Modelling regime shifts in the southern Benguela: a frame-based approach

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Abstract

Small pelagic fish populations in productive upwelling systems are characterised by long-term patterns of alternating dominance. Sardine and anchovy are the most important small pelagic species in the southern Benguela ecosystem, which has been shown to have undergone regime shifts during the past 50 years. Modelling regime shifts at an ecosystem scale can be of great importance in fisheries management, to aid in long-term planning and fishing strategy evaluation. Frame-based modelling has been successfully applied to regime shift dynamics in terrestrial ecosystems. The pattern of abrupt shifts between quasi-stable regimes suggests the usefulness of a frame-based approach in the southern Benguela ecosystem, with separate frames describing each small pelagic fish dominance pattern. Frame-based modelling is applied to sardine/anchovy dynamics under the influence of climate variability involving interaction with the small pelagic fishery. Four frames are used in the model: Both Species High; Sardine High / Anchovy Low; Anchovy High / Sardine Low; and Both Species Low. Switching rules for transition between the frames are described. Rapid prototyping is used to construct and test first- and second-generation prototypes of a frame-based model. A sensitivity analysis of the model is performed, and the model is found to be sensitive to the frame switching rules. The model is also reasonably sensitive to the sardine population model parameters, and the influence of juvenile sardine bycatch is noticeable in the "Sardine Low" frames. The model behaviour is relatively insensitive to climate variability, but the inherent degree of stochasticity in the sardine recruitment calls for continuous population monitoring and adjustment of fishing levels to avoid crashing the modelled sardine stock. Frame behaviour in the model is sensitive to sardine fishing activity. The model is exercised in a variety of scenario analyses, and confidence in the model is strengthened by the observed parallels to the real world. The use of the model as a "test platform" is explored to improve understanding of fishing impact on the dynamics of small pelagic populations. Previously identified advantages of the frame-based modelling technique include their particular usefulness in inter-disciplinary teams and the ease with which a frame-based model can be expanded and modified, and the experiences of this project support these findings. The use of frames as indicators adds information about the condition of the modelled stock at a given point beyond what can be inferred by population levels alone. Frame-based modelling is also found to be an approach well-suited to the development and maintenance of the computer software which encapsulates the model, and as a common interface between biologists, programmers and non-specialist model users. Suggested applications of the model include deriving "probabilities of change" for use in an expert system to predict long-term ecosystem changes. Applications of the model in understanding the impact of survey data error and compliance issues are discussed.

Keywords: *frame-based modelling, ecosystem, rapid prototyping, fisheries management, regime shifts, southern Benguela*

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1. Introduction

1.1 Dynamics of small pelagic fish dominance in upwelling systems

The objective of this research is to evaluate the usefulness of the frame-based modelling technique to provide an adequately realistic simulation of sardine and anchovy interactions in the southern Benguela upwelling region over multi-decadal time-scales to serve as a test-bed for evaluating the effectiveness and benefits of different fisheries management strategies. An important goal of fisheries science is to assess the trade-offs between the conflicting objectives of ecological stability and long-term human well-being. In view of the high uncertainties in our understanding of marine systems, models such as the one described here are invaluable in assisting decision-makers to weigh the advantages and disadvantages of competing fisheries strategies in a changing environment. We intend to explore the usefulness of the frame-based modelling technique in approaching this kind of ecosystem challenge.

1.1.1 Interactions between sardine and anchovy populations

Sardine and anchovy (*Sardinops* spp. and *Engraulis* spp.) are two of the most widespread and consistently fished of commercial stocks. Collectively, the small pelagics are the largest component of the global capture fisheries, representing over 25% of the total catch each year (FAO, 2005). As a result of the important fisheries they sustain, the population dynamics of these fish have received much attention. Although there are certain regional variations in the details of species and the exact dynamics of the upwelling systems in which they flourish, there are sufficient similarities to draw useful parallels.

The dynamics of the food web in an ecosystem with small pelagics can display top-down characteristics (e.g. Japan, Ghana), or bottom-up (e.g. Benguela, Humboldt), but the small pelagics occupy a niche notable for very low species richness – the “wasp-waist” position (Cury et al., 2000).

This means that the population variance of a very small number of species, whether through climate variability or human exploitation, can have significant effects on the ecosystem as a whole. In the southern Benguela ecosystem, the local species of sardine (*Sardinops sagax*) and anchovy (*Engraulis encrasicolus*) provide food for several threatened bird species (e.g. Cape Gannet and albatross), Cape fur seal, cetaceans and larger predatory fish. In South Africa, the sardine and anchovy fishery is the largest fishery by volume and the second largest in value (Shannon et. al., 2006), and so the success of the sardine and anchovy fishing industry is also of considerable human importance.

These species are also remarkable for the extremely high degree of variability in population sizes which they exhibit (e.g. Pauly and Tsukayama, 1987), and the biomass trajectory record from the southern Benguela (Figure 1) is fairly typical. Superimposed on the inter-annual variability are decadal-scale population fluctuations, which are generally characterised by one or other of the sardine and anchovy dominating, rather than both populations being simultaneously high or low. This pattern of variation has been noted in all ecosystems where the two species co-exist, not only the southern Benguela (e.g. Lluch-Belda et al., 1992; Schwartzlose et al., 1999; Jarre et al., 1998). The root causes of the fluctuations are believed to lie in long-term, low-frequency environmental factors (Alheit and Niquen, 2004), although the sardine population in particular may be severely affected by fishing (Boyer and Hampton, 2001; Fairweather et al., 2006a; Coetzee et al., 2006).

Because juvenile sardine school with anchovy in the southern Benguela, anchovy fishing inevitably results in significant juvenile sardine bycatch, and thus the sardine population may be affected even when not targeted (Shannon et al., 2006). This complication may be even more pronounced where the sardine population is already low, as there appears to be an increased incidence of juvenile sardine schooling with adult anchovy as the sardine population declines (e.g. Jordán et al., 1978), making them particularly susceptible to the "school trap", where the feeding and survival strategy of a mixed school is determined by the adult anchovy, resulting in sub-optimal schooling behaviour, reduced growth and higher mortality for the juvenile sardine stock (Bakun and Cury 1999; Bakun, 2001; Cury et al., 2000).

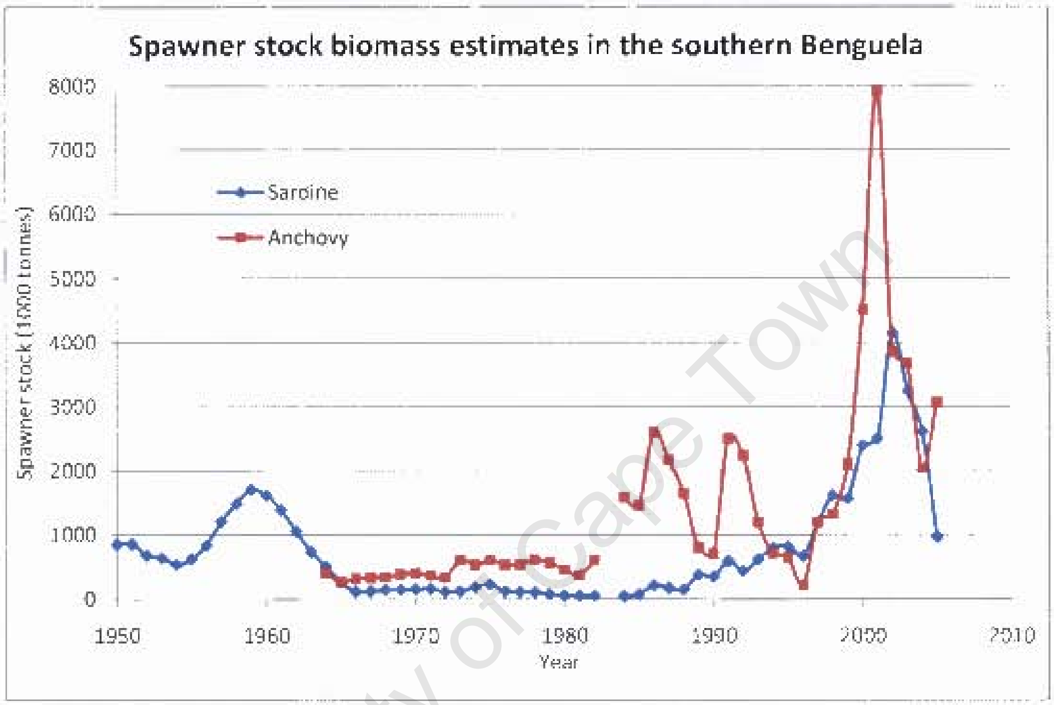


Figure 1 - Spawner stock biomass estimates of sardine and anchovy in the southern Benguela, showing a high degree of inter-annual variability. Note: figures before 1984 are reconstructed virtual population assessment (VPA) data (van der Lingen et al. 2006a, updated by Marine and Coastal Management).

The most likely natural controlling factor to induce a strong change in the biomass of small pelagics is the availability of food (van der Lingen, 1994). Although both sardine and anchovy tend to exist in each system, and a particular system tends to be dominated by either one or the other at any given point, direct competition does not appear to explain the data as the two species eat different food, with anchovy predominantly employing particulate feeding on large zooplankton and sardine overwhelmingly choosing to filter-feed on small zooplankton and phytoplankton (van der Lingen, 1994). For both sardine and anchovy, food availability is related to upwelling strength, but in different ways: anchovy require strong upwelling and cold water for spawning success and survival of larvae to recruitment, as these conditions favour the growth of large zooplankton. Sardine, in contrast, depend on warmer water for the preferential growth of smaller zooplankton, and exhibit reduced recruitment success under conditions of strong upwelling (Borges et al., 2003). Although a strong inverse correlation between small pelagics and their favoured prey is generally observed, it is difficult to determine whether this is due to top-down or bottom-up control: i.e., whether there is an increase in large zooplankton due to decreased predation by anchovy, or whether the increase in large zooplankton occurs because the small pelagic system is moving towards sardine dominance as a result of reduced predation pressure on sardine (Verheye and Richardson, 1998).

Historical records under negligible or non-existent fishing also support the regime shift patterns between sardine and anchovy dominance in upwelling systems, even in the absence of human intervention (Baumgartner et al., 1992). Natural fluctuations of the populations in the upwelling system off California are believed to have operated historically in alternating cycles of anchovy and sardine dominance, as evidenced by scale-deposition analysis of sediment samples (Baumgartner et al., 1992).

1.1.2 Regime Shifts

Regime shifts are described as major changes in the structure of an ecosystem which alter the energy flows in the system across several trophic levels and species (Jarre et al., 2006). The transition period should also be short in relation to the time spent within each regime (Jarre et al., 2006). Within the data record for the Benguela system, there have been clear regime shifts due to human influences (i.e. fishing pressure) and also regime shifts from largely environmental forcing (Cury and Shannon, 2004).

The data for the time series from 1950 in the southern Benguela have been analysed through the sequential t-test algorithm for regime shifts (STARS), and there was clear evidence of two major ecosystem changes in the 1960s and early 2000s (Howard et al., 2007). The first of these was thought to be due to excessive fishing pressure, while the later change was driven more by environmental influences than human activity (Howard et al., 2007). There is also some evidence of ecosystem shifts in the 1950s and the mid-1970s (Howard et al., 2007).

The STARS analysis included a broad range of data series from Marine and Coastal Management, in part unpublished, which were kindly made available to us, complemented by oceanographic data series pertaining to coast and shelf extracted and kindly put at our disposal by Dr. Claude Roy (IRD Brest, France). With the oceanographic data it is possible to assess the suitability of the environmental conditions to either anchovy or sardine recruitment, even in the absence of survey data. Further support is found in seabird abundance data from the 1950s to present, which critically depend on small pelagics. Another helpful data series stems from snoek (*Thyrsites atun*), which feeds largely on small pelagics, but is enough of a generalist that its stomach contents are thought to reflect prey species availability in the sea (McQueen and Griffiths, 2004). Snoek diet composition data suggest low anchovy abundance in the late 1950s, and an increasing proportion of anchovy in snoek diet (most likely due to depleted sardine stocks and relatively high anchovy abundance) in the late 1960s and early 1970s (Marine and Coastal Management, unpublished data) suggest anchovy dominance over sardine.

Indicators for such ecosystem regime shifts would ideally be data at a primary productivity level (e.g. Tester et al., 1997). In the southern Benguela ecosystem, however, the current understanding of the dynamics of primary production is not sufficient to observe regime shifts from phytoplankton data (Demarcq et al., 2008), and multiyear gaps as well as seasonal restriction in the zooplankton data (Verheye et al., 1998) hinder the understanding of long-term zooplankton dynamics (Verheye et al., 1998). The data from the planktivores, at the basis of the intermediate and high levels of the food web, allow for analysis of regime shifts at an ecosystem scale (Howard et al. 2007).

1.1.3 Modelling for fisheries management

The modelling exercise conducted for this research is seen as a step in a larger process of building more useful systems for providing scientific support for fisheries management decisions. The models described and built in this study are all highly stochastic, as the pertinent features of the system (sardine and anchovy population levels, climate characteristics, etc.) are all characterised by high variability. Any outputs from the models are thus qualitative and probabilistic in nature: it is not possible to say, in a stochastic system, that if the fisheries are managed with a certain plan, that there will be a certain precise level of harvest of sardine and anchovy which can be expected. It is possible, however, to begin to assign probabilities to certain outcomes under various management strategies.

Models such as those described in this paper allow us to explore consequences on an ecosystem scale and then contribute to the "probability of change" for expert systems (such as proposed by Jarre et al., 2006). In the context of a complex ecosystem, models which look at the stocks at an ecosystem level (rather than single species under fishing pressure) are far more useful for exploring the effects of long-term ecosystem changes in a way which provides realistic outputs for management (Jarre et al., 2006). Importantly, objective-focussed models allow us to start linking management actions and strategies with specific objectives. Through the exercise of constructing and experimenting with the models built to meet specific objectives (rather than all-purpose simulations), an understanding can develop of what indicators are pertinent for a decision-making procedure. This helps to give more relevance to the current inputs to the decision process (survey fish stocks, climate data, etc.), and also may suggest additional data which would be useful as indicators for fisheries management. Indicators are valuable as tools for management and allow for multi-disciplinary analysis of collected data and the development of a knowledge base for management (Fairweather et al., 2006b).

Rule-based modelling is particularly valuable in a multi-stakeholder context, where the comparative ease of understanding inherent in a rule-based system can make it easier to win support from non-scientific users and decision makers (Jarre et al., 2008).

1.2 Frame-based modelling of ecosystem dynamics for management

1.2.1 The frame-based modelling paradigm

Our specific area of investigation in this study is the applicability of frame-based modelling to evaluating fisheries management strategies. Traditional modelling techniques have faced challenges when attempting to describe complex ecosystem interactions. Classical predator-prey models such as those described by Lotka and Volterra in the 1920s are mathematically neat, but fail to account for the complexities of real-world food webs and the stochasticity of species populations in an unpredictable environment. The other extreme, involving massively complex combined ecosystem models in which each physical and biological element is modelled individually, typically becomes too complex to be either reliable or useful. Compounding uncertainties in each of the components in such a model are an inescapable challenge, and the time and expense of developing such a system for management purposes is difficult to justify (Degnbol, 2003). In this light, it is useful to build a model by starting with a specific objective, and then create the simplest model which can adequately meet that objective. Any layer of complexity which is not strictly relevant in light of the objective can then be omitted for simplicity (Starfield and Bleloch, 1991).

To illustrate with a practical example, let us consider a model for the management of the sardine and anchovy fishery. A complex ecosystem model incorporating the climate and physical dynamics of the southern Benguela upwelling system would be extremely difficult and time-consuming to develop, and may not be realistic in its reactions to external factors such as fishing pressure. Although such models are under development (Shin et al., 2004; Shannon et al., 2009), it has not yet been possible to bridge the dynamics at various scales into a model useful for management. In pursuing an alternative approach, we rather start with a general objective:

> "We need to model the population response of sardine and anchovy to the influences of fishing pressure and climate variability, such that we can make recommendations as to the most appropriate management strategy for their fisheries under given conditions of population structure and climate."

With this as our goal, anything which does not influence the management strategy can be disregarded. Seabird activity, benthic structure, interactions between all other parts of the ecosystem can all be eliminated. We do not pretend that the resulting model will be an accurate and comprehensive description of the ecosystem, and for the successful implementation of an ecosystem approach to fisheries (EAF), we may need to introduce some of these factors into a later version of the model. But we do believe that a model can be built which will answer our questions in a way which suggests an appropriate course of action for the fisheries management and takes into account the long-term trends and underlying health of the small pelagic populations.

We observe that ecosystem dynamics can often be considered in terms of quasi-stable periods of equilibrium, punctuated by relatively abrupt shifts to a new, also quasi-stable, state (e.g. Jarre et al., 2006). An early application of frame-based modelling described shifts in the character of a pine forest in terms of stable states (or "frames") which last for several decades, until an abrupt shift moves the forest to an alternative, also stable, state (Tester et al., 1997). Each frame in such a system can be modelled independently, provided that the rules which determine the switching between frames are adequately described. The objective of the pine forest model was to optimise time spent in certain frames for the purposes of forestry management, and so while in any particular frame, the model needed only to determine whether it stayed in that frame for another year or switched to an alternative frame.

For the pelagic fisheries, we observe that each of sardine and anchovy populations appear to fluctuate in a way that could be described by a “high” and “low” population state for each species. The ecosystem as a whole displays periods of “high” population for both sardine and anchovy, periods where only one species is dominant, and periods where both species are in a “low” population state. If our aim is to understand the frame-switching well enough to consider management implications, we need to describe each frame well enough to determine whether the system stays in that frame or moves into another frame. It will of course also be necessary to have a reasonable understanding of the mechanics within the individual frames.

Inherent in frame-based modelling is the concept of a “daemon”, which is described as an agent (independent of the frames) which monitors the dynamics within the frames, and which will prompt the model to switch frames. The default behaviour of the overall model is to stay within a frame unless a daemon prompts a shift to a new frame. The switching rules are thus encapsulated in the daemon, not within each specific frame.

1.2.2 Spatial aspects

The general approach for using frames to model ecosystem dynamics is a three-part process (Starfield and Chapin, 1996; Rupp et al., 2000a):

1. Break down the system into suitable spatial units (or blocks).
2. Model the dynamics within a particular spatial unit with a frame-based model
3. Model the dynamics between adjacent blocks with cellular automata.

For this study, a fine-resolution partition of the area into blocks is not useful, as the spatial aspects within a region (e.g. Southern Benguela, Eastern Cape, etc.) are not relevant: the populations under consideration are mobile throughout the region, rather than being spatially discrete. Furthermore, management of the fisheries is not spatially specific: the TAC (Total Allowable Catch) quotas for each species are allocated annually to the entire region. Thus the ecosystem dynamics of the entire area can be described by frame-based modelling alone.

2. Materials and methods

2.1 Description of frames and frame-shifts in the Southern Benguela

An important feature of frames in small pelagic systems is the potential for short residence times and fast frame switching due to the short lives of the species involved. In contrast to, for instance, a model of a forest in which the trees can live for many decades, the species that we are modelling recruit after one year and live for 3-8 years. Thus there is the potential for a significant change to take place in the population levels in time periods of the order of 1-2 years (van der Lingen et al., 2006a).

The regime shifts in the southern Benguela are driven by bottom-up ecosystem influences, in contrast to the less productive northern Benguela, which appears to be more susceptible to the top-down influence of fishing to initiate regime shifts (Cury and Shannon, 2004). The southern Benguela saw a sharp decline in sardine stock sizes after poor recruitment and heavy fishing in the 1960s, followed by a recovery in the sardine stocks from the mid-1980s (van der Lingen et al., 2006a). In the northern Benguela, by contrast, when the sardine population declined after heavy fishing and poor recruitment from 1965-75, the system did not exhibit a simple shift to an anchovy regime, as the ecosystem niche had been filled instead by other planktivorous fish such as horse mackerel (*Trachurus capensis*) and bearded goby (*Sufflogobius bibarbatus*) (Boyer and Hampton, 2001). It is believed that heavy fishing on anchovy during the 1970s exerted a top-down control which prompted the switch to an alternative goby / horse mackerel regime in the northern Benguela (Cury and Shannon, 2004).

The northern and southern Benguela show sharply contrasting regime shifts and responses to fishing pressure, despite the many similarities between the ecosystems (Cury and Shannon, 2004). An advantage of frame-based modelling in the face of such systems is that it allows for adaptation and inclusion of alternate new frames in the event that an ecosystem undergoes a fundamental change, rather than requiring an entirely new model (Rupp et al., 2000b). Changes within a single frame, such as the behaviour of anchovy in periods of "low" population, can also be confined to that particular frame and do not affect the rest of the model.

The traditional approach to modelling small pelagics has been to model alternating dominance of sardine and anchovy in a two state system (Jarre et al., 1998; Shannon et al., 2003). We believe that there is evidence of alternative states in which both species are simultaneously "high" or "low" (Howard et al., 2007; Jarre et al., 2007), and so we have included four frames in our model.

The frames we consider may be illustrated as in Figure 2. Note that the colours used for the frames in Figure 2 are retained throughout the paper and used in frame indicator bars for each prototype.

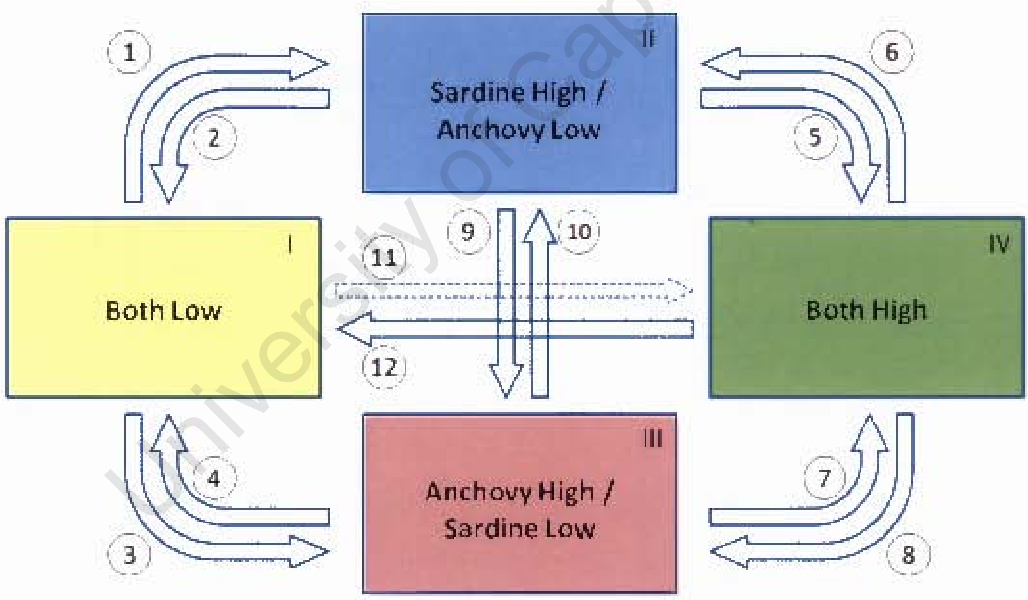


Figure 2 - Schematic of frames and transitions for the model. Numbered arrows refer to the shifts described in the Table 2

The frames which we consider are described in Table 1:

Table 1 - Frames considered for the modelled small pelagic ecosystem of the southern Benguela.

Frame Name	Frame Characteristics	Examples / Literature
I. Both Species Low	Low stock sizes and low to moderate recruitment of both species. Likely the result of simultaneous over-fishing of sardine in conjunction with an environment which is unfavourable for anchovy.	Mid-1960s [1]
II. Sardine high / anchovy low	High sardine population with moderate to high recruitment, and poor to moderate anchovy recruitment.	Late 1950s (snoek diet data and small pelagic larvae monitoring data suggest sardine dominance [1]) Mid-1990s [1]
III. Anchovy high / sardine low	Low sardine population with high anchovy population and highly variable anchovy recruitment. Most likely due to (previous or continued) overfishing of sardine in an environment favourable for anchovy. Heavy anchovy fishing may also have a negative influence on sardine due to juvenile sardine bycatch.	Early 1980s [1]
IV. Both species high	Anchovy will tend towards a "high" state under suitable environmental conditions. Sardine will tend to remain "high" under carefully managed, light fishing even if environmental conditions are sub-optimal.	Early 2000s [1]. Appears to also have been influenced by the increased habitat made available by increased upwelling along the south coast.[2]
[1] Marine and Coastal Management (unpublished data) [2] Roy et al. (2001)		

The conditions which would prompt switching between these frames are detailed in Table 2.

Table 2 - Shift conditions for switching between the frames described in Table 1.

Shifts	**Mechanism**	**Examples and Literature**
From Both Species Low:		
Switches to Sardine High (1)	in conditions of weak upwelling (which favours small meso-zooplankton and flagellates). Such conditions are not as favourable to anchovy due to reduced productivity of large diatoms [1].	Early to mid-1990s.
Switches to Anchovy High (3)	under continuous fishing pressure on sardine and strong upwelling (which favours diatom growth and large meso-zooplankton, good for anchovy).	Possibly occurred with the shift in upwelling strength in the early 1970s [2]
Switching directly to Both High (11)	is not thought to be possible. Under a theoretically "favourable for all" situation, the anchovy population should recover faster due to their faster population growth rate and younger age at maturity, so the system should move through the Anchovy High frame first.	Unobserved and considered implausible.
From Sardine High:		
Switches to Both Low (2)	in conditions of continued weak upwelling (which remains unfavourable to anchovy recovery) and excessive fishing pressure on sardine. This may either be direct sardine fishing or excessive bycatch of juvenile sardine from anchovy- directed fishing.	Early 1960s, following heavy sardine-directed fishing
Switches to Anchovy High (9)	under excessive fishing pressure on sardine and strong upwelling (which favours diatom growth and is thus good for anchovy). As before, fishing pressure on sardine may be either direct or bycatch-driven.	Observed in other systems.
Switches to Both High (5)	under continued low fishing pressure on sardine (or a reduction in sardine fishing) coupled with improving environmental factors for anchovy recruitment (such as stronger upwelling).	1999/2000. The oceanography through the late 1990s became more favourable for anchovy, particularly with the cooling of the Agulhas Bank [3]

Table 2 (contd.)

From Anchovy High:		
Switches to Both Low (4)	in conditions of continued fishing pressure on sardine (which inhibits sardine recovery) and deteriorating environmental conditions for anchovy.	Mid 1980s?
Switches to Sardine High (10)	under low fishing pressure on sardine (which allows the sardine to recover) and reduced environmental favourability for anchovy. Environmental factors which are less favourable for anchovy will tend to aid the sardine recovery with sufficiently low sardine fishing.	Observed in other systems.
Switching to Both High (7)	would occur under continued favourable environmental conditions for anchovy recruitment (strong upwelling, etc) and reduced fishing pressure on sardine, which would allow for a recovery of the sardine population while remaining conducive to a high anchovy population.	Hypothesised for southern Benguela
From Both High:		
Switches to Both Low (12)	under excessive fishing pressure on sardine coupled with deteriorating environmental conditions for anchovy.	Hypothesised for southern Benguela
Switches to Anchovy High (8)	under excessive sardine-directed fishing and continued favourable environmental conditions for anchovy.	2005-present [2]
Switching to Sardine High (6)	would occur under continued low or absent fishing pressure on sardine, coupled with deteriorating environmental conditions for anchovy.	Hypothesised for southern Benguela
[1] van der Lingen et al. (2006b) [2] Howard (2007) [3] Roy et al. (2007)		

The driving forces of the shifts described above are:

- Fishing pressure, both from the sardine and from the anchovy fishery. Most influence from the fishery is felt in the sardine population, whether from direct increased sardine mortality from targeted fishing of the sardine stock, or from increased juvenile sardine bycatch mortality from the anchovy fishery. Sardine bycatch should be more significant in the "low"" sardine frames due to increased mixed schooling (Bakun, 2001).

- Environmental factors, which operate most markedly on anchovy but also affect sardine, (albeit to a lesser degree as they are less selective planktivores (van der Lingen et al, 2006b)). In addition to upwelling strength and the related availability of suitable plankton prey, factors such as the strength of transport currents towards and around the Cape of Good Hope in Novermber-December and the water temperature on the Agulhas Bank in September-October are important for successful anchovy recruitment (Miller and Field, 2002). Both species predominantly spawn on the Agulhas Bank and rely on transport currents to carry the larvae to the West Coast (van der Lingen et al., 2001). Relatively minor environmental shifts have been shown to produce significant shifts in geographical and population structure of anchovy (Roy et al., 2007).

- Current population level may be a factor due to sardine recruitment being limited by density-dependence (e.g. van der Lingen et al., 2006c), and the higher probability of the "school trap" phenomenon when the sardine population is low (Bakun, 2001).

Note that the default behaviour in all frames is to remain in that frame. A shift will only occur if conditions are met to force that shift. The rules which govern the shifts and the definitions of the frames are believed to be a useful representation of the underlying ecosystem, and thus are retained throughout the modelling exercise. The specific details of the models for each frame and the details of the daemons which prompt shifts between the frames will be determined individually for each successive prototype.

The time-step for the model is one year. Both sardine and anchovy spawn annually, and fisheries management strategy is unlikely to be updated more frequently than annually (although the TAC may be updated throughout the season), so reducing the time-step does not appear to confer any advantage.

2.2 Rapid prototyping

The modelling paradigm which is employed in the frame-based approach uses rapid prototyping to test initial hypotheses and assumptions. Based on the success (or limitations) of an initial prototype, a more detailed model can be developed, incrementally adding more complexity as gaps are identified and confidence in the general usefulness of the model grows. This allows the modeller to test an hypothesis during the model development and quickly adapt the model in light of the results.

There is also a great practical advantage to producing successive generations of models which are complete in themselves, because at any stage of the process there is a model available which can be exercised to address any urgent questions (Starfield, 1997). It may not be the best possible model, or the final generation of what is planned, but it is more immediately useful than a large and complex system which will only be useable once all the pieces are in place.

There are also advantages to starting with a simplified model even in cases where it is predicted that a detailed model will ultimately be needed. A simple initial model aids in clarifying objectives of the final model and improves understanding of the system which is being modelled (Starfield and Bleloch, 1991). Assumption and sensitivity analyses performed on an early prototype can then be used to inform the next generation of model (Starfield, 1997). Through the process of constructing a simplified "thought experiment" prototype and subjecting it to a rigorous analysis of assumptions and sensitivities, it will likely become clearer what data are needed, where the deficiencies in understanding are, and how to plot the course for a more complex version if necessary (Starfield and Jarre, in review). There is also a need for a thorough examination of plausible alternatives to the mechanisms involved wherever assumptions are made in the model (Nicholson et al., 2002).

As a mechanism and laboratory for conducting thought experiments, simple models may be more useful for communicating ideas and clarifying objectives in an inter-disciplinary team. In contrast to inscrutable or "black-box" models, which may be counter-productive at promoting common understanding in a an inter-disciplinary environment, simple models serve well as clarifying tools (Nicholson et al., 2002). Simple models can be adapted and redeveloped easily and cheaply as the group objectives become clearer.

For this study, all model design work was done in custom-written computer programmes (each prototype in a separate programme). The software for each prototype was developed entirely by the author. The code was written in C#, and the graphical user interface (GUI) for each model was designed for Microsoft® Windows® compatibility.

The term "crash" is often used in fisheries modelling to indicate a precipitous decline in stock size. With reference to our model, we refer to a "crash" of the sardine stock as an event in which the modelled sardine population drops to zero. Although a zero-size population is seldom achieved in real-world fishing (as the increasingly scarce target fish offer decreasing financial returns for the fishing effort), it is a useful simplification to allow our population model to be fished to zero for two reasons. Firstly, if the sardine were fished to extremely low stock sizes, it is possible that the ecosystem dynamics would be fundamentally affected (e.g., shift to a jellyfish/goby regime, as observed in the northern Benguela). Secondly, our model is designed as a prototype training tool for fisheries management. In this respect, a situation of totally depleted sardine should be regarded as a failure of the fisheries management for that model run.

3. First Prototype

3.1 Description of the first prototype

3.1.1 Programme overview

The initial prototype simulates 50 years of operation with a 1-yr time-step. The forcing factors which are included are:

- Sardine fishing activity, which is seen as influencing the sardine population model
- A general "Environmental Suitability Index" (ESI), which acts as a proxy for upwelling strength, sea surface temperature, spawning success, larvae condition, transport strength around the Cape of Good Hope and food availability. This factor strongly influences the modelled recruitment success of the anchovy population, and has a much weaker inverse influence on the sardine recruitment.
- Current population level of sardine, which is understood to influence recovery rate of the population due to density-dependent factors when the population is high.

Factors which are consciously ignored by this prototype include:

- More specific details on the factors making up the ESI, which would provide excessive additional complexity for the first prototype.
- The influence of the anchovy fishery on the anchovy population. Anchovy appear to have sufficiently random recruitment at observed levels of spawning stock size that it was not considered useful to use a detailed population model for that species.
- The influence of juvenile sardine bycatch from the anchovy fishery. A potential factor to be considered in later prototypes is that in reduced populations of sardine, increased frequency of juvenile sardine schooling with anchovy has been reported. This would lead to a higher

rate of juvenile sardine bycatch when the sardine population is already low if anchovy fishing continues.

- Compliance issues within the fishing industry. Examples of compliance issues would be illegal, unregulated and unreported (IUU) fishing operations, including unreported discard mortality. Either of these would result in a higher fishing mortality than the TAC set by fisheries management would suggest.

- Specific ecosystem influences, such as predator species populations.

We assume that the frame forcing factors which operate in the ecosystem actually operate only on individual species, and so our initial prototype operates with an independent forcing agent (daemon) operating on each species.

For this prototype, as the species are modelled independently, the models within each of the frames are effectively the sum of whichever state the individual species are in. Thus the programme includes a sardine model which behaves differently in "high" and "low" states, and an anchovy model, similarly with two states. The model for the "Anchovy High / Sardine Low" frame is the combined model of the "high" state anchovy model and the "low" state sardine model.

> **Note:** All population numbers used in the models are more or less arbitrary, and are useful only for comparative purposes. Some understanding of the stock biomasses involved could be obtained by assuming that all figures are in units of million tonnes of fish. This would bring stock sizes into the same order of magnitude as the historical biomass estimates.

> **Note:** All random numbers have been generated to fit a truncated Gaussian distribution (by averaging three random numbers), rather than a standard "flat" random number generation.

3.1.2 Anchovy Model

The anchovy population is modelled entirely stochastically. The population is random about a defined midpoint, with a defined variability.

- Anchovy Low: the population fluctuates about 0.5, with a variability of +/- 0.3
- Anchovy High: the population fluctuates about 1.5, with a variability of +/- 0.8

Note that the model for anchovy looks at the frame rather than the ESI for a specific year. We will see later that the anchovy daemon will prompt a shift to a new frame for anchovy based on the ESI, but the actual determination of the population is done according to the frame.

3.1.3 Sardine Model

The sardine follow a stochastic population model. The model determines the population for each successive year according to Equation 1.

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

- N_t : the modelled sardine population in year t. We use an arbitrary initial value of $N=1$ for the model.
- z : the natural mortality, is considered to be constant (set to 0.5).
- B : which determines the recruitment, is constant (set to 0.3).
- F_t : which represents the modelled sardine mortality due to fishing in year t.
- b : the recovery rate, is variable both within and between frames:

- To introduce a level of stochasticity to the population, b_t (the actual value of *b* used for the population generation of a particular year) is also randomised. The base value for *b* is 0.6, with a variance of +/- 0.3 in any given year.
- *b* is scaled down by a factor of 0.8 for a given year if ESI > 5 (indicating that the environment favours anchovy and is therefore less favourable for sardine).
- Based on density-dependency, the term is scaled up by a factor of 1.3 if the current frame is a Sardine Low system.

3.1.4 Forcing factors

The two forcing factors we consider are:

a. Environmental Suitability Index (ESI)

We consider the ESI to act as a proxy for the net effect of all the climatic and geographic forcings which affect the small pelagics. With our time-scales, the most significant observed effect is a roughly decadal temperature cycle, which is reflected in variation of sea-surface temperature (SST) data. The ESI is an integer value from 0-9, with a higher value indicating a more favourable environmental situation for anchovy recruitment.

Our model for the ESI involves a randomly generated integer which moves about a defined midpoint. Over the 50 year cycle, the ESI is determined according to this pattern:

- Year 0-9: ESI = 2, +/- 1
- Year 10-19: ESI = 6, +/- 1
- Year 20-29: ESI = 2, +/- 1

- Year 30-39: ESI = 8, +/- 1
- Year 40-50: ESI = 2, +/- 1

b. Sardine fishing

We use a Total Allowable Catch (TAC) model for the fisheries management, assuming 100% compliance by the fisheries and 100% success in catching the full TAC for a given year. In order to be able to compare the effects of different fishing strategies, we have modelled the following scenarios:

- No fishing.
- A fixed TAC for the entire 50-yr run. While unrealistic in practice, this does give an interesting reference point for alternative strategies. The model allows for a user-defined figure for the fixed TAC.
- Variable TAC. Under this setting, a simulated "robot manager" reacts to the changing population levels. This function looks at the stocks annually and sets the TAC for the following year according to a set of rules:
    - If $Pop_{(t-1)} > 0.6$, TAC = 0.4
    - If $0.6 \geq Pop_{(t-1)} > 0.4$, TAC = 0.2
    - If $0.4 \geq Pop_{(t-1)}$, TAC = 0

3.1.5 The Daemons

Prototype 1 has a separate daemon for each of sardine and anchovy, such that the sardine daemon will push that species between "high" and "low" frames, and the anchovy daemon will operate similarly on the anchovy stock to prompt a shift between "high" and "low" frames.

The state of the population will not shift frame unless it is specifically prompted: i.e., the default response of system is to remain in its current frame.

a. Sardine Daemon

The sardine daemon is directed by the current population of sardine.

- If sardine is in a "high" state, the daemon will prompt the system to shift to a "low" frame if the sardine population is below 0.4 for each of three consecutive years.
- If sardine is in a "low" state, the daemon will prompt a shift to "high" if the yearly sardine population exceeds 0.7 for three consecutive years.

b. Anchovy Daemon

The anchovy daemon considers the Environmental Suitability Index, not the anchovy population.

- If the anchovy is in a "high" state, the daemon will prompt a shift to "low" if the ESI has been below 4 for three consecutive years.
- If the anchovy is in a "low" state, the daemon will prompt a shift to "high" if the ESI has been above 5 for three consecutive years.

Looking back at the rules for ESI variation, this means that the modelled anchovy stock will invariably follow the following pattern (with a lag time of approximately 3 years):

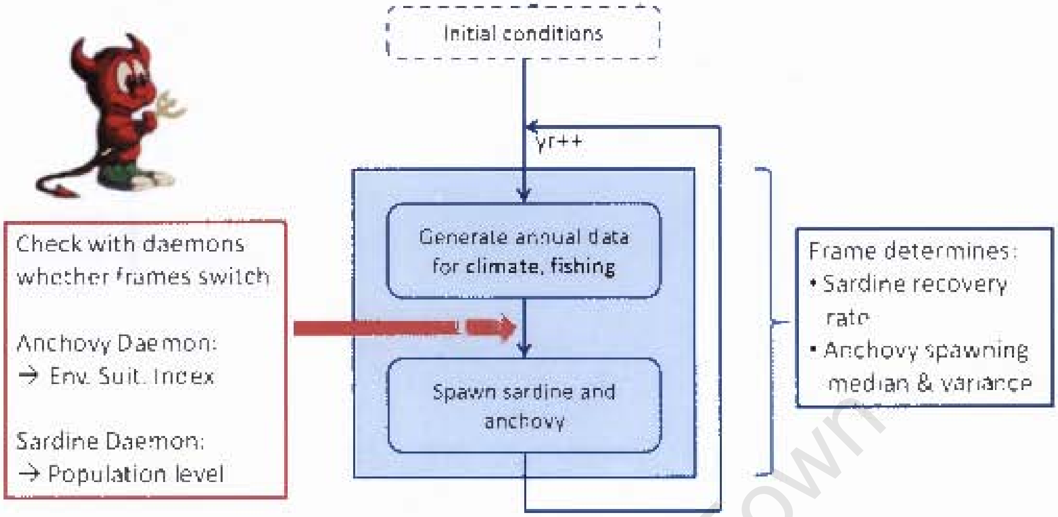
- 1st decade: "low" frame.
- 2nd decade: may shift to a "high" frame for some or all of the decade.
- 3rd decade: "low" frame.
- 4th decade: definitely shift to a "high" frame.
- 5th decade: "low" frame.

3.1.6 Running the First Prototype

The model in the first prototype runs according to this routine:

- After establishing the initial conditions, the programme generates data for fishing activity and climate effects based on the current frame.
- The daemons then look at the current and historical environmental situation and population levels, and decide whether to shift to a new frame or remain in the current frame.
- The sardine and anchovy stocks spawn, with their recruitment characteristics based on the current frame.
- Repeat for each subsequent year in the run.

A conceptual overview of the programme is shown in Figure 4.



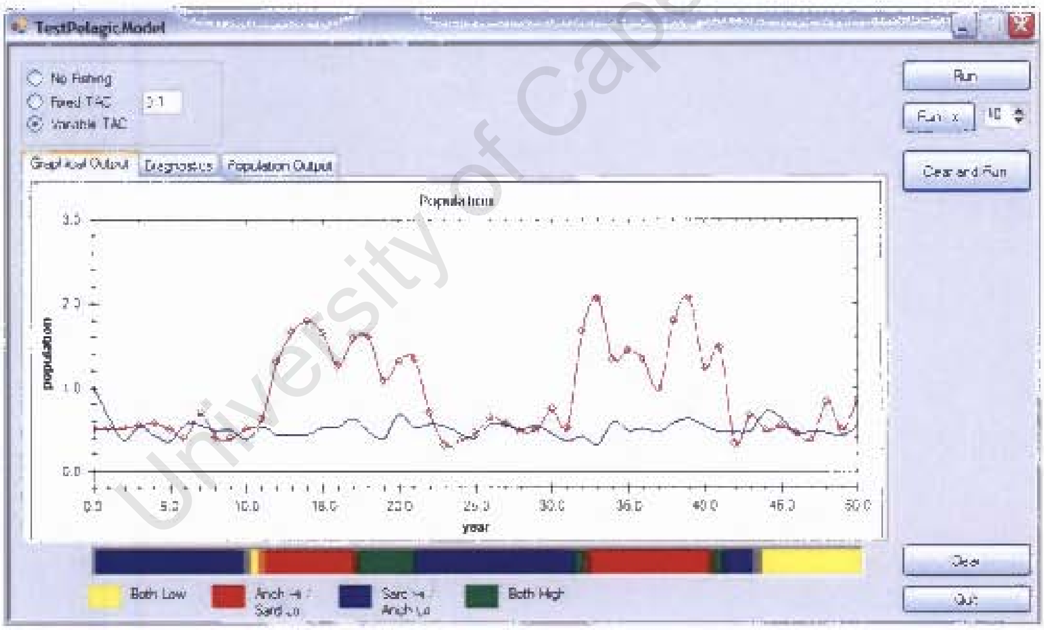


Figure 3: The graphical user interface (GUI) of the first prototype. The red line indicates the modelled anchovy stock, the blue line indicates sardine. Under the Variable TAC setting, the robot manager tries to maximise sardine catch without endangering the stock. The colours used by the frame indicator bar are labelled on the GUI.

3.2 Results from the first prototype

A sample output from the first prototype is shown in Figure 5. The model run was for 50 years, with no fishing throughout the run. The blue line indicates modelled sardine population; the red line indicates modelled anchovy population.

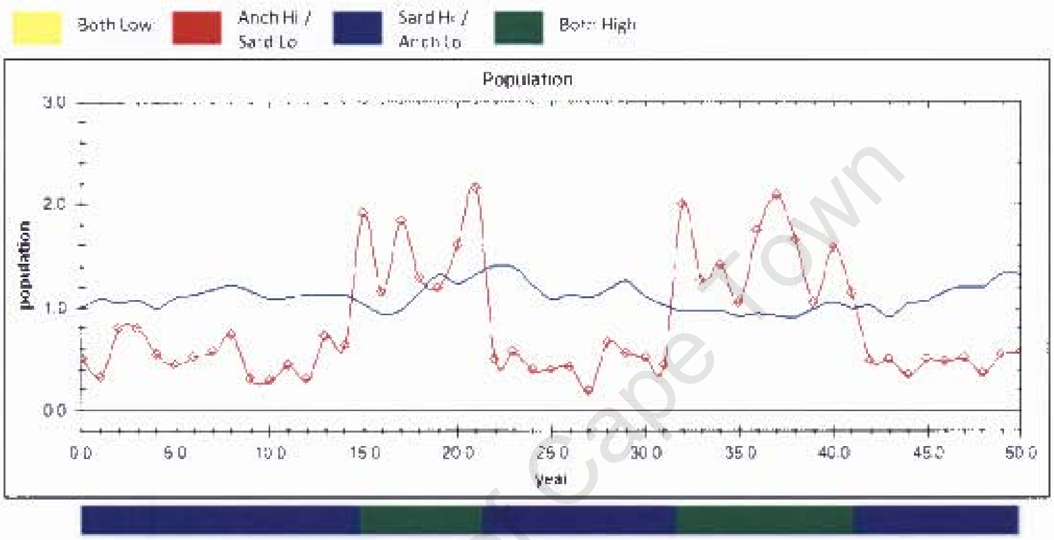


Figure 5 First Prototype output for a single run, no fishing. The blue line indicates sardine, the red indicates anchovy. Note that in the absence of fishing the sardine stock stays continually in a high frame.

Figure 6 shows a similar result, also with no fishing, but in this case the results from ten runs have been superimposed in each other. Note that the sardine stay continually in a "high" frame in the absence of fishing. A mild trend in the sardine population due to the ESI variation can also be observed.

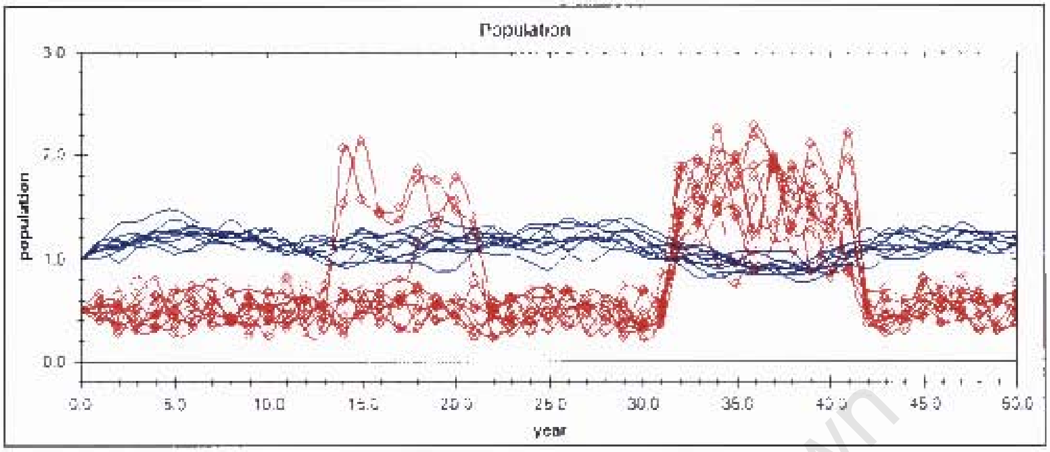


Figure 6 - Ten consecutive runs on the first prototype with no fishing. The blue lines indicate sardine, the red indicate anchovy. The anchovy only sometimes switch to a "high" frame for some or all of the second decade, but always switch to 'high' for the fourth decade. The moderate trend in the sardine population due to the ESI influence is clearly visible.

Figure 7 shows the effect of moderate fishing (constant TAC). Although the sardine population is not yet impacted by fishing, the pressure is sufficient to prompt a frame switch into the "low" sardine frames.

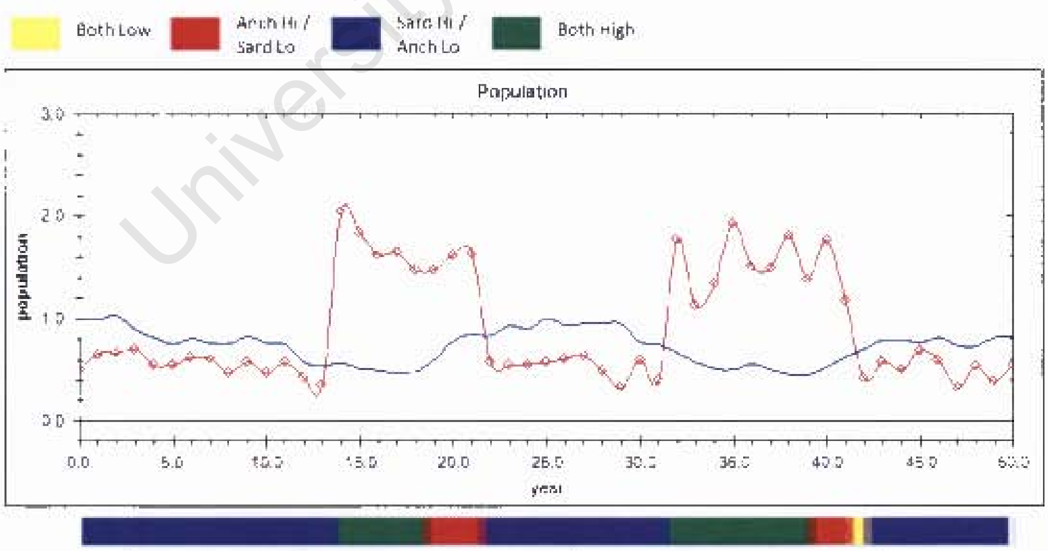


Figure 7 - A single run on the first prototype with moderate fishing (the blue line indicates sardine, the red indicates anchovy). Note the emergence of "low" sardine frames.

If the fishing level is increased, it may exert sufficient pressure that the sardine stock collapses. By using multiple successive runs, an estimate can be made of the likelihood of stock collapse at various levels of fishing. Figure 8 shows the result of ten runs at a dangerous level of sardine fishing:

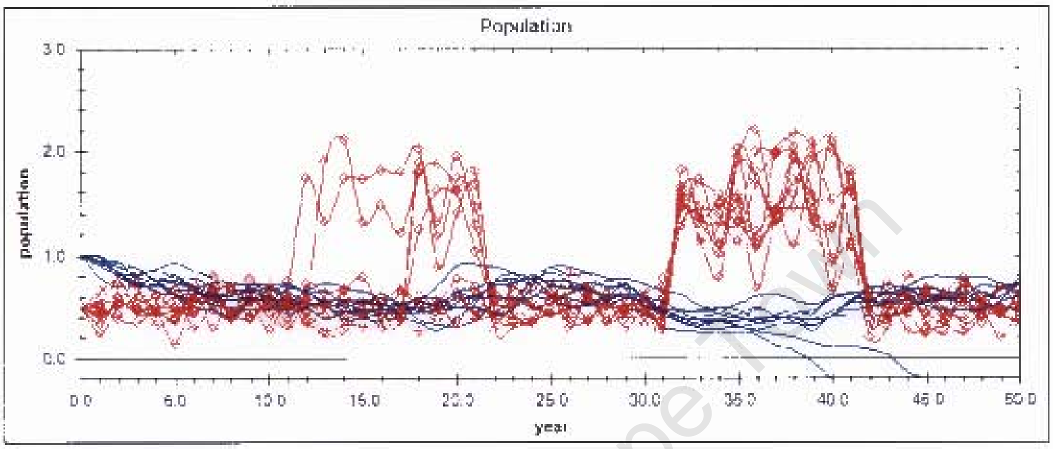


Figure 8 - First prototype, ten runs with high sardine fishing pressure (blue lines indicate sardine, red indicate anchovy). The stock collapsed completely during two of the runs.

Results such as those in Figure 8 allowed us to evaluate "safe" fishing limits of sardine under the modelled constraints. Comparing data on crash likelihood and average annual catch for different levels of fishing would be the first step towards establishing management guidelines concerning the optimal levels of fishing pressure which can safely be sustained by the modelled sardine stock.

Although the results from the first prototype were encouraging, there was insufficient species interaction to usefully simulate the complexities of the real ecosystem. Certain aspects of the individual species behaviour also indicated room for improvement, particularly the inter-annual population variability in the modelled sardine stock and the density-dependent reaction of the sardine in the "low" frames. Additional data could also be collected from the model to support management decisions. There was clear indication that a more advanced model would be able to handle these issues more satisfactorily.

3.3 Analysis of results and recommendations for second prototype

Looking at the results of the first prototype, certain limitations became apparent which would need to be addressed in a more complex version:

- The model needed inter-species interaction, specifically in order to be able to model the effect of juvenile sardine bycatch from the anchovy fishing industry. As this can have a marked effect on the recovery of a struggling sardine population, it is a vital aspect for management consideration (de Moor and Butterworth, 2008).
- The capacity for an interactive approach to the fisheries management is needed, allowing the model user to adjust strategy in response to modelled population changes. This would be a more realistic scenario than simply setting a blanket policy for an entire 50-year run, and also allow the model to serve as a training tool to help users understand the impact of management intervention in the fisheries of the two stocks.
- The first prototype was not aliased with respect to starting population conditions. The starting conditions affected the modelled populations for the first 3-5 years, which has an impact on the statistical data collected for each model run. The record of each model run should rather start once the impact of initial conditions is no longer observable, so that the statistics more accurately reflect the behaviour of the system.
- Additional metrics for the system performance could be recorded, such as the standard deviation of populations in each frame and the bycatch of sardine from the anchovy fishery (once the anchovy fishery has been included).
- The sardine population was far more stable than the survey data would suggest. The recruitment variability in the sardine model should be adjusted to give a modelled population behaviour which is more consistent with the data record.

- The ideal fishing strategy for sardine in the first prototype is to keep them in a “low” frame, where the increased recovery rate allows us to fish more heavily. This is inconsistent with the data record of fishing sardine in “high” and “low” states: in the real ecosystem, a “low” sardine population cannot be heavily fished without risking total collapse of the fishery, and this should be reflected in the model. The stems from two features in the model:
    - The variability of the sardine recruitment is too low: with more variability there is a much greater chance that an unusually low recruitment in one year could critically imperil an already low sardine population.
    - The implementation of density-dependence in the model is flawed: it implies that the optimal situation for the species is to be permanently fished down into a “low” frame, which contradicts our understanding of a “low” frame as one where the species is vulnerable to collapse. For instance, we note that a “low” sardine frame is characterised by sub-optimal species behaviour such as a propensity to school with anchovy.

The theoretical benefit from density dependence in a “low” frame should be out-weighed by the relative scarcity of adult sardine and the resultant sub-optimal schooling. In a healthy population (i.e., in a “high” frame) the density dependence should still be a factor.

4. Second Prototype

This section consists of a description of the second prototype model, followed by two results sections. After building the revised model, we performed a sensitivity and assumption analysis to build confidence in the model outputs. These analyses form the first results section. We then exercised the model in various scenario evaluations to explore some of the potential applications where the model could be useful.

4.1 Description of second prototype

The second prototype is based on the first model, with several significant enhancements and changes. Although the results from the first prototype were encouraging, it was recognised that there were aspects to both the model design and the parameters used that failed to give sufficiently useful outputs.

Like the initial model, the second prototype simulates 50 years of operation with a 1-yr time-step in each model run. Details for the modelled populations of sardine and anchovy are given below, along with an overview of the forcing factors and model mechanics.

4.1.1 Sardine Model

The sardine stock follows a simple stochastic population model, with the same underlying population equation as the first prototype (Equation 1). The parameters of the population model were adjusted to give higher variability, as the first prototype had produced a sardine population which was excessively stable compared to real-world data. The mortality, recovery rate and recruitment variability were all adjusted to provide a higher average population in the unfished system, but with a much higher inter-annual variability. The default parameter values for the second prototype can be seen on the interface in Figure 13.

Other specific improvements are detailed below:

- The parameter representing the fishing mortality in the population model was adapted to include a bycatch mortality of juvenile sardine from the anchovy fishery. The sardine model was also refined to store the recruitment level of each year, which was used as the population of juveniles for the following year's bycatch calculations.

  The bycatch of juvenile sardine caught by the anchovy fishery in a given year was modelled as a product of the anchovy fishing level and the propensity for common schooling in the sardine population. We assumed a relatively conservative 20-40% propensity for juvenile sardine to school with anchovy (based on Fairweather et al., 2006a: Fig. 8a). This is represented in the model as a "school trap factor" (f_{st}), which is determined as in Table 3.

Table 3 - School trap factor by frame

Frame	**School Trap Factor**
Both high	$f_{st} = 0$ When the sardine population is healthy (in a "high" frame), the juvenile sardine are assumed to be able to find adult sardine schools to swim with easily.
Sard Hi / Anch Low	
Anch Hi / Sard Low	$f_{st} = 0.4$ The highest incidence of common schooling occurs when anchovy schools are abundant and sardine are scarce.
Both Low	$f_{st} = 0.2$ Due to the low level of sardine, the juveniles would tend to school with anchovy. However, the lack of suitable anchovy schools limits their ability to do so.

Once the school trap factor has been set, the level of juvenile bycatch is determined by the population of juvenile sardine (from the recruitment in the sardine population model for the previous year). The proportion of anchovy (as a percentage of population) which are caught in that year is given by the anchovy fishing model, and it is assumed that the same proportion of the vulnerable juvenile sardine (i.e., the population of sardine juveniles which are schooling with anchovy) will be caught as bycatch. The final calculation of the bycatch mortality is made according to Equation 2. In the equation, *S* indicates sardine and *A* indicates anchovy.

$$S_{bycatch} = S_{juveniles} \times f_{st} \times \frac{A_{catch}}{A_{population}} \tag{2}$$

The bycatch mortality is then added to the total sardine fishing mortality for the year.

- The density dependence of the sardine model was redesigned. The first model had a higher recovery rate in a "low" frame, which resulted in a more robust modelled sardine population which escaped a "low" frame very easily, even under significant fishing pressure. This is inconsistent with the data record, and also implies that the highest recovery rates are seen when the population is dangerously low, which is biologically unrealistic. The second prototype handles density dependence by modifying the recovery rate in the population model with a factor, f_{DD}, which is determined as in Table 4.

Table 4 - Determination of the sardine density dependence factor (f_{DD}) by frame in the second prototype.

Frame	**Density Dependency (in sardine)**
Both High	f_{DD} increases from a base value of 1 as the population drops. The increase is proportional to the difference between the current population and the theoretical carrying capacity (p_{max} - $p_{current}$). If the population exceeds p_{max}, the density dependence remains flat at 1.
Sard Hi / Anch Low	
Anch Hi / Sard Low	f_{DD} stays at 1 throughout. The assumption is that density dependence does not operate in the sardine low frame as the population is too low.
Both Low	

A conceptual plot of the recovery rate with population would be as in Figure 9.

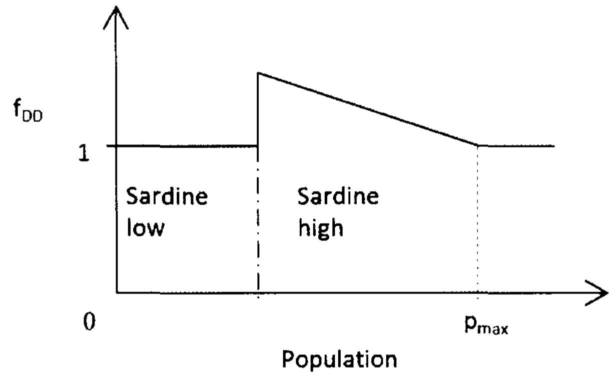


Figure 9 - A conceptual graph of the sardine density dependence factor (f_{DD}) as implemented in Prototype 2.

4.1.2 Anchovy Model

As with the first prototype, the anchovy population is modelled entirely stochastically, with the population fluctuating randomly about a defined mid-point, with a defined variability (listed below). The mid-point and variability used are determined by the anchovy frame state, and have been scaled to produce a modelled anchovy population which varies on a similar scale to the modelled sardine population.

- Anchovy Low: The population fluctuates about 0.6, with a variability of +/- 0.4
- Anchovy High: The population fluctuates about 2.5, with a variability of +/- 2.0

Also as with the first prototype, the model for the anchovy population reacts to the current frame state rather than the ESI for the current year.

An anchovy fishery was included. The impact of the anchovy fishery is limited in that the fishery is not modelled to have any effect on the underlying anchovy population. The biological rationale in this model is that the caught anchovy would overwhelmingly have died by other means had they not been fished (e.g. Jarre et al., 1998). The advantage of including the anchovy fishery is that it allows us to model juvenile sardine bycatch from the anchovy harvesting operations. The modelled anchovy population is still determined for each year by the frame state of the model.

4.1.3 Forcing functions

The forcing factors affecting the modelled ecosystem are:

a. Environmental Suitability Index (ESI)

As with the first prototype, we parameterise the various climatic and environmental effects (temperature fluctuation, nutrient availability, transport currents, etc.) into a single factor. The ESI is an integer value from 0-9, with a higher value indicating a more favourable environmental situation for anchovy recruitment.

The ESI in the second prototype is based on a sine function with a 20-year periodicity (10 years high, 10 years low). Using this sine function as a midpoint, the actual ESI for a given year (which is rounded to the nearest integer) has a small degree of random variability from the base function. The sine function is centred on a value of 5, and has amplitude of +/- 3. The variability of the ESI is +/- 1 from the base function.

The anchovy daemon (which drives the anchovy frame-switching) bases its switching rules on the ESI values. As the anchovy population is determined by frame state, the population will still switch abruptly between high and low states, despite the sinusoidal forcing function.

b. Sardine fishing

The fisheries model for the sardine population has been substantially refined, with more complex fishing strategies possible than in the first prototype. There are several possible scenarios for setting the total allowable catch (TAC) and general management strategy for a given simulation:

- No fishing.
- A fixed TAC (defined by the user) for the entire 50-yr run.
- As with the first prototype, there is an AutoManage function (the "robot manager"), which controls the fishing according to a set of predefined rules and adjusts fishing effort annually. The guidelines for the robot manager have been scaled to correspond to the values typically observed in the modelled populations.

  The AutoManage function was given a sensitivity setting which allows the user to set the fishing strategy along a scale from "conservative" to "severe". Using the more "severe" management strategy, the robot manager would be quite likely to crash the sardine stock, but would also take far higher catches in a run for which the sardine survived. Note that the adjustment does not change the frame definitions or the modelled population settings, only the fishing settings.

  All adjustments of management parameters on the scale from "conservative" to "severe" were done linearly between the maximum and minimum settings. The "conservative" settings represent the maximum yield with zero risk of crashing the sardine stock.

  Moving the strategy from conservative towards severe increases the sardine catch in the high and moderate population levels, and the threshold for being considered "high" or "moderate" population is reduced. The TAC in the "low" population level is 0 for all settings, although the threshold for classifying the stock in a "low" population is reduced under more severe management.

Table 5 summarises the scales used for the robot manager at the default "conservative" values. The maximum adjustments under the most "severe" settings are given in parentheses. TAC settings are based on the previous year's population estimate.

Table 5 - AutoManage function parameters for sardine fishing in Prototype 2 under the most "conservative" setting. Numbers in parentheses indicate the maximum adjustment of figures under the most "severe" management strategy.

	Low population:	**Moderate population:**	**High population:**
Range	$0 \leq Pop < 0.5$ $(0 \leq Pop < 0.3)$	$0.5 \leq Pop < 1.0$ $(0.3 \leq Pop < 0.6)$	$1.0 \leq Pop$ $(0.6 \leq Pop)$
TAC	0 (0)	0.2 (0.4)	0.4 (0.6)

- The option for medium-term management evaluation was added. In the "Active Management" mode, the user is asked every three years for a decision on the TAC for each species, and these values will be used for the next three years of fishing. In this way, the user can practice reacting to the data in an ongoing manner, and adjusting the fishing strategy in real-time in response to observed population changes.

c. Anchovy Fishery

The second prototype includes an anchovy fishery in order to model the effects of juvenile sardine bycatch (from the anchovy fishery) on the modelled sardine population. As in the sardine fishery, there are several different management models that the user can select:

- No fishing
- A fixed (user-defined) TAC for the entire run
- The AutoManage function was also expanded to include the anchovy fishery. The TACs for the anchovy fishery are set differently from the automated sardine management,

however: the AutoManage function considers the anchovy frame which the model is currently in, and bases the catch as a percentage of the spawner stock biomass (taken from the previous year's population estimate).

As with the sardine fishing management, the thresholds for anchovy fishing are also adjusted on a sliding scale from "conservative" fishing to "severe". Table 6 summarises the anchovy TACs under the AutoManage function. Again, the maximum levels (under the most "severe" setting) are given in parentheses.

Table 6 - AutoManage function parameters for anchovy fishing in Prototype 2 under the most "conservative" setting. Numbers in parentheses indicate the maximum adjustment of figures under the most "severe" management strategy.

	Anchovy Low Frame	**Anchovy High Frame**
TAC	20% (30%) of Pop	40% (60%) of Pop

- The "Active Management" mode, allowing for medium-term management evaluation, is also available with the anchovy fishery. Under this mode, the user must set fishing levels for both species every three years.

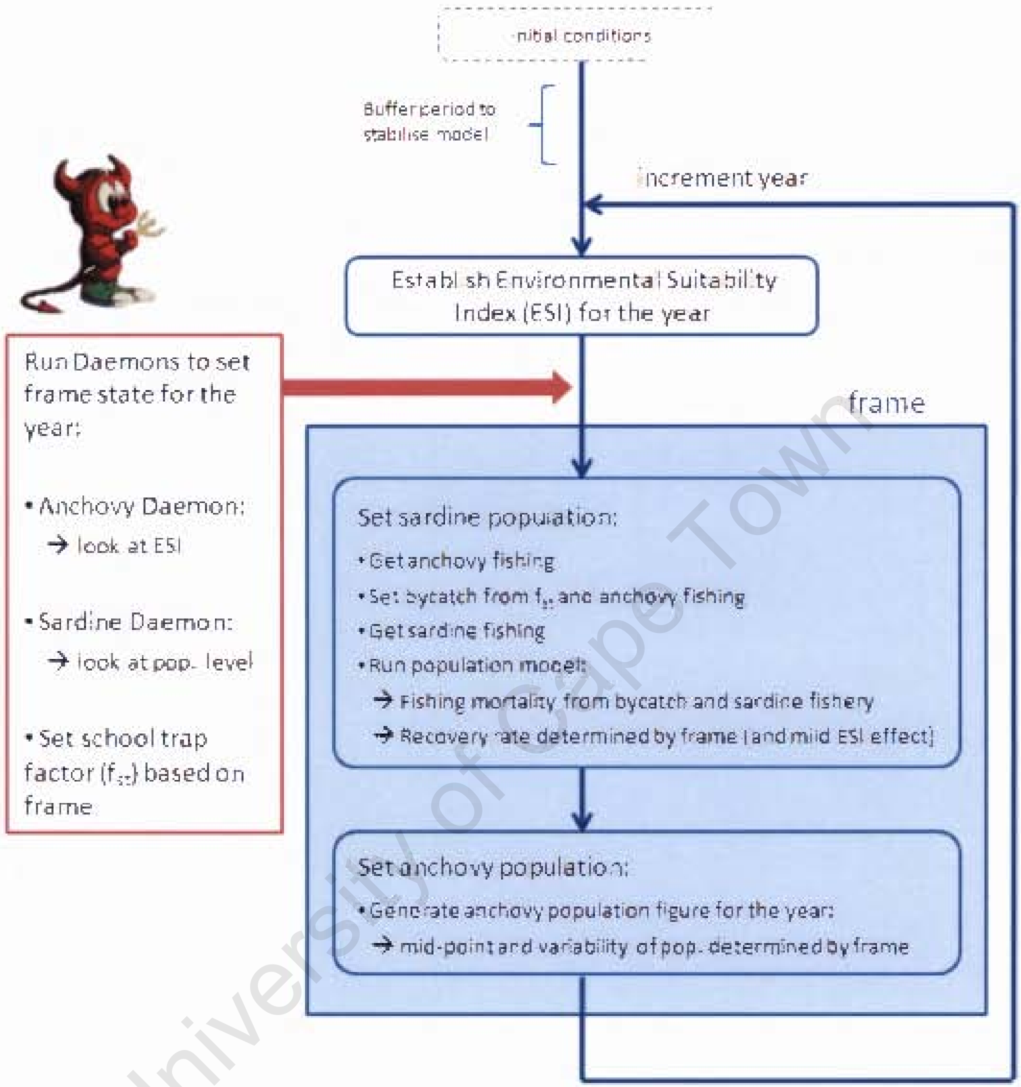


Figure 10 - Programme overview for Prototype 2. See text for a detailed description.

4.1.4 The Daemons

As with the first prototype, we consider a separate daemon for each of sardine and anchovy, so that the sardine daemon will push that species between "high" and "low" frames, and the anchovy daemon will operate similarly on the anchovy stock, to prompt shifts between "high" and "low" frames. The default response of the model is to remain in its current frame.

The rules of the daemons were refined to give more plausible mechanisms for frame switch. Cumulative indicators with "reset catastrophe" events are used rather than arbitrary arithmetic operations. The new daemon rules are described below:

a. Sardine Daemon

The sardine daemon was redesigned to consider the sum of the sardine populations over the last three years, rather than requiring three successive years above a particular level (as was the case in the first prototype).

- If sardine is in a "low" frame:

  The new daemon required a total population from the past three years of at least 3.0 to shift the sardine to a "high" frame, rather than an equivalent rule requiring three successive years of at least 1.0 population.

- If sardine is in a "high" frame:

  The sardine will switch to a "low" frame if there is a total population of less than 1.8 from the past 3 years.

This is more representative of the actual operations in the ecosystem, as two sufficiently poor sardine year classes would be likely to shift the population to a low frame in spite of a single moderate year class in between them. Likewise, two sufficiently strong year classes with one moderate year class between them should be sufficient to push the sardine into a "high" frame.

Note also that these rules do not require three years before a new switch can take place. If there are two consecutive extraordinarily good years which have a total population over 3.0, then under these rules the daemon will prompt a frame shift without waiting for the third year.

b. Anchovy Daemon

The anchovy daemon considers the Environmental Suitability Index, not the anchovy population. Unlike the first prototype, the anchovy daemon does not look for three consecutive years with ESI above a certain threshold. The ESI for each year is added to a running total, and when the cumulative value is over 15, the daemon will prompt a shift to a "high" frame. To avoid a long succession of poor years prompting such a shift, the cumulative total is reset and the daemon prompts a shift to a "low" frame if the ESI for a given year is below 4. Table 7 shows an example of the frame shifts which would take place under an arbitrary series of ESI values.

Table 7 - Example run of ESI values and associated anchovy frame behaviour. Annual ESI is added to the running total unless annual <4, in which case the running total is reset to the annual figure. Daemon switches to "high" if running total >15, and switches to "low" if running total <4 (i.e., if annual ESI <4).

Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
ESI for the year	2	3	4	6	7	8	6	4	3
Running total ESI	2	3	7	13	20	28	34	38	3
Anchovy frame state	low	low	low	low	high	high	high	high	low

Because of the fairly regular sinusoidal variability of the ESI, the anchovy daemon will prompt for a switch between "high" and "low" frames at approximately 10-year intervals, and the switching will lag the ESI function by approximately 2 years. This is in line with previous treatment of the lag time of anchovy population response to change in conditions (Howard et al., 2007).

4.1.5 Additional enhancements to the second prototype

a. Introduction of variable survey accuracy

In order to simulate errors in the survey data, it is possible to introduce a specified level of inaccuracy in the surveyed sardine population with respect to the modelled population. If the AutoManage function is selected with this feature enabled, the robot manager will react to the surveyed (i.e., inaccurate) population changes, and not to the actual population. A sample run of this type is shown in Figure 11.

The simulated survey results are also shown during the run of an Active Management exercise, with the actual population levels shown at the end of the run.

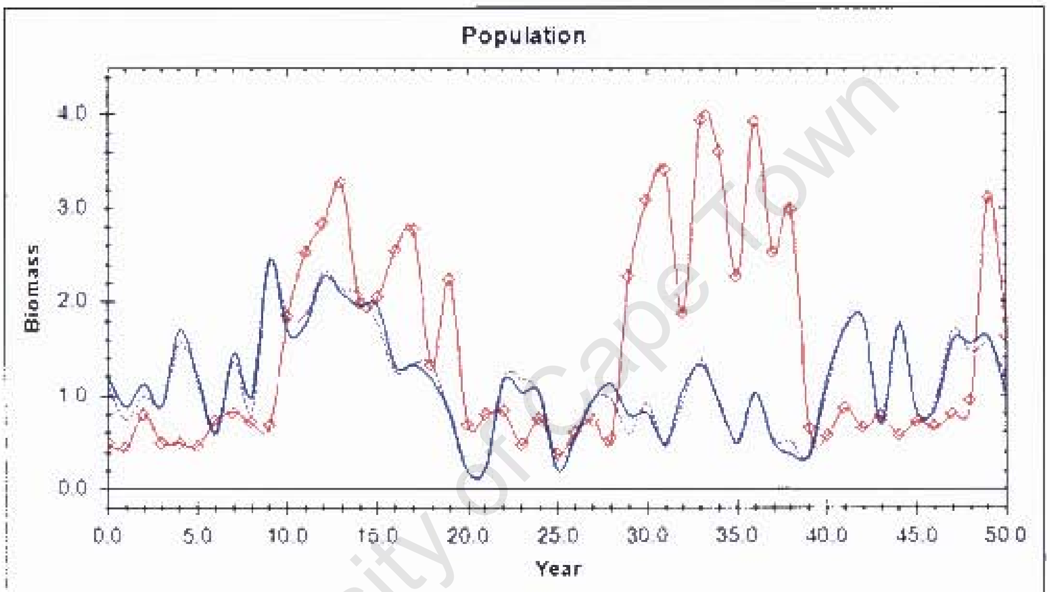


Figure 11 - A single model run on Prototype 2 under moderate fishing with survey errors. The red line indicates the modelled anchovy stock, the blue line indicates the modelled sardine stock. The reported (inaccurate) sardine biomass is indicated by the dotted blue line.

b. Improved diagnostics

Metrics are improved to answer more interesting questions. Note that this is merely a post-processing aspect: the operation of the model is unaffected, but we are able to extract more value from it. Standard functions which have been included are the standard deviation of various outputs (catch data, populations, etc.), and the percentage of years in which a value surpasses a certain threshold (e.g. catch is at least 80% of mean catch for the run). This is particularly useful in the context of the management objectives which this model is designed to support, as it is a more easily understandable way of representing the inter-annual variance for stakeholders (both management and fishers).

As in the first prototype, if the model is used with multiple runs, these metrics are averaged in the final output. For a "multiple runs" test, the model can also record the number of runs for which the modelled sardine population crashed.

The full list of metrics provided at the end of each run for the second prototype given below. Note that all figures (other than total number of sardine stock crashes) are averaged for multiple runs.

- Total time spent in each frame
- Average residence time in each frame before switching out
- Number runs in which the sardine stock crashed
- Sardine metrics:
    - Average annual population
    - Total catch (over 50 yrs)
    - Average annual catch
    - Std. deviation of annual catch
    - Percentage of years in which the catch exceeds 80% of the average catch
    - Average annual juvenile bycatch

- Anchovy metrics:
    - Average annual population
    - Total catch (over 50 yrs)
    - Average annual catch

As with the first prototype, the graphical output uses a blue line to indicate the modelled sardine stock, and a red line to indicate the modelled anchovy stock. The colours used by the frame indicator are labelled in Figure 12.

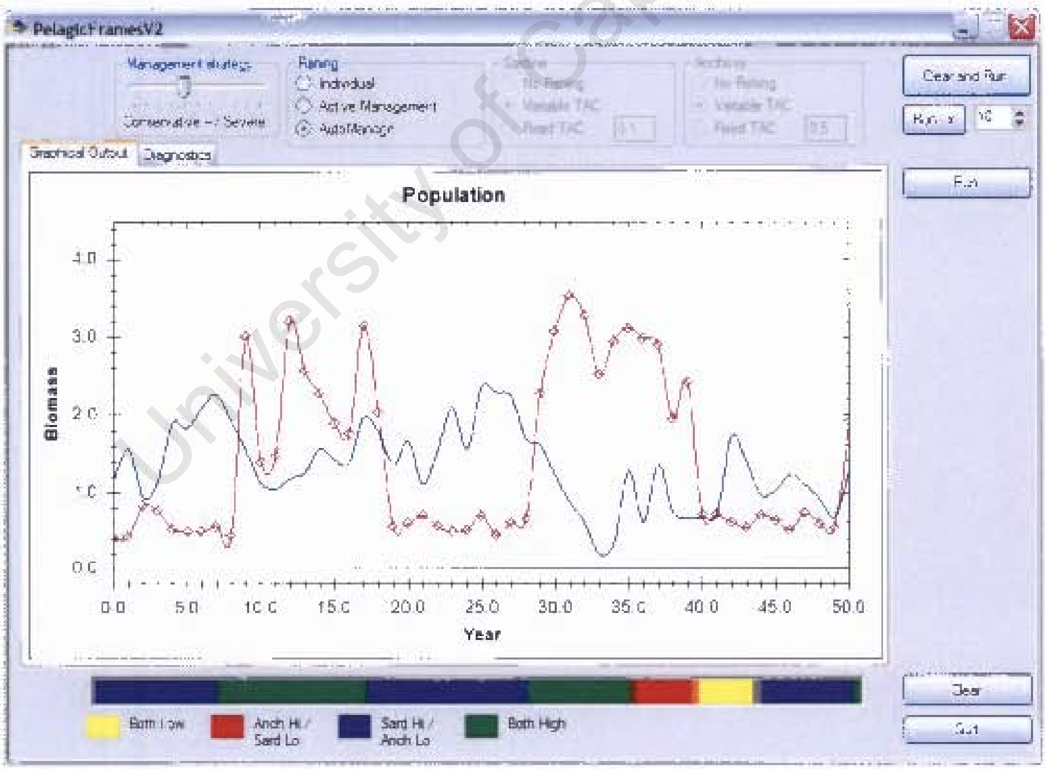


Figure 12 - A sample run under automated management on the second prototype (blue line indicates sardine, red indicates anchovy). The colours used by the frame indicator bar are labelled on the GUI.

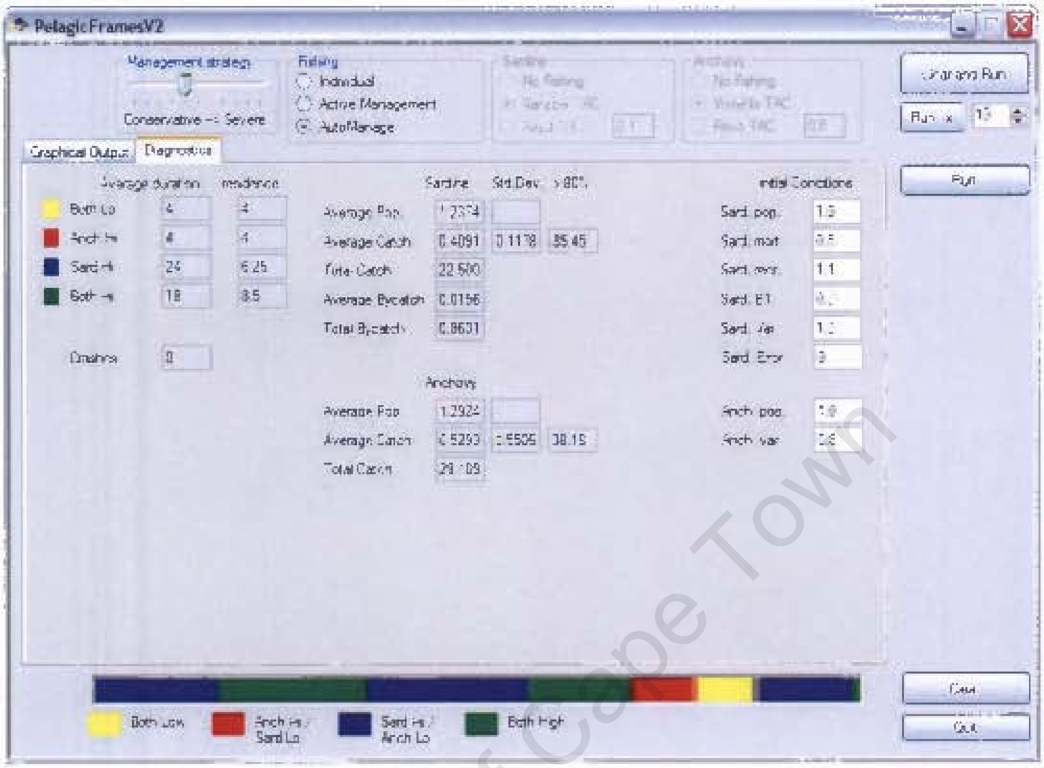


Figure 13 - The sample run from Figure 12, showing the diagnostics tab with the metrics for the run

4.2 Results: Assumption and sensitivity analysis

Implicit in the modelling approach is the need to test the assumptions used to build the ecosystem representation, and an analysis of the sensitivity of the outputs to input parameter values. The model has several inputs, many of which require numerical values. Such data as exist from the real world often have a high degree of uncertainty, and as such an analysis needs to be performed of the sensitivity of the model to the values of those inputs (Starfield and Jarre, in review).

In light of our objective of investigating how a management strategy designed around a frame-based model might operate, it is important to understand the sensitivities to the frame states. The key sensitivities to test in our model are therefore the thresholds for frame switching of both the sardine and anchovy daemons. Several other outputs of the model, such as the sardine bycatch and the anchovy population level, are directly related to the time spent in certain frames. Other outputs, such as the sardine population level, are not directly tied to frame residence, but are nonetheless influenced by it. We are also interested in the sensitivity of the model to density dependency of the sardine population, as well as the parameters of the "school trap" relationship.

The model also incorporates certain assumptions that required testing:

a. Daemon indicators

The new daemon rules included in the second prototype were believed to represent the ecosystem better, but this assumption needs to be tested.

Assumption analysis on the second prototype indicated that changing the sardine daemon to a "cumulative population" indicator (rather than three successive good years) had negligible effect on the sardine output parameters. There was a significant effect on the sardine bycatch from the anchovy fishery and the frame behaviour.

The change of indicators for the anchovy daemon from a switch based on three successive good years to a cumulative ESI forcing agent (with an abrupt crash in a poor year) was found to have little effect on any of the output parameters other than frame behaviour.

Certain other assumptions were not tested:

b. Anchovy fishing

Our model has assumed that the anchovy population is totally unaffected by fishing pressure. Ideally, we would like to test the effect of the anchovy fishery on the anchovy population. In the current model, the anchovy population parameters are determined by the ESI, and as a result the modelled population actually cannot crash, no matter how hard it is fished. This is a limitation of the model, as there is data evidence that it is possible to crash an anchovy population through sustained excessive fishing in conjunction with poor recruitment (as observed in Peru in the 1970s (e.g. Pauly and Palomares, 1989)). Anchovy in the Benguela have not had consistently poor recruitment conditions for more than two years running within the data record (Miller and Field, 2002), so this is a useful simplification with the caveat that it assumes that reasonably conservative fishing strategies continue to be practiced in the southern Benguela.

To address this issue in more detail it would be necessary to use a population model for anchovy, so that the anchovy population in a given year was dependent to some degree on the previous year's population. This may be a suitable area of the model to explore in a later version (see Section 5.5.1).

c. Survey data accuracy

The model has been built with the capacity to introduce a random error into the survey data with respect to the actual modelled sardine population. It would be useful to explore the impact of a certain level of error on the validity of fisheries management strategies. The results of the scenario evaluations concerning this question are shown in Section 4.3.2.

4.2.1 Sensitivity overview

The initial sensitivity analysis was performed across a broad range of model parameters, and the effects were recorded against a broad range of model outputs. The results were generally as expected, and in this way served to reinforce confidence in the model. In some areas, the results also indicated that a more directed analysis may be beneficial.

The parameters were tested under two sets of conditions: with no fishing; and with the AutoManage function simulating fishing activity. To understand the expected level of sensitivity of the model to the tests themselves, an analysis was performed on the AutoManage rules as well:

- The modelled frame behaviour was found to be strongly sensitive to the AutoManage rules, and as a result, the sardine bycatch was also strongly affected. This is to be expected, as the bycatch is related to the propensity of sardine to school with anchovy, and the common schooling is only incorporated into the "low" sardine frames of the model.
- The sardine catch was significantly sensitive to the AutoManage settings, particularly as regards TAC levels.
- The sardine population was also significantly affected. Increased fishing had a significant negative impact on the modelled sardine population, and reduced fishing conversely resulted in a higher average model population. Lowering the population through fishing could also force the sardine into a "low" frame, in which the recruitment is reduced (as density-dependence does not operate in the model's "low" sardine frames).

Once satisfied that the tests would give useful results, a more detailed analysis was made of the sensitivity of various other factors. A summary of the results of the sensitivity analysis is given in Table 8. The colours for each cell indicated in the table represent the aggregate assessment of all the results of tests performed for that cell. The detailed results of all the tests are provided in Appendix A.

Table 8 - Summary results from sensitivity and assumption analysis. The numbers in the table refer to the test results in Appendix A (Section 9.1). Coloured cells indicated an assessment of the overall sensitivity of the output parameter (columns) to all the tests involving the given input parameter (rows).

	Average Population		Sardine catch		Anchovy catch		Frame behaviour	
	Sard	Anch	Avg	std. dev.	Avg.	bycatch	Duration	Res.
AutoManage sardine thresholds								
AutoManage sardine TAC levels								
Sardine Daemon: Cumulative vs 3 years	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8
Sardine switching limits: Thresholds	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8
Anchovy Daemon: Cumulative vs 3 years	3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8
Anchovy switching limits: Upper threshold	4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8
Anchovy switching limits: Poor year threshold	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
Sardine recovery rate: scale factor	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Sardine school trap factor	7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8
Variance of climate	8.1	8.2	8.3	8.4	8.5	8.6	8.7	8.8

Colour key:
Negligible effect → Extremely sensitive

The specific trends observed are discussed below:

1. Sardine daemon rules: Cumulative population vs. 3 consecutive years over a threshold:

   The frame behaviour was mildly sensitive to the daemon rules, and as a result the modelled sardine bycatch showed some sensitivity.

2. Sardine switching threshold:

   The robot manager is designed to try and operate at the lower edge of the "high" sardine frames. Thus, if the threshold for switching is raised, the model will more easily go to a "low" sardine frame. Bycatch of juvenile sardine from the anchovy fishing will increase (as bycatch is only implemented in the "low" sardine frames), and the average sardine population will be reduced by the combination of increased bycatch and reduced recruitment (as the density dependence does not operate in the "low" sardine frames).

3. Anchovy daemon: Cumulative ESI vs. consecutive good or bad years

   The model was largely unaffected by which of the daemon rule sets was implemented.

4. Anchovy switching limits

   This had a slight effect on frame behaviour, and thus a slight effect on anchovy catch and sardine bycatch. As the anchovy population is largely determined by frame state (which sets both the midpoint and the variance of the annual population), lowering the threshold for switching to the "high" anchovy frames results in more time spent in the these frames, and thus an increased average population. The modelled sardine bycatch operates in both the "Anchovy High / Sardine Low" and the "Both Low" frames but the school trap factor is stronger in the former, and thus with more time in the "high" anchovy frames there is an overall increase in sardine bycatch. Raising the threshold had the reverse effects on both average anchovy population and sardine bycatch.

5. Anchovy poor year threshold

   Although the poor threshold seems to have a strong effect on the anchovy population, anchovy catch and frame switching, this is in fact more to do with the magnitude of the shift in the sensitivity analysis: because the ESI is limited to a small number of discrete values, it is only possible to adjust it by a relatively large amount. Thus although the magnitude of the resultant changes in the output parameters appears high, it is consistent with the relatively large changes to the threshold which were made. Using smaller graduations of the ESI would allow this to be tested more precisely, but that precision may not be useful with respect to the high uncertainty inherent in evaluating environmental factors.

6. Sardine recovery rate scale factor

   The scaling of the density dependence has a fairly strong effect on the sardine population, as well as on the variability of sardine catch and the bycatch. The density dependence generally helps the modelled sardine population to avoid the “low” frames by increasing recruitment as the population declines. With the scale factor lowered, the sardine population more easily declines low enough to prompt a switch to a “low” frame, and the average sardine population is consequently also lower. As a result of more time in the low frames, there is also a significant increase in juvenile sardine bycatch. Increasing the sardine recovery rate had the opposite effect, with more time spent in sardine “high” frames, lower juvenile sardine bycatch and higher average sardine population.

7. Sardine school trap factor

   The results for the sensitivity of the model outputs to the school trap factor were inconclusive. A limitation of the tests in this regard is that the school trap factor only comes into play where the system is in a “low” sardine frame, and the robot manager is generally good at avoiding fishing the sardine down to that level. In the unfished system, the modelled sardine population stays in a “high” frame continually.

   Observations of the modelled populations under managed fishing indicate that the implementation of the school trap factor gives rise to a realistic reaction of the stocks to anchovy fishing in frames where the sardine population is in a “low” frame. This is further explored in the scenario evaluations (see Section 4.3.1).

In order to test the behaviour of the system in the "low" sardine frames and study the sensitivities of sardine bycatch, the robot manager was adjusted to a more severe fishing strategy. Although this would crash the stocks on some of the runs, it would also allow us to observe automated runs with sardine spending considerable time in the "low" states.

8. Climate variance

   With the same underlying waveform and periodicity, the inter-annual variance of the ESI around the wave function had no significant impact. Note that the underlying waveform determines the upper and lower bounds of the ESI function, and thus the frame switching behaviour of anchovy is not significantly affected. The cumulative ESI indicator used by the anchovy daemon effectively smoothes out a lot of the effect of year-to-year climate variance on the anchovy population, which is reasonable for a species which lives 3 years.

4.2.2 Analysis of stochasticity and averaging effects

Averaged results from large numbers of runs were used extensively in the sensitivity analysis as a way of filtering out the influence of the high degree of stochasticity on the results from any individual model run. A model "run" is regarded as a simulation of a single 50-yr time series. Because the programme allows for multiple sequential runs to be performed in a row and the averaged results displayed, test for the sensitivity analysis were often performed on sets of 100, 500 or 1000 runs. Even at high numbers of runs, repeated tests often displayed a high degree of variability, and thus the tests were generally repeated three times to give some idea of the consistency of a particular metric. These repeated tests (sets of multiple "runs") are referred to as "replicates" in the descriptions of the sensitivity analyses.

The initial tests of the sensitivity and assumption analysis (which are represented in Table 8) were performed over 100 runs, with three replicates. In several cases a high degree of variability of the results was observed, even averaging over such a large number of runs. Even in a stochastic system, the law of large numbers would be expected to steer the results towards uniformity when enough runs are being averaged. It was therefore decided to do an analysis of the variability of the averaged results over different numbers of runs.

a. Effects of the number of model runs performed on the results

Runs were done with the AutoManage function set at 50% severity and the averaged results recorded for 20, 100 and 500 runs. In each case, the results taken were the total time spent in the "low" sardine frames (per run), and the number of crashes of the modelled sardine stock in the series. Results are listed in Table 9.

Table 9 – Analysis of stochasticity and averaging effect. All runs performed with AutoManage at 50% severity. Standard deviation of Sardine Low frame duration reduced greatly as the number of runs increased.

Replicate:	1	2	3	4	5	6	7	8	9	10	Diagnostics
20 runs											
Sardine Low duration	5.2	1.5	1.9	2.7	3.1	2.8	3.6	4.3	3.0	7.6	Mean: 3.57 stdDev: 1.78
No. of crashes	3	0	0	0	1	1	0	0	0	1	p(crash) ≤ 15%
100 runs											
Sardine Low duration	4.1	4.1	4.1	3.3	2.2	5.5	2.7	3.4	5.1	2.6	Mean: 3.71 stdDev: 1.07
No. of crashes	0	0	2	4	0	7	5	3	5	2	p(crash) ≤ 7%
500 runs											
Sardine Low duration	5.0	3.5	3.1	3.3	4.2	3.3	5.0	4.7	3.7	3.5	Mean: 3.93 stdDev: 0.73
No. of crashes	13	17	3	12	3	12	17	3	15	5	p(crash) < 4%

Although the mean duration over ten replicates is reasonably consistent, the standard deviation is higher with fewer runs. The confidence with which the probability of crash can be predicted is also far higher at 500 runs per test.

When viewing the highly variable results of the "20 run" replicates, it is perhaps worth noting that the total number of comparative time-series for fished small pelagic systems worldwide is considerably less than 20. A certain level of caution may therefore be recommended in analysing the historical data: although the cause and effect relationships often seem convincing, the degree of stochasticity inherent in the system may be remarkably high. The uncertainty in deductions made from such a small number sample size should be understood. Again, the manner in which the model reproduced real-world features serves to increase confidence in the model.

b. Effect of the severity of fishing under environmental and recruitment uncertainty

The number of crashes is particularly interesting in this analysis, as the runs are performed with a robot manager which is programmed to compensate annually for stock fluctuations and avoid imperilling the sardine stock. Although the manager has been set at a less conservative setting to ensure some comparative results, it is still actively adjusting the fishing strategy to try to avoid crashes. However, the degree of stochasticity inherent in the system sometimes exceeds the robot manager's ability to do so. In light of this, we investigated how the relative levels of severity of the AutoManage function affected the risk of crash.

The default (most "conservative") setting of the AutoManage function was designed to maximise sardine catch while minimising the risk of sardine stock collapse. To investigate whether the settings were too conservative, replicates of 500 runs were performed at increasing levels of AutoManage severity and the probability of crash observed. The results are detailed in Table 10.

Table 10 - Number of crashes at 500 runs with increasing AutoManage severity

Severity of management	Number of crashes (at 500 runs) for each replicate:				
	1	**2**	**3**	**4**	**5**
0%	0	0	0	0	0
10%	3	0	0	0	0
20%	0	2	0	0	0
30%	0	0	5	4	2

With any increase in severity of fishing strategy there is an increased risk of crashing the modelled sardine stock. Of course, increasingly severe fishing strategies also result in increased modelled catch, provided that the stock survived the simulation. Tests were done with 1000 runs at different AutoManage severity settings to get an indication of the trade offs between average annual catch and risk of stock crash.

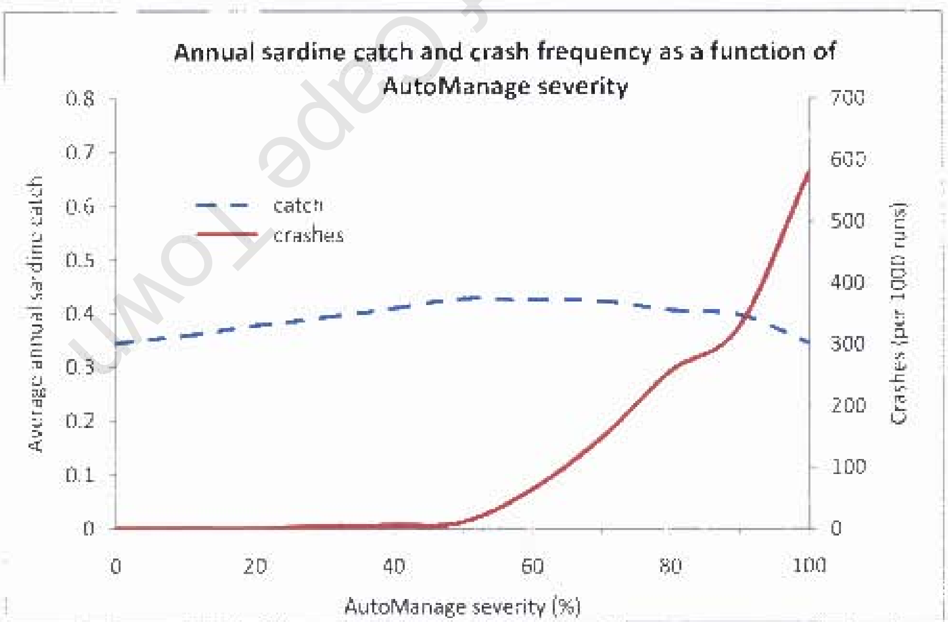


Figure 14 - Average annual sardine catch and risk of crash with increasing AutoManage severity. Data consists of averaged replicates of 1000 runs. Crashes are negligible up to 50% severity, from which point crash frequency increases to a maximum of almost 60% at maximum severity. Total catch increases with increasing severity up to 50%, from which point the higher incidence of crashes offsets the higher catches obtained under higher fishing pressure.

There was a low increase in probability of crash up until about 50% severity, above which the probability increased rapidly. The results are summarised in Figure 14.

When considering the results of the catch/crash risk assessment, it is important to consider the ecosystem challenges involved. The risk of crash accelerates rapidly from the 50% severity level, which also approximately gives the maximum average annual yield over the 50 years of each single run. Although the ultimate crash risk is of the order of 60%, the average catch at the maximum severity level is roughly equivalent to the most conservative setting. This result comes from two factors which may not be immediately apparent:

Firstly, the crashes may only occur near the end of the 50-year simulation, and thus the modelled fishery will already have enjoyed decades of high-yield (and high-risk) fishing, resulting in a high average catch for a crashed run even with a few zero-yield years at the end of the run. Secondly, the levels of fishing allowed by the AutoManage function under the most severe levels of management afford extremely high yields in the runs which are fortunate enough not to crash the stocks at all.

c. Inter-annual stability of the modelled sardine catch

Although standard deviation is a concept which is familiar to the scientific community, it can be somewhat intangible for other stakeholders (e.g. fishers or managers). To improve the communicability of results, the inter-annual variability of sardine catch for a given run was expressed as the percentage of years in that run which were "acceptable". An acceptable year was defined as one in which the sardine catch was > 80% of the average annual catch for that run.

The two major goals of the robot manager are to achieve the highest sustainable yield (with an appropriate level of caution with regards to crashing the sardine stock), while at the same time keeping the inter-annual variability of catch (and thus fisher income) as small as possible. An exceptionally high income year would not be of such concern, of course: avoiding years with exceptionally low sardine catch is the important point.

A comparison was made of the percentage of "good" years of fishing at increasing levels of AutoManage severity. As with the previous experiment, the tests were done with 1000 runs, with three replicates at each level.

There is a clear trend of increasing variability of catch with increasingly severe fisheries management. As with the sardine crash risk assessment, the situation is relatively stable up to approximately 50% severity. The results are summarised in Figure 15.

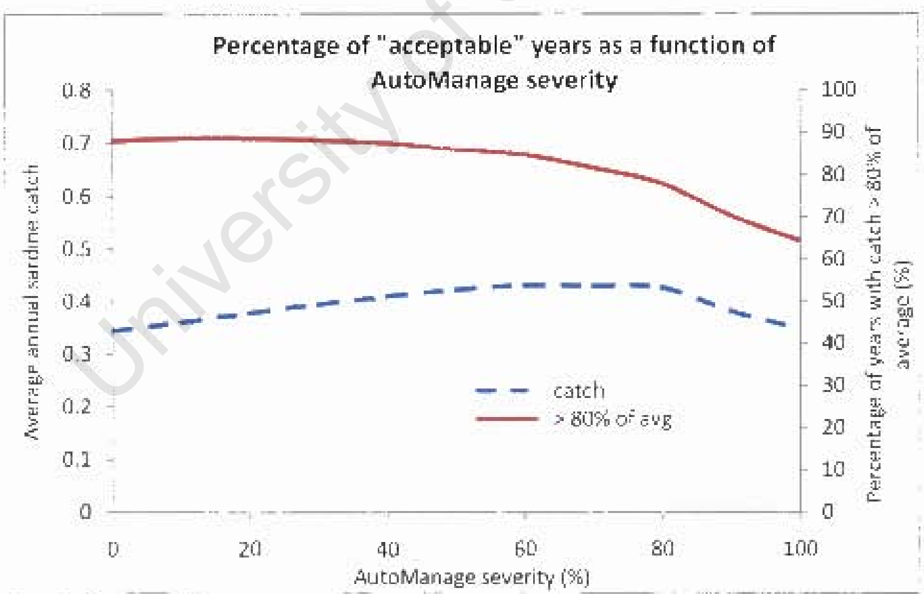


Figure 15 - Frequency of "acceptable" years (sardine catch >80% of average catch) with increasing AutoManage severity. Data consists of averaged replicates of 1000 runs. Although the average annual catch increases up to approximately 60% severity, there is also an increase in the frequency of "poor" fishing years

To give some perspective to the performance of the robot manager, it was attempted to manually replicate a similar level of average catch and consistency as is seen when the AutoManage function is set to a reasonably conservative level. Under Active Management (i.e. setting the catches manually every three years of a model run) it was very difficult to reliably match the figures for both catch and consistency that the rule-based AutoManage function was able to achieve. The robot manager, setting catches every year, was found to be good at keeping catches stable in a highly stochastic model.

4.2.3 Periodicity of climate function

The underlying frequency of the ESI forcing function is set at a 20yr periodicity for the model (10 yr cycles alternating between good and bad ESI). With many of the daemon indicators looking at cumulative figures over 3 years, it is useful to investigate the effect of changing the cycle time of the ESI function on the frame behaviour of the model, particularly as it approached the timescale of the daemon indicators.

The ESI function was moved from its decadal cycle time to cycles of 13, 7 and 5 years, and the average time spent in either Sardine High or Both High was compared. Tests were performed over 1000 model runs, with 3 replicates averaged for each cycle time. No fishing was included in the simulations, so the frame state of the system only alternated between Sardine High / Anchovy Low and Both High. Because of the differing number of natural cycles which will be accommodated in a 50-year span, the cycle ratio must also be considered to understand the frame behaviour.

To clarify: with a 10-yr cycle time and a 50-yr model run, we would expect three full cycles of one state and two full cycles of the other, with a total of five cycles fitting into the 50-yr run. Thus we would have a natural frame ratio of 3:2. The exact ratio is also determined by the timing of the frame switches in the run – again, for example, with a 10-yr cycle time, a 1:1 ratio could be achieved if the first switch occurred five years into the run. The results are summarised in Table 11.

Table 11 - Ratios of SardHi frame to BothHi in the unfished system with varying cycle time of ESI function.

Cycle Time (yrs)	**5**	**7**	**10**	**13**
Observed SardHi : BothHi	28.8 : 21.2	27.5 : 22.5	28.8 : 21.2	24.6 : 25.4
Expected Cycle ratio	25 : 25	26 : 24	29 : 21	25 : 25

Recall that the anchovy daemon requires multiple consecutive good years to switch to a "high" anchovy frame, but can switch to a "low" frame after a single bad year. Thus we see that with short cycle duration, the system spends more time in the anchovy "low" frames than might have been expected from the cycle ratios alone. Some of the implications of this result are explored further in the environmental scenarios (Section 4.3.2).

4.3 Results: Exercising the model from second prototype

4.3.1 Fishing strategy scenarios

Several managed runs were performed with interesting results of sardine recovery from an initial low population level. The low level was precipitated in each case by heavily fishing the modelled sardine stock, and then different management options were explored from that position. It rapidly became clear that the "low" sardine frames, regardless of fishing severity, were highly vulnerable to crash. In these frames, the margins of safety were small enough that inter-annual variability of recruitment could imperil the modelled stock at very low populations.

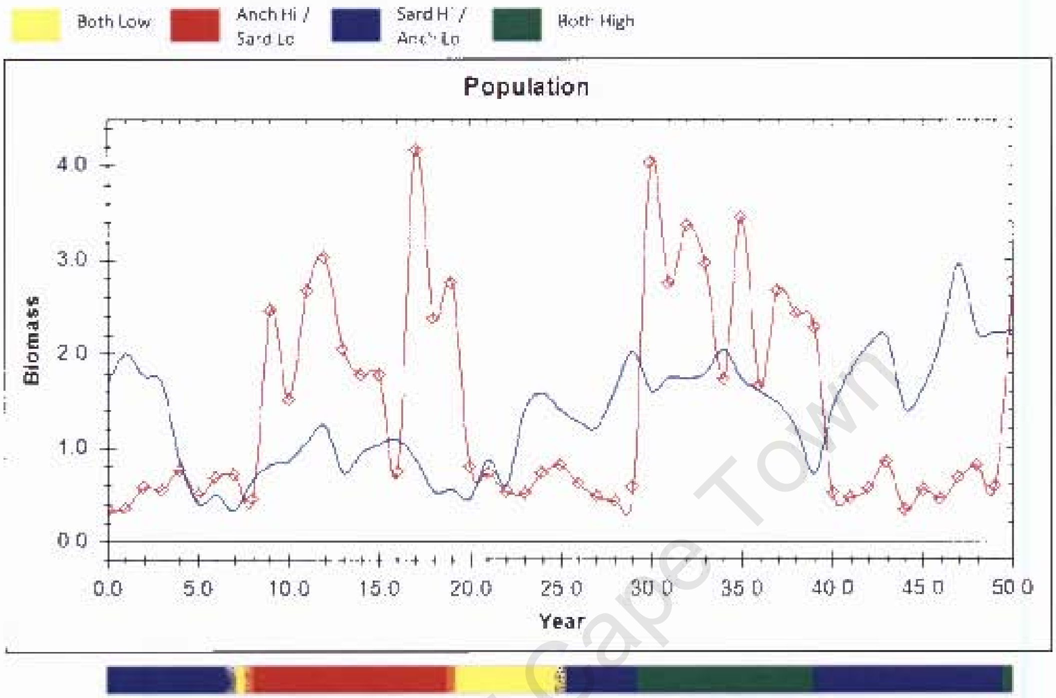


Figure 16 - Prototype 2, sardine fished heavily (at 0.6) for the first six years, then fished conservatively (at 0.3) for the rest of the run (blue line indicates sardine, red indicates anchovy). The "low" sardine frames delayed the sardine recovery for almost two decades, but once back in the "high" frames, the stock remained there under sustained moderate fishing.

In the model run shown in Figure 16, which was performed with Active Management, the sardine stock was heavily exploited (at 0.6) for the first six years to force the ecosystem into a sardine "low" frame. From that point, the sardine fishing was moderate (0.3) for the rest of the run. Despite the relatively conservative level of fishing, the sardine population took twenty years to escape the "low" frames, although once in the "high" frames it remained high for the rest of the model run. The performance of the modelled sardine stock in this example somewhat mirrors the population data from the mid-1960s through the '70s and early '80s, where heavy exploitation in the early '60s precipitated a low population state for the next 20 years.

The effect of juvenile sardine bycatch from anchovy fishing was also very clear. Heavy fishing on anchovy in a "low" sardine frame could prevent or delay a recovery of the modelled sardine population. Figure 17 shows a recovering sardine model population being crashed by excessive juvenile sardine bycatch due to increased anchovy fishing. Again, the sardine stock was heavily fished (at 0.6) to prompt a shift to a "low" sardine frame, and then the sardine fishing was greatly reduced (to 0.2). From year 30 the anchovy fishing was increased dramatically in response to the "high" anchovy frame. This halted the sardine recovery and ultimately crashed the sardine stock.

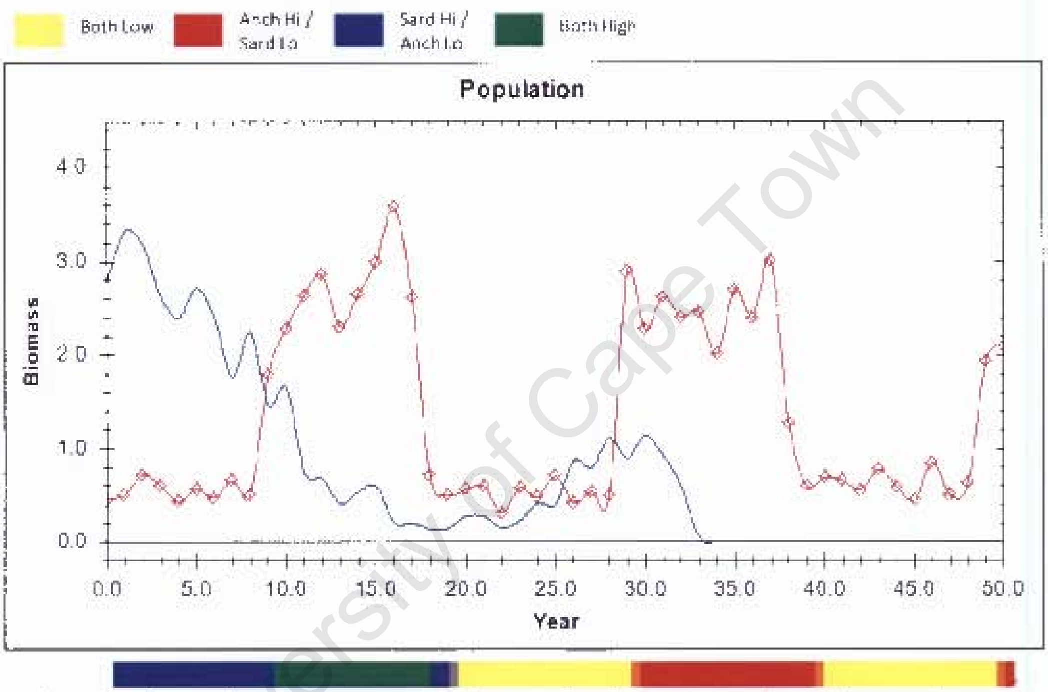


Figure 17 - Sardine fished to vulnerability (at 0.6), then allowed to recover (blue line indicates sardine, red indicates anchovy). From year 30, anchovy are fished heavily in response to high stocks. Bycatch from the anchovy fishing causes a collapse of the sardine population even under light (0.2) fishing.

With the sardine density dependence of Prototype 2, the sardine population showed good resilience to fishing pressure in the "high" sardine frames, although sufficiently high fishing could always crash the stocks (note the deliberate initial overfishing which was used in the previous two examples). In the "low" frames, however, the combination of bycatch and reduced recruitment made the population highly vulnerable to overfishing.

The vulnerability of the modelled sardine stock in the "low" frames calls for active management and ongoing monitoring. The high variability of recruitment can cause sufficient decline in the population even under moderate fishing to prompt a shift to a "low" frame, and if management intervention is not taken, sustained fishing in "low" sardine frame can quickly cause a collapse. Figure 18 shows ten successive runs of an unmonitored system with sustained fishing at constant TACs. Although the level of the TAC was conservative (0.4), and on nine of the runs the population stayed high, on one run the population declined far enough that it crashed. Intervention when the sardine went into a

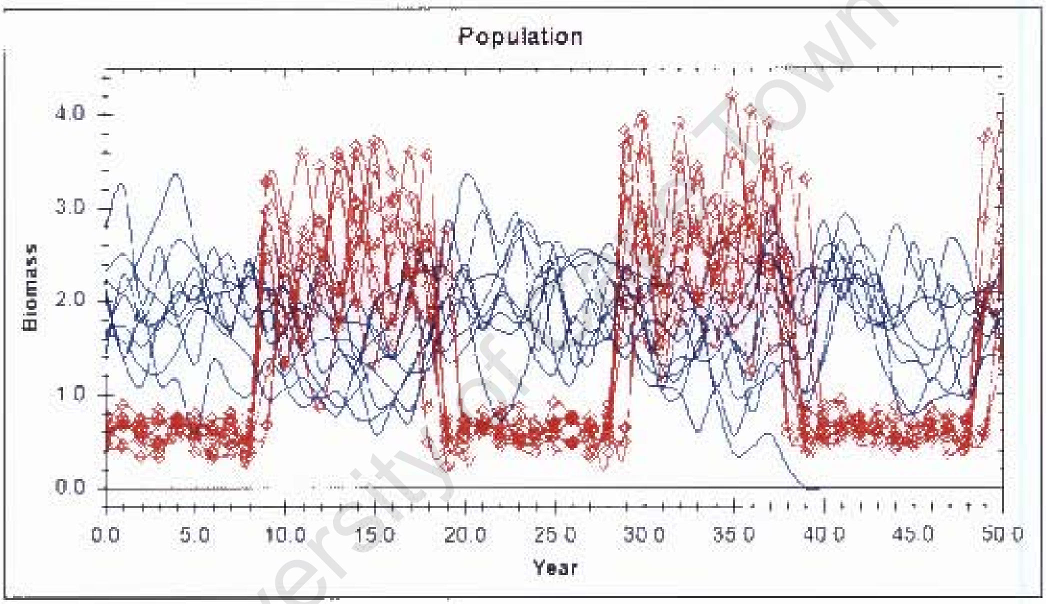


Figure 18 Prototype 2, with ten successive runs of the model on sustained, unmonitored fishing at a moderate level (0.4) for each entire run (blue lines indicate sardine, red indicate anchovy). Although the sardine population remains healthy for nine runs, on one of the runs the stochasticity of recruitment drives the stock to a vulnerable state, and lack of management compensation crashes the stock.

"low" frame on that run would most likely have avoided the crash. Thus management which adapts to regular and reliable survey data is necessary for safe exploitation of the stocks, as implemented to some degree in the current OMPs (de Moor and Butterworth, 2008). Importantly, the model is seen to behave in a realistic way, reinforcing its potential value as a training tool for management.

4.3.2 Environmental scenarios

a. Impact of ESI periodicity on management

After observing the effect of ESI periodicity on the anchovy frame behaviour of the model, a comparison was made of the sardine fishing performance under different ESI cycle times. Measurements were taken at the standard ESI cycle of 10 years and compared with readings from the model running a 5 year cycle. The experiments were repeated at AutoManage severity settings of 0%, 50% and 100%. The indicators recorded for the sardine fishery were average total time spent in the "low" sardine frames, the average annual catch and the frequency of sardine stock crashes. Measurements were taken over 1000 model runs with three replicates of each test, and the results averaged. The measurements are summarised in Table 12.

Overall, the performance of the fishery is similar at 5 and 10 year ESI cycle times. The shorter period did significantly improve performance of the fishery at higher severity of fishing strategy, showing a small reduction in crashes and time in "low" sardine frames, despite the average catches being unchanged. It was shown in the sensitivity analysis (section 4.2.3) that with a shorter cycle time, the anchovy population spends increased time in the "low" anchovy frames. The greatest risk of sardine stock crash occurs in the Anchovy High / Sardine Low frame, where the school trap factor is at its maximum, and thus it is possible that the reduced time in the "high" anchovy frames under a 5-yr cycle time reduces the risk of sardine stock crash. The modelled anchovy population respond to climate forcing after a 2-3 year lag time, and the impact of climate function on frame behaviour increases as the wave periodicity approaches the lag time.

Table 12 - Comparison of sardine fishing performance at various levels of AutoManage severity with ESI cycle times of 5 and 10 years

ESI cycle time (yrs)	AutoManage severity	Low Sardine frames (yrs)	Average annual catch	Crashes (per 1000 runs)
5	0%	0.13	0.342	0
10	0%	0.14	0.343	0
5	50%	3.40	0.420	25
10	50%	4.23	0.419	30
5	100%	25.99	0.338	574
10	100%	26.53	0.337	601

In terms of recommendations for the fishing management, the model suggests that a variation in ESI cycle time does not require a different management strategy, as the comparative fisheries performance across different severity settings under the 10- and 5-yr cycles times is very similar.

b. Effects of survey accuracy

Introducing random sampling error into the survey results could lead to interesting thought experiments. An example of the impact of survey error is seen in Figure 19. This model run was conducted with the AutoManage function at a fairly conservative setting (20% severity), and with a random simulated survey error each year of up to 20%. Typical survey errors assumed by stock assessors in the region are of the order of 15-30% (e.g. de Moor et al., 2008). Over-estimation in the years 30-32 resulted in excess fishing when the sardine stock was at a sensitive level and forced the stock into a "low" frame, where it remained for 15 years.

Note that at other stages of the model run, there was little observable effect from survey inaccuracy. During the years 30-32, however, the sardine stock was at a vulnerable level, and the over-estimation and subsequently increased fishing forced the system out of a "high" sardine frame. Unlike other points in the run where the survey data was inaccurate, during these years the actual modelled sardine population was on the threshold of a "low" frame transition, and the high fishing likely tipped the balance. The sensitivity of the model to fisheries management decisions based on inaccurate survey data should be explored further.

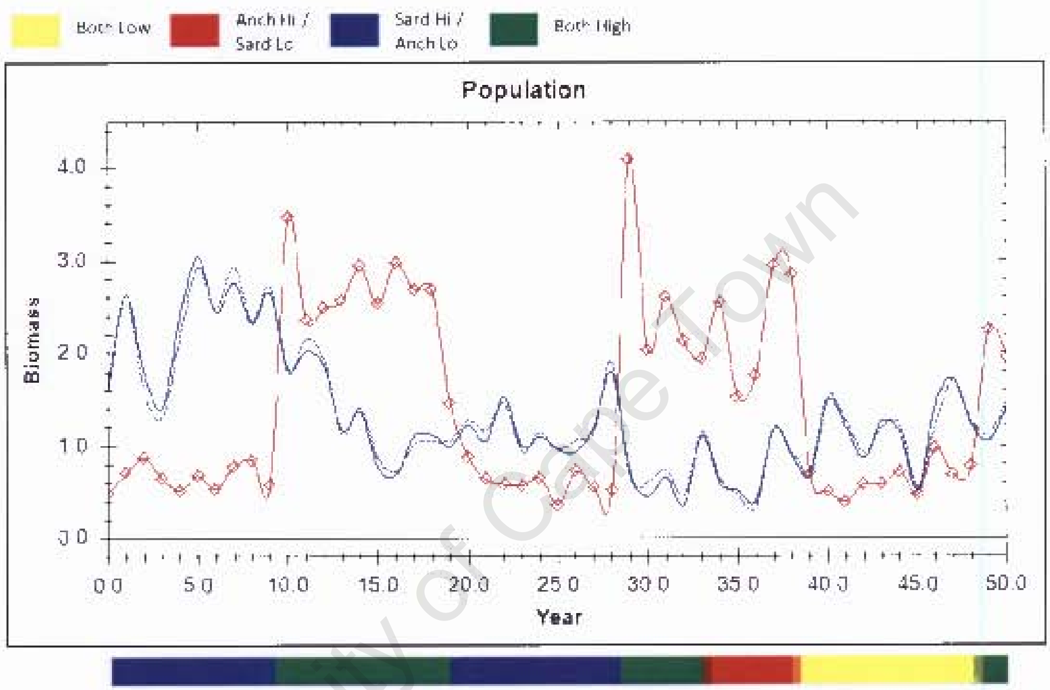


Figure 19 - A model run on Protype 2 with survey data error under a conservative AutoManage setting (20% severity). The solid blue line is the actual modelled sardine population, the dotted blue line is the (inaccurate) assessed population (the red line is the modelled anchovy population). Survey error is set at up to 20% of the modelled sardine biomass for each year. Generally, there was little observable effect from inaccurate surveys except in the case of years 30-32, where the actual population was close to a frame switch threshold. Over-assessment (and subsequent over-fishing) in this period resulted in the switch to a 'low' sardine frame.

5. Discussion

5.1 Is the model useful?

The purpose of this study is to explore the usefulness of the frame-based modelling technique with respect to small pelagic populations in the southern Benguela. Attempting to represent "real" ecosystem dynamics in a model presupposes a detailed understanding of the ecosystem dynamics which may be difficult to achieve. The development of a model may be useful as a thought experiment to investigate assumptions about the operation of the real ecosystem. The model allows us to explore the operation of our idealised "model world", and in doing so, improves our understanding of the real ecosystem.

To clarify the distinctions between the real world and our "model world", consider Figure 20. The real world is represented by an irregular shape because it is complex and not fully understood. We reduce the real world to a more orderly "model world" by making appropriate assumptions and simplifications, based on the aspects of the real world that we wish to explore and our understanding of the dynamics of the real world. It is in this idealised world that our model exists. The simplicity and clear relationships of the model world allow us to observe and interpret interactions which result from our experiments with the model. Because our understanding of the dynamics in the model world is good, we can then interpret these results in the real world. This will either support or challenge our understanding of the real world.

"Data" is also a simplified representation of the real world, rather than being a complete picture of it. How good the representation is depends on the quality the sampling and also on the nature of the relationships we are trying to represent. We use data to calibrate the model, but our stochastic model does not aim to reproduce a certain data set: we are rather interested in representing the system dynamics, a particular replicate of which happened to produce the set of available data (because in a stochastic world, reality is just one replicate). Discrepancies between the model results and the data record can thus inform our understanding of both systems: the model results can be challenged where they appear to be giving results inconsistent with the data, but the model outputs may also highlight shortcomings of the data.

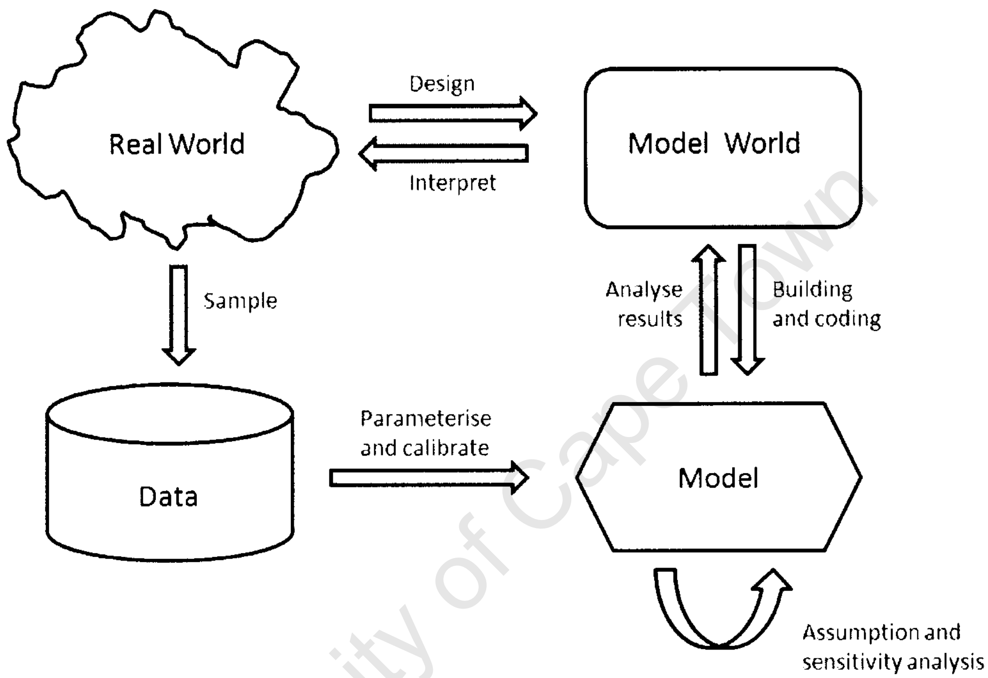


Figure 20 - Relationships between the model world (in which our model is built and tested) and the real world. The model world is an appropriately simplified version of the real world which retains the system dynamics of the real-world interactions that our model is designed to explore (After Starfield and Jarre, in review). Note that data from the real world is used to calibrate the model, but our model does not aim to directly reproduce the data.

With this in mind, we aimed to include the key characteristics of the small pelagic ecosystem in the southern Benguela in our model. It is admittedly less accurate than a stock assessment model (e.g. de Moor et al., 2008), but it was not developed with the objective of performing stock assessment. The frame-based model described here has the advantage that it provides a long-term perspective for model users trying to understand the implications of management strategies. It also includes the effects of climate variability and climate change, and the intuitive user interface makes it far more accessible as a training tool for users who may not come from a highly mathematical or scientific background. This is taken up further in Section 5.5.1.

5.2 Usefulness of the frame-based approach

5.2.1 Frame-based modelling in a context where the understanding of the system is evolving

The modular design of a frame-based model has important advantages in a system where the underlying mechanics may be subject to change, or may be poorly understood. Because each frame is effectively a separate model (although different frames may share many characteristics), the predominant forcing factors and significant components of each frame can be established independently.

In the southern Benguela ecosystem at present, there appears to be a movement of many species (including the small pelagics) from the West Coast to the South Coast. It is not clear whether this is in response to human intervention, changing climatic conditions, or is simply a cyclical trend with a particularly long frequency. But even while the causes are poorly understood it can be handled fairly simply under a frame-based model with the inclusion of additional frames. As the data for a theoretical "South Coast frame" improve, it would be possible to refine and re-test that frame without influencing the behaviour of other frames. Of course, the switching rules for the daemons may need certain adaptations.

In this respect, the frame-based approach stands distinct from more complex deterministic approaches such as NEMURO.FISH, where the dynamics of the system (particularly at a primary productivity level) are well understood. Although the NEMURO approach allows for detailed numerical outputs, it requires a fine-scale tuning of regional parameters to large volumes of data. The time and cost of development of a large and complex ecosystem model are orders of magnitude greater than for a frame-based model. The stochastic processes in our model also allow us to explore probabilities of certain outcomes (such as regime shifts or particular stock levels being maintained), which may be non-deterministic in the real world.

With regards to the crashing model sardine population, it could be argued that reducing a fish stock to zero is unrealistic: if the sardine were truly fished down to such a low level, the effort required to find and catch the few remaining schools would not be worth the value of the fish. An argument could thus be made, for instance, for setting the sardine at an arbitrary "very low" figure in the event of a crash. This would simulate stocks dropping to an "unfishable" level, although over decades they may still recover. Although this might be marginally more accurate in terms of representing the ecosystem, it is not necessary in terms of our model objectives: if the modelled sardine population drops to zero, the management has failed. Equally important, assumptions of an "inevitable" sardine recovery neglect to consider the possibility that the ecosystem may change irrecoverably to a new frame in the absence of the species. In the northern Benguela such a change appears to have taken place, as the niche previously filled by sardine and anchovy has largely been taken over by jellyfish and gobies following over-exploitation of the sardine stocks (Roux and Shannon, 2004). As with the suggested "South Coast frame", if an entirely new ecosystem state such as jellyfish/goby dominance were to emerge in the southern Benguela, such a shift could be incorporated into the current model by invoking additional frames.

5.2.2 Extracting more information from population thresholds

Traditional fisheries biology frequently uses two reference points for the biomass indicator of the target stock (e.g. ICES, 1998: p. 6-7). Above the precautionary (upper) reference point, the stock is considered to be in good condition, but once the stock size drops below this point, management measures are recommended to assist the stock recovery. If the stock size drops below the limit (lower) reference point, the stock is unacceptably low and harsher management measures (such as closure of the fishery) are requested or required. Such reference points are used for North Sea Cod (ICES, 2000: p. 239). Including the frame state allows us to draw different conclusions from the same biomass in different situations. The sardine daemon in the model has thresholds for switching frames which are similar to the precautionary and lower reference points: if the sardine is in a "high" frame, the stock must drop right down below the lower reference point (annual average <0.6 for three years) before a frame switch is caused. But once in the "low" frame, the stock must recover past the upper reference point (annual average >1.0 for three years) before it is considered to be in a "high" frame again. In the real population, a healthy sardine stock should recover from a temporary period of excessive fishing more easily than a stock which has been suppressed for a long period. Sardine at an intermediate population level (for example 0.8) in a "low" frame would be more likely to have sub-optimal schooling behaviour and therefore show reduced productivity than sardine in a "high" frame at the same population level. Thus the frame state allows us to easily consider the condition and behaviour of the stock as well as its size.

The health of the stock is considered in many fisheries, but is typically determined by a lengthy evaluation process. By encoding the evaluation into the daemon rules, our model gives a quick and easily understood indicator for the state of the modelled stock.

The examples below show the implications of frame state on two modelled sardine populations under similar management. In Figure 21, the modelled sardine stock was fished heavily (at 0.6) for years 0-9, which caused a rapid decline in the population. From year 9, the fishing pressure was reduced to 0.3, and because the modelled sardine stock was still in a high frame, it recovered quickly and the continued moderate fishing did not imperil the stock.

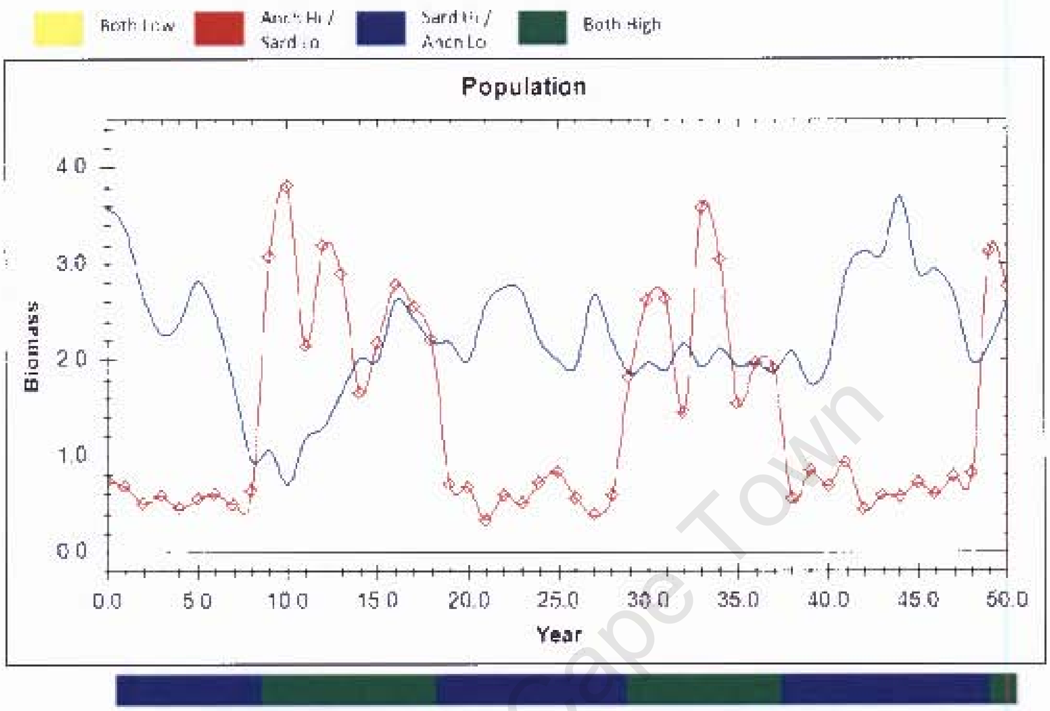


Figure 21 - Prototype 2 under heavy sardine fishing (at 0.6) for the first 9 years (blue line indicates sardine, red indicates anchovy). In response to the decline of the modelled sardine stock, fishing was reduced to 0.3 for the rest of the run, and sardine remained in a "high" frame

By contrast, Figure 22 shows a similar trend for the first 9 years of the model run, which also resulted from 9 years of heavy fishing (at 0.6).The sardine fishing was stopped entirely from year 9 until year 21, but the same recovery did not take place. While the initial trend in the modelled sardine population is similar to the previous example, in this run the population dropped below the critical transition threshold and the system switched to a sardine "low" frame. Recall that the fishing strategy in these two tests was identical, and the difference in frame behaviour is due to the stochasticity of sardine recruitment. The transition to a "low" frame in this case necessitated a closure of the fishery and resulted in 12 years of vulnerable sardine. Although years 14-21 exhibit a sustained modelled sardine population of > 0.8, the frames indicate that the sardine stock is still vulnerable and advise a conservative management approach. From year 21, sardine fishing was resumed at 0.3 for the remainder of the run.

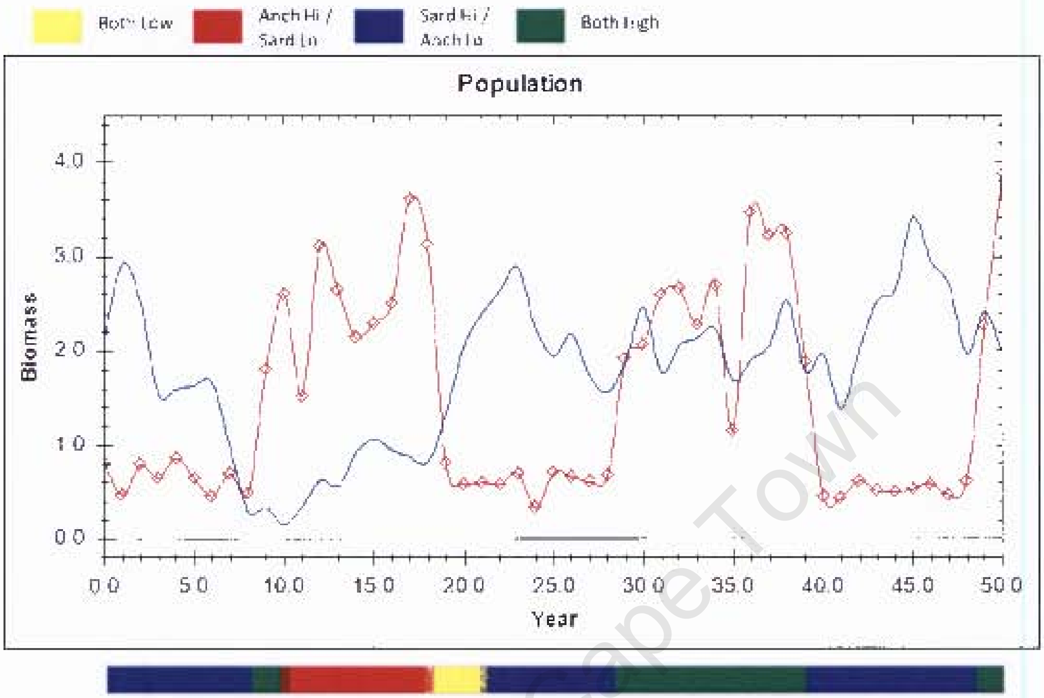


Figure 22 - Prototype 2 under heavy sardine fishing (0.6) for the first 9 years (blue line indicates sardine, red indicates anchovy). In response to the decline in sardine population, sardine fishing was stopped completely until year 21, when it was resumed at 0.3 for the rest of the run.

5.2.3 Frame-based models as aids to inter-disciplinary communication

From a development perspective, the frame-based paradigm serves as a useful interface between software developers and ecosystem biologists. In an environment in which the coding and model design work are often performed by programming specialists, based on descriptions from biologists with perhaps limited programming expertise, it is vital to be able to communicate concepts between the different groups.

Frame-based models are also a useful way for biologists and managers to describe ecosystems, as they help to move thinking towards long term effects of management actions. By setting the ecosystem into a specific frame for each time step, the frame-based system highlights the important factors which are at play in the system at that point. For instance, if a real ecosystem goes into a "low" sardine frame, the user of this model now understands the hazards implicit in that state.

Such models also fit naturally into well-encapsulated computer code. It has already been noted that an ecosystem model which is compartmentalised into multiple sub-models (the frames) is easy to expand if a new ecosystem description becomes necessary (such as the proposed "South Coast frame" in the southern Benguela model), or if the understanding of the behaviour of a particular frame changes. This kind of model also translates into well-structured and easily maintained programme code.

Ill-defined software specifications rarely result in well-written or stable programmes. However, with high inherent uncertainty in ecosystem dynamics and major gaps in our understanding it is difficult (or rather impossible) for biologists to give an exact specification of the requirements of an ecosystem model. Frames and rapid prototyping are modelling techniques well suited to dealing with incremental increases in knowledge and understanding of the real world.

5.3 Advantages of rapid prototyping

The experiences with modelling sardine density dependence are illustrative of the strong advantages of rapid prototyping as a modelling technique. We were able to build a first model based on initial assumptions, test those assumptions, build a refined model, test it, refine the parameters of the second model and retest it very quickly. The development of the first prototype, including planning, software development and testing, took about one month to complete. By eliminating unnecessary complications from the model, it became much clearer to see which components were influencing the population behaviour in different ways, and refine and test the model accordingly.

Our first attempts to model the sardine density dependence were over-simplified, and even with the second prototype our initial levels of density dependence resulted in a modelled sardine population that was excessively resistant to fishing: the effect of the increase in recovery rate at low population levels was such that the sardine were very hard to fish down, which is not consistent with historical evidence (e.g. Boyer and Hampton, 2001; Fairweather et al., 2006a; Coetzee et al., 2006). Density dependence should help a healthy sardine population to recover from a mild setback, but in fact the recruitment variability was far more significant in our model. A classic Schaeffer model would imply that it is possible to keep the stocks at a constant moderate population level and rely on density dependence to keep the system stable, but the results from our model suggest that this may be over-simplified. With such high variability in recruitment, if sardine fishing is to achieve maximum sustainable yields (in the classical sense), the importance of recruit surveys can scarcely be overstated (Csirke, 1988). Estimating the actual stock size for a given year is vital for setting safe fishing levels, particularly if the stocks are in a vulnerable state, for instance in a "low" frame or near a frame transition point.

5.4 Applications of the model

The model was not built to perfectly replicate the real ecosystem, and it is admittedly a much simplified representation. However, it is sufficiently realistic to show potential to perform as a "training tool" for management. By providing a mechanism to exert varying degrees of fishing pressure on the stocks, the model allows a prospective manager to experiment with a simplified version of the stocks and immediately see the impact of their actions. Such experiments also help a prospective manager to appreciate the levels of unpredictability in the system and the need for a conservative approach to fisheries management. By separating the graphical interface from the complicated programming behind it, the model gives easily understood outputs of modelled populations and frame states to a non-specialist user, while also displaying more detailed statistics on the diagnostics tab for the more advanced user.

Further uses of the model involve generating probabilities of outcomes based on particular management actions, in order to feed into an expert system for predicting long-term ecosystem changes. This is discussed in more detail in Section 5.5.2.

5.5 Proposed further research and model expansion

5.5.1 For use as a training tool

The influence of variability in accuracy of survey data should be explored further. In particular, it would be interesting to evaluate the effect of decreasing survey accuracy on the system, investigating to what extent fisheries management strategy informed by inaccurate data affects the sardine population performance. In the model, the survey data is equally likely to over-report or under-report, but the consequences of these errors are very different. An under-estimated sardine stock would result in less fishing activity for the year, and thus less income for the fishing industry than could otherwise have been enjoyed, but the impact of the error (benefit for the sardine population, loss of potential bonus catch for the fishing industry) will only span that single year. An over-reported stock size, in contrast, would result in higher catches than would have been recommended from an accurate survey. Depending on the stock level, this increased fishing could not only increase the income of the fishing industry in that year, but it could also imperil the sardine stock, potentially even crashing the population. Thus although the magnitude of survey error may be symmetrical in either direction, we would expect it to have an overall negative effect on sardine performance. A thorough exploration of this (with a study of important thresholds of accuracy) would be useful in suggesting the extent of biomass surveys which were necessary for safe fishing.

With respect to the current user interface, the inclusion of help screens and explanatory notes providing more information on the reaction of the system to user inputs would increase the value of the programme as a training tool. A well-designed and interactive user interface greatly increases the potential user base of the tool, allowing (for instance) fisheries managers, conservationists and researchers to experiment with and learn from the model (as also observed by Quadling and Starfield, 2002).

Including a population model for anchovy would allow us to test the assumptions of the response of the anchovy stock to fishing pressure. The anchovy daemon would still need to base its switching rules largely on the ESI, as the environmental factors are by far the most significant on the anchovy population (Miller and Field, 2002). In the current sardine population model, the recruitment parameter receives a small negative adjustment in an Anchovy High frame based on the assumption that the environment is sub-optimal for sardine. A similar approach could be taken with an anchovy population model, where the recruitment parameter was increased significantly in the "high" anchovy frames (i.e., when the climate is favourable), and thus the modelled anchovy population would recover very quickly from severe fishing in these frames. In the "low" anchovy frames, with no environmental boost, they could be crashed by similar fishing levels.

In order to increase model accuracy, the population model used for sardine could be refined by including age-structure. The different spawning potentials of different age-classes of adult fish do not currently affect the model, but there is evidence that this is a factor in the real fish population (van der Lingen et al., 2006c; de Oliveira, 2006).

5.5.2 For use in an expert system to predict regime shifts

Models which offer a long-term view to species population changes are an important component in attempting to predict regime shifts on an ecosystem scale (Jarre et al., 2006). Although such an ecosystem shift would have impact on a wide range of species, indicators of shifts at a community level may be difficult to measure (see various contributions in Daan et al., 2005). A synthesis of such data as are available is necessary to derive an holistic view of trends in a multi-species system incorporating several trophic levels (Jarre et al., 2006). Small pelagic populations are particularly well suited as an indicator, due to their "wasp-waist" position in the ecosystem, with a small number of species supporting a relatively high species richness at higher trophic levels.

Ideal indicators at an ecosystem level would come from the primary productivity (Tester et al., 1997; Rupp et al., 2000b). Many of the physical data (such as sea surface temperature, transport current strength and upwelling strength) which are summarised in the Environmental Suitability Index in the model are available for use as indicators, and show evidence of regime shifts (Howard et al., 2007). However, our understanding of plankton dynamics is currently insufficient to observe regime shifts in the available data (Demarcq et al., 2008). As small pelagics occupy a low trophic level in the food web, it is useful to employ them for modelling ecosystem regime shifts.

Predators such as seabirds, seals, predatory fish and some cetaceans are highly sensitive to changes in small pelagic fish abundance, as well as suffering incidental mortality from small pelagic-directed fishing activity (Shannon et al., 2004). Predator species at higher trophic levels could be added to the existing model, preying on the small pelagics which "escape" the fisheries, but this extension was outside the scope of the present project. Certain aspects of predator dynamics (such as the need for available forage near seabird nesting sites) would not be suitable for inclusion because these interactions occur at specific spatial scales.

A suitable synthesis of environmental and small pelagic indicators in the model, as well as the long-term perspective, offer potential to contribute to the assessment of probabilities of change for an expert system to predict regime shifts. Modelling the likely effect of fishing activity on small pelagic populations, such as implemented in this model, can give probabilities of fishing activity initiating or contributing to an ecosystem shift. For this to be possible, the model should be configured to specifically record probabilities of relevant outcomes rather than averaged data. At present, the data displayed at the end of each run are more geared towards the training applications, with averaged figures, crash data and thresholds for specific performance evaluation (e.g. the >80% "good year" index). The individual data for each year of each model run are retained in the programme, so configuring the outputs to provide probability data rather than averages would be straightforward.

5.5.3 Additional possibilities

We have so far assumed no long-term trend in the climate parameters in the ESI. It would be interesting to investigate the frame and population behaviour in the model if the baseline ESI (the midpoint about which the function fluctuates) were gradually increased over the course of the model run.

It may be useful to link the existing frame-based model to a similar model of the social system (as proposed by Jarre et al., 2007) in order to connect the influence of social drivers (and their changes in the long term) to fishing pressure. However, there is already potential to increase the scope of questions which can be addressed with the existing model by including, for example, economic indicators. The inclusion of economic indicators might allow us to evaluate, for example, different catch compositions due to different market values of sardine and anchovy. Along similar lines, a sensitivity analysis which evaluated the effects of varying levels of illegal, unregulated and unreported fishing (perhaps by varying the catch above the suggested TAC level for a particular year) could also be of benefit in establishing suitable levels of monitoring and compliance enforcement.

6. Conclusions

- A semi-qualitative second prototype model was developed to investigate dominance shifts between sardine and anchovy in the southern Benguela. The modelled sardine population was found to be sensitive to the fishing strategy, including both sardine-directed fishing and modelled sardine bycatch from the anchovy fishery. Frame-switching behaviour was moderately sensitive to the daemon parameters, and highly sensitive to sardine fishing strategy.
- While our general results increased confidence in the model, the high degree of stochasticity in the modelled system suggested caution in analysing real-world data series and inferring cause-and-effect relationships.
- Although not suitable for stock assessment, the frame-based model described here offers a long-term perspective to aid understanding of the impact of fisheries management strategies under long-term climate variability and change on small pelagics in the southern Benguela.
- The modular design which results from a frame-based modelling approach results in a flexible and easily adapted model which can be incrementally updated as understanding of the system evolves. Additional frames can even be added to the model where it appears that the ecosystem is entering a previously unobserved state. Rapid prototyping allowed us to test assumptions quickly and refine the model accordingly during the development cycle.
- The frame-based paradigm provides a natural "common ground" to facilitate communication between biologists and computer programmers. Frame-based models encourage well-structured and easily maintained computer programmes.

- The graphical population output and clear frame display allow a user to experiment with the model and learn from it even without a detailed understanding of the programming behind it. Further development in this regard could broaden the potential user base of the model as a training tool. The model allows users to explore differing fisheries strategies and see the likely impact on the modelled stocks.

- Some minor data processing adaptations would allow the model to contribute probabilities of change to an expert system for predicting long-term ecosystem changes.

- The inclusion of frames in the outputs gives the user a greater depth of understanding of the condition and behaviour (and hence vulnerability) of the modelled stocks than simple population indicators would. The frame concept is also valuable in highlighting the most important factors at play in the system at any particular point in the model run. By encoding any calculations and rules within the daemons, the frames state serves as a quick "summary" indicator of the modelled stock condition.

7. Acknowledgements

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9. Appendices

9.1 Appendix A: Sensitivity and assumption analyses data (for Table 6, Section 4.2.1)

Section 4.2.1 contains a summary table of the results of the tests performed for the broad sensitivity and assumption analysis. Included are the data from the tests themselves. Frame behaviour figures record the time spent in the "Both High" frame. Fished system figures are all performed on the AutoManage function at the most "conservative" setting.

	Average Population		Sardine catch		Anchovy catch		Frame behaviour	
	Sard	Anch	Avg	std. dev.	Avg	bycatch	Duration	Res.
AutoManage sardine thresholds								
AutoManage sardine TAC levels								
Sardine Daemon: Cumulative vs 3 years	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8
Sardine switching limits: Thresholds	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8
Anchovy Daemon: Cumulative vs 3 years	3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8
Anchovy switching limits: Upper threshold	4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8
Anchovy switching limits: Poor year threshold	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8
Sardine recovery rate scale factor	6.1	6.2	6.3	6.4	6.5	6.6	6.7	6.8
Sardine school trap factor	7.1	7.2	7.3	7.4	7.5	7.6	7.7	7.8
Variance of climate	8.1	8.2	8.3	8.4	8.5	8.6	8.7	8.8

Colour key:

Negligible effect ... Extremely sensitive

The final indicator colour given to a cell was based on all the contributing figures. For example, for cell 1.1, the colour was based on the observed changes in average sardine population level in the unfished and fished system at both the "cumulative sum" and the "set of 3" settings.

Validation 1: AutoManage Sardine Thresholds

Tests on the AutoManage function were only performed on the fished system. The standard configuration regards the sardine as safe for high exploitation at a population of 1.0, and moderate exploitation if the population is above 0.5. The robot manager will stop fishing if the population is below 0.5. Tests were performed with thresholds lowered to 0.8 and 0.4, or raised to 1.2 and 0.6.

Test Settings	Metric	Test runs			avg
Thresholds 1.0/0.5 Fished system	Sard. Avg. Pop.	1.063	1.0364	1.0335	1.0443
	Anch. Avg. Pop	1.2693	1.2715	1.2816	1.2741
	Sardine catch	0.3278	0.3341	0.3313	0.3311
	Sardine Catch std. deviation	0.1002	0.1001	0.1058	0.102
	Anchovy catch	0.4204	0.4236	0.4273	0.4238
	Juvenile sardine bycatch	0.0084	0.0112	0.01	0.0099
	Both Hi frame duration (yrs)	17.48	18.59	17.52	17.863
	Both Hi frame residence (yrs)	8.55	8.74	8.055	8.4483
Thresholds 0.8/0.4 Fished system	Sard. Avg. Pop.	0.7908	0.9063	0.8485	0.8485
	Anch. Avg. Pop	1.2602	1.2574	1.2683	1.262
	Sardine catch	0.3111	0.3207	0.3102	0.314
	Sardine Catch std. deviation	0.1128	0.1017	0.1021	0.1055
	Anchovy catch	0.418	0.4168	0.4209	0.4186
	Juvenile sardine bycatch	0.0181	0.0151	0.0139	0.0157
	Both Hi frame duration (yrs)	11.6	13.35	13.46	12.803
	Both Hi frame residence (yrs)	6.385	6.665	6.825	6.625
Thresholds 1.2/0.6 Fished system	Sard. Avg. Pop.	1.2149	1.2385	1.1823	1.2119
	Anch. Avg. Pop	1.2636	1.2575	1.265	1.262
	Sardine catch	0.3108	0.3082	0.3058	0.3083
	Sardine Catch std. deviation	0.0968	0.1018	0.1032	0.1006
	Anchovy catch	0.4181	0.418	0.4204	0.4188
	Juvenile sardine bycatch	0.0002	0.001	0.0018	0.001
	Both Hi frame duration (yrs)	20.93	20.98	20.62	20.843
	Both Hi frame residence (yrs)	9.655	9.645	9.505	9.6017

Validation 2: AutoManage TAC levels

The standard configuration of the AutoManage function has a high sardine exploitation level of 0.4, and uses a TAC of 0.2 for moderate exploitation. Tests were performed with TAC levels lowered to 0.2 and 0.1, or raised to 0.5 and 0.3.

Test Settings	Metric	Test runs			avg
TAC levels 0.4/0.2 Fished system	Sard. Avg. Pop.	1.063	1.0364	1.0335	1.0443
	Anch. Avg. Pop	1.2699	1.2576	1.278	1.2685
	Sardine catch	0.3278	0.3341	0.3313	0.3311
	Sardine Catch std. deviation	0.1002	0.1001	0.1058	0.102
	Anchovy catch	0.422	0.4126	0.4173	0.4173
	Juvenile sardine bycatch	0.0084	0.0112	0.01	0.0099
	Both Hi frame duration (yrs)	17.48	18.59	17.52	17.863
	Both Hi frame residence (yrs)	8.55	8.74	8.055	8.4483
TAC levels 0.3/0.1 Fished system	Sard. Avg. Pop.	1.3037	1.3264	1.333	1.321
	Anch. Avg. Pop	1.2638	1.2769	1.2802	1.2736
	Sardine catch	0.2644	0.2652	0.2656	0.2651
	Sardine Catch std. deviation	0.0416	0.0426	0.0405	0.0416
	Anchovy catch	0.4218	0.4182	0.4199	0.42
	Juvenile sardine bycatch	0.002	0.0012	0.0018	0.0017
	Both Hi frame duration (yrs)	20.35	20.97	20.68	20.667
	Both Hi frame residence (yrs)	9.47	9.69	9.46	9.54
TAC levels 0.5/0.3 Fished system	Sard. Avg. Pop.	0.7794	0.7832	0.7218	0.7615
	Anch. Avg. Pop	1.2578	1.2621	1.2612	1.2604
	Sardine catch	0.3665	0.3642	0.3421	0.3576
	Sardine Catch std. deviation	0.1766	0.1832	0.1831	0.181
	Anchovy catch	0.4191	0.4184	0.4192	0.4189
	Juvenile sardine bycatch	0.023	0.0232	0.0207	0.0223
	Both Hi frame duration (yrs)	11.13	10.34	10.17	10.547
	Both Hi frame residence (yrs)	6.51	5.89	5.705	6.035

Test 1: Sardine Daemon switching rules (cumulative sum vs set of three good years)

Cumulative sum:

- switch to low if total pop from last three years < 1.5
- Switch to high if total pop from last three years > 3.0

Set of 3:

- Switching to low if 3 consecutive yrs of pop < 0.5
- Switching to high if 3 consecutive yrs of pop > 1.5

Test Settings	Metric	Test runs			avg
Cumulative sum: Unfished system	Sard. Avg. Pop.	2.0526	2.1055	2.2044	2.1208
	Anch. Avg. Pop	1.2853	1.2697	1.2515	1.2688
	Both Hi frame duration (yrs)	21.13	21.14	21.51	21.26
	Both Hi frame residence (yrs)	9.74	9.725	9.91	9.7917
Set of 3: Unfished system	Sard. Avg. Pop.	2.1512	2.1585	2.1678	2.1592
	Anch. Avg. Pop	1.2533	1.2569	1.2517	1.254
	Both Hi frame duration (yrs)	21.06	21.12	20.99	21.057
	Both Hi frame residence (yrs)	9.725	9.685	9.655	9.6883
Cumulative sum: Fished system	Sard. Avg. Pop.	1.0489	1.0983	1.0578	1.0683
	Anch. Avg. Pop	1.2837	1.2653	1.2705	1.2732
	Sardine catch	0.3388	0.3371	0.3372	0.3377
	Sardine Catch std. deviation	0.0988	0.0937	0.0963	0.0963
	Anchovy catch	0.4279	0.4219	0.4227	0.4242
	Juvenile sardine bycatch	0.0124	0.0080	0.0109	0.0104
	Both Hi frame duration (yrs)	16.65	16.84	18.08	17.19
	Both Hi frame residence (yrs)	8.305	8.16	8.67	8.3783
Set of 3: Fished system	Sard. Avg. Pop.	1.0565	1.0716	1.0378	1.0553
	Anch. Avg. Pop	1.2547	1.2633	1.2729	1.2636
	Sardine catch	0.3337	0.3351	0.3214	0.3301
	Sardine Catch std. deviation	0.0906	0.0907	0.0986	0.0933
	Anchovy catch	0.4169	0.4183	0.424	0.4197
	Juvenile sardine bycatch	0.0033	0.0035	0.0018	0.0029
	Both Hi frame duration (yrs)	20.09	19.82	19.91	19.94
	Both Hi frame residence (yrs)	9.475	9.31	9.455	9.4133

Test 2: Sardine Daemon switching thresholds: threshold sensitivity

- Switching to low if total pop < 1.5 from last three years
- Switching to high if total pop > 3.0 from last three years

For the "lowered" and "raised" settings, both thresholds are lowered or raised by 0.3.

Test Settings	Metric	Test runs			avg
p < 1.5, p > 3.0 Unfished system	Sard. Avg. Pop.	2.1479	2.1035	2.2186	2.1567
	Anch. Avg. Pop	1.259	1.267	1.3462	1.2907
	Both Hi frame duration (yrs)	21.19	21.08	21.27	21.18
	Both Hi frame residence (yrs)	9.7	9.745	9.81	9.7517
p < 1.2, p > 2.7 Unfished system	Sard. Avg. Pop.	2.1758	2.1263	2.0954	2.1325
	Anch. Avg. Pop	1.264	1.2596	1.2775	1.267
	Both Hi frame duration (yrs)	21.13	21.51	21.16	21.267
	Both Hi frame residence (yrs)	9.745	9.915	9.725	9.795
p < 1.8, p > 3.3 Unfished system	Sard. Avg. Pop.	2.1342	2.1161	2.1202	2.1235
	Anch. Avg. Pop	1.2586	1.2486	1.2647	1.2573
	Both Hi frame duration (yrs)	21.02	21.1	20.88	21.00
	Both Hi frame residence (yrs)	9.68	9.77	9.595	9.6817
p < 1.5, p > 3.0 Fished system	Sard. Avg. Pop.	1.063	1.0364	1.0335	1.0443
	Anch. Avg. Pop	1.276	1.2646	1.2452	1.2619
	Sardine catch	0.3278	0.3341	0.3313	0.3311
	Sardine Catch std. deviation	0.1002	0.1001	0.1058	0.102
	Anchovy catch	0.4254	0.4212	0.4126	0.4197
	Juvenile sardine bycatch	0.0084	0.0112	0.01	0.0099
	Both Hi frame duration (yrs)	17.48	18.59	17.52	17.863
	Both Hi frame residence (yrs)	8.55	8.74	8.055	8.4483
p < 1.2, p > 2.7 Fished system	Sard. Avg. Pop.	1.0662	1.0472	1.0347	1.0494
	Anch. Avg. Pop	1.2831	1.2577	1.2698	1.2702
	Sardine catch	0.3335	0.3295	0.3303	0.3311
	Sardine Catch std. deviation	0.0932	0.0974	0.0971	0.0959
	Anchovy catch	0.4281	0.4173	0.4232	0.4229
	Juvenile sardine bycatch	0.0058	0.0048	0.0056	0.0054
	Both Hi frame duration (yrs)	18.34	19.05	19.23	18.873
	Both Hi frame residence (yrs)	7.91	8.483	8.305	8.2327
p < 1.8, p > 3.3 Fished system	Sard. Avg. Pop.	1.0881	1.0423	1.0774	1.0693
	Anch. Avg. Pop	1.2611	1.2634	1.2863	1.2703
	Sardine catch	0.3391	0.3349	0.3347	0.3362
	Sardine Catch std. deviation	0.0928	0.0971	0.0972	0.0957
	Anchovy catch	0.4186	0.4202	0.4296	0.4228
	Juvenile sardine bycatch	0.0085	0.0102	0.0096	0.0095
	Both Hi frame duration (yrs)	17.06	18.81	16.99	17.62
	Both Hi frame residence (yrs)	8.335	8.86	8.61	8.6017

Test 3: Anchovy Daemon switching rules: Cumulative ESI vs three good years

Cumulative:

- Switch to high if running ESI total > 15
- Switch to low if ESI < 4

Set of 3:

- Switch to high three consecutive years with ESI > 5
- Switch to low if three consecutive years with ESI < 4

Test Settings	Metric	Test runs			avg
Cumulative sum: Unfished system	Sard. Avg. Pop.	2.1017	2.1735	2.1257	2.1336
	Anch. Avg. Pop	1.2827	1.2635	1.2774	1.2731
	Both Hi frame duration (yrs)	21.3	21.06	21.36	21.24
	Both Hi frame residence (yrs)	9.79	9.715	9.835	9.78
Set of 3: Unfished system	Sard. Avg. Pop.	2.1179	2.1507	2.1061	2.1249
	Anch. Avg. Pop	1.2668	1.2901	1.2768	1.2779
	Both Hi frame duration (yrs)	24.98	25.29	25.3	25.19
	Both Hi frame residence (yrs)	7.96	8.073	8.07	8.0343
Cumulative sum: Fished system	Sard. Avg. Pop.	1.1011	1.011	1.0089	1.0403
	Anch. Avg. Pop	1.272	1.2749	1.2507	1.2659
	Sardine catch	0.3399	0.3273	0.3298	0.3323
	Sardine Catch std. deviation	0.0928	0.1067	0.1061	0.1019
	Anchovy catch	0.4227	0.425	0.4131	0.4203
	Juvenile sardine bycatch	0.0097	0.011	0.0101	0.0103
	Both Hi frame duration (yrs)	17.51	16.6	16.73	16.947
	Both Hi frame residence (yrs)	8.43	8.215	8.36	8.335
Set of 3: Fished system	Sard. Avg. Pop.	1.0249	1.0489	1.0363	1.0367
	Anch. Avg. Pop	1.2491	1.2816	1.264	1.2649
	Sardine catch	0.3312	0.3319	0.3322	0.3318
	Sardine Catch std. deviation	0.1042	0.1042	0.1049	0.1044
	Anchovy catch	0.4196	0.4305	0.4244	0.4248
	Juvenile sardine bycatch	0.0111	0.0096	0.0117	0.0108
	Both Hi frame duration (yrs)	20.58	21.1	19.76	20.48
	Both Hi frame residence (yrs)	6.693	6.995	6.59	6.7593

Test 4: Anchovy switching limits: Upper threshold sensitivity

Anchovy switch to high if running total ESI > 15. Sensitivity tests done at +/- 3.

Test Settings	Metric	Test runs			avg
ESI > 15	Sard. Avg. Pop.	2.167	2.126	2.1565	2.1498
Unfished system	Anch. Avg. Pop	1.2784	1.2577	1.2614	1.2658
	Both Hi frame duration (yrs)	21.06	21.36	21.42	21.28
	Both Hi frame residence (yrs)	9.71	9.825	9.885	9.8067
ESI > 12	Sard. Avg. Pop.	2.1363	2.1223	2.1789	2.1458
Unfished system	Anch. Avg. Pop	1.3075	1.3002	1.2944	1.3007
	Both Hi frame duration (yrs)	22.11	22.14	22.05	22.1
	Both Hi frame residence (yrs)	10.055	10.07	10.025	10.05
ESI > 18	Sard. Avg. Pop.	2.0849	2.1283	2.1649	2.126
Unfished system	Anch. Avg. Pop	1.2016	1.2005	1.2073	1.2031
	Both Hi frame duration (yrs)	19.14	19.25	19.14	19.177
	Both Hi frame residence (yrs)	9.07	9.125	9.07	9.0883
ESI > 15	Sard. Avg. Pop.	1.0412	1.0655	0.9843	1.0303
Fished system	Anch. Avg. Pop	1.27	1.2742	1.2798	1.2747
	Sardine catch	0.3383	0.34	0.3312	0.3365
	Sardine Catch std. deviation	0.1007	0.0917	0.1028	0.0984
	Anchovy catch	0.4226	0.4239	0.4269	0.4245
	Juvenile sardine bycatch	0.0117	0.0081	0.0108	0.0102
	Both Hi frame duration (yrs)	17.03	18.35	18.02	17.8
	Both Hi frame residence (yrs)	8.35	8.795	8.255	8.4667
ESI > 12	Sard. Avg. Pop.	1.0198	1.0301	1.0392	1.0297
Fished system	Anch. Avg. Pop	1.3008	1.2927	1.2877	1.2937
	Sardine catch	0.33	0.3353	0.3328	0.3327
	Sardine Catch std. deviation	0.105	0.1055	0.1003	0.1036
	Anchovy catch	0.438	0.4345	0.4321	0.4349
	Juvenile sardine bycatch	0.01	0.0119	0.011	0.011
	Both Hi frame duration (yrs)	18.31	17.88	17.66	17.95
	Both Hi frame residence (yrs)	9.09	8.44	8.465	8.665
ESI > 18	Sard. Avg. Pop.	1.0783	1.09	1.0553	1.0745
Fished system	Anch. Avg. Pop	1.1894	1.2017	1.1904	1.1938
	Sardine catch	0.338	0.3391	0.3322	0.3364
	Sardine Catch std. deviation	0.0911	0.0938	0.1008	0.0952
	Anchovy catch	0.3853	0.3905	0.3849	0.3869
	Juvenile sardine bycatch	0.0072	0.0078	0.0083	0.0078
	Both Hi frame duration (yrs)	16.51	16.54	15.81	16.287
	Both Hi frame residence (yrs)	7.975	8.185	7.915	8.025

Test 4: Anchovy switching limits: poor year threshold sensitivity

Anchovy switch to low and reset running ESI total if yearly ESI < 4. Tests done at +/- 1 of normal.

Test Settings	Metric	Test runs			avg
ESI < 4 Unfished system	Sard. Avg. Pop.	2.1654	2.1338	2.1112	2.1368
	Anch. Avg. Pop	1.2544	1.2651	1.2601	1.2599
	Both Hi frame duration (yrs)	21.07	21.01	21.17	21.083
	Both Hi frame residence (yrs)	9.7	9.72	9.74	9.72
ESI < 3 Unfished system	Sard. Avg. Pop.	2.1486	2.1472	2.1564	2.1507
	Anch. Avg. Pop	1.392	1.3925	1.3831	1.3892
	Both Hi frame duration (yrs)	24.62	24.75	24.87	24.747
	Both Hi frame residence (yrs)	11.485	11.525	11.535	11.515
ESI < 5 Unfished system	Sard. Avg. Pop.	2.1352	2.1236	2.1284	2.1291
	Anch. Avg. Pop	1.1278	1.1404	1.1284	1.1322
	Both Hi frame duration (yrs)	17.75	17.52	17.41	17.56
	Both Hi frame residence (yrs)	8.085	7.99	7.97	8.015
ESI < 4 Fished system	Sard. Avg. Pop.	1.0582	1.0917	1.0211	1.057
	Anch. Avg. Pop	1.2636	1.2613	1.2543	1.2597
	Sardine catch	0.3402	0.3397	0.3319	0.3373
	Sardine Catch std. deviation	0.0992	0.0941	0.1026	0.0986
	Anchovy catch	0.4197	0.4184	0.4154	0.4178
	Juvenile sardine bycatch	0.0121	0.0092	0.0101	0.0105
	Both Hi frame duration (yrs)	16.69	17.5	17.09	17.093
	Both Hi frame residence (yrs)	7.95	8.34	8.282	8.1907
ESI < 3 Fished system	Sard. Avg. Pop.	1.0614	0.9962	1.0433	1.0336
	Anch. Avg. Pop	1.4023	1.3886	1.3934	1.3948
	Sardine catch	0.3358	0.3294	0.3319	0.3324
	Sardine Catch std. deviation	0.0976	0.1056	0.1024	0.1019
	Anchovy catch	0.4843	0.4785	0.4811	0.4813
	Juvenile sardine bycatch	0.01	0.0126	0.0102	0.0109
	Both Hi frame duration (yrs)	20.77	18.9	20.29	19.987
	Both Hi frame residence (yrs)	9.717	9.205	9.522	9.4813
ESI < 5 Fished system	Sard. Avg. Pop.	1.0665	1.0183	1.0327	1.0392
	Anch. Avg. Pop	1.153	1.1424	1.1452	1.1469
	Sardine catch	0.3356	0.3254	0.3319	0.331
	Sardine Catch std. deviation	0.1008	0.1014	0.0978	0.1
	Anchovy catch	0.3667	0.1014	0.3641	0.2774
	Juvenile sardine bycatch	0.0085	0.0083	0.0077	0.0082
	Both Hi frame duration (yrs)	14.89	14.23	14.96	14.693
	Both Hi frame residence (yrs)	7.46	6.9	6.975	7.1117

Test 6: Sardine recovery rate: scale factor

In the high sardine frames, the density dependent increase in recovery rate is based on how low the population is from a capacity figure, scaled by a factor of 0.1. Tests were done with f_{DD} at +/- 0.1 of the normal figure.

Test Settings	Metric	Test runs			avg
f_{DD} = 0.1	Sard. Avg. Pop.	2.2602	2.2484	2.2475	2.252
Unfished system	Anch. Avg. Pop	1.2805	1.2528	1.2619	1.2651
	Both Hi frame duration (yrs)	21.31	21.01	21.07	21.13
	Both Hi frame residence (yrs)	9.77	9.62	9.675	9.6883
f_{DD} = 0	Sard. Avg. Pop.	2.1421	2.1326	2.1396	2.1381
Unfished system	Anch. Avg. Pop	1.2529	1.2595	1.256	1.2561
	Both Hi frame duration (yrs)	21.05	21.12	21.3	21.157
	Both Hi frame residence (yrs)	9.755	9.765	9.76	9.76
f_{DD} = 0.2	Sard. Avg. Pop.	2.3663	2.3582	2.3771	2.3672
Unfished system	Anch. Avg. Pop	1.2904	1.2693	1.2788	1.2795
	Both Hi frame duration (yrs)	21.6	21.17	21.5	21.423
	Both Hi frame residence (yrs)	9.96	9.75	9.89	9.8667
f_{DD} = 0.1	Sard. Avg. Pop.	1.4265	1.4446	1.4607	1.4439
Fished system	Anch. Avg. Pop	1.2736	1.2728	1.2769	1.2744
	Sardine catch	0.3336	0.3316	0.3353	0.3335
	Sardine Catch std. deviation	0.081	0.0808	0.0754	0.0791
	Anchovy catch	0.4235	0.4235	0.4256	0.4242
	Juvenile sardine bycatch	0.0003	0.0007	0	0.0003
	Both Hi frame duration (yrs)	21.12	21.36	20.96	21.147
	Both Hi frame residence (yrs)	9.735	9.835	9.665	9.745
f_{DD} = 0	Sard. Avg. Pop.	1.186	1.185	1.1955	1.1888
Fished system	Anch. Avg. Pop	1.2562	1.2695	1.276	1.2672
	Sardine catch	0.305	0.3026	0.3092	0.3056
	Sardine Catch std. deviation	0.1012	0.1052	0.1021	0.1028
	Anchovy catch	0.4173	0.4234	0.4255	0.4221
	Juvenile sardine bycatch	0.0015	0.0017	0.0011	0.0014
	Both Hi frame duration (yrs)	20.7	20.68	20.93	20.77
	Both Hi frame residence (yrs)	9.64	9.63	9.595	9.6217
f_{DD} = 0.2	Sard. Avg. Pop.	1.6427	1.6633	1.6621	1.656
Fished system	Anch. Avg. Pop	1.2538	1.2651	1.2838	1.2676
	Sardine catch	0.3479	0.3482	0.3468	0.3476
	Sardine Catch std. deviation	0.0611	0.0619	0.0635	0.0622
	Anchovy catch	0.4158	0.4204	0.4282	0.4215
	Juvenile sardine bycatch	0.0002	0.0004	0	0.0002
	Both Hi frame duration (yrs)	21.05	21.16	21.6	21.27
	Both Hi frame residence (yrs)	9.66	9.765	9.91	9.7783

Test 7: School trap factor

The school trap is only effective in the fished system, as the unfished system never goes into a sardine "low" frame. Normal f_{st} value is 0.2 / 0.4 in frames Both Low / Anchovy High. Tests were done at 0.1 / 0.3 and 0.3 / 0.5.

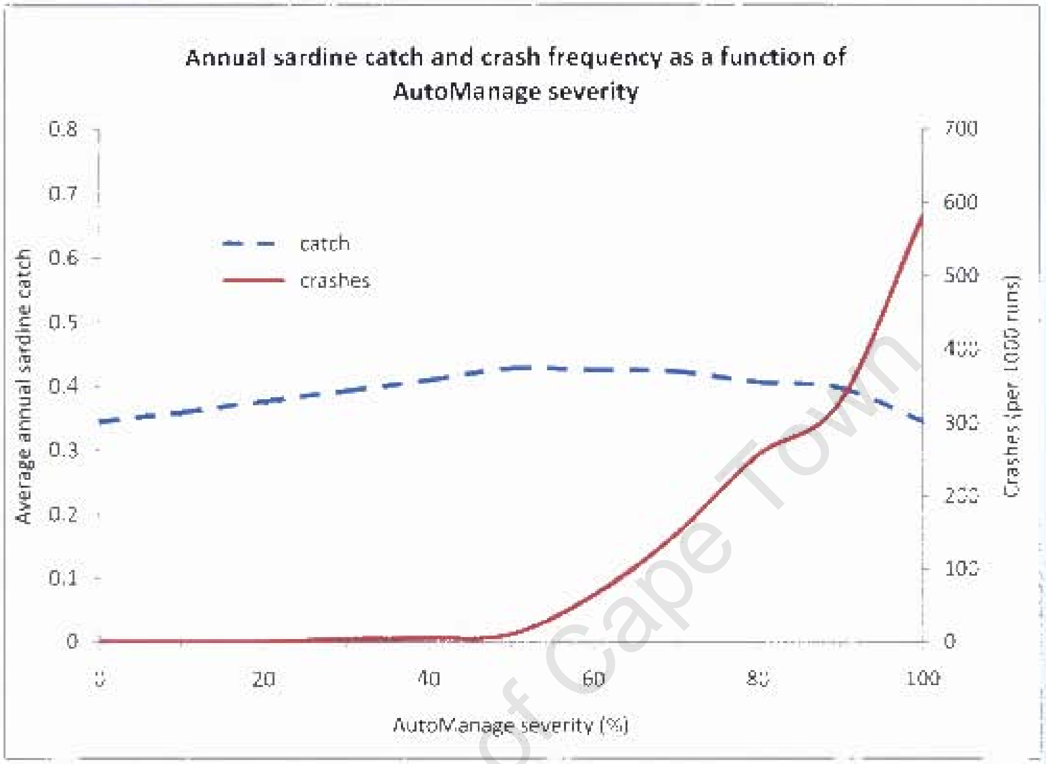
Test Settings	Metric	Test runs			avg
f_{st} = 0.2 / 0.4 Fished system	Sard. Avg. Pop.	1.118	1.0968	1.117	1.1106
	Anch. Avg. Pop	1.2625	1.2561	1.2698	1.2628
	Sardine catch	0.3	0.2946	0.2978	0.2975
	Sardine Catch std. deviation	0.106	0.1097	0.1075	0.1077
	Anchovy catch	0.4198	0.4174	0.4217	0.4196
	Juvenile sardine bycatch	0.0029	0.0048	0.0019	0.0032
	Both Hi frame duration (yrs)	19.86	19.12	20.36	19.78
	Both Hi frame residence (yrs)	9.365	9.215	9.46	9.3467
f_{st} = 0.1 / 0.3 Fished system	Sard. Avg. Pop.	1.0999	1.1461	1.1023	1.1161
	Anch. Avg. Pop	1.2756	1.2631	1.2652	1.268
	Sardine catch	0.2971	0.3027	0.2967	0.2988
	Sardine Catch std. deviation	0.1069	0.1018	0.107	0.1052
	Anchovy catch	0.4253	0.4197	0.4201	0.4217
	Juvenile sardine bycatch	0.0018	0.0007	0.0017	0.0014
	Both Hi frame duration (yrs)	20.17	20.76	20.1	20.343
	Both Hi frame residence (yrs)	9.515	9.695	9.45	9.5533
f_{st} = 0.3 / 0.5 Fished system	Sard. Avg. Pop.	1.1159	1.1389	1.1195	1.1248
	Anch. Avg. Pop	1.2582	1.2598	1.2531	1.257
	Sardine catch	0.2975	0.3005	0.3003	0.2994
	Sardine Catch std. deviation	0.1076	0.1062	0.1045	0.1061
	Anchovy catch	0.4168	0.4188	0.416	0.4172
	Juvenile sardine bycatch	0.002	0.0019	0.0016	0.0018
	Both Hi frame duration (yrs)	20.3	20.78	20.83	20.637
	Both Hi frame residence (yrs)	9.435	9.655	9.63	9.5733

Test 8: Climate variability

Base variability of the ESI is +/- 1 about the underlying climate function. Tests were done at +/- 0 (i.e., the ESI follows the underlying function exactly), and +/- 2.

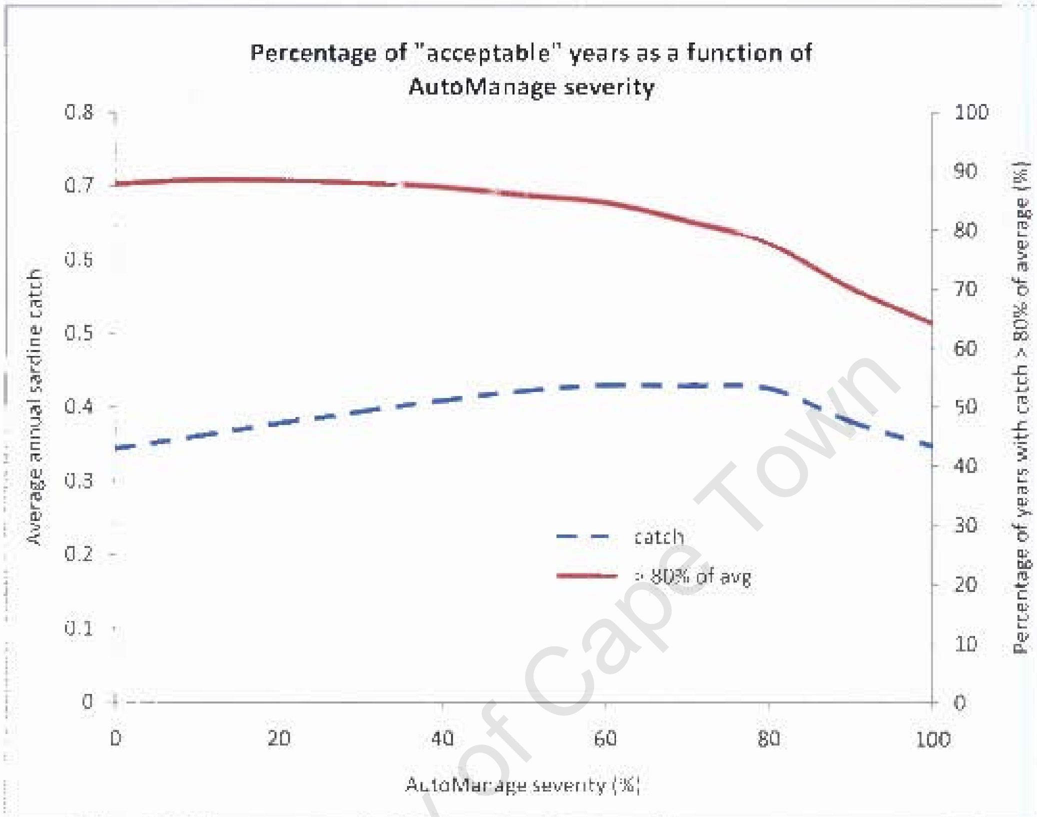
Test Settings	Metric	Test runs			avg
ESI = function +/-1 Unfished system	Sard. Avg. Pop.	2.261	2.2512	2.2879	2.2667
	Anch. Avg. Pop	1.2699	1.2576	1.278	1.2685
	Both Hi frame duration (yrs)	21.27	21.24	21.09	21.2
	Both Hi frame residence (yrs)	9.785	9.81	9.685	9.76
ESI = function Unfished system	Sard. Avg. Pop.	2.2796	2.2487	2.2513	2.2599
	Anch. Avg. Pop	1.2679	1.2741	1.2813	1.2744
	Both Hi frame duration (yrs)	21.22	21.31	21.42	21.317
	Both Hi frame residence (yrs)	9.835	9.73	9.845	9.8033
ESI = function +/-2 Unfished system	Sard. Avg. Pop.	2.2657	2.2784	2.2972	2.2804
	Anch. Avg. Pop	1.2656	1.2432	1.2367	1.2485
	Both Hi frame duration (yrs)	21.09	20.53	20.92	20.847
	Both Hi frame residence (yrs)	9.685	9.435	9.63	9.5833
ESI = function +/-1 Fished system	Sard. Avg. Pop.	1.4512	1.4886	1.4793	1.473
	Anch. Avg. Pop	1.2693	1.2715	1.2816	1.2741
	Sardine catch	0.3335	0.3367	0.337	0.3357
	Sardine Catch std. deviation	0.082	0.0758	0.0762	0.078
	Anchovy catch	0.4204	0.4236	0.4273	0.4238
	Juvenile sardine bycatch	0.0002	0	0.0001	0.0001
	Both Hi frame duration (yrs)	20.76	21.44	21.31	21.17
	Both Hi frame residence (yrs)	9.54	9.86	9.845	9.7483
ESI = function Fished system	Sard. Avg. Pop.	1.4491	1.4416	1.4587	1.4498
	Anch. Avg. Pop	1.2834	1.2793	1.2662	1.2763
	Sardine catch	0.3355	0.3306	0.3363	0.3341
	Sardine Catch std. deviation	0.0798	0.0815	0.0787	0.08
	Anchovy catch	0.4286	0.4256	0.4209	0.425
	Juvenile sardine bycatch	0.0004	0.0001	0.0004	0.0003
	Both Hi frame duration (yrs)	21.43	21.29	21.19	21.303
	Both Hi frame residence (yrs)	9.805	9.785	9.71	9.7667
ESI = function +/-2 Fished system	Sard. Avg. Pop.	1.4284	1.4855	1.4462	1.4534
	Anch. Avg. Pop	1.2396	1.2525	1.2584	1.2502
	Sardine catch	0.3316	0.3376	0.3353	0.3348
	Sardine Catch std. deviation	0.0846	0.0748	0.0767	0.0787
	Anchovy catch	0.4087	0.4133	0.4173	0.4131
	Juvenile sardine bycatch	0.0002	0.0002	0.0001	0.0002
	Both Hi frame duration (yrs)	20.6	20.58	20.79	20.657
	Both Hi frame residence (yrs)	9.495	9.48	9.575	9.5167

AutoManage Severity Test Data: Catch vs Crashes (section 4.2.2)



Severity (%)	Test 1		Test 2		Test 3		Averaged results	
	catch	crashes	catch	crashes	Catch	crashes	catch	crashes
0	0.3456	0	0.3435	0	0.3435	0	0.3442	0
10	0.3585	0	0.3596	0	0.3579	0	0.358667	0
20	0.3793	0	0.3746	0	0.3747	0	0.3762	0
30	0.3912	0	0.3939	0	0.3908	12	0.391967	4
40	0.4101	0	0.4079	17	0.4074	0	0.408467	5.666667
50	0.427	0	0.4262	16	0.4271	16	0.426767	10.66667
60	0.438	19	0.4218	87	0.4135	85	0.424433	63.66667
70	0.4034	187	0.4392	114	0.4239	140	0.422167	147
80	0.4151	244	0.4028	260	0.3988	262	0.405567	255.3333
90	0.413	269	0.3873	371	0.3887	345	0.396333	328.3333
100	0.3462	566	0.3535	609	0.3347	561	0.3448	578.6667

AutoManage Severity Test Data: Catch vs Acceptable years (section 4.2.2)



Severity (%)	Test 1		Test 2		Test 3		Averaged results	
	catch	> 80%	catch	> 80%	catch	> 80%	catch	> 80%
0	0.3426	87.3618	0.3441	88.4979	0.3429	87.5416	0.3432	87.80043
10	0.3605	88.9018	0.3599	88.5765	0.3585	87.8437	0.359633	88.44067
20	0.3779	88.6439	0.3766	88.4928	0.3766	88.0256	0.377033	88.38743
30	0.3936	87.891	0.3942	88.4184	0.3924	87.4235	0.3934	87.91097
40	0.4087	87.1144	0.4086	87.2419	0.4088	87.3054	0.4087	87.22057
50	0.419	85.3782	0.4214	85.7473	0.4236	86.4364	0.421333	85.85397
60	0.4236	83.2255	0.4327	85.2999	0.4319	85.2799	0.4294	84.60177
70	0.4303	81.9872	0.4258	81.1965	0.428	81.2436	0.428033	81.47577
80	0.4132	77.2528	0.4192	77.8361	0.4428	78.0764	0.425067	77.72177
90	0.375	69.2837	0.3791	70.2857	0.3867	70.9582	0.380267	70.17587
100	0.3316	62.1727	0.3524	65.231	0.3567	65.3584	0.3469	64.25403

Climate Function Periodicity Tests

Full results for the tests on adjusting climate cycle time in Table 11 (section 4.2.2):

Cycle Time	**5 yrs**		**7 yrs**		**10 yrs**		**13 yrs**	
	Sard Hi	**Both Hi**	**Sard Hi**	**Both Hi**	**Sard Hi**	**Both Hi**	**Sard Hi**	**Both Hi**
Test 1	28.816	21.184	27.523	22.477	28.821	21.179	24.635	25.365
Test 2	28.738	21.262	27.498	22.502	28.755	21.245	24.604	25.396
Test 3	28.776	21.224	27.478	22.522	28.752	21.248	24.622	25.378
Average	28.7767	21.2233	27.4997	22.5003	28.776	21.224	24.62033	25.37967

Full results for the effect of climate cycle time on sardine performance at various levels of AutoManage severity in Table 12 (section 4.3.2):

5 yr cycle periodicity	**0% severity**			**50% severity**			**100% severity**		
	sard lo (yrs)	avg catch	crash	sard lo (yrs)	avg catch	crash	sard lo (yrs)	avg catch	crash
Test 1	0.13	0.3408	0	3.44	0.4202	26	26.7	0.3316	594
Test 2	0.08	0.3424	0	3.18	0.4175	34	26.11	0.3449	573
Test 3	0.19	0.3419	0	3.58	0.4223	14	25.15	0.3368	554
Average	0.1333	0.3417	0	3.4	0.4200	24.67	25.987	0.3378	573.67
10 yr cycle periodicity	**0% severity**			**50% severity**			**100% severity**		
	sard lo (yrs)	avg catch	crash	sard lo (yrs)	avg catch	crash	sard lo (yrs)	avg catch	crash
Test 1	0.15	0.3429	0	4.31	0.4176	36	25.95	0.3463	563
Test 2	0.21	0.3425	0	4.6	0.4184	29	26.51	0.338	616
Test 3	0.07	0.3441	0	3.77	0.4208	26	27.13	0.3273	624
Average	0.1433	0.3432	0	4.2267	0.4189	30.333	26.53	0.3372	601