominance shifts. Notable differences in the trophodynamics of sardine and anchovy were subsequently shown to exist (van der Lingen et al., 2006b, Fig. 3), with anchovy favouring the large copepods produced by colder, strongly upwelled waters and sardine favouring the small copepods that are more abundant in warmer, more stable waters.

2.2 Sardine Population Dynamics

Russell (1931) lists the four intrinsic processes affecting population levels of marine resources as recruitment, growth, natural mortality and mortality due to fishing. Since this study considers the entire southern Benguela ecosystem, extrinsic factors such as emigration and immigration are not taken into consideration. The role that each process plays in the sardine population of the southern Benguela is now briefly presented, in light of the modelling exercise.

2.2.1 Recruitment and Growth

When implementing recruitment in a population model, a central problem is that of deriving an expression for the number of recruits entering the population each year. This consists of two sub–problems: firstly the number of eggs produced each year must be defined and secondly the egg, larval and pre–recruit survival rates must be defined. In the southern Benguela, the problem is approached pragmatically: the recruit surveys provide an estimate of the number of recruits and the November surveys provide estimates of adult biomass, but neither provide information on larval survival rates or the number of eggs produced, so recruitment is modelled purely as a function of the spawner stock biomass (with stochastic variation about this function). Statistical curves fitted to stock–recruit data usually contain large residuals and stock–recruit curves come in various forms notably the Beverton & Holt type (Beverton and Holt, 1957), the Ricker type (Ricker, 1954), and linear types (singular or piecewise).

For a monotonically increasing stock–recruit curve (or portion thereof), higher population biomass levels represent increased spawning ability, yet the age structure typically gets "smoothed out" when calculating the population biomass (due to the weighted average across age classes), so a large number of younger fish could have the same spawning potential as a smaller number of older fish. This is because the older fish in an age–structured population model usually contribute more to the total spawner stock biomass because of the increased average mass per specimen in higher year classes. Larger length classes also have to the ability to spawn more than shorter ones Le Clus (1989).

Sardine are a short–lived species and population levels are highly susceptible to inter–annual fluctuations in environmental suitability, with egg and larvae survival determined by concentration, enrichment and retention processes, as proposed by Bakun (1996). This, along with fishing pressure, contributes to the highly variable population sizes reflected in the historical catch and survey data. For the purposes of this study, the early life history of sardine will not be modelled explicitly i.e. variability in recruitment will be determined by stochastic variation about a stock–recruit curve.

Growth may be incorporated into population models in various ways. For an individual based model, growth functions (e.g. von Bertalanffy, 1934) may be used to model growth explicitly. Alternatively, when modelling populations in an aggregate fashion, mean mass at age numbers (usually derived statistically from commercial catch data) can be used to project biomass numbers into the future. Due to the different feeding methods of anchovy and sardine — particulate versus filter feeding, respectively — the optimal growth rate conditions for each seem to be different (van der Lingen et al., 2006b). This follows from the fact that the optimal growth conditions for small and large zooplankton are different.

2.2.2 Natural Mortality

Natural mortality encompasses many factors such as predation, starvation due to detrimental environmental conditions, disease, pollution and starvation due to excessive intraspecific competition. These may all be lumped into a single natural mortality term, M, or they may be modelled explicitly as age–invariant or age–dependant parameters.

Both adult and juvenile sardine prefer warmer waters and they have been found to be negatively impacted by strong upwelling conditions (Borges et al., 2003; van der Lingen et al., 2006b). This is likely due to the fact that sardine are better able to utilize the smaller zooplankton that are more prevalent during weak upwelling periods (van der Lingen et al., 2006b). Sardine, along with other small pelagics, occupy an important position in the food web of upwelling ecosystems as they are preyed upon by many species of birds, marine mammals and other fish. Sardine form the major constituent of Cape gannet (*Morus capensis*), Cape cormorant (*Phalacracorax capensis*) and African penguin (*Spheniscus demersus*) diets. Among the fish which prey on sardine are hake, snoek, tunas and yellowtail, and marine mammals which consume sardine include Cape fur seals and various species of dolphins.

Survey data for sardine in the southern Benguela are available as proportion–at–age estimates of the adult biomass from the November surveys and estimates of the juvenile biomass from the recruit surveys in May, where adults are defined as fish aged one and older. Information on the adult stock age–structure is also available from the November surveys as proportions–at–age for five year classes. With these time series, separate adult and juvenile mortality rates are calculated in the assessment, and the approach currently used in South Africa's small pelagic stock assessment is to use a constant adult mortality rate across all adult age classes (de Moor et al., 2011).

2.2.3 Fishing

Sardine and anchovy are the main targets of the South African small pelagics fishery, which is the country's largest by volume of total landings and second largest in terms of wholesale value. Within the fishery, canned products (mainly sardine) are the most valuable, followed by fishmeal and fish oil (Lees, 1969). It is the most dynamic of all the fisheries due to the highly fluctuating population levels (both in time and space), complications due to mixed shoaling and relatively short lifespans of the targeted species.

When targeting sardine, the fleet deploys 32 mm purse–seine nets, whereas anchovy directed fishing uses 13 mm nets. Because juvenile sardine school with anchovy (Armstrong et al., 1991), anchovy directed fishing results in juvenile sardine bycatch and this complicates the small pelagic fishery and its management. Furthermore, it has been observed that there is an increased tendency of juvenile sardine to school with adult anchovy when the sardine population levels are low, thereby making it more difficult for the sardine population to recover if anchovy directed fishing continues (Cury et al., 2000). There are therefore two major sources of fishing mortalities for the sardine population: catches from sardine directed fishing and bycatches from anchovy directed fishing.

Fishing mortalities directly affect the population count of a species and in the extreme case may result in unintended stock collapse (e.g. Butterworth, 1983; Frank et al., 2005). However, due to the highly coupled nature of marine ecological systems, there are also indirect effects such as altered functional responses of predators and decreased top down control of prey. Using Ecopath with Ecosim (an aggregate ecosystem modelling tool), various fishing scenarios were modelled by Shannon et al. (2000) and it was shown that the model was sensitive to the assumptions about the control methods pertaining to component interactions. Different results were obtained for bottom–up, wasp–waist and mixed control configurations across a range of fishing pressure scenarios. It is therefore critical to understand the ways in which ecosystem components interact when modelling fishing pressure in an ecosystem approach to fisheries context. For the purposes of this project, wasp–waist control is assumed to be the dominant control mechanism — in accordance with the findings of Cury et al. (2000), Shannon (2004) and Shannon et al. (2009).

Fishing mortality may be modelled in various ways and should aim to use as much of the relevant and available information as possible. In an age–structured model, the total fishing mortality for year y may be written as

$$F_y = \sum_i F_{i,y}$$

where $F_{i,y}$ denotes the fishing mortality in age–class i. The fishing mortality observations from the South African small pelagic fishery (commercial catch–at–age) are calculated according to the algorithm provided in Section A.2.2 of de Oliveira (2002).

2.3 Frame–based Modelling Techniques

In many modelling applications a static equation (or system of equations) that describes system behaviour is unsuitable. This usually occurs when the operating conditions are subject to drastic change. For example, when modelling air flow dynamics, there is a model for regular flight and another (drastically different) model for supersonic flight. Similarly, frame–based ecosystem modelling (Starfield et al., 1993; Starfield and Chapin, 1996) defines a set of frames, with each frame containing a unique ecosystem behaviour specification. The system switches from frame to frame according to predefined rules, with the dynamics in the current frame determined by the current or past operating conditions (or both). Note that only one frame is operational at any given time. The frame switching rules must be formulated in accordance with the best available ecological knowledge about the ecosystem dynamics.

Frame–based modelling has been applied successfully in terrestrial scenarios requiring long–term analysis of natural resources for management purposes (e.g. Rupp et al., 2000; Hahn et al., 1999). Recently, progress has been made in applying the frame–based paradigm to a marine ecosystem (Smith, 2009; Smith and Jarre, 2011). Smith's model consists of four frames for anchovy/sardine population levels (High/High, High/Low, Low/High and Low/Low) in the southern Benguela. Each frame represents a unique ecosystem regime state. Certain parameters are monitored by software processes called *daemons* which control the switching between frames. Specifically, the sardine daemon monitors sardine population levels and the anchovy daemon monitors an Environmental Suitability Index (ESI). Each frame contains population models for both anchovy and sardine, with sardine bycatch calculated from the anchovy fishery. Yearly catches were either set at run–time, or automatically by a software routine named AutoManager.

The sardine population equation used by Smith did not contain information on the age structure of the population and it has been suggested that an age–structured model would more closely resemble real world population dynamics. An age–structured sardine model, implemented by de Oliveira (2002), was identified as a suitable candidate.

This study begins by implementing the age–structured population model from OMP–02 within the FBM implemented in Smith (2009) to test the sensitivity to the underlying sardine population model. This requires that the various levels and thresholds used by the daemons, the AutoManager, etc. are reproduced from the previous version of the model (Smith, 2009) as closely as possible. It also means that, while the structure of the OMP–02 population dynamics equations are precisely replicated in this thesis, some deviation from the parameter values has to be expected during implementation — this is due to the objective of comparing the results of this thesis to those of Smith (2009).

When employing rapid prototyping as a model design paradigm, it is important to perform a thorough sensitivity analysis before constructing subsequent prototypes (Starfield and Jarre, 2011). The results of a thorough sensitivity analysis may be used to derive the relative magnitude of influence of input variables on output variables. The most common form of sensitivity analysis is based on the derivative $\partial Y_j/\partial X_i$ of an output Y_j versus an input X_i yet the results from this method may be misleading when the model inputs are unknown and/or the model is not linear (Saltelli et al., 2007). Whilst increasing confidence in model outputs, a sensitivity analysis can also reveal areas in the model design that require further attention, such as unexpected sensitivity to processes percieved as unimportant, or insensitivity to processes perceived to be important. This in turn sheds light on the modeller's understanding of the ecological system.

2.4 Population Models Underlying Stock Assessment and Management Advice

As mentioned, sardine population models within each frame are modelled in accordance with those used in the fish stock assessment and for generation of management advice. Fish stock assessments use data from measurements and provide managers with critical information about the resource. The stock assessment methods used by the Department of Agriculture, Forestry, and Fisheries of the South African government for management of the small pelagics fishery are drawn from specifications that are part of "Operational Management Procedures" (OMPs) and usually get revised every three to five years. The current version is OMP–08, but since this study only pertains to the west coast conditions, OMP–02, developed by de Oliveira (2002) for his Ph.D. thesis, is being used.

In his thesis, de Oliveira performed an assessment of the sardine and anchovy resources. He then presented two methods for incorporating a trade–off decision between sardine and anchovy in management procedures. Finally he investigated two additional factors which might be taken into account: the use of environmental indices and the modelling of regime shifts as sinusoids. A qualitative description of the methods used in OMP–02 is now provided. Thereafter the sardine population model used in OMP–02 is described. Finally the work done by de Oliveira on modelling regime shifts is summarised.

2.4.1 OMP–02 summary

The OMP–02 approach translated data from two research surveys into recommended catch levels by a set of rules that were developed through computer simulation testing. Multiple candidate Management Procedures (MPs) were generated and all but one were eliminated. The candidate MPs aimed to (1) maximise resource yields while minimising the risk of stock collapse and (2) minimise inter–annual variation of the Total Allowable Catches (TACs).

OMP–02 provided a framework for making the trade–off decision between anchovy and sardine catches which necessitates from the fact that juvenile sardine school together with anchovy i.e. their fisheries must be managed jointly. The final trade–off decision could either be made externally (by the responsible Minister) or internally (by stakeholders).

OMP–02 set TACs in four stages throughout the year:

- provisional TACs and bycatch allowances were set in October,
- TACs for sardine and anchovy were set in January/February,
- the revised anchovy TAC and sardine Total Allowable Bycatch (TAB) was set in May/June and

- the anchovy 3$^{\text{rd}}$ TAC was set during the anchovy additional sub-season (August/September).

The provisional TAC was set to allow industry to mobilise its fleet in time for the start of the fishing season but did not reflect current stock status. In January/February the sardine TAC was set as a fraction of the total sardine population biomass (as calculated from the November surveys). The 2$^{\text{nd}}$ TAC/Bs were set with the most recent data from the November and recruit surveys. Finally, the 3$^{\text{rd}}$ anchovy TAC was generated "to achieve better utilisation of the anchovy resource" (de Oliveira, 2002). Note that the final TACs could only be adjusted upwards, not downwards from the provisional TAC, because by the time the final TAC had been set the provisional TAC could have been caught.

The rules and formulas for setting the TACs relied on a set of parameters. Each candidate MP consisted of a unique combination of these parameters. Performance summary statistics were used to evaluate each MP at the end of the projection period of 20 years. The statistics were either resource based (risk of collapse, average biomass at the end of the projection, etc.) or financial (e.g. mean annual catch). Certain candidate MPs which were deemed susceptible to higher levels of risk (where the risk pertains to stock collapse) then underwent robustness tests, while the MP variants that were considered more conservative with regard to resource utilisation were omitted from the robustness tests.

The MP variants that were considered more conservative with regard to resource utilisation were omitted

The framework used for testing of candidate MPs consisted of four components:

- the assessment procedure, which used the survey and catch data to estimate the parameters of the operating model,
- the operating model, which simulated the underlying (possibly "true") dynamics of the resource,
- the management procedure, which implemented rules and constraints independently of the underlying dynamics and
- the summary performance statistics, as described.

The assessment procedure and operating model are of direct consequence to this study and are now described in further detail.

Sardine Assessment Procedure

The sardine assessment procedure took the time series data from commercial catches and the two hydroacoustic research surveys, and fitted them to population models using maximum likelihood estimation. The method required adult and juvenile natural mortality values to be input, along with the November survey bias, because they could not be estimated satisfactorily in the likelihood estimation process due to a lack of information in the data. Estimable parameters included the 20 values for annual sardine recruitment for the years $1980, \ldots, 1999$. Results from the likelihood estimation process showed that a best fit was obtained for an adult natural mortality rate of $0.4.\text{year}^{-1}$, but that the model was insensitive to juvenile mortality rates; a juvenile mortality rate of $1.0.\text{year}^{-1}$ was settled upon (see Section 2.4 of de Oliveira's thesis for details). Based upon advice from the scientists responsible for accoustic survey, a value of 1.0 was chosen for the November survey bias, implying that the November surveys were unbiased[1]. Other estimable parameters of interest were those relating to the stock–recruit curves. A stock–recruit curve forms the basis of generating future recruitment values for simulations. Three stock–recruit curves are considered namely Single–Sloped (SS), Beverton–Holt (BH) and Double–Sloped (DS), where the SS curve is also known as the hockey-stick curve.

OMP–04 integrates Bayesian statistics into the sardine assessment procedure by using the Markov Chain Monte Carlo method on a minimum log-likelihood function (similar to that used by OMP–02) together with the negative of 36 log–prior distributions (de Moor and Butterworth, 2009). Natural mortality rates for adult and juvenile sardine were fixed at the same values of 0.4 and $1.0.\text{year}^{-1}$.

Sardine Operating Model

The operating model simulates the dynamics of the resource (in this case the sardine population) and interfaces with the candidate MP currently being tested. The operating model projects numbers–at–age forward in time from a stock–recruit curve. It then simulates survey data and feeds these to the MP under consideration. The operating model also requires values for future catches to be supplied to it and these future TACs are generated by the MP currently being tested. The operating model also splits TACs into catches–at–age, calculates biomass levels according to generated survey data and adjusts bycatch due to an observed drop–off after May. The catches–at–age for 1–year–old and older sardine are calculated annually, and the sardine and anchovy 0–year–old catches are calculated before and after the recruit survey. Further details of the framework for testing alternative MPs may be found in Appendix 5.1 of de Oliveira's thesis.

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[1] Since 2004 a non–unitary November survey bias term has been used (de Moor and Butterworth, 2009).

2.4.2 The OMP–02 sardine population model

The population model used by OMP–02 in the assessment of sardine consists of two age–structured equations with parameters for abundance and proportions–at–age, fishing mortality and natural mortality. The equations calculate the numbers–at–age at the beginning of each year by assuming that pulse fishing occurs six months after the birth date and therefore applies half the mortality rate twice — once before fishing and once after fishing. As described, values of 0.4 and $1.0.\text{year}^{-1}$ for adult and juvenile mortality rates, respectively, were used.

It is important to note that, as in Smith's thesis, the population model only applies to the situation before the eastward shift of sardine i.e. when the majority of sardine were found on the west coast.

2.4.3 Modelling Regime Shifts as Sinusoids

In his thesis, de Oliveira models regime shifts as sinusoids. He cites two studies of fish scale deposits from the Californian system (Soutar and Isaacs (1969) and Baumgartner et al. (1992)) as motivation for using sinusoids. These studies found that, based upon reconstruction of data from fish scale sediments, anchovy and sardine regime shifts occur roughly periodically with a dominant peak at 57–years in the spectra for both. However, de Oliveira noted that shifts with a shorter periodicity could potentially have a more serious impact on management. He therefore chose 30 and 50 year periods for the modelled sinusoids.

This is not the approach that will be used in this study, for two reasons. Firstly, it is not known whether the results from the Californian system are directly applicable to the southern Benguela. Secondly, the reconstruction data reflect fish population levels in the absence of fishing pressure and these historical results are not necessarily applicable to present day dominance shifts. It has been noted that human activity may contribute to ecosystem regime shifts, such as the regime shift of the 1960s in the southern Benguela (Howard et al., 2007) and the more recent shift in the northern Benguela (Cury and Shannon, 2004). Therefore, in the presence of fishing pressure, it is possible that aperiodic regime shifts could occur.

Chapter 3

Model Design and Implementation

In this chapter the key model design decisions are presented in light of the sardine and anchovy biology. The age–structured sardine population equations are analysed and their subsequent implementation is shown. Thereafter the sardine recruitment equations are analysed and implemented. Finally the necessary modifications to the frame based rules are discussed and implemented. Where necessary, implementation details of Smith (2009) are reproduced here to highlight key decision factors. Many of the model design decisions are not of biological interest and the full source code is made available with the thesis. A block diagram of the Frame Based Model (FBM) is provided in Figure 3.1.

3.1 Overview of the Population Submodels

The anchovy and sardine populations were previously implemented as time series of biomass without age structure which were only very roughly calibrated to observed biomass levels. The addition of age structure to the sardine population model and the use of biomass units compatible with the stock assessment equations from OMP–02 for sardine and anchovy are now described.

3.1.1 Anchovy Population

The anchovy and sardine population submodels differ in that the sardine cohorts are modelled explicitly, whereas the anchovy population count is directly dependant on the current anchovy frame (which is in turn dependant on the ESI record[1]). This is based on the assumption that anchovy population levels are largely dependent on environmental conditions and that there is a limited impact on the anchovy population by the anchovy fishery (e.g. Jarre et al., 1998; Miller and Field, 2002). Anchovy are therefore modelled by stochastic

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[1] The ESI is modelled as a noisy sinusoid with decadal scale frequency, as per Smith (2009).

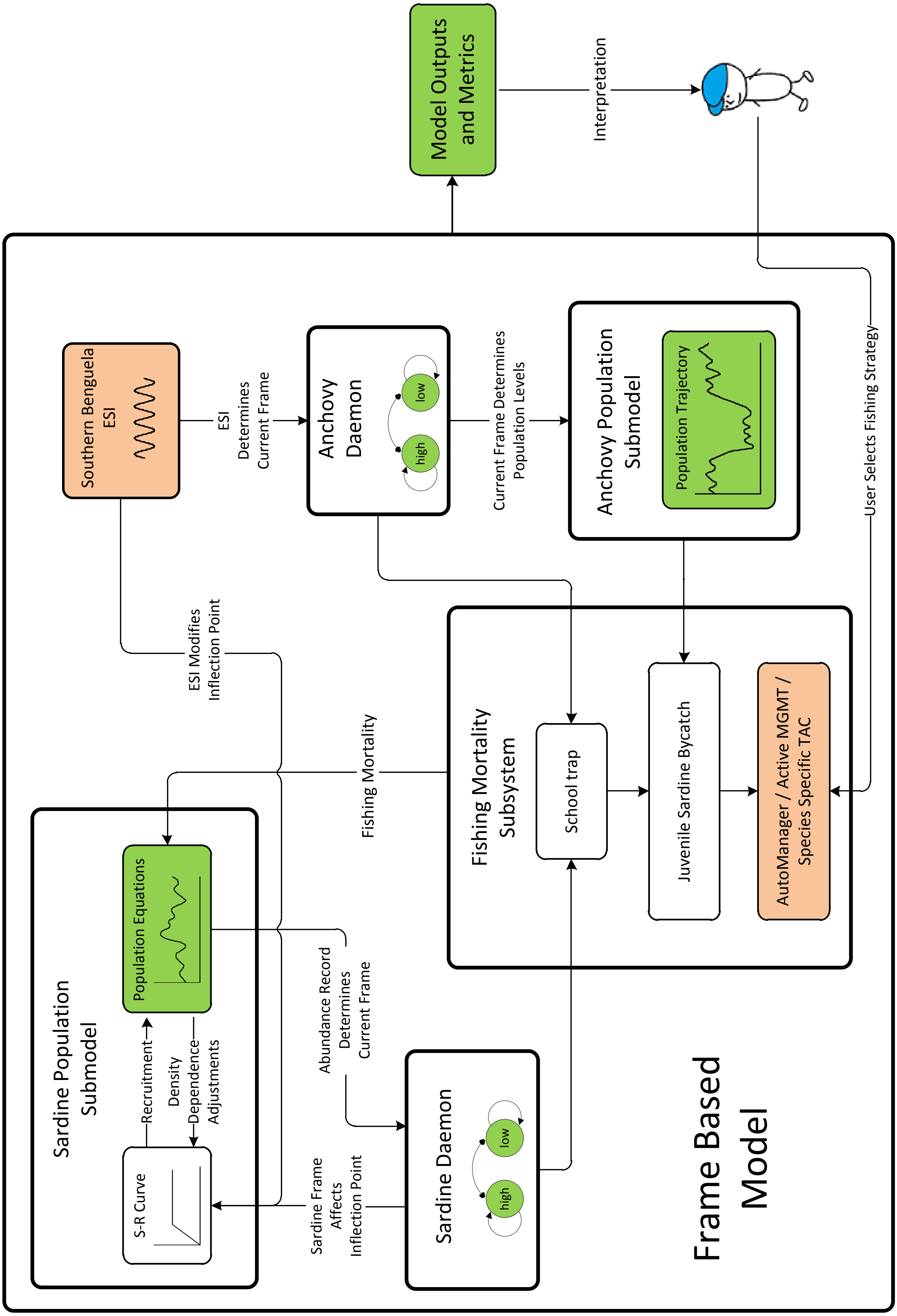

Figure 3.1: The Frame Based Model block diagram. Model outputs such as population time series are filled green, forcing components such as the Environmental Suitability Index are filled orange, and all other model subcomponents are filled white. Arrow directions represent dependencies.

variation about predefined mid points, with the variation and mid point levels dependent on the current anchovy frame:

- Anchovy Low - the population fluctuates about 600 kt, with a variability range of ±400 kt
- Anchovy High - the population fluctuates about 2 500 kt, with a variability range of ±2 000 kt

The midpoint and variability levels are obtained by multiplying the previous figures by 1 000 and assigning units of 10^3t. The variability is implemented by sampling from a truncated normal distribution ($\mu = 0$, $\sigma^2 \simeq 0.02$). Note that Smith (2009) sampled random numbers from this truncated normal distribution by averaging the sum of three uniformly distributed random numbers (central limit theorem) as the standard C# .NET Framework does not provide a default class that generates normally distributed variables. However, for generating random numbers from the standard normal distribution ($\mu = 0$, $\sigma^2 = 1$), as required by the OMP–02 recruitment equations, the Box-Muller transform is used in this thesis.

3.1.2 Sardine Population

Previously, the sardine population was modelled as a single dimensionless number, using the following non-linear recurrence relation:

$$N_{t+1} = N_t e^{-z} + b_t \left(\frac{N_t}{N_t + B} \right) - F_t \tag{3.1.1}$$

where:

N_t is the modelled sardine population in year t,
z represents the natural mortality,
B represents the yearly recruitment,
F_t is the modelled sardine mortality due to fishing in year t and
b is the recovery parameter (density dependent).

For this study, Equation 3.1.1 is replaced with the age–structured model used by de Oliveira[2]:

$$N_{y+1,1} = \left(N_{y,0} e^{-M_{ju}/2} - \frac{C_{y,0}}{\overline{w}_{0c}} \right) e^{-M_{ju}/2} \tag{3.1.2}$$

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[2] Note that all terms are superscripted with a 'P' (for pilchard) in de Oliveira's thesis. That superscript is dropped in this text to ease readability.

$$N_{y+1,a+1} = \left(N_{y,a} e^{-M_{ad}/2} - \frac{C_{y,a}}{\overline{w}_{ac}} \right) e^{-M_{ad}/2} \tag{3.1.3}$$

where:

$N_{y,a}$	is the number of sardine (in billions) aged a at the beginning of year y,
a	$= 1, \ldots, 4$: sardine die after turning 5 (see Appendix B)
$C_{y,a}$	is the mass (in kilotons) of sardine of age a caught in year y,
$\overline{w}_{ac}$	is the mean mass (in grams) of sardine associated with the catch $C_{y,a}$,
M_{ju}	is the natural mortality of juvenile sardine
	and
M_a	is the natural mortality of adult sardine.

The derivation of this recurrence relation is not provided in de Oliveira (2002), but it is derived during this study and is supplied in Appendix A. Note that Leslie matrices (Leslie, 1945) can not be used here, because there are multiple operations which occur each year — namely spawning, fishing and natural mortality — and the order of the operations is important. The order of these operations form part of the model assumptions and are reproduced from de Oliveira (2002) in Appendix B.

Equation 3.1.1 (the simple model's population equation) models various biological processes, not all of which are implemented by the new Equations 3.1.2 and 3.1.3. These biological processes and their corresponding terms in the equations are listed in Table 3.1.

Table 3.1: Key processes in the sardine population model equations. Natural mortality is now age–variant (yet time–invariant), with values of 0.4 and 0.8 used for M_{ad} and M_{ju} respectively, as per de Oliveira (2002).

Process	**Previous Term**	**New Term(s)**
Natural mortality	z	M_{ju} and M_{ad}
Recovery	b_t	missing
Recruitment	B	$N_{y,0}$
Fishing mortality	F_t	$C_{y,a}/\overline{w}_{ac}$

Note that the only term from the simple model (Equation 3.1.1) that is not reproduced in the OMP–02 equations is the density dependent recovery factor, so it must be implemented elsewhere (direct modification of the OMP–02 population equations was not considered in this work). Given that the recovery factor directly affects sardine recruitment levels, it was decided to include its effect it in the model's recruitment logic.

3.2 Sardine Recruitment Equations

There are three important aspects to recruitment which must be included in the model: stochastic variability, density dependent recovery and environmental suitability. Recruitment was implemented by Smith in Equation 3.1.1 with the following term:

$$b_t \left(\frac{N_t}{N_t + B} \right)$$

where B, the unitless biomass parameter determining recruitment, was set to a constant level of 0.2 and b_t was defined as

$$b_t = f_{VAR} \times f_{ESI} \times f_{DD}$$

where f_{VAR} is the stochastic recruitment variability in the model. The Environmental Suitability Index (ESI) was incorporated into the recruitment model by the f_{ESI} term:

$$f_{ESI} = \begin{cases} 0.8 & \text{if ESI for a given year} > 5 \\ 1 & \text{otherwise} \end{cases}$$

Note that scaling F_{ESI} down by 20% indicates that the environment favours anchovy (and is therefore less favourable for sardine). Smith (2009) implemented the ESI function as a sinusoid with an amplitude of ±3. When the ESI value was rounded to the nearest integer, a fraction of up to 0.5 was truncated. This resulted in a loss of roughly 8% of the information in the signal. All ESI signal amplitudes and rule–based comparison levels are multiplied by a factor of 10 in this study — resulting in a worst case information loss of roughly 0.8% during rounding.

Density dependence was implemented in the simple model by increasing the f_{DD} factor when sardine population levels declined in the high frame, but f_{DD} was reset to a base value of 1 when the sardine were in a low frame (Figure 9 in Smith, 2009).

The future projection of recruitment during OMP–02 simulations is implemented by stochastic variation of $N_{y,0}$ about a stock–recruit (SR) curve. OMP–02 provides three SR curves namely hockey–stick (HS), Beverton–Holt and Double–Sloped. As a starting point for this study, the HS stock–recruit curve type is used. $N_{y,0}$ is assumed to be log–normally distributed about the SR curve as follows:

$$N_{y,0} = f(B_y) e^{\varepsilon_y \sigma_r} \tag{3.2.1}$$

where

$$\varepsilon_y = s_{cor} \varepsilon_{y-1} + \sqrt{1 - (s_{cor})^2} \cdot \omega_y \tag{3.2.2}$$

and σ_r is the standard deviation of the residuals about the log of the stock-recruit relationship for sardine, with ω_y drawn from the standard normal distribution ($\mu = 0, \sigma^2 = 1$). The s_{cor} parameter is the recruitment serial correlation. These parameters are discussed next.

3.2.1 Analysis of the Recruitment Equation Parameters

A descriptive analysis of these parameters is now presented to provide the reader with an intuitive sense of how they influence recruitment in the model.

Shape of the Hockey Stick

The shape of the curve is defined as:

$$f(B_y) = \begin{cases} a & , \quad \text{if } B_y \geq b \\ \dfrac{a\,B_y}{b} & , \quad \text{if } B_y < b \end{cases}$$

where B_y, the 1^+ biomass from the November survey in year y, is defined as

$$B_y = \sum_{a=1}^{5} N_{y,a}\overline{w}_a \tag{3.2.3}$$

Note that the shape of the SR curve is fully determined by the two parameters a and b of the inflection point (b, a). The $\overline{w}_a$ term in Equation 3.2.3 is the mean mass at age (in grams) of adult sardine from the November surveys. Note that mass has now also been introduced into the model, and is both year and age–class variant. However, as a starting point, the values used for $\overline{w}_a$ during the entire model run are the 1989–2000 averages, as per Table A.2.2.2 (de Oliveira, 2002):

$$\overline{w}_1 = 34.326 \qquad \overline{w}_2 = 69.537 \qquad \overline{w}_3 = 86.538 \qquad \overline{w}_4 = 98.706 \qquad \overline{w}_5 = 111.525$$

Recruitment Serial Correlation

The recruitment serial (auto) correlation parameter, s_{cor}, can be thought of as the amount of interannual *persistence* in recruitment levels. A low value for s_{cor} implies that next year's recruitment will *likely* differ from this year's recruitment. From the time series data of sardine abundance in the southern Benguela (de Moor and Butterworth, 2009) it is clear that this would not necessarily be true: high recruitment levels in one year are more likely to result in high recruitment levels in the subsequent year, meaning that there is probably a certain amount of serial correlation in the signal.

The effect of this parameter on sardine recruitment is also evident when substituting the upper and lower limits of s_{cor} into equation 3.2.2 as follows:

$$\lim_{s_{cor} \to 0} \varepsilon_y = \omega_y$$

which implies that, in the absence of any serial correlation, subsequent recruitment will vary entirely stochastically and

$$\lim_{s_{cor} \to 1} \varepsilon_y = \varepsilon_{y-1}$$

which shows that, in the extreme case of total serial correlation, recruitment will remain constantly proportional to the spawner biomass. A value of 0.374 is used for s_{cor} in this study, as per de Oliveira (2002).

Residual Standard Deviation

The σ_r parameter specifies the "spread" of the recruitment variability — the variability of the residuals — about the SR curve. On average, a larger value of σ_r will result in increased variability about the base SR function, and vice versa.

3.2.2 Parameter Assignments

The updated implementation of recruitment incorporating the three dynamic processes (natural variability, environmental suitability and density dependence) is now shown.

Natural Variability

The natural variability of sardine recruitment is incorporated into the model by setting $\sigma_r > 0$. A value of 0.499 is chosen, as per de Oliveira (2002).

Environmental Suitability

The ESI used in the model is a proxy for a range of factors such as upwelling strength, larval survival and sea surface temperature all of which influence sardine recruitment (Hutchings et al., 2002). For the purposes of this study, it is assumed that an ESI that is favourable for sardine results in an increased survival rate of the early life history stages which results in higher recruitment (on average). The reverse also holds true: an ESI that is detrimental to sardine results in decreased recruitment success. This is implemented in the model by decreasing a (and by implication the carrying capacity) when the ESI favours anchovy and increasing a when the ESI favours sardine, as per Figure 3.2.

The values for a_1 and a_2 are 14.42 and 21.64, respectively, with a_2 used as is from OMP–02 and a_1 calculated as two thirds of a_2. The values for b_1 and b_2 are initially calculated from these values at model run time using a slope of roughly 0.05 (413.7/21.64 as per OMP–02). However, sardine recovery from the low frame occurred too rapidly using this value, so a slope of 0.0357 (Table 2, de Moor and Butterworth, 2009) is used to reduce the recovery rate of sardine from the low frame; this type of *ad hoc* parameter tuning is done to

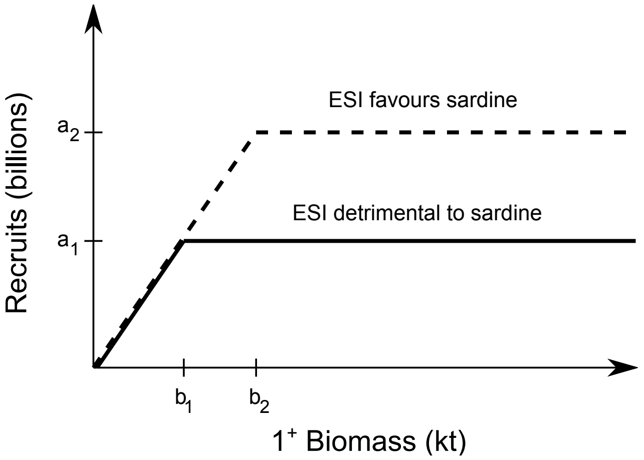


Figure 3.2: Incorporating the Environmental Suitability Index into the stock–recruit curve.

get the model outputs to more closely resemble the historical abundance data of sardine in the southern Benguela.

Density Dependence

The density dependent recovery of the sardine population in the model is defined as per the Allee–effect (Allee, 1931): recruitment increases as biomass levels drop, up to a certain point at which population levels are so low that successful spawning becomes difficult. This is implemented in the model by increasing the slope (decreasing b) of the S–R curve (the part of the curve that connects the origin to the inflection point) as the spawner biomass decreases, in the sardine high frame only. The steepness of the curve ($\frac{a}{b}$) is varied linearly from a base value to a maximum value over the span of the 1^+ biomass in the sardine high frame, and is reset to the base value when the sardine enter the low frame, as depicted in Figure 3.3. The result of this approach is that, given that density dependent recruitment is only implemented in the "sardine high" frame, and that the biomass thresholds under which the sardine daemon switches to a high frame (described in Section 3.4.1) are greater than both b_1 and b_2, sardine will mostly be recruiting at the upper limits (a_1 or a_2 in Figure 3.2) i.e. the increasing slope of the S–R curve will result in maximum recruitment occurring at decreasing biomass levels, *on average*.

Four values fully determine the shape of this curve: B_{min}, B_{max}, s_{min} and s_{max}. The value of B_{min} varies from run to run because the rule that switches the sardine frame from high to low evaluates the moving average of the 1^+ biomass over three years so the biomass in the year that the actual switch takes place will not always be the same. As a starting point a value of B_{max} is chosen as 2 000 and the OMP–02 value of $\frac{21.64}{413.7}$ was used for s_{max} although this

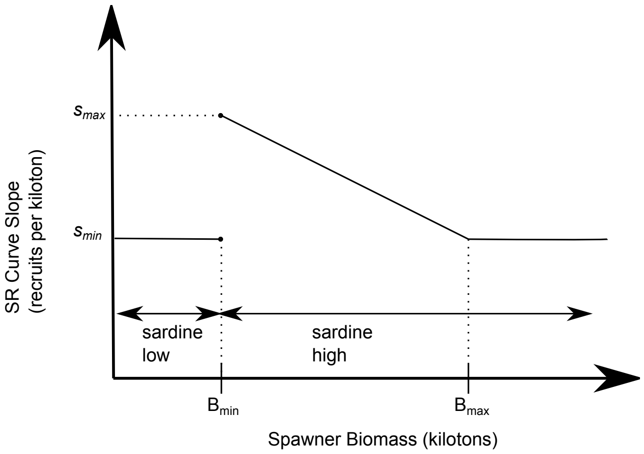


Figure 3.3: Density dependent Hockey Stick curve slope adjustment.

resulted in excessively rapid sardine recovery from the low frame which did not resemble the historical abundance records so the updated OMP–04 value of $\frac{91.8}{2570}$ is used and this results in more realistic recovery periods. The value of s_{min} is chosen as 50% of s_{max}.

3.3 Sardine Fishing Mortality

An important aspect of this study is to explore the long term effects of various fishing strategies on fish population levels. Three fishing strategy types were previously implemented: species specific TACs, active management by the user and automatic management which resembles currently applied rules of deciding a TAC for each year. TACs were split amongst the age classes in accordance with the method used by OMP–02. Note that anchovy fishery is implemented as per Section 4.1.3c in Smith (2009).

3.3.1 Individual TACs

In this fishing strategy, a fixed individual TAC is set for sardine and anchovy which is applied to the stock each year for the entire model run. TACs are assumed to equal the year's commercial landings i.e. complete success by industry in landing the full TAC and no unaccounted bycatch. TACs were set as unitless real numbers in the previous version of the FBM and these numbers were used directly in each year of the model run. The anchovy TAC was only used to calculate bycatch of juvenile sardine, as it was assumed that the anchovy fishery does not have a significant effect on the anchovy population and the sardine TAC was used to implement yearly sardine fishing mortality. However, due to the introduction of age–structure in the current model, the sardine TAC must be split amongst the age–classes. This is done using S_a, the selectivity at age estimated by the OMP–02 operating model, to calculate $C_{y,a}$, the catch (in billions) of sardine aged a in year y:

$$C_{y,a} = TAC_y \cdot \frac{N_{y,a}S_a}{\sum_{a=1}^{4} N_{y,a}S_a\overline{w}_{ac}} \quad , \quad a = 1, \ldots, 4 \tag{3.3.1}$$

Intuitively, this is multiplying the TAC in year y by the ratio of selectable a–year olds to the total biomass of fish available to the fishery, to calculate the catches at age. The selectivities at age used are those of the base-case assessment in Table 2.8 of de Oliveira (2002):

$$S_1 = 0.537 \quad S_2 = 1.000 \quad S_3 = 0.852 \quad S_4 = 0.445$$

Note that there is no catch of juveniles from the sardine directed fishery in the model, although there is an inevitable juvenile bycatch in the commercial catches. To calculate the juvenile sardine bycatch from the anchovy–directed fishery, Equation 2 from Smith (2009) is used and can be reformulated using notation similar to that of OMP–02 as:

$$C_{y,0} = \overline{w}_{0c} \times N_{y,0} \times f_{st} \times \frac{C_y^A}{B_y^A} \tag{3.3.2}$$

where:

$\overline{w}_{0c}$	is the mean mass of sardine juveniles associated with the catch $C_{y,0}$,
f_{st}	is the "school trap factor" (0, 0.2 or 0.4),
C_y^A	is the anchovy TAC (in kilotons) in year y and
B_y^A	is the anchovy biomass (in kilotons) in year y.

Using this method to split the TACs can result in a situation where there are not enough sardine in a cohort to fill the TAC for that age–class. In reality this would result in the TAC for that age–class being filled by individuals from other age–classes. This type of adjustment would be interesting to include but it is not implemented here. However, a rule is included in the fishing mortality subsystem that checks whether the TAC is greater than or equal to the current adult biomass and sets the adult biomass to zero if this is the case. Note that because there is no bycatch of juvenile sardine from the sardine directed fishery in the model, it is possible to fish all the adults with the sardine directed TAC, but not all the juveniles. This means that the adult directed sardine TAC alone is insufficient to reduce the model population biomass to zero.

3.3.2 Active Management

The implementation of the active management fishing strategy is left unchanged from Smith (2009), with the user being prompted for future TACs every three years. In the current study, these TACs are split into catches–at–age as per Equation 3.3.1.

3.3.3 Automatic Management

The automanager functionality is left unchanged, except that all levels are adjusted using the same parameter tuning heuristic used during the implementation of the inflection points of the HS curve, resulting in the scales shown in Table 3.2

Table 3.2: AutoManage levels for sardine fishing under the most "conservative" setting (numbers in parentheses indicate the maximum adjustment under the most "severe" setting). All units in kilotons.

	Low population	**Moderate Population**	**High Population**
Range	$0 \leq B_y < 600$ $(0 \leq B_y < 250)$	$600 \leq B_y < 900$ $(250 \leq B_y < 480)$	$900 \leq B_y$ $(480 \leq B_y)$
TAC	0 (0)	80 (280)	180 (480)

3.4 Daemon Rule Updates

All the daemon rules needed to be updated due to the move from arbitrary units to kilotons, and these updates are now described.

3.4.1 Sardine Daemon

The previous sardine daemon considered the sum of the population levels over the past three years when evaluating the frame switching rules. With the age–structured population model, there is not a single population figure which can be summed over three years. One or all of the age classes will need to be considered by the algorithm. The options are:

- consider all age classes equally (arithmetic mean of the total population over a certain number of years),
- assign different weights to various age classes (weighted sum/average),
- consider only juvenile sardine or

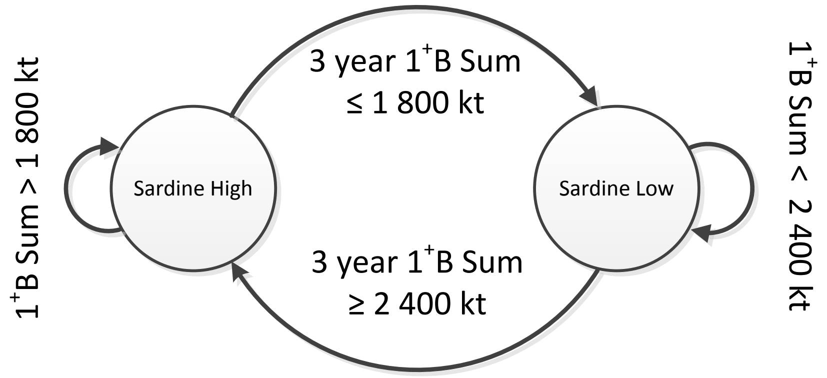


Figure 3.4: Sardine daemon switching levels.

- consider only adult sardine.

Note that the first and last two items above are special cases of the weighted sum. As a starting point for this study the 1^+ biomass are used when evaluating the sardine daemon rules. The daemon levels implemented by Smith can then be used, after multiplying them by a constant factor of 1 000. In accordance with the previous version of the sardine daemon, the moving average of the adult biomass sum is calculated over a period of three years and is considered according to the levels shown in Figure 3.4.

3.4.2 Anchovy Daemon

The modified anchovy daemon is identical to the previous version, except that the ESI threshold is 150 as opposed to 15 to compensate for the reduced information loss in the ESI signal.

Chapter 4

Testing and Analysis

A range of testing methods are used to verify the model outputs and these are discussed in this chapter. Data visualisation is used to amplify cognition and assist in verification of model outputs. Descriptive statistics are used to compare time series data qualitatively. Numerical metrics relating to outputs of the FBM — such as frame residence ratios — are also used to interpret model results. Given that one of the main objectives of this thesis is to explore modifications to an existing model, the overall testing methodology is that of exploratory data analysis with a focus on sensitivity analysis rather than formal statistical testing.

In Section 4.1 general testing of the model components is performed to gain confidence in the model outputs. In Section 4.2 further tests are performed to explore the sensitivity of sardine recovery durations to the underlying sardine population equation. These sensitivity tests aim to reject the following null hypothesis:

- $H_0^{sardpop}$: the FBM is insensitive to variations in the sardine population submodel.

This null hypothesis exists to confirm that the introduction of age structure in the sardine population model has had an effect on the FBM.

In Section 4.3 a global sensitivity analysis is performed during which a second null hypothesis is tested:

- $H_0^{srcurve}$: the FBM is insensitive to variations in the underlying SR curve.

This null hypothesis explores whether the FBM is sensitive to variations in the shape of the underlying Hockey Stick Stock–Recruit curves.

Throughout the thesis the term “simple model” refers to the FBM without age–structure as implemented in Smith (2009) and the term “age–structured model” refers to the FBM as implemented in this study.

4.1 General Model Tests

It is important to verify that the components representing the biological processes in Figure 3.1 are functional. To this end, a series of simple tests are performed on the following:

- ESI dependent SR curve adjustment (Figure 4.2),
- fishing mortality of adult sardine (Figure 4.3),
- bycatch of juvenile sardine from the anchovy fishery (Figure 4.4) and
- density dependent variation of the SR curve (Figure 4.6).

Throughout the thesis, a model run is defined as a single 50–year simulation.

4.1.1 Testing the ESI Dependent SR Curve Adjustment

In this test, the capacity for increased sardine recruitment during periods of sardine–favourable environmental conditions is verified.

Test Setup and Procedure

A single model run is performed in the absence of fishing. Due to the stochasticity and autocorrelation parameters present in the recruitment equation, model run outputs resemble Figure 4.1. It is therefore useful to disable the stochasticity ($\sigma_r = 0$) and to set unitary autocorrelation ($s_{cor} = 1$) during this test.

Expected Results

It is expected that the recruitment and biomass levels are higher during periods when the ESI favours sardine, and lower during periods when the ESI is detrimental for sardine (and therefore favourable for anchovy).

Actual Results

The model run output is plotted in Figure 4.2.

Analysis of Results

From inspection, it is evident that recruitment in the sardine high frame is occurring at the values assigned to a_1 and a_2. It is interesting to note that it takes the adult population five years to stabilise at the maximum value (of around 1 700 kt) in the presence of continued maximum recruitment — this is due to the age structure of the population model. Note that the absence of stochasticity and presence of unitary autocorrelation prevent the adult biomass

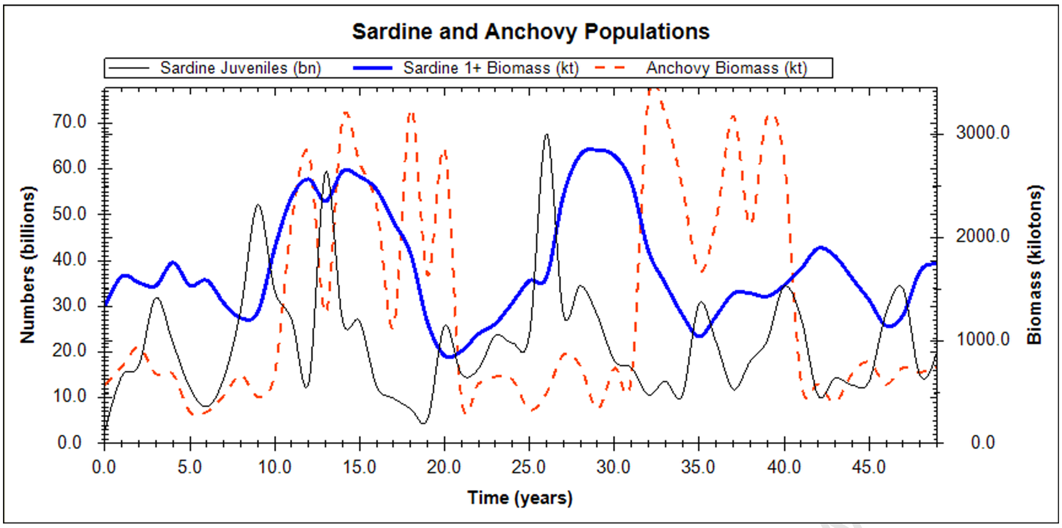


Figure 4.1: Stochastic model run with zero fishing mortality. Note the presence of two Y–axes: sardine juveniles (light black line) are plotted in billions against the first Y–axis and the sardine 1^+ biomass (strong blue line) and anchovy biomass (dashed orange line) are plotted in 10^3 t against the second Y–axis.

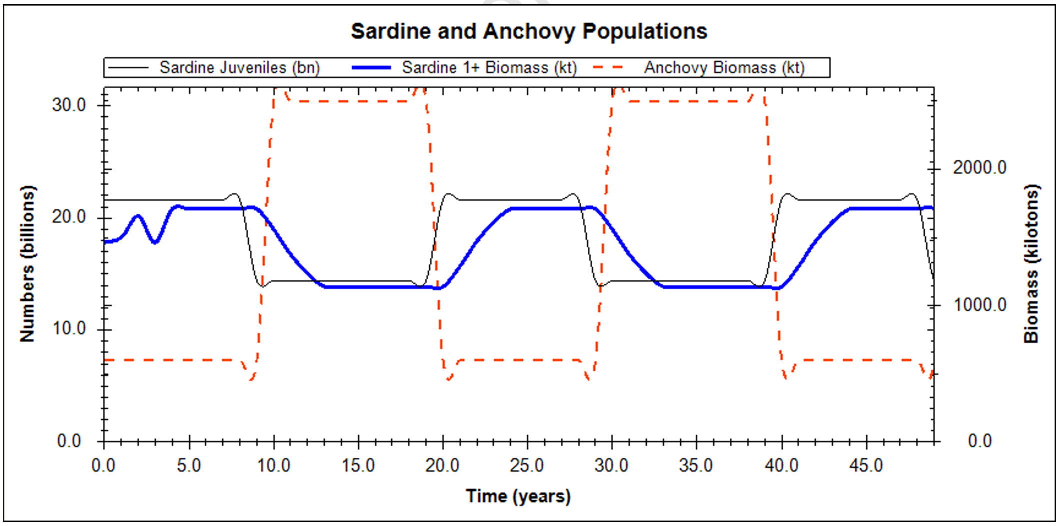


Figure 4.2: Model run with zero fishing mortality and stochasticity disabled. Note that the sardine population is in a high frame for the entire model run.

from reaching abundance values above 2 000 kt, which is realistic in terms of observed sardine abundance levels on the west coast between the 1950s and late 1990s. From this test it is concluded that the shape of the SR curve varies in accordance with the ESI fluctuation and that when environmental conditions are favourable for anchovy, sardine recruitment in the high frame is impaired.

4.1.2 Testing Sardine Directed Fishing Mortality

There are various ways to test that the fishing mortality is correctly implemented. Due to the model's potential for use as a training tool, it was decided to test the implementation of adult fishing mortality using the model's graphical user interface.

Test Setup and Procedure

The model is run by enabling the Interactive Management mode of the fishing mortality subsystem with a step size of three years, fishing the sardine heavily (in the order of the landed catches of the early 60s — 400 kt) for the first three years, reducing fishing mortality for the next three years to 200 kt, fishing at 30 kt for the next three and then halting all fishing for the remainder of the run. The anchovy TAC was set to zero for the entire run.

Expected Results

It is expected that certain runs appear to be unaffected by the chosen fishing mortality due to the stochasticity in the sardine submodel. However, on average, it is expected to see a decrease in the biomass levels due to fishing mortality.

Actual Results

A typical result of one of the model runs is displayed in Figure 4.3.

Analysis of Results

There is clearly a decline in the sardine adult biomass due to the sardine directed fishery, with the population taking 11 years to recover from the low frame. From this result it is concluded that sardine directed fishing mortality of adults is functional. However it is important to keep in mind that the result could be an outlier (due to the model stochasticity) and it is for this reason that it can be important to perform multiple runs and look at probability densities. This concept is further explored later in the thesis where repeated model runs are performed during the sensitivity analyses and the unobservable underlying

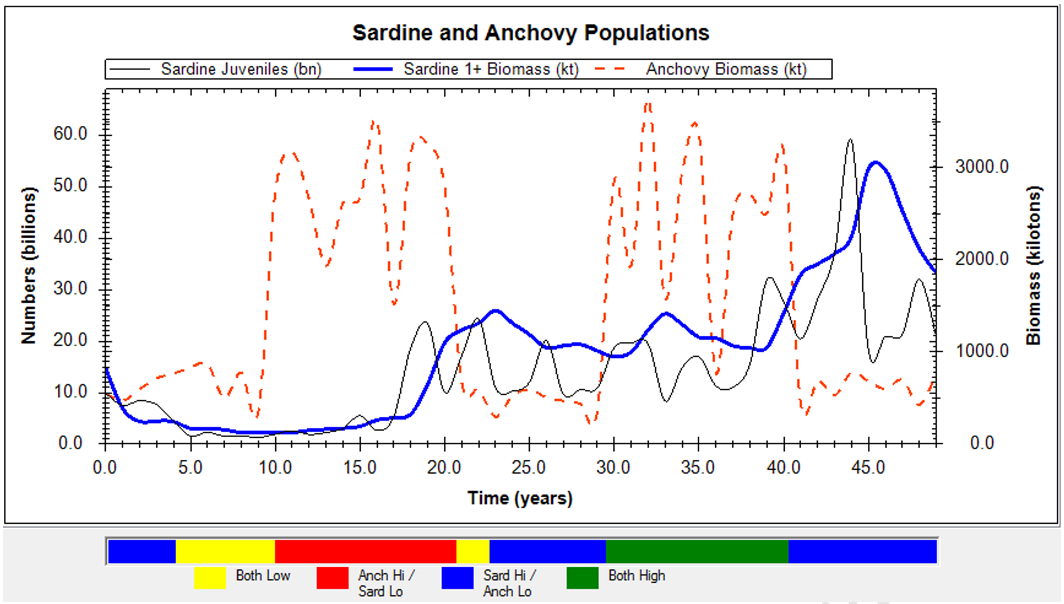


Figure 4.3: Single model run with actively managed fishing mortality.

densities are estimated by using histograms. Nonetheless, this type of result is sufficient for simply testing that fishing mortality has been implemented.

4.1.3 Anchovy Bycatch

The aim of this test is to verify whether the anchovy fishery has an effect on the sardine population.

Test Setup and Procedure

Sardine are fished heavily (300 kt/year) in the Active Management mode until they reach the low frame then the sardine TAC is set to zero. Anchovy are then fished very heavily (600 kt/year) for the remainder of the run. This is then compared with a model run wherein sardine are fished heavily until they reach the low frame, but then both sardine and anchovy TACs are set to zero.

Expected Results

Insight may be gained into the expected results by substituting some upper and lower bounds into Equation 3.3.2. Note that the values of the anchovy biomass, anchovy TAC and school trap factor are all strongly bounded within the model, as described in Chapter 3. The anchovy biomass has an upper bound of 4 500 kt in the high frame and a lower bound of 200 kt in the low frame. The anchovy TAC is by necessity capped by the same upper limit, although the minimum anchovy TAC is zero. Furthermore, given that the

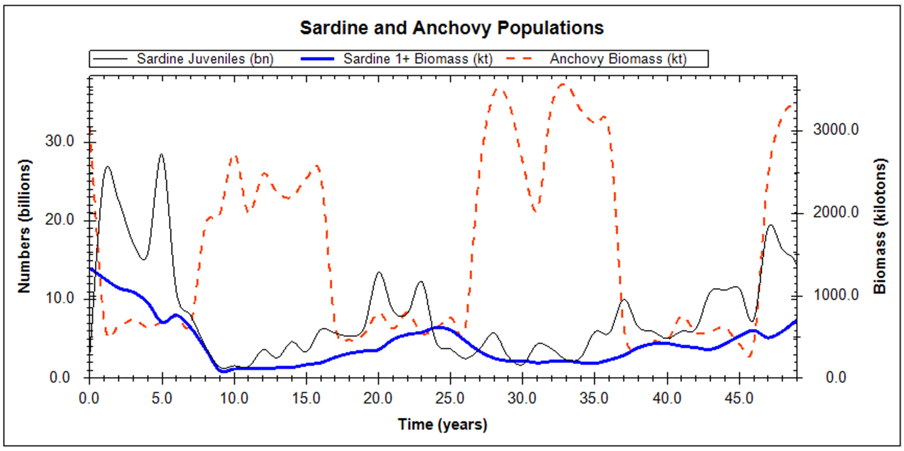


Figure 4.4: Single model run with bycatch from the anchovy fishery.

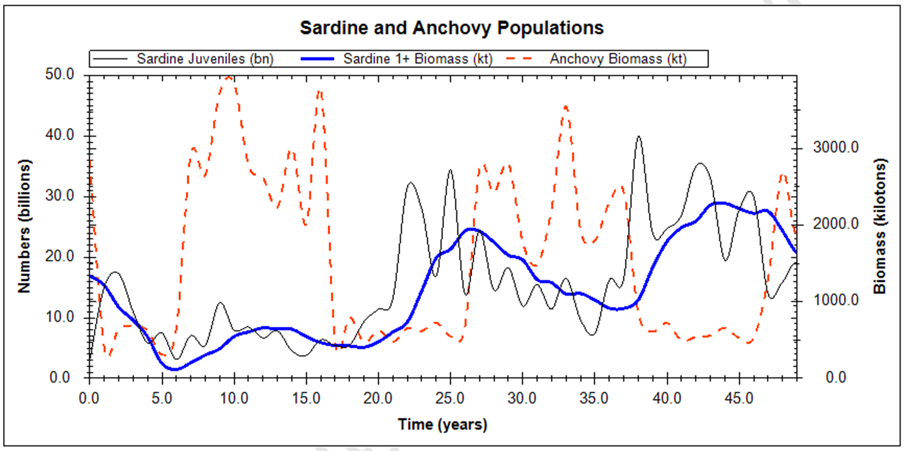


Figure 4.5: Single model run with zero bycatch.

school trap takes on one of three values (0, 0.2 and 0.4), the sardine juvenile bycatch may be expressed as a fraction of the total number of juveniles.

Concretely, the total number of sardine juvenile bycatch is a fraction of the total number of juvenile sardines multiplied by the school trap factor. The size of the fraction ranges from zero (when the anchovy TAC is zero) to the extreme case of one (when the anchovy TAC equals the anchovy biomass i.e. the *entire* anchovy population has been fished out) i.e. $C_{y,0} \in [0,\, 0.4 \cdot N_{y,0}]$.

Actual Results

The results of a model run with expected juvenile sardine bycatch are displayed in Figure 4.4, and the results of a run without any bycatch are shown in Figure 4.5.

Analysis of Results

From the results it is clear that recovery of the sardine population is being impaired by the anchovy fishery. It is therefore concluded that juvenile sardine fishing mortality is taking place within the model when an anchovy TAC is being set.

4.1.4 Density Dependent Sardine Recruitment

In this test the density dependent variation of the sardine stock–recruit curve slope is verified.

Test Setup and Procedure

A single model run is performed, with stochasticity enabled, and zero fishing mortality. A phase plot of all the inflection points (which define the shape of the SR curve) generated by the model is then created and inspected.

Expected Results

The variation of the inflection point is expected to appear on the plot as points along two parallel lines corresponding to the two y–axis values (the high y–value being the increased recruitment level during periods of sardine–favourable ESI).

Actual Results

The phase plot is depicted in Figure 4.6.

Analysis of Results

From the plot it is evident that the slope of the SR curve is being adjusted as the biomass varies within the sardine high frame and it is concluded that the density dependence in the model is functional.

4.2 Sensitivity to the Underlying Sardine Model

One of the objectives of the study is to explore the sensitivity of the frame based model to the underlying sardine population model. This is done by comparing the outputs — with a focus on those outputs pertaining to the sardine population — of the two versions of the model yet this goal presents some difficulties. One of these difficulties is that a direct comparison between the sardine population trajectories of the two models is not possible because

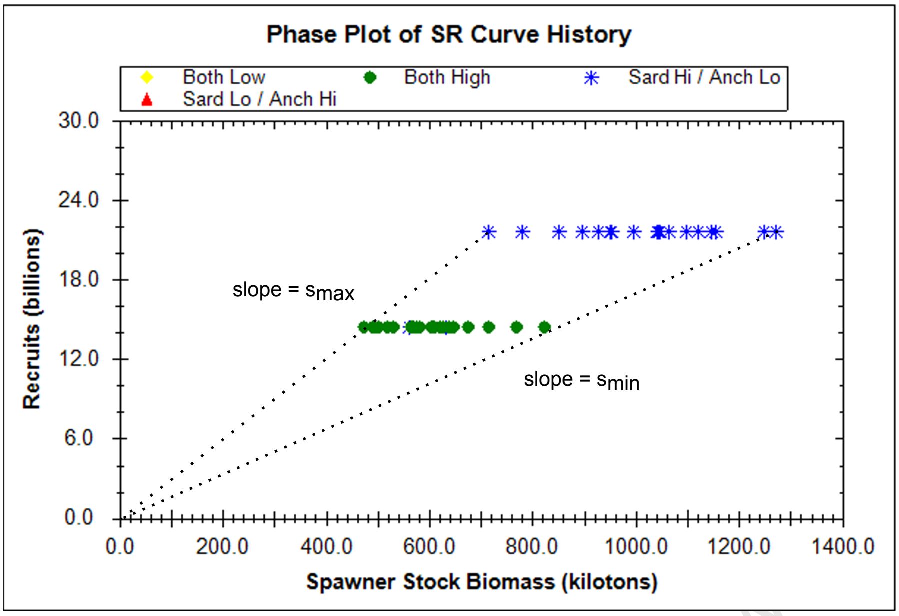


Figure 4.6: Testing the density dependence by using a phase plot.

how does information in the six age–classes from the age–structured model get compared to the single unitless sardine population number from the simple model? In contrast, the sardine daemons from both models output identical units (one frame per year) so a direct comparison between the sardine daemon outputs of the two models is possible. However, the rules determining the frame states at the start of each year are different for each model: the rules for the age–structured model evaluate a weighted sum (the 1^+ biomass in 10^3 tons) whereas the sardine daemon in the simple model evaluates a single number representing the sardine population. This means that key underlying mechanics that influence the frame states operate in fundamentally different ways in the two models, and makes comparing frame state residence durations difficult.

Furthermore, the yearly age–invariant natural mortality in the simple model occurs at the same time as recruitment and fishing mortality whereas there is a specific sequence of events in the age–structured model: spawning occurs in November, six months of age–dependant natural mortality takes place until pulse fishing occurs in May and then the final six months of natural mortality take place. Drawing any direct conclusions as to the cause of variations in outputs between the two models is therefore not possible. In fact, the sardine population submodel from the simple model has not been modified to include age–structure, it has been completely replaced by a different sardine population submodel (and by necessity a different frame based model structure) using different equations. High level, qualitative comparisons of model outputs are possible, but because so much has changed it is not possible to

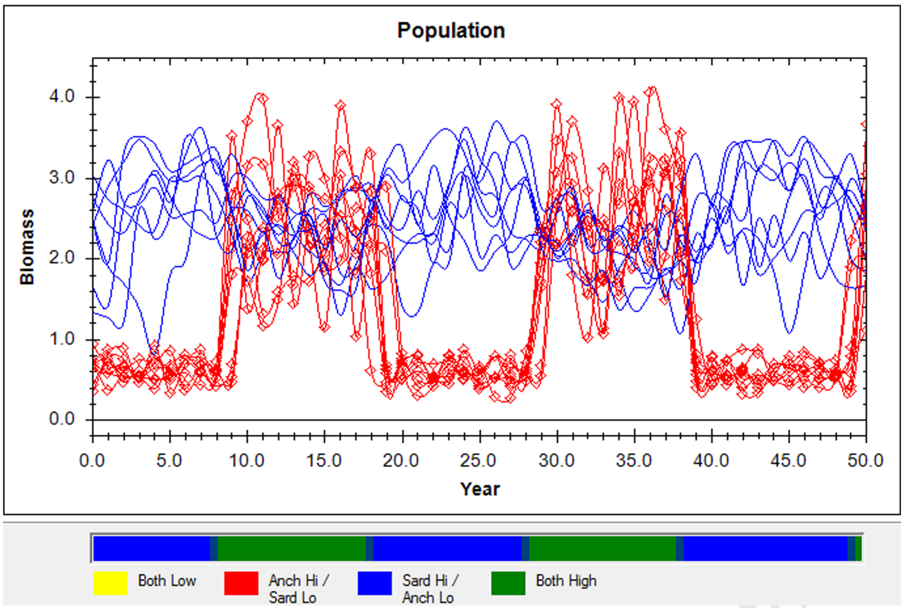


Figure 4.7: Ten runs of the simple model with no fishing.

directly ascribe any noted differences in model outputs to the introduction of age structure alone as the system is so highly coupled. It is important to keep this in mind while the sensitivity of the frame based model to the underlying sardine population model is explored.

4.2.1 Qualitative Comparison of Biomass Levels

Both models are run ten times without fishing and the biomass levels are observed. The outputs of the simple and age–structured models are displayed in Figures 4.7 and 4.8 respectively. The sardine biomass levels in the age–structured model mostly fluctuate between 1×10^6 and 2×10^6 tons, which resembles the VPA figures for sardine in the southern Benguela in the late 50s / early 60s (Armstrong et al., 1983). The average "biomass" during the runs displayed in Figure 4.7 is about 2.3 and the average of the run in Figure 4.8 is about 1 500 kt. Also note that the frame residence durations of both versions are roughly equal.

4.2.2 Sardine Recovery Duration: Test 1

An interesting metric to explore is the mean period of recovery from the sardine low frame after a switch from high to low has occurred, as per Smith (2009). The goal for this test is to drive the sardine into the low frame as quickly as possible — using directed fishing and without crashing the population — and then recording how many years the sardine daemon spends in the low frame

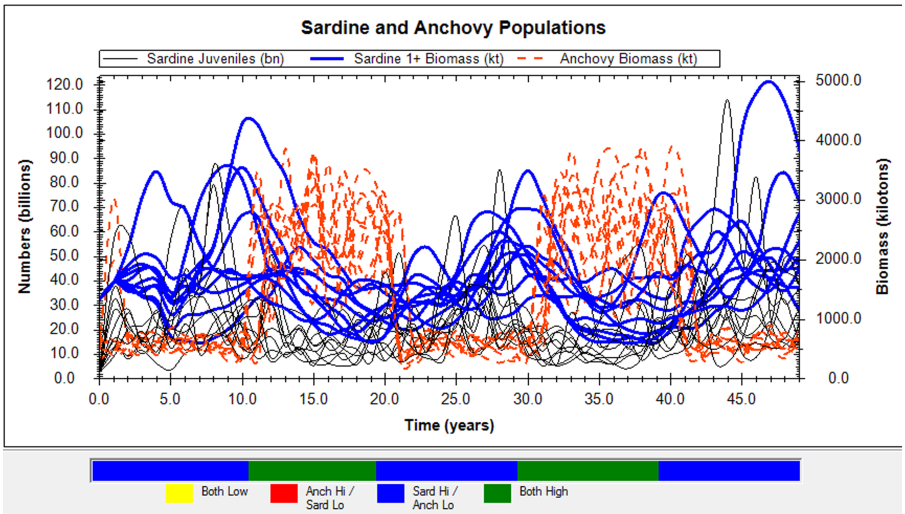


Figure 4.8: Ten runs of the age–structured model with no fishing.

before recovery. Driving sardine into the low frame quickly without crashing them can be difficult due to the stochasticity in the model as some years will experience such strong recruitment that the start–of–year biomass is relatively unaffected by fishing mortality. This stochastic effect is compensated for by implementing a fishing strategy that sets the yearly TAC equal to 50% of the start–of–year sardine biomass. Note that this fishing strategy is only useful for testing the sardine recovery durations from the low frame in the model and is not a proposed management strategy for the sardine fishery.

Test Setup and Procedure

Simulation software is developed which runs this test on both models: in the simple model the yearly sardine TAC equals half of the sardine population at the start of the year. The TAC for the age–structured model is set as 50% of the 1^+ biomass at the start of the year. Anchovy TACs are set to zero so that there is no bycatch of juvenile sardine. If the sardine reach the low frame then all TACs are set to zero for the remainder of the run to allow recovery of the population. The duration of the sardine recovery to the high frame is then recorded (given that recovery occurs) and this process is repeated $K = 10^5$ times for both models to smooth out stochasticity effects. The sample space for this experiment is depicted in Figure 4.9.

Expected Results

Due to the multiple processes taking place (variable fishing mortality, stochastic recruitment, density dependent recovery) during this test it is difficult to predict what the results will be. However the following metrics are analysed:

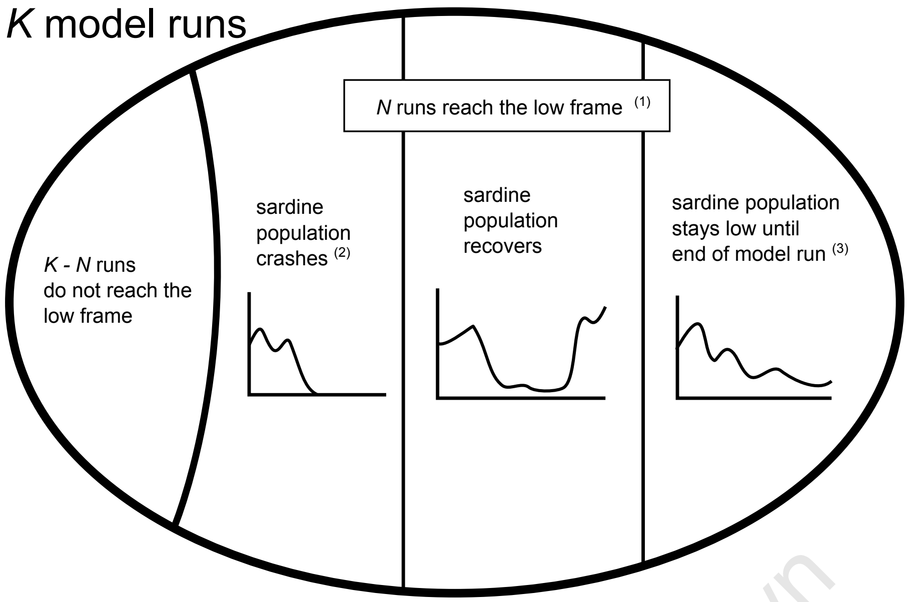


Figure 4.9: Sample space for the mean recovery duration experiments. $K = 10^5$ in the text. Metric labels used in subsequent tables are provided in parentheses (superscript).

out of the 10^4 runs, how many actually resulted in the sardine daemon reaching the low frame (as a percentage of the total number of runs). Furthermore the minimum, maximum and mode for the number of years spent in the low frame are of interest for the runs during which sardine recovered, as are the histograms of the low frame durations for those runs. The statistical mode is calculated due to the positive skew in the histograms. Note that the number of bins in the histograms are set to the maximum low frame duration, so that information is not lost during the binning process. The number of runs wherein the model population adult biomass reaches zero (has crashed) and the number of runs wherein the model sardine population does not recover from the low frame are also counted.

Actual Results

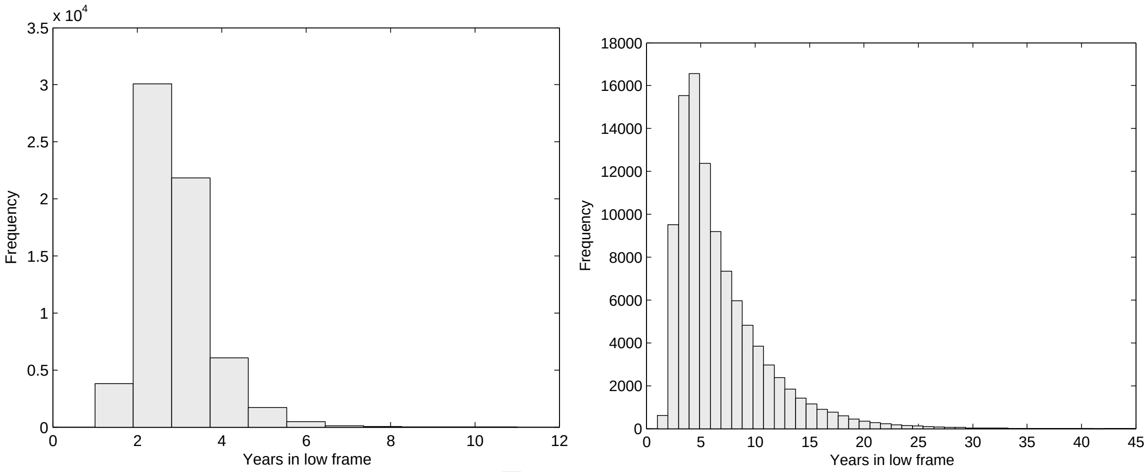
The results from the experiment are displayed in Table 4.1 and the histograms are displayed in Figure 4.10.

Interpretation of Results

From the first experiment, it is evident that the two models react quite differently to fishing pressure. The sardine population in the simple model is more resilient *to the chosen fishing strategy*, as the low frame is entered 67% of the time with roughly 1% of the runs resulting in a crashed population, whereas

Table 4.1: Metrics for comparing sardine recovery durations: test 1

Metric	Simple Model	Age–Structured Model
(1) Low Frame Reached	67%	100%
(2) Runs that Crashed	0.08%	0%
(3) No Recovery to High	1.9%	0.38%
Min Low Frame Duration	1	1
Max Low Frame Duration	10	45
Mode of Low Frame Duration	2	4
1/99 percentiles	1/6	3/25



(a) simple model **(b)** age–structured model

Figure 4.10: Histograms of recovery durations from low to high frames for sardine under no directed fishing and no bycatch. After reaching the low frame all TACs were set to zero.

the age–structured model *will* go into the low frame under the same fishing strategy and does not crash if fishing is halted completely. The reason for the seemingly low rate at which the simple model enters the low frame can be understood by substituting the chosen fishing strategy ($F_t = N_t/2$) and a natural mortality of 0.5 (Smith, 2009) into Equation 3.1.1:

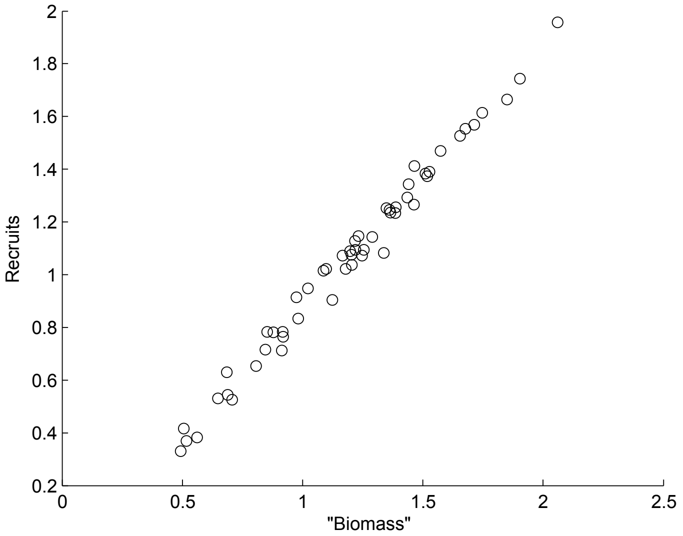


Figure 4.11: SR points generated by the simple model (Smith, 2009) during a "Test 1" run in which the low frame is not reached. The linear trend is due to the chosen fishing strategy (see text for details).

$$\begin{aligned} N_{t+1} &= N_t e^{-z} + b_t\left(\frac{N_t}{N_t+B}\right) - F_t \\ &= N_t e^{-0.5} + b_t\left(\frac{N_t}{N_t+B}\right) - \frac{N_t}{2} \\ &\simeq N_t\left[0.6065 + b_t\left(\frac{N_t}{N_t+B}\right) - \frac{1}{2}\right] \\ &= 0.1065N_t + \underbrace{b_t\left(\frac{N_t}{N_t+B}\right)}_{\text{recruits}} \end{aligned}$$

This shows that the next year's biomass roughly equals the recruits plus a relatively small proportion (0.1065) of the current biomass. Intuitively this result can be understood by looking at the shape of the SR model outputs in Figure 4.11 for a run where the low frame is not reached. The fact that next year's biomass roughly equals this year's recruitment can be seen from linear relationship between biomass and recruitment. It is therefore concluded that the chosen fishing strategy is not satisfactory for evaluating the recovery durations of the simple model and a subsequent test was performed using discrete TAC values as per Smith (2009).

4.2.3 Sardine Recovery Duration: Test 2

The goal of this test is to explore the effect that continued fishing pressure has on sardine recovery durations.

Test Setup and Procedure

The fishing strategy for this test is chosen as: enforce heavy fishing on sardine until the low frame is reached, then fish sardine conservatively until the end of the run and record the recovery duration. The terms "heavy" and "conservative" need to be quantified for both models. For the simple model, it is noted that heavy and conservative fishing are defined as 0.6 and 0.3, respectively (Smith, 2009). For the age–structured model, it is noted that Armstrong et al. (1989) refer to "heavy exploitation" in the 60s, with a maximum TAC of 410 kt being landed in 1962 (Fairweather et al., 2006). However, since this is the largest landing on record, it was decided to use 60% thereof so a TAC of 250 kt is used for the age–structured model, with zero bycatch, as heavy fishing. A directed TAC of 90 kt was chosen for conservative fishing – the level at which the OMP–04 Biomass/Directed "without constraint" TAC curve levels off (see Figure 5a de Moor et al., 2011).

Expected Results

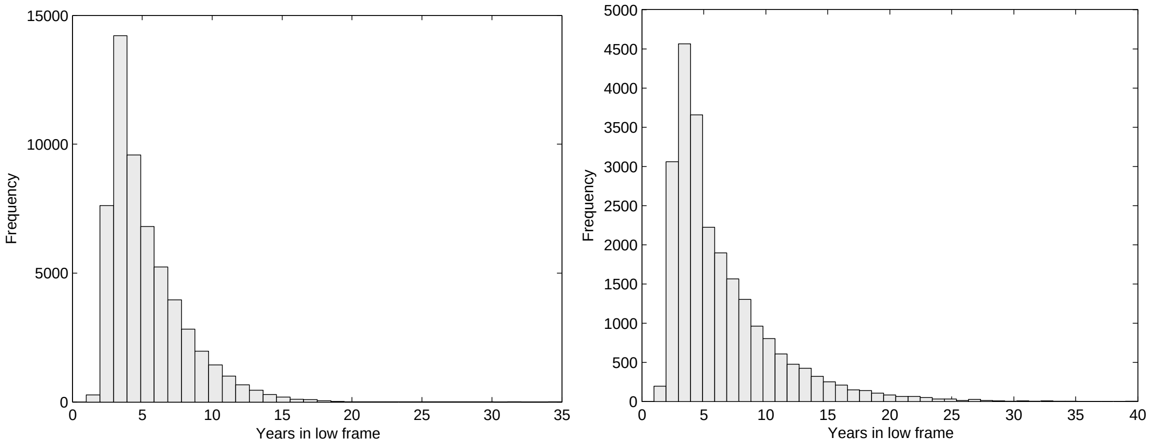
It was expected that the sardine populations in both models enter the low frame as observed in the southern Benguela during the late 60s to mid 80s. It is also expected that recovery periods are slower due to the sustained fishing pressure with expected crashes occurring after the population has entered the low frame.

Actual Results

The histograms for the recovery durations from the experiment are shown in Figure 4.12 and the metrics are shown in Table 4.2. A scatter plot of the SR points for one of the simple model runs wherein the low frame was not reached is displayed in Figure 4.13.

Interpretation of Results

It is evident that sustained fishing following a period of heavy fishing has a high probability of crashing the sardine in the age–structured model although it should be noted this result is dependent on the value of the high frame classification threshold used by the sardine daemon and the chosen TACs. The fixed TAC has allowed the stochastic parameters in the simple model to generate the desired highly variable recruitment, as can be seen in Figure 4.13. It is also evident that the two models react quite differently to similar fishing



(a) simple model **(b)** age–structured model

Figure 4.12: Histograms of recovery durations from low to high frames for sardine under constant directed fishing and no bycatch. After reaching the low frame all directed sardine TACs were set to conservative levels (defined in text) and anchovy TACs kept at zero.

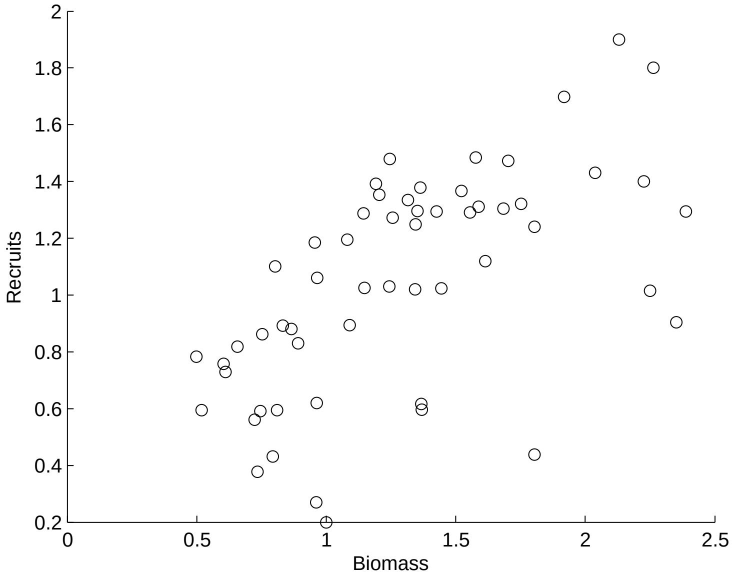


Figure 4.13: SR points generated by the simple model during a “Test 2” run in which the low frame is not reached. Note that choosing a TAC that is not directly proportional to the biomass results in the desired recruitment variability.

Table 4.2: Metrics for comparing sardine recovery durations: test 2.

Metric	Simple Model	Age–Structured Model
(1) Low Frame Reached	98%	99%
(2) Runs That Crashed	40%	74%
(3) No Recovery to High Count	0.3%	6%
Minimum Recovery Duration	1	1
Maximum Recovery Duration	35	40
Mode of Low Frame Duration	3	3
1/99 percentiles	2/14	2/22

strategies, with the low frame recovery durations of the age–structured FBM generally being longer than those of the simple model, and with an increased probability of crashing the sardine stock in the age–structured model. It is interesting to note that in the age–structured model, during runs in which the population did not crash, recovery durations were very similar to those from the previous experiment when the TAC was set to zero after sardine entered the low frame. Based on these qualitative observations, $H_0^{sardpop}$ is rejected and it is concluded that the introduction of age–structure has had an effect on the FBM outputs.

The tests performed thus far have a very static nature, and do not reveal much about the dynamics of the model to a range of input parameters. A sensitivity analysis is therefore performed in Section 4.3 to gain a deeper understanding of the model outputs over a range of inputs.

4.2.4 Sensitivity of the Low Frame Recovery Tests to the ESI

The aim of this experiment is to test the following null hypothesis:

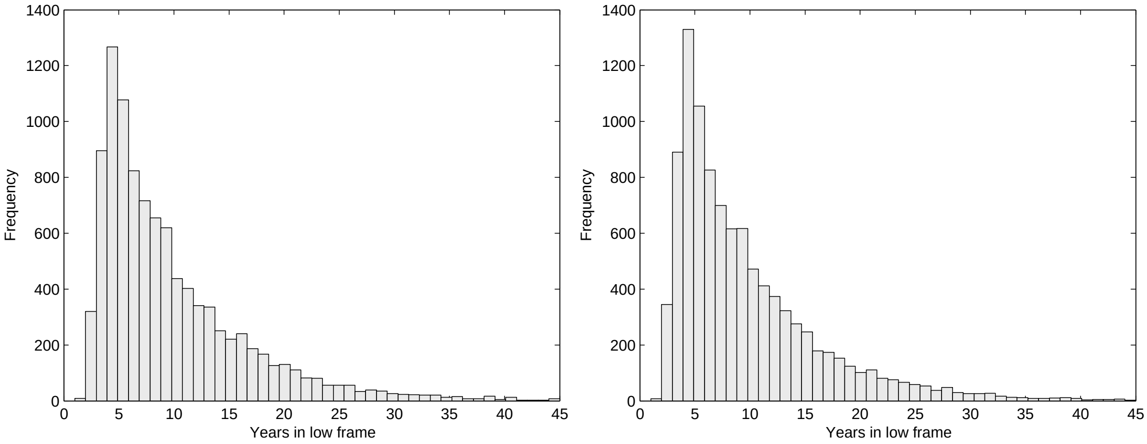
H_0^{ESI} : the mean recovery duration from the sardine low frame is unaffected by the ESI.

Test Setup and Procedure

Two sets of 10^4 runs each are performed. In the first set of runs, the ESI is manually forced to be consistently favourable for sardine as soon as the sardine reach the low frame. In the second set, the ESI is set to be detrimental to sardine once the sardine daemon enters the low frame.

Expected Results

It is expected that, on average, recovery from the low frame occurs more rapidly when the ESI favours sardine and vice versa.



(a) ESI forced low **(b)** ESI forced high

Figure 4.14: Histograms of recovery durations from low to high frames for sardine under different environmental conditions.

Actual Results

The histograms of the low frame residence periods are displayed in Figure 4.14.

Interpretation of Results

It is evident from inspection of the histograms that there is no significant difference between the two sets. This is confirmed by calculating mean/mode pairs for the recovery durations of the tests: 9.2/7 for the test with the ESI forced low and 9.3/7 for the test with the ESI forced high. The reason for this interesting result becomes evident when the mean 1^+ sardine biomass – during the low frame residence period – is calculated as 476 and 467 kt for the first and second set respectively. These values are well below both b_1 and b_2 (Figure 3.2) which means that low frame recovery durations are unaffected by variations in the ESI, using the values chosen for b_1 and b_2 in Section 3.2.2. This test therefore fails to reject H_0^{ESI}.

4.3 Sensitivity Analysis

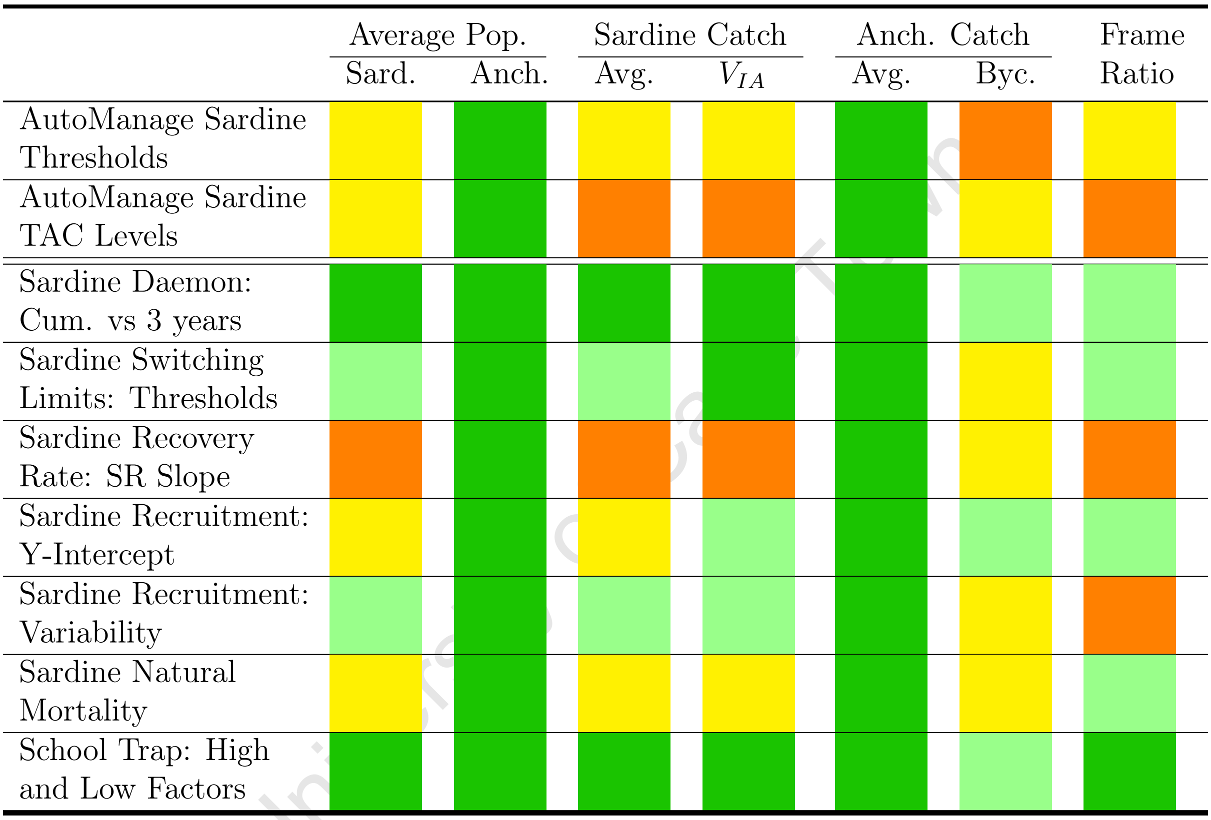
To further explore the response of the model to varying inputs, a sensitivity analysis was performed. In order to perform a thorough sensitivity analysis the following factors must be taken into account:

- model inputs need to be defined,
- an appropriate sampling strategy for the inputs must be selected,
- model outputs and metrics must be defined,

- stochasticity effects (if any) must be dealt with and
- the variations in the outputs must be classified and interpreted.

Each of these factors is thoroughly discussed in the subsequent sections of this chapter. A summary of the sensitivity analysis results is presented in Table 4.3 with the surface plots and other details of each analysis presented in Appendix C.

Table 4.3: Overview of Sensitivities.



	Average Pop.		Sardine Catch		Anch. Catch		Frame
	Sard.	Anch.	Avg.	V_{IA}	Avg.	Byc.	Ratio
AutoManage Sardine Thresholds	🟨	🟩	🟨	🟨	🟩	🟧	🟨
AutoManage Sardine TAC Levels	🟨	🟩	🟧	🟧	🟩	🟨	🟧
Sardine Daemon: Cum. vs 3 years	🟩	🟩	🟩	🟩	🟩	▨	▨
Sardine Switching Limits: Thresholds	▨	🟩	▨	🟩	🟩	🟨	▨
Sardine Recovery Rate: SR Slope	🟧	🟩	🟧	🟧	🟩	🟨	🟧
Sardine Recruitment: Y-Intercept	🟨	🟩	🟨	▨	🟩	▨	▨
Sardine Recruitment: Variability	▨	🟩	▨	▨	🟩	🟨	🟧
Sardine Natural Mortality	🟨	🟩	🟨	🟨	🟩	🟨	▨
School Trap: High and Low Factors	🟩	🟩	🟩	🟩	🟩	▨	🟩

Negligible Effect 🟩 ▨ 🟨 🟧 🟥 Extremely Sensitive

4.3.1 Model Inputs

Model inputs were previously defined as the independent components coloured orange in Figure 3.1. This definition is broadened for the purposes of the sensitivity analysis to include additional significant components such as population parameters and frame switching rules. The model inputs used in the sensitivity analysis can be classified as "continuous" (all values stored on a computer are discrete, these are just a class of discrete variables with a fine resolution) or discrete. The continuous inputs are:

- the AutoManager sardine thresholds (used to classify sardine biomass as Low, Moderate or High),
- the AutoManager (Low, Moderate and High) sardine TACs ,
- the sardine daemon switching thresholds at which frame state changes occur,
- the parameters defining the shape of the SR curve (which implement the ESI and density dependent effects),
- the stochastic and correlation parameters determining variation of recruitment about the SR curve,
- the natural mortality parameters and
- the school trap factor

The two discrete inputs are:

- the AutoManager fishing strategy (conservative to severe) and
- the sardine daemon switching strategy (cumulative sum vs. set of three).

Other model inputs such as sardine selectivity–at–age, proportions–at–age and mean mass–at–age are kept constant for all model runs, with the OMP–02 levels used for them in all the tests. Furthermore, anchovy–related model inputs such as the anchovy daemon switching thresholds are also kept constant, as the anchovy population submodel and the anchovy daemon are effectively unchanged in this study, and their sensitivity has been analysed in Smith (2009). The sampling strategy for these inputs is defined next.

4.3.2 Sampling Strategy

Once the model inputs have been defined, values need to be assigned to them and to thoroughly test the model sensitivity a range of values must be chosen for each parameter. The difficult choice is the sampling strategy from the input parameter space. A common approach, known as One At a Time (OAT) sampling, is to keep all parameters constant except one, and run the model after each change to the parameter across its entire range. Any changes in the output metrics can then be ascribed to the modification of this single parameter. This approach may be incomplete when the input parameters are not independent in the sense that it is nonexplorative of the input sample space.

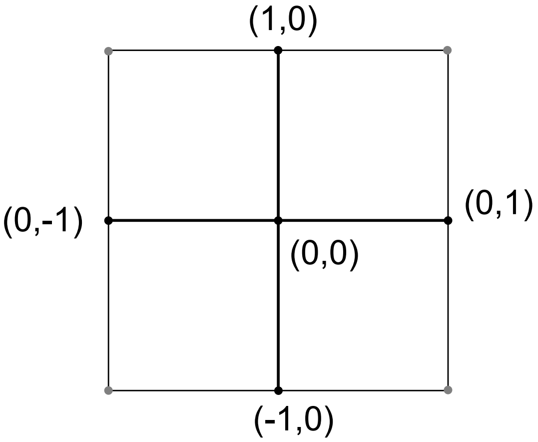


Figure 4.15: Example input space for a model with two variables. OAT sampling only explores the points on the cross. The white space is only covered in factorial sampling.

As an example consider the input space for a model with two discrete input variables, depicted in Figure 4.15, with each variable able to take on three values. Using OAT sampling only the points on the cross are explored and the four corners are left untested. The volume of the unexplored space increases exponentially as the number of input parameters increases. The method used in Smith (2009) could be termed Two At a Time sampling — parameter pairs are changed simultaneously during each test. This is equivalent to exploring the grey corners in Figure 4.15 in addition to the midpoint (default settings) but leaves the other points on the cross and all the white space untested.

To guarantee an exhaustive exploration of the input space, all combinations of input parameters need to be tested and this method is known as factorial sampling. However, for k input parameters, each able to take on s values, the total number of simulations required is s^k. For this study, the number of continuous input parameters is 22. If each parameter were able to take on a conservative amount of values, say 10, this would require 10^{22} simulations (excluding stochasticity effects and discrete parameter values) so the computational effort required is immense. Furthermore, because all models are only sensitive to a few input parameters, many computational cycles are wasted on the unimportant parameters, and this is also the case for OAT sampling.

Implementing a more intelligent sampling strategy – such as multivariate stratified sampling – was beyond the scope of this study, so a compromise was made between OAT and factorial sampling, termed Two At a Time Factorial sampling. In this method the model outputs are computed for a gridded input space with a fine grid resolution, but only for two input parameters at a time. This method has the advantage that model sensitivity can be visually displayed using surface plots and this allows more information to be extracted from the output metric signal, but it has the disadvantage that the exploration of the input space is unexhaustive, and certain model sensitivities may remain unexplored. However, due to the *sparsity of effects* principle (Montgomery, 2009), there is a low probability of model sensitivity to high–order interactions.

Nonetheless, the objective of the sensitivity analysis performed in this study was not to identify an exhaustive list of all model sensitivities, but rather to perform a comparison of the sensitivity analysis results from Smith (2009) with the sensitivity of the FBM after the inclusion of age–structure in the sardine population model. In this regard the Two At a Time Factorial sampling method implemented here is an improvement on the method implemented by Smith — as co–dependant output sensitivities can easily be identified — yet the strategy is similar enough to allow for a meaningful comparison of sensitivities.

4.3.3 Model Output Metrics

As a starting point for this study the output metrics from (Smith, 2009) are used although some modifications are required. The output metrics that remain unchanged are summarised as:

- average biomass levels — the sardine 1^+ and anchovy biomass averages over the model runs are calculated and
- average catches — directed sardine, directed anchovy and juvenile sardine bycatch are calculated.

The new and modified metrics are now discussed.

Variability of Adult Sardine Landings

The inter–annual stability of the modelled sardine catch is a metric that is of interest to industry as it is valuable during financial forecasting. Communicating the inter–annual variability to industry stakeholders needs to be performed in a simple and unambiguous manner. The metric used in Smith (2009) to communicate this result for a given run was the percentage of years in that run that were greater than 80% of the average annual catch for the run. This metric is generally reliable when catch levels are high, but Table 4.4 shows two hypothetical examples illustrating how this metric could potentially be misleading when describing inter–annual catch variability.

This study therefore defines a new metric, V_{IA}, as:

$$V_{IA} = \sum_{y=1}^{k} \sqrt{(TAC_y - TAC_{y-1})^2} \qquad (4.3.1)$$

where k is the number of years in the model run, typically 50 in this study. This number may then be converted into a qualitative value such as “high” or “low” using a piecewise linear transformation (e.g. Jarre et al., 2008) to

Table 4.4: Comparison of various TAC statistics

Annual TAC sequence (kt)							mean	std dev	% of runs > 80% of mean	V_{IA}
250	250	250	80	80	80	80	152.9	90.9	41.7	170
80	250	80	250	80	250	80	152.9	90.9	41.7	1020
250	250	250	250	250	0	0	178.6	122	71.4	250
250	250	250	250	250	80	80	201.4	83	71.4	170

facilitate ease of cognition however for the purposes of this sensitivity analysis the resulting value for V_{IA} is scaled by a "worst–case" factor V_{IA}^{max} which is defined as the maximum amount of inter–annual TAC variability that can be generated by the AutoManager. For example if the maximum and minimum TACs for sardine are 250 and 0 kt respectively, then $V_{IA}^{max} = (250 - 0) \times (k - 1)$ where k is the number of years in the model run. Note that this worst-case value corresponds to the hypothetical TAC sequence $[0, 250, 0, 250, \ldots]$. Scaling by V_{IA}^{max} allows the inter–annual variability to be expressed as a percentage (e.g. Figure C.1e). In this study the V_{IA} metric is used instead of the standard deviation as the metric describing inter–annual variability of the sardine catch.

Frame Residence: Average Time Spent in Sardine High Frame

The two metrics in Smith (2009) describing frame behaviour are frame duration (defined as the total number of years spent in each frame throughout the run) and average frame residence (defined as the average length of each frame subsequence). These metrics are then calculated for the frames during which both sardine and anchovy are high. For the purposes of this study, the metrics are only calculated for the frames during which the sardine population is high (and anchovy can be either high or low). This is because the anchovy frame sequences are independent of any sardine–related parameters and by removing them there is less noise in the final metric.

Furthermore only the frame duration metric is considered, as the hypothetical frame sequence HHHHHHHHHHHHHHLLHLL will have an average frame residence value of 40% for H, whereas the system has actually spent 80% of its time in the H frame. Another factor to consider is that of the final frame sequence (LL in this example). It is not known whether this frame sequence is part of a longer sequence of Ls or whether the next frame will be different (H). The final frame sequence is therefore removed before calculation of the frame behaviour statistics, so the above sequence becomes HHHHHHHHHHHHHHLLH. The caveat to this rule is that if final frame length ≥ 10% of the model run duration it is considered significant and does not get removed.

4.3.4 Stochasticity Effects

In prognostic models where the phenomena are relatively well understood, the sensitivity analysis is usually performed before the addition of stochastic noise. However, because this model is a diagnostic tool with many inputs which are qualitatively estimated during calibration i.e. there is no statistical fitting of the parameters to measurements, and because the stochasticity is built into the model recruitment equations, the sensitivity analysis must cater for stochastic effects and this is achieved by running the model repeatedly after each input parameter adjustment. For the purposes of this study the model was run 10^4 times after each parameter increment to smooth out the stochastic variation in the metrics.

4.3.5 Interpretation of Variability in Output Metrics

The definition of the sensitivity of an output parameter Y to an input parameter X is the ratio of change of Y to X. Consider the logistic function in Figure 4.16. How does the sensitivity of this function get calculated? In certain regions of X there is a high sensitivity (e.g. $-1 \leq X \leq 1$) but in other regions little to no sensitivity (e.g. $-8 \leq X \leq -7$). Computing the derivative $\partial Y/\partial X$ is therefore only meaningful at the point at which it was calculated and is not very useful for nonlinear models such as this. This problem is simplified when the probability distributions of the input parameters are known. If it is known that the input parameter X of the logistic function is likely to lie in (-8,-7) then the model may safely be classified as insensitive. However if it is known that X is likely to lie in (-1,1) it is more accurate to classify the model as highly sensitive to X.

A strategy for classifying sensitivities can now be formulated. For the purposes of this study the final classification of an output metric's sensitivity to an input parameter is performed as follows. Firstly a probability distribution is assigned to the input parameters being varied based on biological knowledge of the system. Secondly the variation of the output metric is evaluated in the region of highest probability for the input parameters by inspection of the surface plots. Finally a qualitative sensitivity of the output metric is assigned on a scale of "negligible effect" to "highly sensitive".

4.3.6 Results of the Sensitivity Analysis

Due to the large amount of data generated by the sensitivity analysis, it is important to formulate the key questions before interpreting the results, and not to formulate the questions from the results. Based on the results of the sensitivity analysis in Smith (2009), the key questions are:

- Is the system sensitive to the AutoManager sardine thresholds and TAC levels?

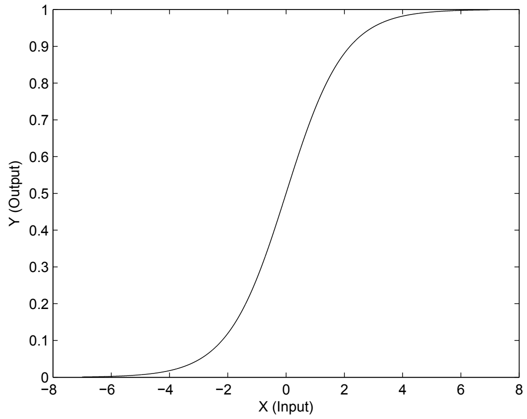


Figure 4.16: Illustration of a model where the sensitivity is highly dependent on the input range.

- Does the sardine daemon strategy affect the sardine bycatch?
- Is the sardine bycatch sensitive to the sardine daemon switching limits? and
- Is the system sensitive to the modelled recovery rate?

All the results are presented as surface plots in Appendix C but these key questions are now addressed.

Sensitivity to the AutoManager settings

In accordance with the simple model, the age–structured model was found to be strongly sensitive to the AutoManager sardine thresholds and TAC levels. The nonlinear surface generated by the frame duration metric (Figure C.1f) reveals a complex relationship between the AutoManager thresholds and the total time spent in the sardine high frame.

The quasilinear surface generated by the sensitivity of the average adult sardine biomass metric to the AutoManager TAC levels (Figure C.2a) also indicates a strong relationship. The sardine bycatch is more sensitive to adjustments in the AutoManager moderate TAC than to adjustments in the high TAC, which is interesting, and is probably explained by the fact that sardine are more likely to be in the low frame when the moderate TAC is applied, than when the high TAC is applied. The variability of the sardine catch is extremely sensitive to the derisory scenarios in which the moderate TAC is larger than the high TAC; these scenarios are considered insignificant. From inspection of the surface plot is is evident that there is a trough which minimises the variability of the sardine catch. This trough is a good example of the type of feature that can be missed during OAT or Two At a Time sampling.

Inspection of the surface plot for the duration that the sardine spend in the high frame (Figure C.1f) reveals a higher sensitivity to the AutoManager high threshold than to the low threshold. This shows how surface plots can be used to tease more information out of the sensitivity signal than is possible using the Two At A Time methodology, where it is not clear which parameter that was changed caused the change in the output metric.

Sensitivity to the Sardine Daemon Frame Strategy

As with the simple model, the duration spent in the sardine high frame was mildly sensitive to the strategy used by the sardine daemon. However, in contrast with the sensitivity of the simple model, the sardine bycatch in the age–structured model is only mildly sensitive to the strategy type.

Sensitivity of Sardine Bycatch to Sardine Daemon Switching Limits

The sardine bycatch is moderately sensitive to the level at which the sardine daemon switches from the low frame to the high frame, but is almost entirely unaffected by the level at which the switching from high to low takes place (for the region that was tested) except near the extremity where the low to high threshold equals the high to low threshold. This result adds confidence to the model's outputs because as the level at which sardine are considered to be in the high frame drops, so will the level of juvenile sardine bycatch. This is because the school trap effect is only implemented in the sardine low frame. Furthermore the AutoManager reduces the TAC once the sardine population drops below 900 kt, and since the sardine daemon threshold gets calculated over three years, the sardine bycatch is relatively unaffected by this threshold (although it will eventually start becoming sensitive at a certain threshold, but that threshold will be so low that using it would disagree with current biological knowledge of sardine population levels).

Sensitivity of the FBM to the Recovery Rate Parameters

Density dependent recovery is implemented in the model by varying the slope of the SR curve in the sardine high frame. The system is shown to be highly sensitive in the slope of the SR curve because the AutoManager attempts to maintain the stock in the high frame and any modification to the density dependent parameters affects the recovery rate of sardine. This result agrees with the sensitivity analysis of the simple model.

Chapter 5

Discussion and Recommendations

5.1 The Usefulness of the Frame–Based Approach

The frame–based approach relies heavily on a single assumption: that the phenomenon or system being modelled can be separated into discrete, functionally distinct frames. For certain classes of problems this approach is not suitable, for example when modelling individual growth using a von Bertalanffy growth equation, the length of an individual is a continuous function of time and does not consist of discrete states — the use of frames is unsuitable here. Note, however, that in this example an FBM may be "superimposed" on top of a growth equation to classify an organism into "length frames" such as "short", "medium" or "long" and this may be useful in certain applications. Similarly, for other classes of problems where multiple ecosystem states occur (e.g Hahn et al., 1999), the use of frames can provide a useful tool for investigating an otherwise intractable problem.

Well understood, data rich systems that oscillate between states may be accurately modelled using probability networks instead of custom frame switching rules. For example, the "head" and "tail" frames of a fair coin model will have a 0.5 probability of switching frames after each "flip" event. The coin model is therefore entirely stochastic, but the probabilities are well defined and the state transitions are therefore best modelled probabilistically using constructs such as Markov Matrices (the system switches from state to state according to predefined and constant switching probabilities).

In contrast, the usefulness of the frame–based approach becomes apparent when the frame switching probabilities themselves are subject to change. The FBM implemented in this study evaluates frame switching rules during each time step which inspect sardine and anchovy biomass levels. These biomass levels depend on recruitment success (which is linked to quasi–decadal fluctuations in environmental suitability) and the management decision that was made during the time step. The management decisions — in the form of a yearly species specific TAC — are external inputs to the model (set by either the user or the AutoManager) and they directly affect the biomass levels in unpredictable ways. The effect of these unknown inputs is that the frame switching probabilities do not remain constant. The frame–based approach therefore provides a useful means to model uncertain external inputs, such as management strategies, and provides a virtual environment for the exploration of various medium to long term management strategies.

Frames also present the interesting possibility of incorporating indicators, as used in the Ecosystems Approach to Fisheries (EAF) context, into the model in two ways. Firstly, the frames (as implemented in this study) are not only quick and simple indicators of the instantaneous state of the modelled population, but also provide an intuitive sense of the historical health of the stock over the past three years, and in the case of the sardine low frame there are inherent implications for recovery durations. Secondly, EAF indicator thresholds could be incorporated into the design of a new FBM by including important indicators in the frame switching rules and then using the existing indicator thresholds as a starting point for the definition of the new frame switching thresholds. In this way existing expert knowledge may be rapidly incorporated into the design of a new model i.e. the flexibility provided by the custom frame switching rules lends itself well to the incorporation of expert knowledge into the model design, even in the absence of large datasets and/or when the expert knowledge of the ecosystem dynamics is qualitative in nature (e.g. Starfield and Chapin, 1996).

However, frames are more than just indicators of the state of the system, they are a means of implementing an additional layer of dynamics in the model. The equations and parameter values in the various states represent the first layer of model dynamics, but the fact that the equations themselves are able to change in an FBM represents a second layer of dynamics, which is useful in applications wherein the system being modelled switches between quasi–stable states.

5.2 What Was Gained From Implementing Age–Structure?

In light of the objective of exploring the sensitivity of the FBM to the inclusion of age–structure, it was shown that direct comparisons of model outputs are difficult when the underlying sardine population submodels are very different. Qualitative, high–level inspection of an output metric such as the mean recovery duration from the low frame showed that the sardine population in the age–structured model was more likely to crash under sustained fishing in the low frame than in the simple model. Sensitivity to the parameters describing the AutoManager behaviour remained relatively unchanged (both models were highly sensitive). This was also the case for the sensitivity to the sardine daemon “cumulative sum vs 3 years” logic and the biomass switching thresholds (both were mildly sensitive).

An obvious advantage of including age–structure is the possibility of implementing observed real world dynamics — such as the increased spawning potential of older sardine — more closely. Including age–structure in a population model makes sense when valid age–specific data from the real world are applicable and available, such as was the case with the OMP–02 sardine assessment model. Model outputs are also presented in terms of concrete units such as biomass and numbers of individuals which aid intuitive interpretation. A criticism of the approach used in this study is that the OMP–02 levels and equations differ from those used by the current OMP. However, one goal of the study was to explore the sensitivity of the frame–based approach to the sardine population submodel in a west–coast scenario, and to this end the strategy was to view the OMP equations as an off–the–shelf component in the FBM, and changes to OMP–02 parameters were avoided, where possible.

The results of the sardine recovery duration tests in Section 4.2.2 show that in 99% of the runs recovery from the low frame took three years or more in the age–structured model, versus the one year or more from the simple model. Again, it is difficult to ascribe this result to a specific change in the model structure; these longer recovery times could be due to the difference in the underlying recruitment mechanism or due to the introduction of age–structure. Nonetheless it is a useful high–level result as these longer recovery durations more closely resemble the sardine biomass time series data as observed in the southern Benguela.

Another interesting result is the increased responsiveness to fishing in the age–structured model: 100% of the runs in the test from Section 4.2.2 reached the low frame, whereas 67% of the runs from the simple model reached the low frame. This result is also difficult to interpret because the definition of a low frame has changed. However, it is shown in Section 4.3 that there was only a mild sensitivity of the sardine biomass levels to the sardine daemon thresholds, so this result is only mildly sensitive to the definition of what a low frame is. It would be interesting to perform this test across a wide range of TAC values to determine the sensitivity of the experiment to the definitions of “heavy” and “conservative” TACs. Notwithstanding any sensitivities, this result is possibly due to the fact that the recruitment variability in the simple model immediately manifests throughout the entire population, whereas recruitment variability in the age–structured model only affects the number of 0–year old sardines. This could indicate a decreased resilience of the modelled sardine population to sustained high fishing pressure. Nonetheless, in the presence of age–dependant fishing mortality data, use of an age–structured model calibrated to this data would further align the implementation of modelled fishing mortality with the real world.

5.3 Results of the Sensitivity Analysis

The sensitivity analysis clearly indicates that certain outputs are co–dependant on input parameter pairs. There is a low probability that more complex dependencies exist (Montgomery, 2009), but these were unexplored. Due to the existence of co–dependant sensitivities in the model it is important to consider the sampling strategy of the input parameters during the sensitivity analysis. The implemented sampling strategy of near–exhaustive exploration of two parameters at a time has the disadvantage that it is an incomplete exploration of the input parameter space. It has an advantage over OAT sampling in that it illuminates co–dependant sensitivities while still being relatively simple to implement.

The sensitivity analysis provides an indication of which input parameters require the most attention in terms of calibration e.g. it is shown that all the relevant output metrics are highly sensitive to the values of the S–R curve parameters. This process helps to ensure that the calibration process prioritises the correct parameters. Once the parameters have been calibrated and the operation of the submodels has been verified, the model becomes more useful for running experiments and more accurate at making predictions.

Results of the sensitivity analysis generally agreed with those of the simple model, and certain output metrics were refined. Due to shortcomings in the interannual variability metric defined in Smith (2009)[1] a new output metric representing the interannual variability of the sardine catch was defined and was shown to be sensitive to the natural mortality and S–R slope parameters. Whilst values for the natural mortality parameters were fixed, as per OMP–02, the sensitivity analysis showed that the model was sensitive to them. Output metrics were generally shown to be sensitive to only certain input parameters, and it is important to note that this is the case for all models — a relatively small number of input parameters will have the largest influence on the model's output (Saltelli et al., 2007).

In accordance with the sensitivity analysis results of Smith (2009), an apparent insensitivity in the output metrics to the school trap factor was shown. However it must be pointed out that this result may be misleading, as the chosen fishing strategy (AutoManager set to the most conservative level) aims to keep the sardine in the high frame at all times, and school trap is only active when sardine enter the low frame. It would therefore be interesting to explore the sensitivity of the model to a range of fishing strategies, and not just a conservative one. Furthermore, it is possible that the school trap factor should not be defined as a function of the frames, but rather as a function of the relative species abundance (Cury et al., 2000).

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[1] For example, the sequence [10, 51, 100, 62, 100, 58] scores an 83% "stability" using the previous metric, yet it is evident that there are large fluctuations in the sequence.

5.4 Recommendations

Specific recommendations for future work that were identified during this study are now addressed.

5.4.1 Revision of the ESI Dependant Recruitment Mechanics

During the experiment in Section 4.2.4, it became evident that the chosen method of linking the S–R parameters to the ESI was inadequate, as the S–R parameter adjustments would have no effect on the recruitment levels when the sardine were in the low frame. This was an unforeseen yet highly useful result. It is critically important to incorporate the ESI parameter in the sardine low frame and this may be done by either adjusting the natural mortality parameters or by adjusting the shape of the S–R curve when sardine are in the low frame.

5.4.2 Inclusion of Spatial Dynamics

In light of the recent southward shift of the sardine population in the southern Benguela, inclusion of spatial dynamics such as a south coast frame in the model could provide insight into how to formulate management strategies for a spatially fluctuating population. Many interesting design decisions would need to be made as the inclusion of a "south coast" frame is just the starting point. Specifically, it must be decided whether the sardine population is modelled as a single unit moving from west to south (as would be the case with the north/south migration of wildebeest referenced previously) or whether there are two distinct groups of sardine, with possible emigration/immigration between the groups. This will determine whether the sardine daemon has a pair of high/low instances, in the case of two distinct groups, or a single high/low instance, in the case of the "migratory" scenario.

Other interesting design decisions would be:

- with west coast environmental conditions being quite different to those on the south coast, it might make sense to implement two separate ESIs,
- the spatial distribution of anchovy in the model will affect the school trap factor,
- the S–R curve will likely also include a spatial parameter and
- the implementation of fishing mortality should possibly change to include a spatial parameter.

5.4.3 Increased Use of Frame Information

During the review process it became evident that the AutoManager module does not consider the current frames when generating TACs. In light of the model objective of exploring various management strategies, it would be useful to redesign the AutoManager to incorporate information about the current anchovy and sardine frames when assigning TACs. For example if the anchovy population were in a high frame and sardine were in a low frame, a frame–aware AutoManager would realise that the sardine juveniles would be more sensitive to bycatch from the anchovy fishery and possibly implement a more conservative anchovy TAC.

5.4.4 TAC Assumptions Analysis

It would be interesting to explore the sensitivity of the modelled sardine population to the assumptions of (a) complete success by industry in landing the yearly TAC and (b) no unaccounted bycatch from the small pelagics or other fisheries. A similar testing strategy as implemented in this study could be used to explore the co–dependency of outputs on this input pair, with an incremental adjustment in unaccounted bycatch and sardine fishery TAC landing success over a meaningful range.

Chapter 6

Conclusion

The age–structured OMP–02 sardine assessment equations were implemented within a frame–based context, and it was shown that the biological processes of density dependent recovery and school trap — which were present in the simple model — could not be implemented without making modifications to the OMP–02 equations. Mechanisms were proposed for incorporating these processes whilst trying to keep changes to the OMP–02 equations to a minimum. These mechanisms were thoroughly tested which increased confidence in the model outputs and it was shown that further work is required to implement the sensitivity of sardine recruitment to environmental variability when sardine numbers are low; this result illustrates the importance of exercising the model by running controlled experiments as the interpretation of the results may reveal aspects of the model design which require modification.

The graphical user interface was updated to include a visual representation of age dependent information in the sardine population trajectory, and a list of computational errors was identified and corrected resulting in more accurate and robust model outputs. A phase plot of the underlying S–R curve points was added to the user interface to provide insight to the model's mechanics without requiring an analysis of the equations. Similarly, a plot depicting the recruitment variability about the S–R curve was included as a visual aid in understanding the inherent stochasticity in the sardine recruitment.

A sensitivity analysis of the FBM was performed using a process similar to that in Smith (2009) and sensitivities generally agreed with the results from the simple model, with increased sensitivity to the implementation of sardine recruitment and recovery. This means that the model outputs are dependant on the tuning of the sardine S–R curve parameters, and because a qualitative adjustment of these parameters was performed, the FBM implemented in this study is not a suitable stock projection tool. Despite this rough calibration process, the model still remains useful as a training tool for prospective managers to understand the effects of long–term environmental and anthropogenic forcing on small pelagics in the southern Benguela. Fitting the parameters to the best available stock assessment data would increase the usability scope of the model outputs.

The sensitivity analysis process identified certain subtle improvements on the output metrics used by Smith and these improvements were implemented. A new output metric that represents the interannual variability of the discrete sardine TAC was defined and was shown to be highly sensitive to the implemented fishing strategy and the steepness of the S–R curve, as is to be expected. All first–order model sensitivities were analysed and a large subset of the second–order sensitivities were analysed using surface plots.

The model can be used to further explore the concept of environmentally dependent S–R curve parameters, as a basis for development of a frame–based model which explores fisheries management decision effects on a spatially shifting sardine distribution and as an educational and training tool.

Appendix A

Derivation of the age-structured sardine population equation

Let $N_p(t)$ be a function determining the number of individuals in a population. The rate at which the population's size changes over time can then be written as

$$\frac{dN_p}{dt} = (b-d)N_p = rN_p$$

where r is the instantaneous rate of growth and incorporates births (b) and deaths (d). To apply this growth equation to a cohort sized N, we note that the numbers in a cohort may only decrease with time:

$$\frac{dN}{dt} = -(F+M)N = -rN \tag{A.0.1}$$

where F and M are the fishing and natural mortality constants, respectively. To solve for $N(t)$, we integrate both sides and perform a separation of variables:

$$\int \frac{1}{N}\mathrm{d}N = \int -r\mathrm{d}t$$

$$\Rightarrow \quad \ln(N) = -rt + K$$

where K is a constant. Taking the antilog yields:

$$N(t) = e^{-rt}e^{K} \tag{A.0.2}$$

To solve for the constant we observe the system at time $t = 0$:

$$N(0) = e^{0}e^{K} = e^{K} \equiv N_0$$

Substituting this value for K into A.0.2 yields:

$$N(t) = N_0 e^{-rt} \tag{A.0.3}$$

Discretisation of Equation A.0.3 is performed by expanding Equation A.0.1 as follows:

$$\begin{aligned}\frac{dN}{dt} &= \frac{N(t+\Delta t)-N(t)}{\Delta t} \\ &= -rN \\ \\ \Rightarrow N(t+\Delta t) &= -r\Delta t N(t) + N(t) \\ &= (1-r\Delta t)N(t) \qquad \text{(A.0.4)}\end{aligned}$$

Next we note that the Taylor series approximation of e^x near 0 is:

$$\begin{aligned}& 1+\frac{x^1}{1!}+\frac{x^2}{2!}+\frac{x^3}{3!}+\dots \\ \simeq\ & 1+x\end{aligned}$$

Setting $x=-r\Delta t$ and substituting into A.0.4:

$$N(t+\Delta t)=e^{-r\Delta t}N(t)$$

Letting the unit of t be years and setting $\Delta t=1$ we have:

$$N(t+1)=e^{-r}N(t)$$

which can be written as $N_{y+1}=e^{-r}N_y$ using subscript notation with y in years, as before. We now set $r=F+M$ to obtain:

$$N_{y+1}=e^{-M}e^{-F}N_y$$

We now make use of the approximation provided by Pope (1972):

$$\begin{aligned}N_{y+1} &= N_y e^{-M} - C_y e^{-M/2} \\ &= \left(N_y e^{-M/2} - C_y\right) e^{-M/2} \qquad \text{(A.0.5)}\end{aligned}$$

where C_y is the total catch in year y. Finally, letting $N_{y,a}$ be the number of sardine aged a in year y, Equation A.0.5 becomes

$$N_{y+1,a+1}=\left(N_{y,a}e^{-M/2}-C_{y,a}\right)e^{-M/2} \qquad \text{(A.0.6)}$$

which is in the same form as Equations 3.1.2 and 3.1.3.

Appendix B

Sardine Population Model Assumptions

These are the assumptions used by the OMP–02 sardine assessment model:

- All fish have a theoretical birthdate of 1 November, but become available to the fishery only from 1 January.
- Sardine spawn for the first time (and are called adult sardine) when they turn one year old.
- Sardine die once they reach five years of age and have spawned a final time.
- Pulse fishing occurs 6 months after the birth date.
- Catches are measured without error.
- Natural mortality is year-invariant for juvenile and adult fish, and age-invariant for adult fish.

Appendix C

Sensitivity Analysis Results

C.1 Test 1: AutoManage Sardine Thresholds

The thresholds at which the AutoManager classifies sardine as low, moderate and high are varied in this test. In the standard AutoManager configuration on the most conservative setting sardine are classified as:

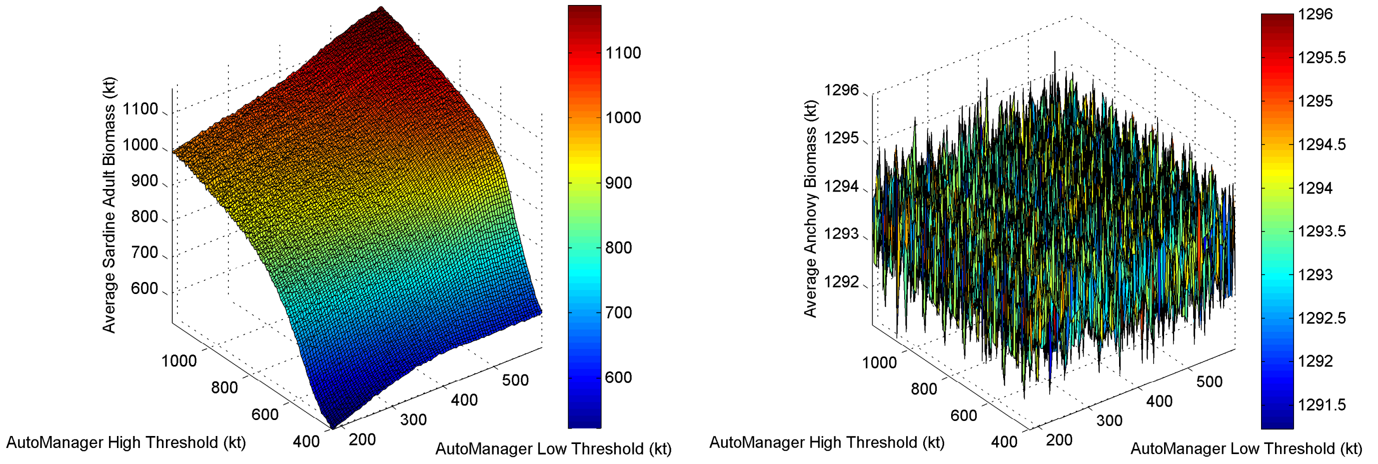
- high if $B_y \geq B_{AM-high}$,
- moderate if $B_{AM-low} \leq B_y < B_{AM-high}$ and
- low if $B_y \leq B_{AM-low}$.

where $B_{AM-high} = 900\,\text{kt}$ and $B_{AM-low} = 600\,\text{kt}$.

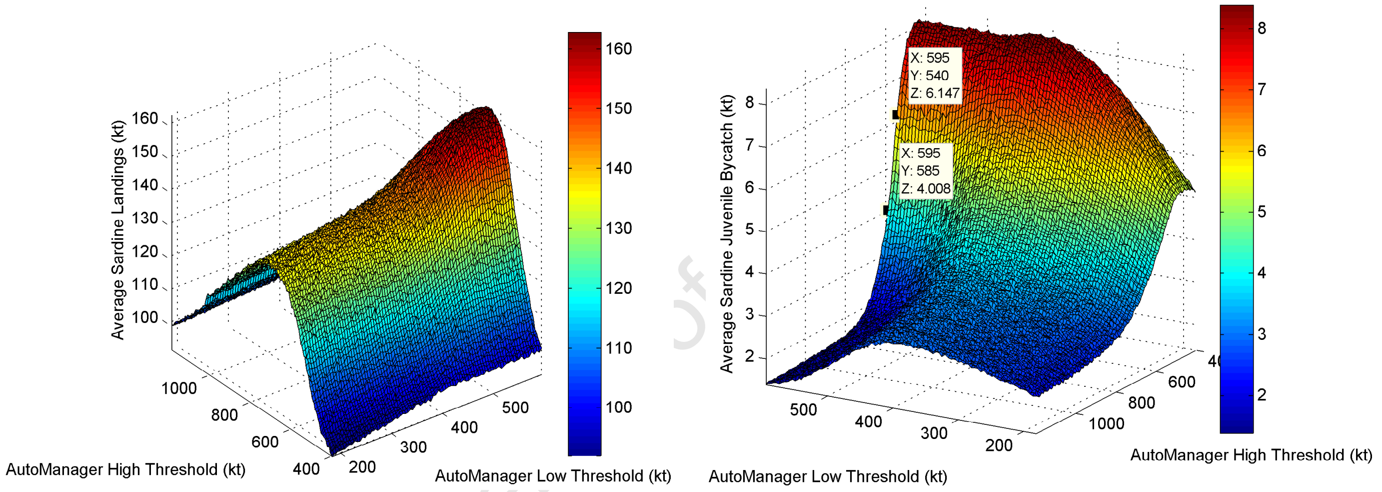
$B_{AM-high}$ is varied between 400 and 1200 in steps of 5 kt and B_{AM-low} is varied between 180 and 600 in steps of 5 kt. The model is run 10^4 times after each parameter increment (a total of 134×10^6 model runs). The results are presented in Table C.1 and displayed in Figure C.1. Note that none of the anchovy related metrics are displayed in the table as they are all unaffected by the input parameter variations.

C.2 Test 2: AutoManage Sardine TAC Levels

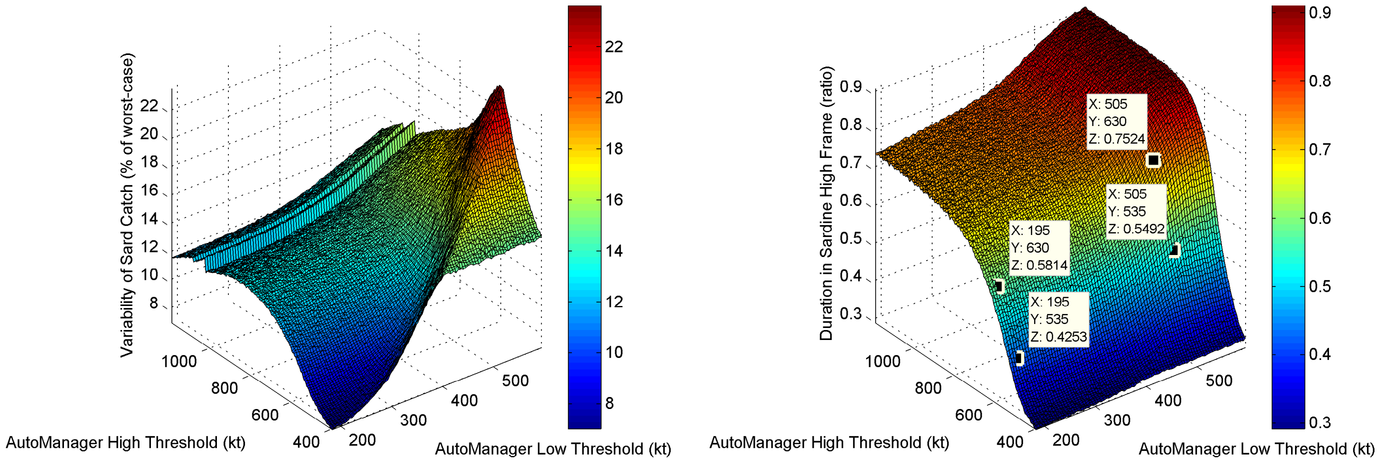
In the standard AutoManager configuration on the most conservative setting the AutoManager sardine TAC when sardine are classified as high, TAC_h, is 180 kt and the TAC when they are classified as moderate, TAC_m, is 80 kt. In this test TAC_h is varied from 100 to 500 kt and TAC_m is varied from 10 kt to 250 kt. The model is run 10^4 times after each parameter increment with an increment size of 5 kt. The results are presented in Table C.2 and displayed in Figure C.2.



(a) Average Sardine Biomass **(b)** Average Anchovy Biomass

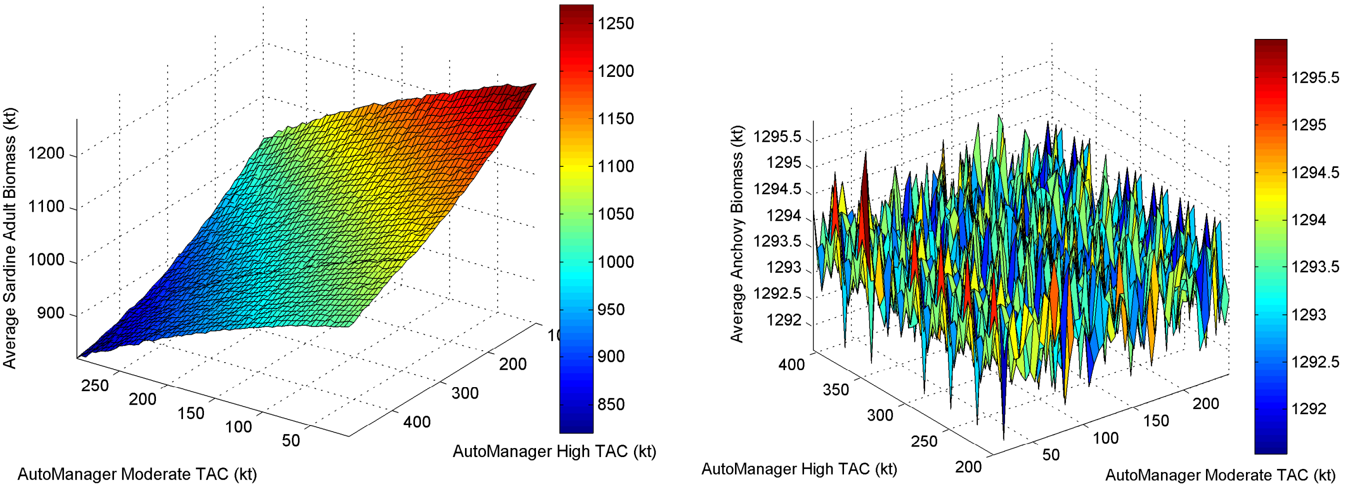


(c) Average Adult Sardine Landings **(d)** Average Sardine Bycatch

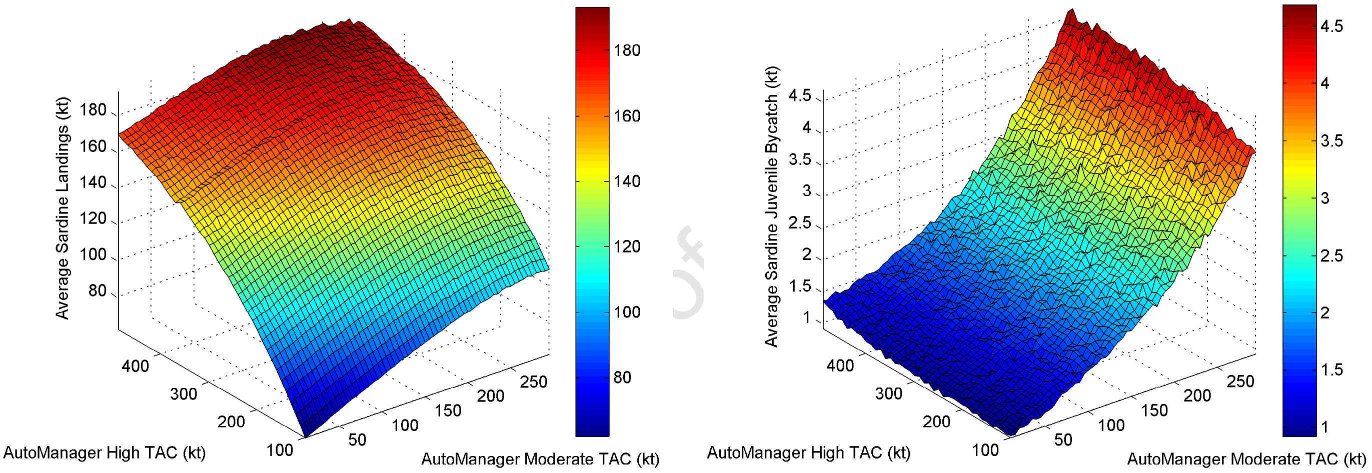


(e) Sardine TAC Variability **(f)** Sardine High Duration

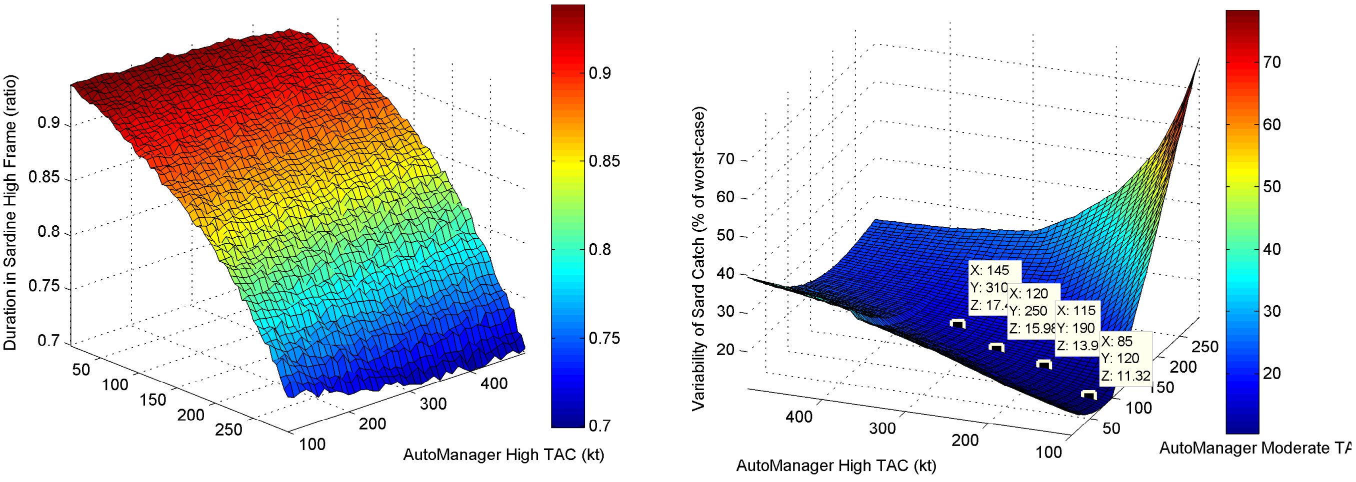
Figure C.1: AutoManager Sardine Threshold Sensitivities



(a) Average Sardine Biomass **(b)** Average Anchovy Biomass



(c) Average Sardine Landings **(d)** Average Sardine Bycatch



(e) Sardine High Duration **(f)** Sardine Catch Variability

Figure C.2: AutoManager Sardine TAC Sensitivities

Table C.1: Sensitivity to the AutoManage Sardine Thresholds

Metric	Description	Range (kt)
Avg. Sard. 1^{+}B	Very sensitive to $B_{AM-high}$ and mildly sensitive to B_{AM-low} within defined ranges.	$400 < B_{AM-high} < 465$ $180 < B_{AM-low} < 415$
Avg. Sard. Catch	Very sensitive to $B_{AM-high}$ and mildly sensitive to B_{AM-low} within defined ranges.	$400 < B_{AM-high} < 465$ $180 < B_{AM-low} < 415$
Variability of Sard Catch	The interesting surface generated suggests a complex dependency on the thresholds, although the apparent discontinuities (in the order of 1%) are a result of the 5 kt step size resolution.	Complex
Sard. Juvenile Bycatch	Very sensitive to $B_{AM-high}$ and mildly sensitive to B_{AM-low} within defined ranges.	$400 < B_{AM-high} < 465$ $180 < B_{AM-low} < 415$
Sard. High Frame Duration	Very sensitive to $B_{AM-high}$ and mildly sensitive to B_{AM-low} within defined ranges.	$400 < B_{AM-high} < 465$ $180 < B_{AM-low} < 415$

C.3 Test 3: Sardine Switching Strategy

The switching strategy used by the sardine daemon is varied from

- evaluating the cumulative sum of the biomass over three years to
- requiring three consecutive years of the biomass above a certain level.

The results are presented in Table C.3.

C.4 Test 4: Sardine Daemon Thresholds

The sardine daemon frame switching rules are:

- switch to sardine high frame if $\sum_{i=k-2}^{k} B_{i,N} > B_{SD-l2h}$ and
- switch to sardine low frame if $\sum_{i=k-2}^{k} B_{i,N} < B_{SD-h2l}$

where k is the current year in the model run, B_{SD-h2l} is the level at which the sardine daemon switches from high to low and B_{SD-l2h} is the level at which the sardine daemon switches from low to high. The high switching threshold,

Table C.2: Sensitivity to the AutoManage Sardine Exploitation Levels

Metric	Description	Range
Avg. Sard. 1^+B	Mildly sensitive to TAC_h and moderately sensitive to TAC_m across all tested values.	Entire range
Avg. Sard. Catch	Very sensitive to TAC_h and mildy sensitive to TAC_m across all tested values.	Entire range
Variability of Sard Catch	There is a maximum distance of roughly 43% variability on the sensitivity surface generated in this test, which indicates a high sensitivity, although the parameters are co–dependant.	Co–dependant, complex
Sard. Juvenile Bycatch	There is a negligible to mild sensitivity in the modelled bycatch to TAC_h and there is a moderate sensitivity to TAC_m.	Co–dependant, complex
Sard. High Frame Duration	There is a negligible to moderate sensitivity of the sardine daemon to TAC_h and the daemon is very sensitive to TAC_m.	Complex

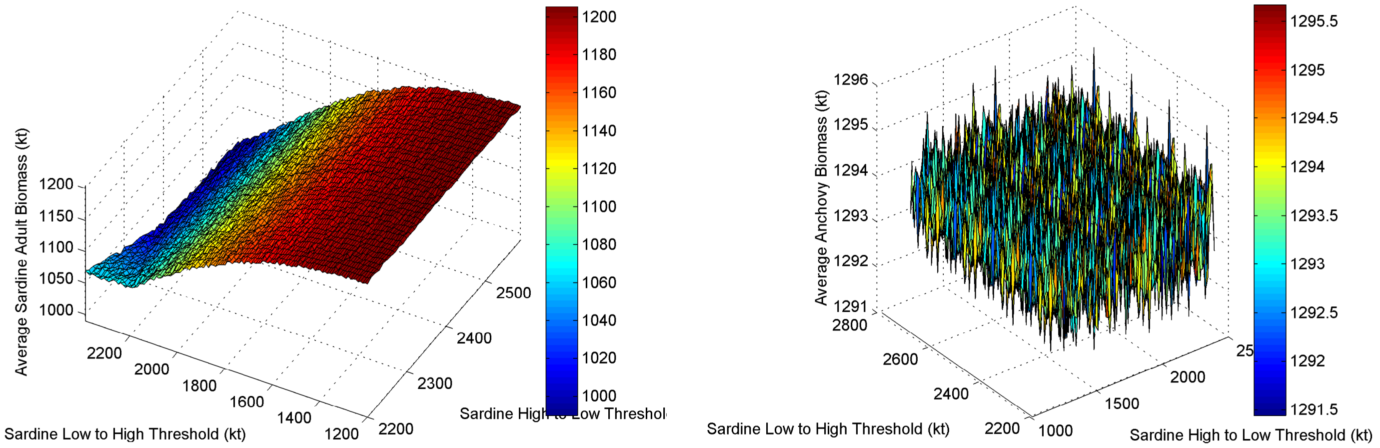
B_{SD-h2l} is varied from 1 200 to 2 400 kt and the threshold at which the sardine daemon switches into low, B_{SD-l2h}, from 2 200 to 2 800 kt. The incremental step size is 10 kt and after each increment the model is run 10^4 times to average the stochasticity effects. The results of this test are presented in Table C.4 and displayed in Figure C.3.

C.5 Test 5: Variations in the Density Dependence Implementation

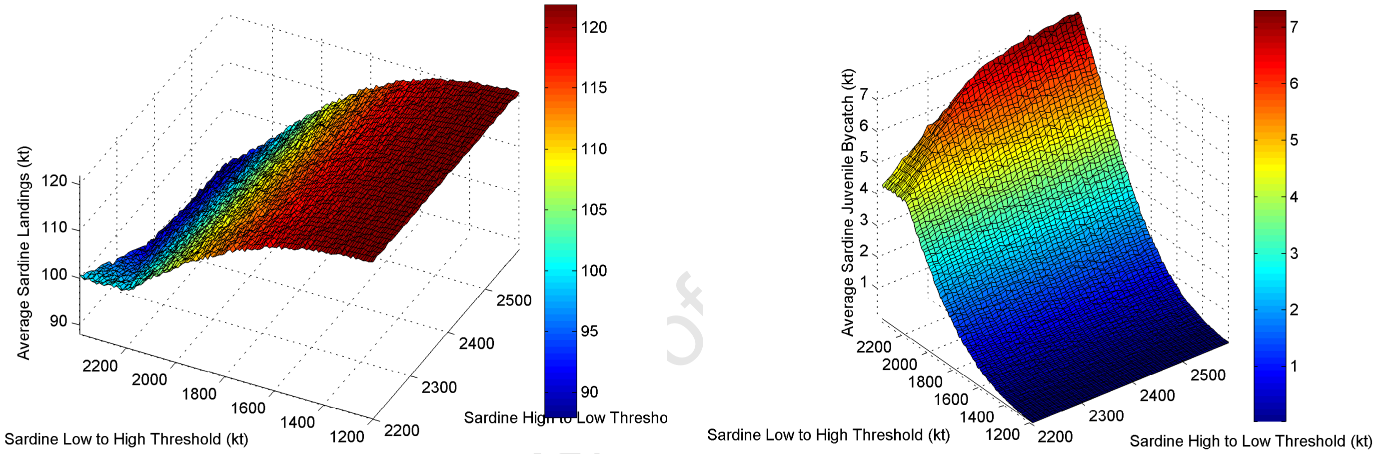
Density dependence is implemented in the model by varying the slope of the S–R curve when sardine are in the high frame and drop below a certain biomass level, B_{max}. The slope is varied linearly between s_{min} and s_{max}. The standard values for these parameters are:

- $s_{max} = 0.0357$ (the OMP–04 value),
- $s_{min} = s_{max}/2$ and
- $B_{max} = 2000$.

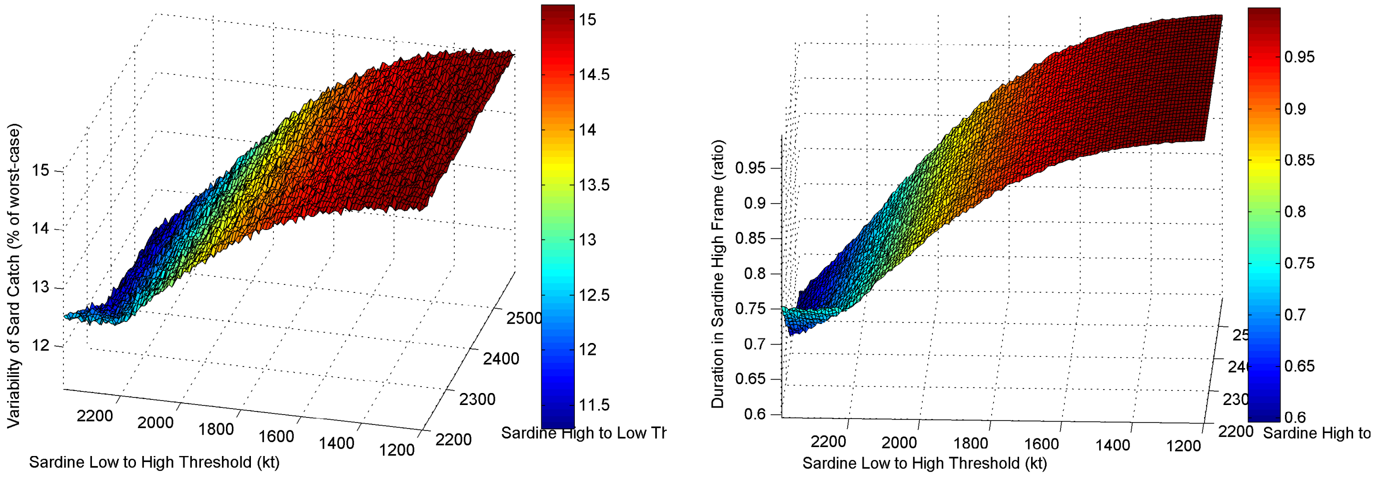
In this test s_{max} is varied from 0.02 to 0.06 in steps of 0.001 with s_{min} always set to half of s_{max}. B_{max} is varied from 1 000 to 3 000 kt in steps of



(a) Average Sardine Biomass **(b)** Average Anchovy Biomass



(c) Average Sardine Landings **(d)** Average Sardine Bycatch



(e) Sardine TAC Variability **(f)** Sardine High Duration

Figure C.3: Sardine Threshold Sensitivities

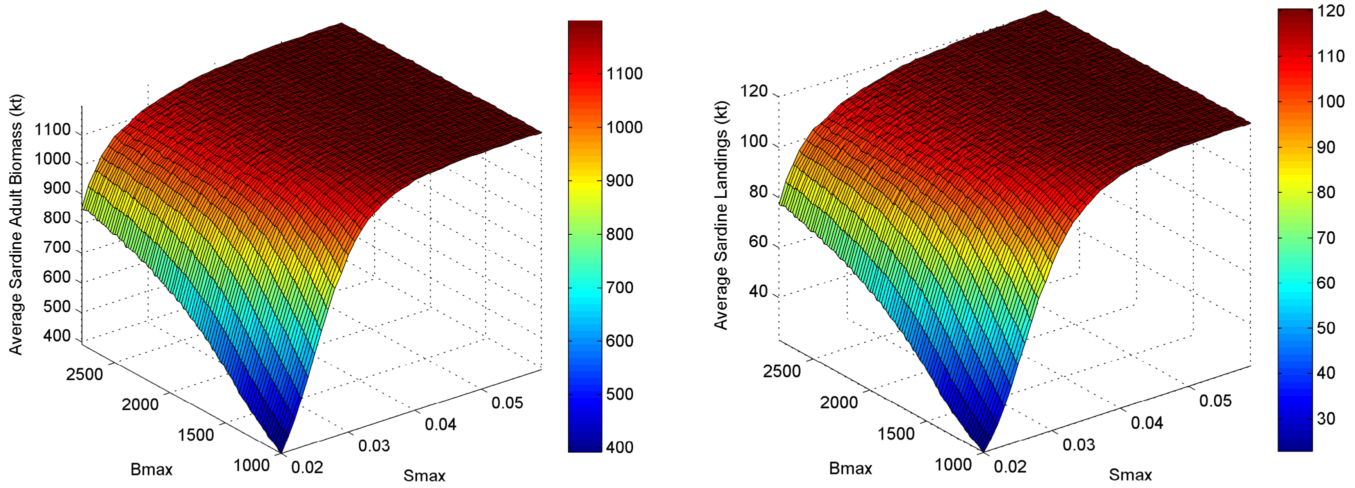
Table C.3: Sensitivity to the Sardine Daemon Switching Strategy

Test Settings	Metric	Value
Cumulative Sum: Unfished system	Sard. avg. 1+B (kt)	1401.05
	Sard. hi frame duration (ratio)	0.97
Set of 3: Unfished system	Sard. avg. 1+B (kt)	1403.56
	Sard. hi frame duration (ratio)	0.98
Cumulative Sum: Fished system	Sard. avg. 1+B (kt)	1167.2
	Sard. avg. catch (kt)	105.69
	Sard. catch variability (V_{IA})	13%
	Juvenile sard. bycatch (kt)	1.4
	Sard. hi frame duration (ratio)	0.91
Set of 3: Fished system	Sard. avg. 1+B (kt)	1189.7
	Sard. avg. catch (kt)	108.08
	Sard. catch variability (V_{IA})	14%
	Juvenile sard. bycatch (kt)	0.89
	Sard. hi frame duration (ratio)	0.94

20. All the output metrics in this test are very sensitive to adjustments of the input parameters within a limited range. The similar shapes evident in Figure C.4 are due to the system frequently entering the sardine low–frame at low combinations of the input parameters. Results for the unfished system are nearly identical and are not reproduced here.

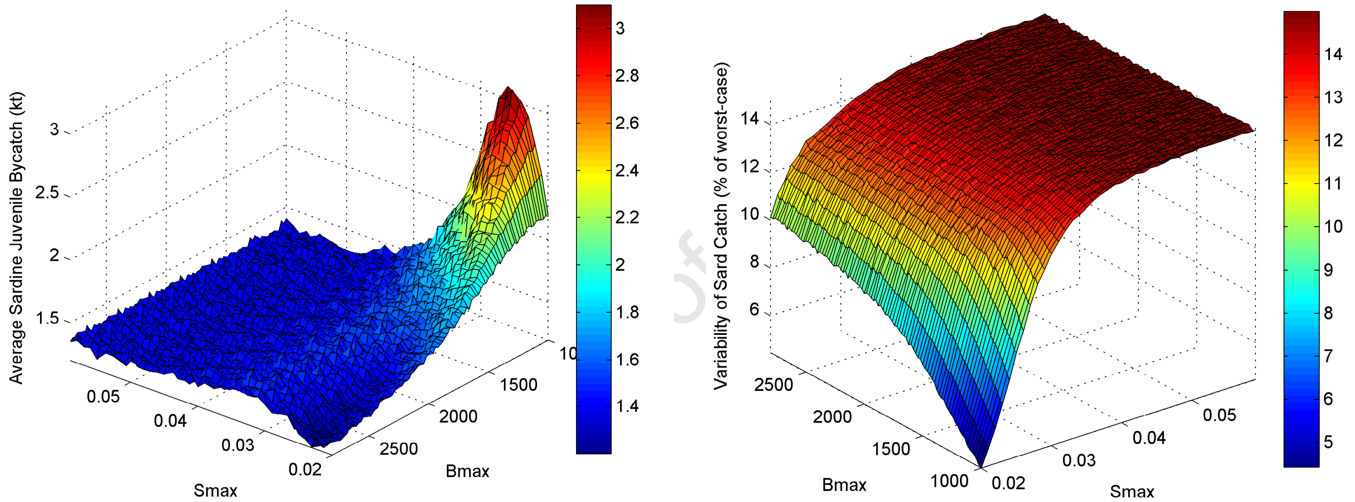
C.6 Test 6: Variations in the ESI–dependent Adjustments of the S–R Curve

The sensitivity of the recruitment to the environmental suitability index are explored in this test by varying a_1 from 10 to 18 in steps of 0.5 and a_2 from 20 to 30 in steps of 0.5. The results are presented in Figure C.5.



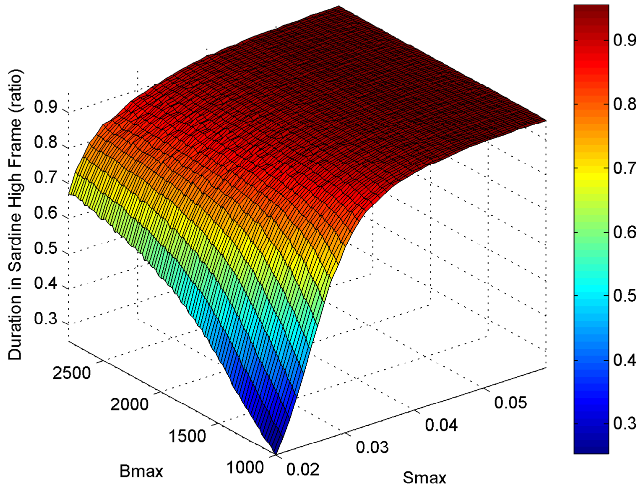
(a) Average Sardine Biomass

(b) Average Sardine Landings



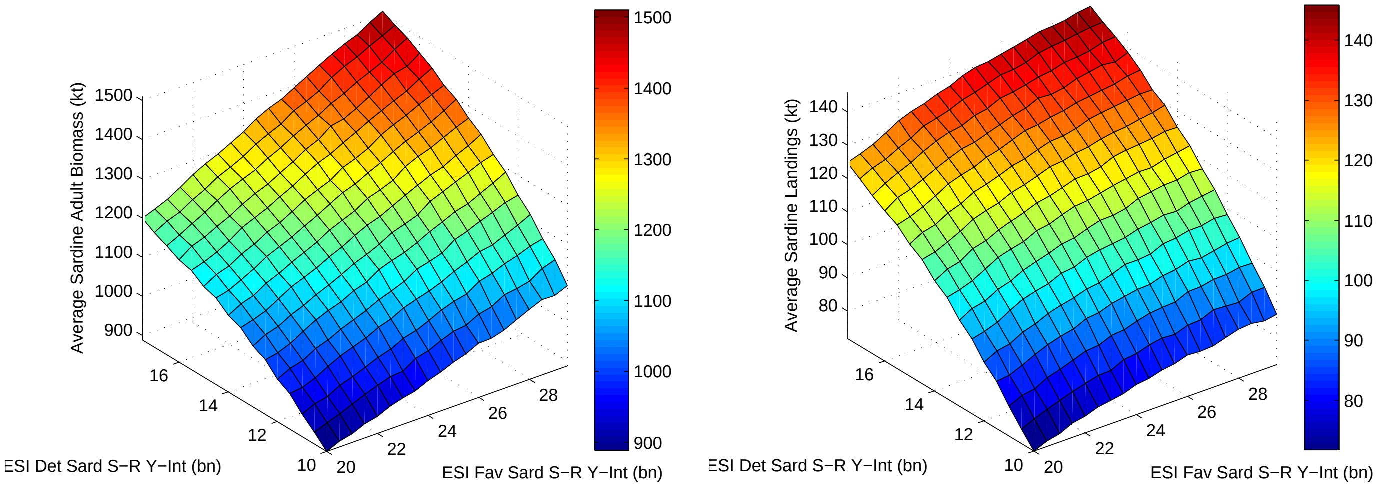
(c) Average Sardine Bycatch

(d) Sardine TAC Variability



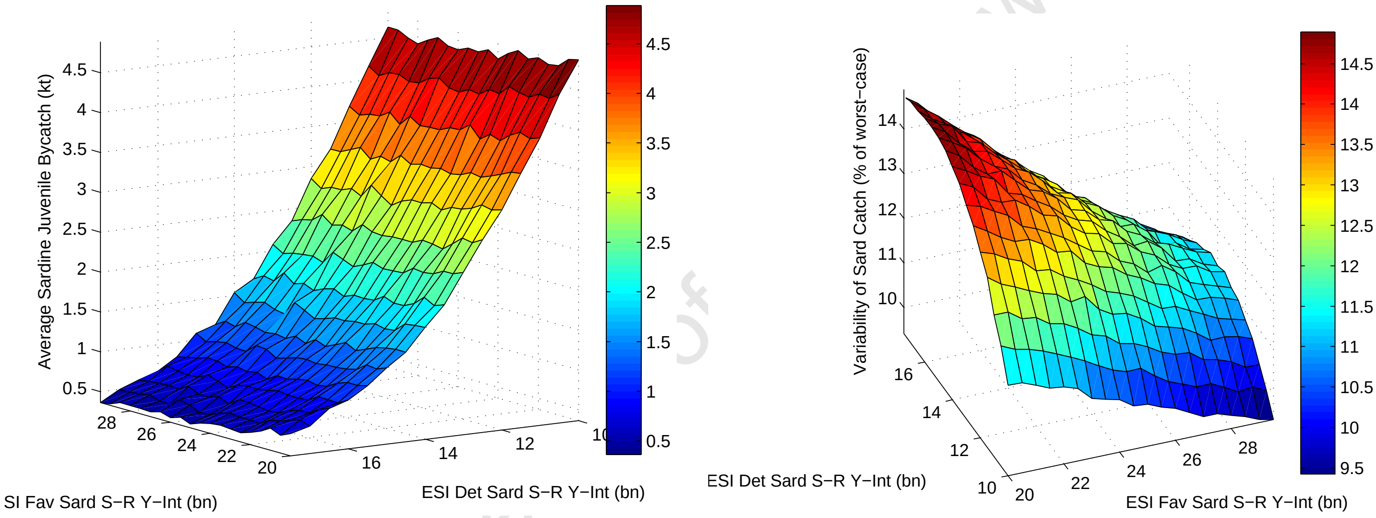
(e) Sardine High Duration

Figure C.4: Density Dependent Recruitment Sensitivities



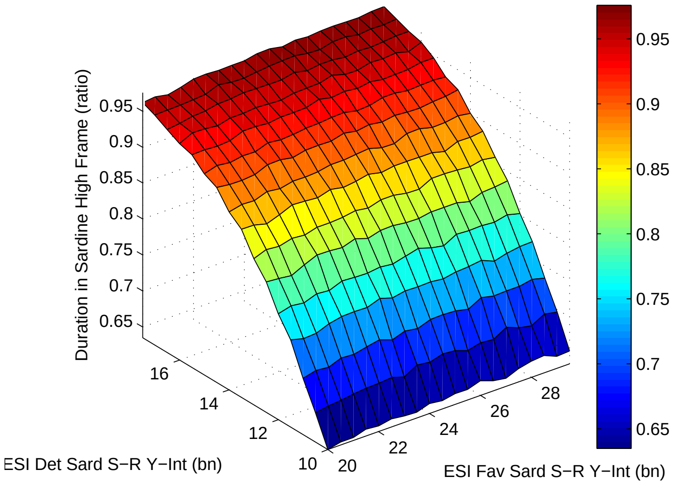
(a) Average Sardine Biomass

(b) Average Sardine Landings



(c) Average Sardine Bycatch

(d) Sardine TAC Variability



(e) Sardine High Duration

Figure C.5: ESI Dependent S–R Curve Parameter Sensitivities

Table C.4: Sensitivity to the Sardine Daemon Switching Thresholds

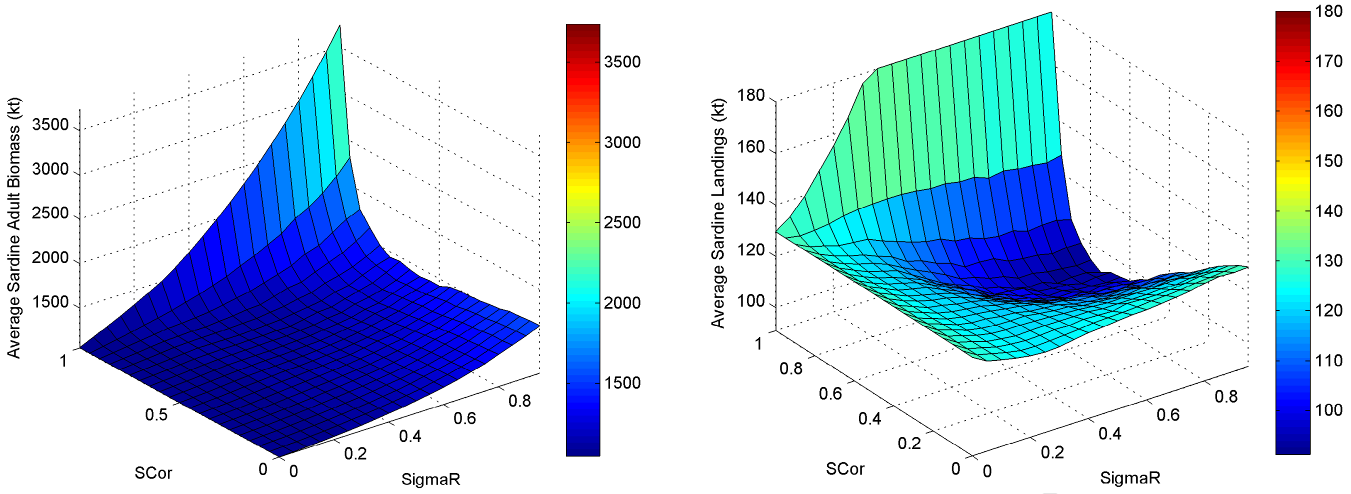
Metric	Description	Range
Avg. Sard. 1^+B	Mostly unnaffected by variations in B_{SD-h2l} and mildly sensitive to B_{SD-l2h} across all tested values.	Entire range
Avg. Sard. Catch	Mostly unnaffected by variations in B_{SD-h2l} and mildly sensitive to B_{SD-l2h} across all tested values.	Entire range
Variability of Sard Catch	Mostly unnaffected by variations in B_{SD-h2l} and mildly sensitive to B_{SD-l2h} across all tested values.	Entire range
Sard. Juvenile Bycatch	Mostly unnaffected by variations in B_{SD-h2l} and moderately sensitive to B_{SD-l2h} across all tested values.	Entire range
Sard. High Frame Duration	Mostly unnaffected by variations in B_{SD-h2l} and mildly sensitive to B_{SD-l2h} across all tested values.	Entire range

C.7 Test 7: Variations in the Stochasticity and Autocorrelation Parameters

While the parameters for this test are drawn from OMP–02, it is nonetheless interesting to explore their effect on the model outputs. The serial correlation parameter s_{cor} and the residual spread parameter σ_r are varied from 0 to 1 in steps of 0.01. The results are displayed in Figure C.6.

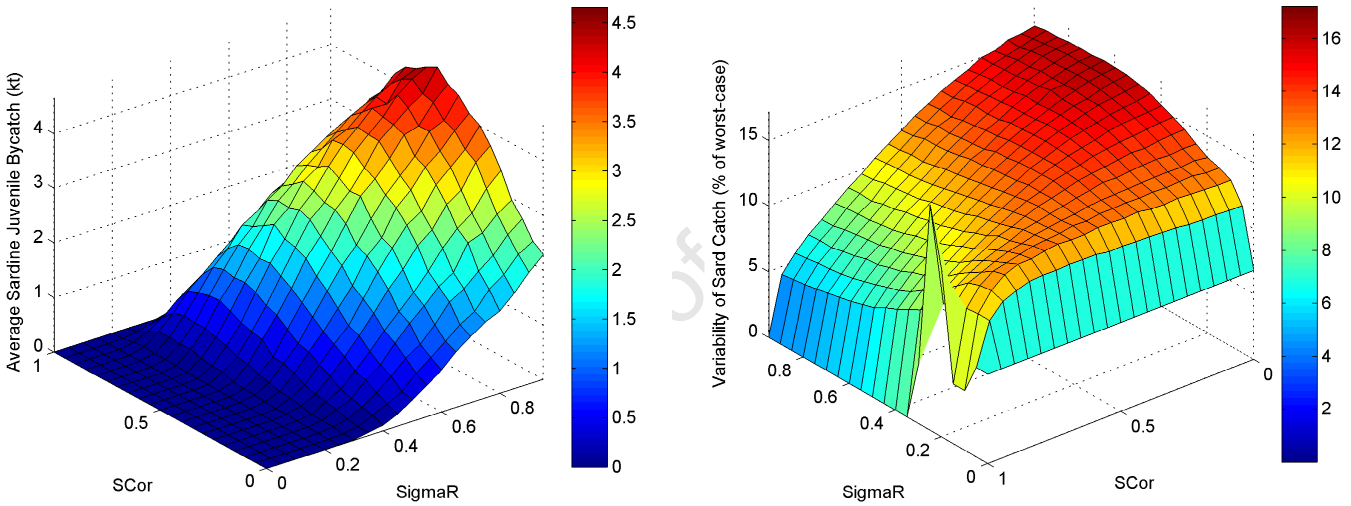
C.8 Test 8: Sensitivity to the Mortality Rate Parameters

These parameters are also drawn from OMP–02 and in this test the adult mortality is varied between 0.2 and 0.8 and the juvenile mortality is varied from 0.4 to 1.0. The results are plotted in Figure C.7.



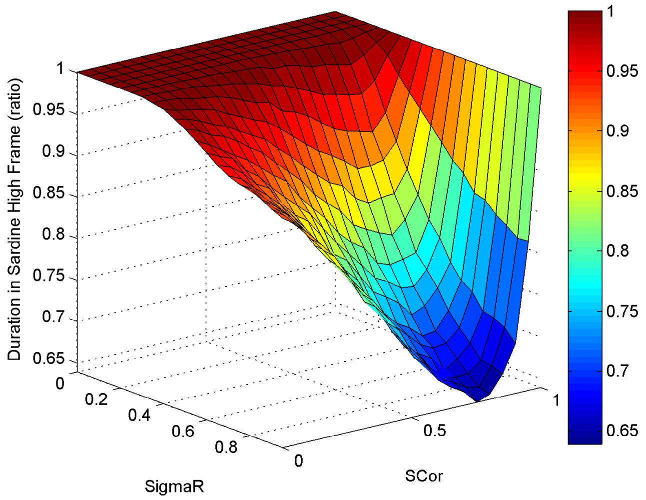
(a) Average Sardine Biomass

(b) Average Sardine Landings



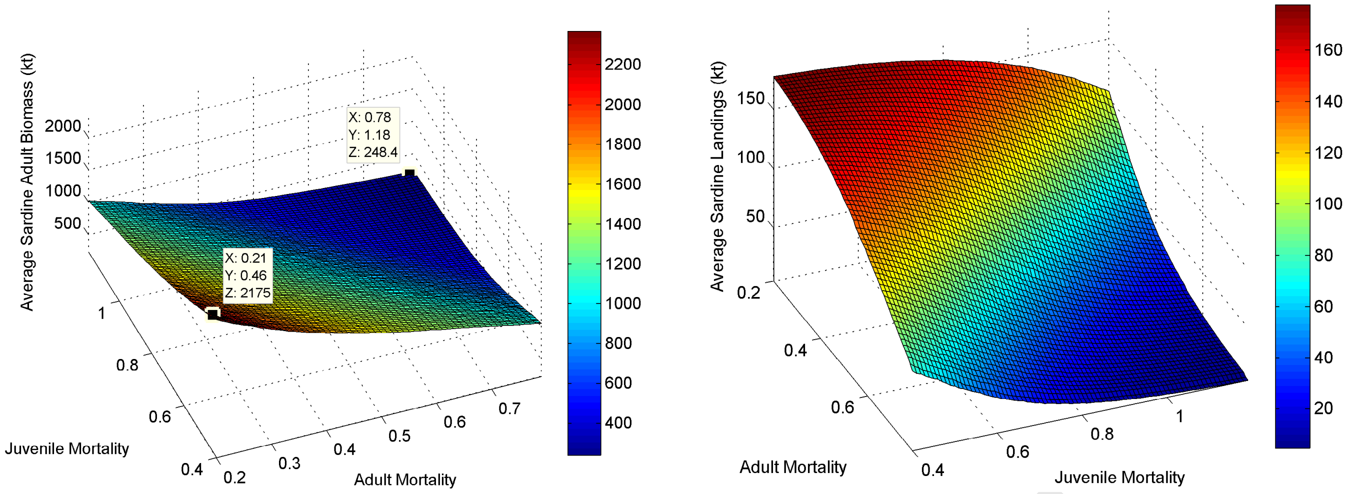
(c) Average Sardine Bycatch

(d) Sardine TAC Variability

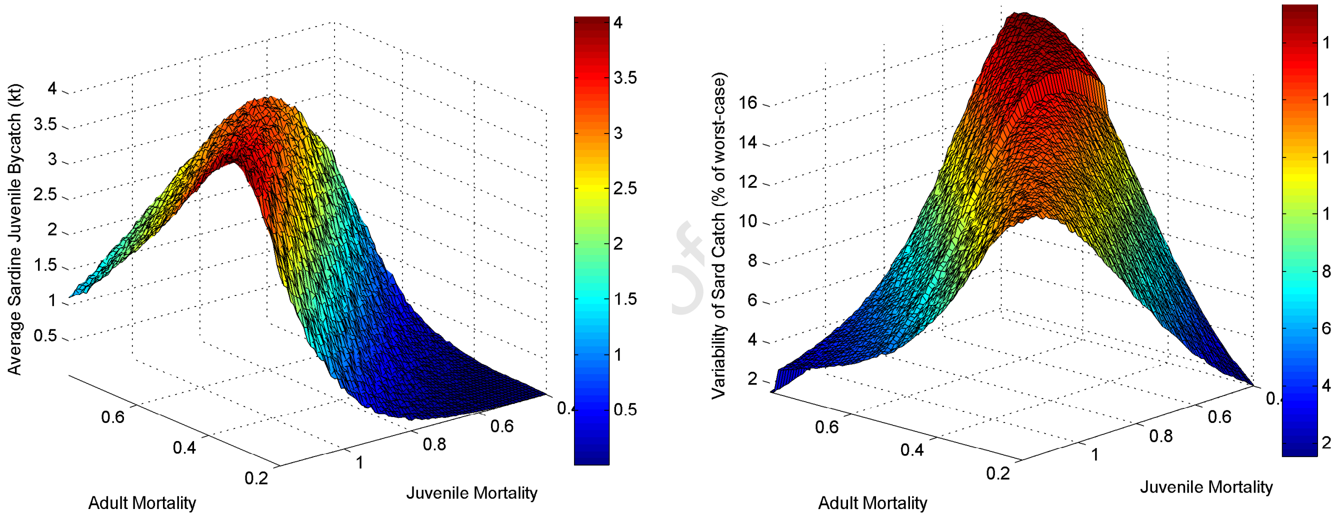


(e) Sardine High Duration

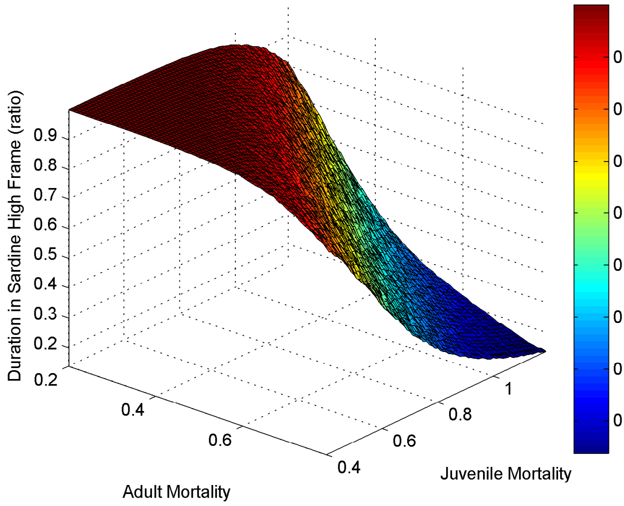
Figure C.6: Recruitment Variability Sensitivities



(a) Average Sardine Biomass **(b)** Average Sardine Landings



(c) Average Sardine Bycatch **(d)** Sardine TAC Variability

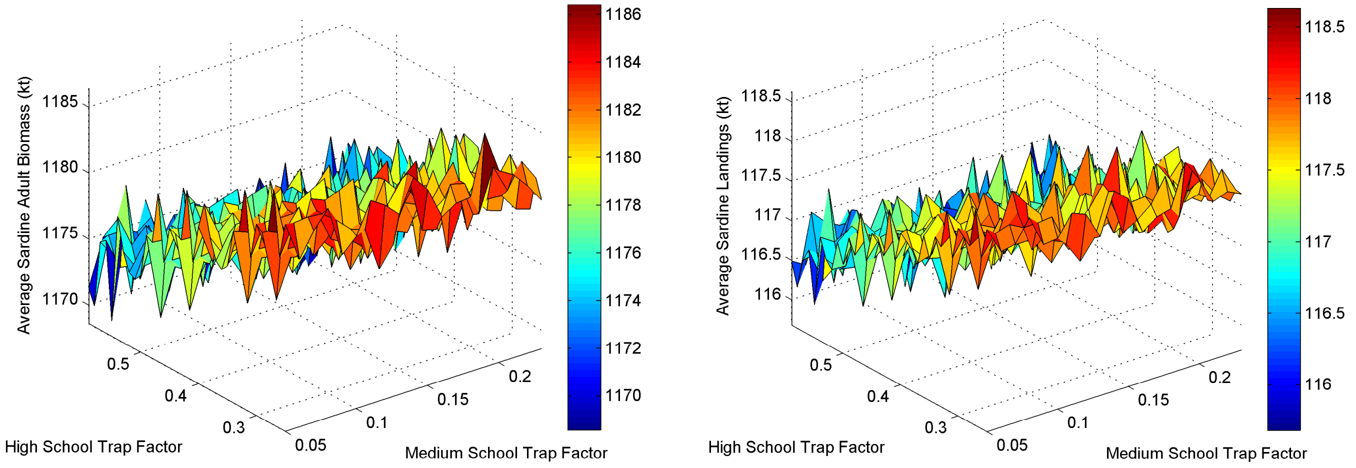


(e) Sardine High Duration

Figure C.7: Mortality Rate Sensitivities

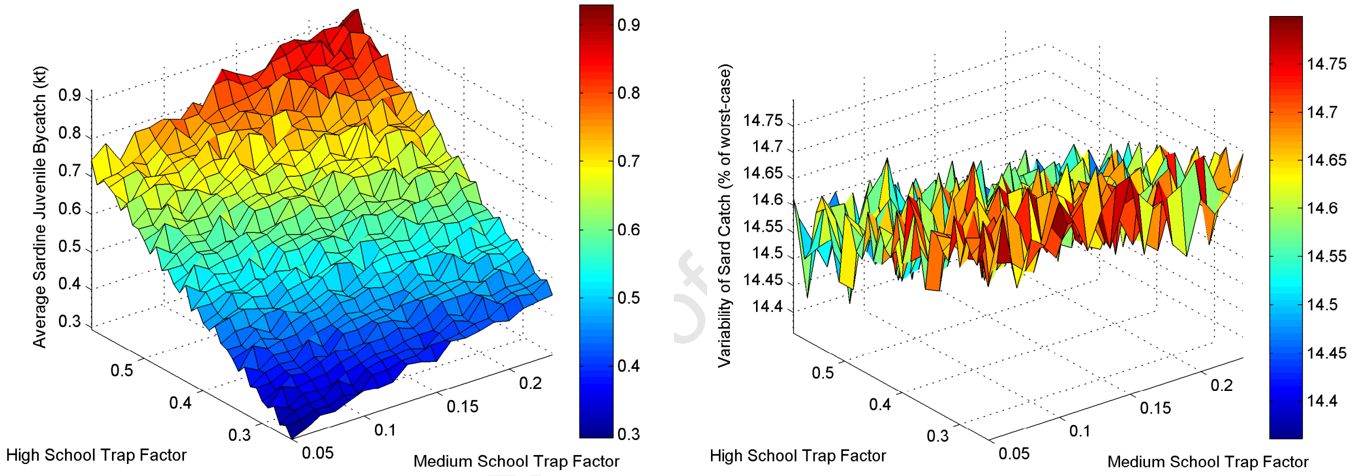
C.9 Test 9: Sensitivity to the School Trap Parameter

In accordance with the simple model, the age–structured model does not show much sensitivity to the school trap factor. This is because the AutoManager is designed to try to keep the sardine daemon in the high frame, and school trap is only effective in the low frame. The sensitivity would be expected to look different under more severe fishing scenarios. The results of the test are presented in Figure C.8.



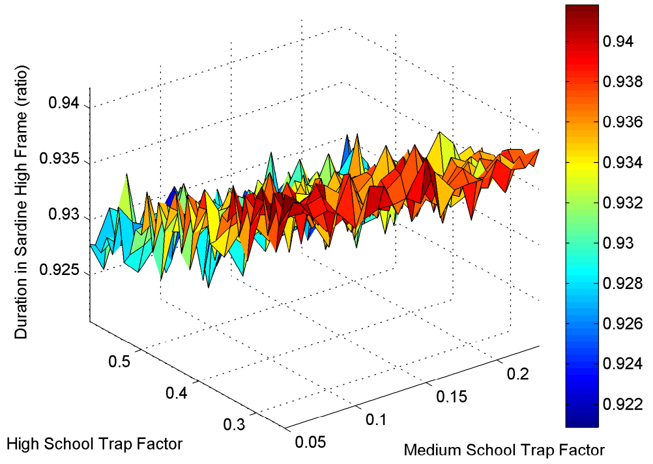
(a) Average Sardine Biomass

(b) Average Sardine Landings



(c) Average Sardine Bycatch

(d) Sardine TAC Variability



(e) Sardine High Duration

Figure C.8: School Trap Factor Sensitivities

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