Testing abalone empirical harvest strategies for setting TACs and associated LMLs, which include the use of novel spatially explicit performance measures.

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Contents

1 Acknowledgments

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2 Executive Summary

Background

The management of abalone stocks is difficult for many reasons including their high value and the exceptional levels of spatial structuring found in their stocks. In Tasmania, for example, suggestions to change such things as a legal minimum length or introduce a formal harvest strategy to replace the current relatively informal process, always engender high levels of sometimes heated debate. An aim of this work, conducted by Malcolm Haddon and Craig Mundy of CSIRO and the University of Tasmania respectively, was to formally examine the implications of changing legal minimum lengths and the importance of such LML to the management of abalone. This was in the context of using management strategy evaluation to test alternative potential harvest strategies for use, in the first place, within the Tasmanian abalone fisheries. With the advent and growth of more public scrutiny of wild fisheries a need for a more defensible, repeatable, and publically available process for setting abalone TACs had become urgent. This project aimed to contribute to the development of such formal harvest strategies that would both successfully generate workable management advice and be defensible under anyone's scrutiny.

Objectives

1. Review objectives and logic of having and setting Legal Minimum Lengths in abalone fisheries and how these interact with TAC levels.
2. Conduct Manager/Industry workshops to inform, identify issues, and to select LML/TAC scenarios within particular harvest strategies for testing by Management Strategy Evaluation.
3. Develop new modules for the present Abalone MSE Framework for testing LML/TAC harvest strategies containing multiple empirical performance measures (MCDA) that can use spatially explicit PMs.
4. Use the modified MSE framework to test new Multi-Criteria Decision Analysis Abalone Harvest Strategy under development in FRDC 2011/201.

Methodology

Testing alternative harvest strategies for abalone, including the use of alternative legal minimum lengths, alternative intervals between altering TACs, and many other settings used when implementing and using empirical harvest strategies, involved developing new modules for the MSE developed during FRDC 2011/201 to enable more flexible management strategy evaluation software to conduct the necessary simulations. In addition, as part of the development of workable harvest strategies for simulation testing, workshops were attended which included industry, managers and researchers, plus some formal reviews by external reviewers. All were aimed at developing harvest strategies that would be acceptable to industry and managers while being credible to external review as well as capable of successfully generating management advice which should, if conditions in the fishery do not radically change, be capable of recovering depleted stocks while maintaining a healthy and sustainable fishery.

Results/Key Findings

This work has reviewed the use of Legal Minimum Lengths to enhance sustainability within harvest strategies for abalone stocks. In addition it has used management strategy evaluation to test alternative potential harvest strategies for use with the abalone fisheries around Tasmania (and in principle elsewhere). A number of conclusions from this work were forthcoming.

At a zone-wide scale the legal minimum length (LML) can obviously affect the amount of exploitable biomass available but it is the total allowable catch (TAC) that dominates management concerns. However, at the local reef scale at which each fishery operates most divers will have access to sufficient quota to cover the abalone they find so at that at the local scale the zone TAC is effectively irrelevant. Because divers can potentially remove virtually all legal sized abalone at a single reef scale and because abalone stocks are made up of very many micro-stocks, sustainability at the local scale is principally maintained by the LML and diver behaviour. If the LML is set at a size where there is a risk in some years of the local mature biomass being reduced down to effectively that which exists below the LML, then the risk of local population extinction will be high. This would be especially the case when stocks are relatively depleted and the TAC remains even slightly higher than the current productivity. A key result from this study is that effective management thus requires that the TAC be set no higher than or below the current productivity and, in addition, that the LML is set at a level that will protect at least a minimum mature biomass should depletion become extreme at local scales. Different ways of determining the value for sustainability of different LML in different places were developed and discussed.

A rarely considered, but nonetheless important aspect of abalone harvest strategies relates to how often each stock is assessed and management interventions made. Such interventions usually take the form of altering the TAC, and the long-term consequences of annual vs biannual TACC adjustments was explored using management strategy evaluation. Arguments had been made that in abalone fisheries a number of years were required for the effects of changing a TAC or LML to become apparent and so TAC changes should not occur every year. The current Industry preference in Tasmania is to use a two year time-frame should TAC changes be required. The management strategy evaluation simulation framework developed in this project was used to compare outcomes of managing a simulated abalone stock using assessment intervals of 1, 2, 3 and 4 years while keeping other important factors constant. Not surprisingly one effect of a longer assessment interval is to slow events down. Thus, although stock recovery from depletion is slowed when longer management intervals are used, this can also prevent very rapid and dramatic changes in catch level within the fishery. However, the delays brought about by increasing the assessment interval also have the effect of increasing the variation in all fishery performance metrics. If a management action interval of more than one year is adopted within the multi-criterion decision analysis (MCDA) then an appraisal of the appropriateness of the TAC set should be conducted each year irrespective of the interval set for changing the TAC, just in case more rapid changes are indicated. In that way the control that might arise from, say, a two-year assessment interval can be obtained without the risk of increasing variation and rapidly declining CPUE through an inability to react quickly. Even when limited to either one or two years, the assessment interval was also found to be highly influential on the harvest strategy outcomes. The longer the assessment interval the more delayed the harvest strategy was in achieving a stable outcome.

An array of meetings were organized and attended, especially in Tasmania, but also in Victoria, recently in South Australia, but also in New Zealand, where the structure and implementation of formal harvest strategies suited to abalone fisheries have been discussed and reviewed. In each case, the fishing industry in each location has been closely involved. In Tasmania this has been especially the case with industry contributing directly to two formal reviews of abalone harvest strategies and numerous meetings of the FRAG and the Spatial Management Evaluation Group to discuss and review the work on harvest strategies as it progressed. The advantages relating to public accountability and credibility given to claims of sustainability for the fishery lead industry leaders to encourage the introduction of formal harvest strategies. Even so, gaining wide acceptance of the need for such a management change would be much more difficult without their on-going input and being given opportunities to address some wider industry forums.

The Multi-Criterion Decision Analysis approach was found to be fully capable of combining different fishery performance measures so that a formal and agreed upon harvest control rule can be used to provide defensible management advice concerning total allowable catches. There are many settings when using such an empirical harvest strategy which can include:

1) Exactly which fishery performance measures to use in the MCDA;
2) How the different performance measures affect the eventual outcome and how they may interact;
3) How often a stock is to be assessed and management changes made (the assessment and consequent management interval);
4) The exact structure of the scoring functions that convert the empirical performance measure values into a particular score;
5) The relative weights to be given to each score when the MCDA combines them; and finally
6) Exactly how the total MCDA score is converted into a change in the catch expected to be taken from the given scale of assessment (e.g. in Tasmania the statistical block).

If any single performance measure dominates the outcomes of the TAC setting process, as the TargetCE performance measure (where the current CPUE is compared with a pre-agreed target CPUE) does in the harvest strategies tested here, then the relative weight attributed to that measure needs careful selection. Importantly, the MCDA process has been designed that it is easily open to including other or alternative performance measures, such as those deriving from the spatial data logging as they become viable as working time series allowing them to act as fishery performance measures.

In the different harvest strategy scenarios explored in the management strategy evaluation the TargetCE performance measure was found to be necessary for the harvest strategy to converge on a final stable outcome in terms of CPUE and spawning biomass depletion. Some combinations of weights on the three performance measures led to a failure of those particular harvest strategies to converge on a stable outcome so care is required in their selection.

There is evidence in Tasmania of an exceptional recruitment event occurring in the early 1990s. This allowed stocks to recover from a badly depleted state evident in the late 1980's quite quickly. It is noteworthy that in the absence of such exceptional recruitment events the simulation modelling suggests that stock recovery, from its current similarly low level, may possibly take decades if further years of relatively low recruitment occur.

There is a trade-off between the amount of catch taken and the rate of recovery and the final depletion level achieved, with greater recovery achieved the less catch that is taken. However, a particular array of settings defining a single optimal harvest strategy was not selected or put forward, as this should be done by those tasked with setting or recommending policy for the fishery. In numerous meetings with industry and managers there are clearly a wide range of opinions as to how best to move the fishery forwards and towards what final goals. Such important decisions for the Tasmanian abalone fishery still need to be more explicitly articulated before an optimum harvest strategy can be selected. Nevertheless, some emphasis is given here to those strategies that lead to low levels of large and dramatic changes in the fishery. However, the implications of the full range of MCDA settings were explored and are now available to guide final selection.

Finally, the testing of the MCDA was only possible because of the developments of the software management strategy evaluation simulation framework. These developments enabled the testing to operate now at any scale from single small populations up to whole fishery zones. There is now a general structure to the control rules used to generate scores for any given fishery performance measure. A large portion of the code required to generate the simulated stock (be it a zone made up of statistical blocks, or statistical block made up of multiple populations) and conduct the MSE replicates is now encapsulated in an R package, although it still requires some less user-friendly software to put together an operational MSE framework suitable for testing harvest strategies in a different jurisdiction. Even so, the time taken now to implement an MSE to test abalone (or similar invertebrate) harvest strategies elsewhere would only be slightly longer than it would take to condition the model onto a different situation of biological properties. In particular, if changes are made to the performance measures used these can quickly be incorporated into the code developed to describe the MCDA process.

Implications for Stakeholders

The results of this project are already being used in the development of a formal harvest strategy within the Tasmanian abalone fisheries. The development of the MCDA process with the testing of harvest strategies conducted in this project will enable at least Tasmania to produce repeatable and defensible management advice for its abalone stocks (and the option is always available to the other States). The discussions concerning, and the explicit formal testing of, alternative harvest strategies for abalone stocks has immediate implications for any jurisdiction contemplating or in the process of introducing a formal harvest strategy in its abalone fisheries.

Recommendations

For use in other jurisdictions, some further development of the MSE software to complete its transfer into a more generally available R package, which is documented and usable to others conversant with abalone and with R may be a useful should they wish to have a testing framework that would work with their own abalone fisheries.

2.1.1 Keywords

Blacklip Abalone, *Haliotis rubra*, formal harvest strategies, MSE, management strategy evaluation, LML, MLS, legal minimum length.

3 Introduction

There used to be an array of valuable commercial abalone fisheries around the world but production in many of these rapidly declined in the late 1980s and a number have now collapsed (Shepherd and Baker 1998; Tarr, 2000; Hobday *et al*, 2001). Such problems and fishery collapses led to a common belief that successful management of abalone stocks is difficult (Breen, 1986). In contrast, Australian abalone fisheries have maintained significant production. These fisheries, based predominantly on Blacklip (*Haliotis rubra*) and Greenlip (*H. laevigata*) Abalone, appear comparatively stable and sustainable, although viral outbreaks, recent poor recruitment events, and marine heat wave events have had negative influences at least in some sub-fisheries in Victoria and Tasmania.

The abalone fisheries around southern Australia, especially those in South Australia, Tasmania, and Victoria have persisted for 50 years leading to optimism in some people that the fundamental management regime is working (Mayfield *et al*., 2012). Even the relatively depressed fishery in NSW appears to be rebounding in the south under improved management (TAC Committee, 2015). Despite this persistence, however, modelling analyses suggest that such stocks may actually have been undergoing a long term slow decline in stock abundance, which can come about by fishing only slightly harder than the maximum sustainable yield (Haddon and Helidoniotis, 2013; Haddon *et al*., 2013), and can take 50 years to lead to serious depletion.

Recent declines in major components of Australian fisheries (e.g. the Western Zone in Tasmania; Tarbath and Mundy, 2015; and Tiparra Reef in South Australia's Central Zone; Chick and Mayfield, 2012) raise questions about the underlying factors contributing to these declines. While acute events such as virus outbreaks have had local effects, it remains uncertain whether recent declines reflect a longer term decline in stock productivity or, more simply, catches being set too high. All of these challenges to current management practices indicate that the need for more detailed and more rapidly reactive and defensible management of Australian abalone stocks is greater than ever.

Management arrangements vary among States, but all now include spatially allocated Total Allowable Catches or TACs (implemented in Tasmania as individually transferrable quota – ITQs; some States use Total Allowable Commercial Catches, TACC) combined with spatially explicit legal minimum lengths (LMLs). There remains differences in management arrangements between the States but all generally included LMLs very early on in the history of each recent fishery and, in addition, limits were placed on the number of licences (Mayfield *et al*., 2012). However, the number of diving licences were set when TACC's where historically much larger than they are now and it may be such that, in Victoria and especially in Tasmania, they appear sufficiently numerous as to be equivalent to over-capitalization in vessels as in some scale fisheries. But deciding precisely how many licences would allow for improved economic performance still needs to be established, although statements regarding 'optimum performance' relate more to policy decisions than scientific findings and changing the number of licenses in most Australian abalone fisheries remains complicated.

A relatively recent innovation in abalone management is the development of more formal harvest strategies in which a monitoring program is defined to determine what data to collect from a fishery, this data is used in assessments to estimate performance measures for each fishery (which might range from formal mathematical model outputs to purely empirical relationships), and, finally, formal control rules are developed that use the estimated performance measures to determine the management response in terms, perhaps, of changing a recommended TAC. South Australia has already introduced formal harvest strategies (e.g. Chick and Mayfield, 2012) and Tasmania is in the process of testing an array of these using management strategy evaluation (MSE; this present work) while developing new performance measures based on the detailed spatial statistics being gathered now using GPS data loggers across all divers (Mundy, 2011). Such management arrangements have the advantage that they remove uncertainty over how management should respond to observed changes in the fishery and stock dynamics, which, importantly, means that management becomes more predictable once one has the information upon which the control rules are based. This is a further advantage of using empirical performance measured based on changes in, for example, catch rates, or the geographical distribution of catches at a fine scale. Model based performance measures are more specialized and difficult to apply validly to abalone stocks, but can still remain of value when they are included in a multi-criteria decision analysis that combines the inputs from an array of different performance measures.

The formal testing of such harvest strategies, using MSE, has advantages over introducing such formal arrangements immediately. South Australia has already introduced such a management framework for its abalone fisheries and has already experienced problems deriving from unintended consequences of, for example, including the level of catches within individual spatial management units (SMUs) and also from the chosen criteria for selecting which SMUs to assess in more detail. Almost any reasonably complex set of management arrangements for any fishery will have unintended consequences, which only become apparent after implementation. MSE testing during the development of formal harvest strategies can help avoid such mishaps and thereby avoid a loss of credibility in the use of formal harvest strategies for managing fished stocks.

The detailed spatial data becoming available as a result of the use of GPS data logging technology is currently producing information in unprecedented detail. At very least this will have a direct input into optimizing the spatial distribution of management regulations (LMLs and expected catches). Importantly, they will also provide new ways of monitoring, and hence responding to, changes in stock dynamics, whether that be decreases in productivity, changes in the location of major hot spots of production, or even increases in production.

4 Project Objectives

1. Review objectives and logic of having and setting Legal Minimum Lengths in abalone fisheries and how these interact with TAC levels.

2. Conduct Manager/Industry workshops to inform, identify issues, and to select LML/TAC scenarios within particular harvest strategies for testing by Management Strategy Evaluation.

3. Develop new modules for the present Abalone MSE Framework for testing LML/TAC harvest strategies containing multiple empirical performance measures (MCDA) that can use spatially explicit PMs.

4. Use the modified MSE framework to test new Multi-Criteria Decision Analysis Abalone Harvest Strategy under development in FRDC 2011/201.

5 General Methods

The two main management levers for managing abalone stocks are to set legal minimum lengths and total allowable catches that match the productivity of different geographical areas. The need for spatially explicit management reflects the heterogeneity observed in the biological properties of different abalone populations, which leads to them having different levels of productivity. Within each identified geographical area there is a requirement for a LML regulation and a TAC or an expected catch. How these are implemented differ in each jurisdiction. The focus of this present work will be on blocks or spatial assessment units within zones or regions, although details of how the fishery behaves at a fishing operation level will also be considered.

5.1.1 Objective 1:

Review objectives and logic of having and setting Legal Minimum Lengths in abalone fisheries and how these interact with TAC levels.

Tasmania is the only abalone producing state in south-eastern Australia with a management plan rule and guidelines for setting Legal Minimum Lengths for different areas – abalone should have two years post-reproductive maturity protection before entering the fishery. Setting a LML for a region entails collecting data on size at maturity and growth so that the average of two years growth can be added to the size at 50% maturity. Once this biological LML is calculated for an array of locations within a region an average, perhaps weighted by the relative production of different areas sampled, is selected as the regulation LML. However, there is a need to establish exactly what such a policy might be achieving (in terms of yield per recruit and protection of spawning biomass), and whether the seemingly extreme spatial and temporal variation observed in some areas might compromise the existing mechanics of determining an LML. The first step will be to conduct a review of the existing LML policy as a model framework for setting LML in Australian abalone fisheries. Detailed spatial information from FRDC 2011/201 (Implementation of GPS based data collection in the Tasmanian Abalone Fishery) will facilitate the characterization of heterogeneity among commercially important abalone populations by provided detailed information on which populations receive the most fishing attention and allowing for more appropriate sampling for biological characteristics. The management strategy evaluation framework developed in FRDC 2007/020 (Identification and Evaluation of Performance Indicators for abalone fisheries) will be articulated further and used to compare the dynamic interaction between alternative LML choices and consequent safe levels of TAC for actual fisheries rather than modelled fisheries which are only conditioned on some of the biological properties of the stocks concerned (as in Haddon and Helidoniotis, 2013; Helidoniotis and Haddon, 2014a).

5.1.2 Objective 2:

Conduct Manager/Industry workshops to inform, identify issues, and select LML/TAC scenarios within particular harvest strategies for testing by Management Strategy Evaluation.

Where possible a multi-state workshop process will be used to communicate the LML policy review, to clarify the challenges in determining a compromise LML, and to identify alternate harvest strategy scenarios for testing within an MSE framework. The workshops will include representatives from managers, researchers, industry from participating states, and FRDC; there will be at least one such workshop in Tasmania and another in Victoria and New South Wales. Others will be held to aid the communication of results to industry and managers. These workshops will be organised in each state so as to facilitate the attendance of as many industry members who would wish to attend. Suitable facilities will be hired in each locale. The objectives of the workshops will be 1) to discover the primary issues and questions to which the industry in different states are interested in finding answers (and what would be required to answer such questions), 2) to communicate preliminary and final results of the modelling and harvest strategy testing, 3) to communicate findings from the spatially detailed fishery dependent data collected by the GPS data loggers, 4) attempt to improve the cohesion and understanding of the southern Australian abalone industry with respect to the commonalities between the various management strategies implemented in different states and even zones.

5.1.3 Objective 3:

Develop new modules for the present Abalone MSE Framework for testing LML/TAC harvest strategies containing multiple empirical performance measures (MCDA) that can use spatially explicit PMs.

The MSE framework developed in FRDC 2007/020 will need additions to be able to analyse the outcomes of using multiple performance measures at the same time (the essence of the new Multi-Criteria Decision Analysis Harvest Strategies; MCDA_HS). The MSE framework can already generate simulated catch, CPUE, and length-frequency data. The additions needed to test the efficacy of combining performance measures based on these data would be modules relating to the rather more complex control rules that the combinations give rise to and the increased spatial detail produced by the geo-referenced Fishery-Dependent data. This capacity is needed for analysing the effect of adding spatial performance measures to the MCDA_HS. This will entail characterizing the spatial dynamics of the fishery operation, which currently can only be done in Tasmania and possibly New South Wales. The most promising avenue to implement such simulations appears to be the simulation of relative hot spots in the geographical location of catches and catch rates. These can change quite markedly between years but also can return to the same locations between years (Mundy, 2011). In addition, the number and distribution of dives conducted by individual divers will need to be characterized to enhance the realism of the simulations.

The GPS data logger data being collected is already suggesting many different potential performance measures and these have more than one character. Some relate to individual diver performance through time while others relate to across the fleet performance by area. The Spatial MSE framework will need to provide for both these options and be sufficiently flexible to allow for other viewpoints of the data. The current MSE framework is written almost completely in R, however the spatial MSE framework may need to include modules in some compiled language (Fortran 2003 or C++) to enable processing to continue at an adequate speed.

5.1.4 Objective 4:

Use the MSE framework to test the new Multi-Criteria Decision Analysis Abalone Harvest Strategy under development in FRDC 2011/201.

The simulation and analysis of explicitly fine scale spatial information from 2011/201. The new spatial data will enable a more realistic model representation of the fishery dynamics, which will be needed to generate fine-scale simulated fishery data. The hot spot analyses developed by Dr Mundy already demonstrate that the productivity of the different reefs can be a patchwork in both space and time. Only by examining the dynamics across the fishery will it be possible to drive the development of the simulated fishery dynamics. This will require the fleet dynamics of the divers to be analysed in detail, along with the patchwork nature, in space and time, of the reef's productivity. One of the objectives of the workshops, from project objective 2, will be to discover the issues of most interest to the industry. By couching the proposed modelling in the form of particular questions to be answered, rather than just to conduct some modelling, the potential value of such MSE work should be communicated to the industry members more successfully. With only four years of spatially explicit data, however, there remains a need for most of the testing of the framework to use currently available data, such as CPUE.

5.1.5 Structure of this Report

The general objective of this work (as above) have been articulated into more specific tasks and will be presented in separate sections. Workshop conclusions will be included in the different sections where appropriate. Each section will have its own methods, and results/discussion, and in addition, there will also be a general conclusions section. There will be major chapters relating to:

a) The current structure and preparation (conditioning) of the management strategy evaluation framework used to test the MCDA harvest strategy and the interactions possible between the TAC and LML.
b) The use of legal minimum lengths for the protection of spawning or mature biomass.
c) The frequency of implementing management decisions.
d) Testing alternative versions of the Multi-Criteria Decision Analysis Abalone Harvest Strategy.
e) The Structure and operation of the MSE model
f) General Conclusions

Chapters '7 The Uses of Legal Minimum Lengths' and '8 Frequency of Management Intervention' will use the MSE framework but will act as introductions focussed on particular questions before the more general testing conducted in Chapter '9 Testing the MCDA Harvest Strategy', where multiple factors influencing the stock and fishery outcomes are tested together.

6 Management Strategy Evaluation

6.1 Introduction

Management strategy evaluation (MSE) uses simulation modelling to evaluate the relative performance of different 'management strategies' (combinations of data collection schemes, stock assessment methods, and harvest control rules). Each simulation replicate run applies a candidate management strategy (often also termed a harvest strategy) to data sampled from an 'operating model', where the operating model provides a representation of the stock dynamics under management. The dynamics of the model are conditioned using biological and fishery data from the stock in question. The management actions (in this case setting a TAC, a catch limit) are used each year to update the stock dynamics underlying the operating model; this feedback aspect of the simulations is what distinguishing an MSE from a risk assessment that uses relatively forward simple projection of constant management (**Figure 1**; Punt *et al.* 2016). Outputs from an MSE are typically performance metrics that attempt to quantify how well each candidate management strategy is able to achieve the management goals (they are termed performance metrics to distinguish MSE outputs from performance measures relating to the fishery). In the case of Tasmanian abalone, however, there are currently no quantified management goals and so for the purposes of this study CPUE targets and other constraints are introduced so relative performance could be judged. This was done with no intention of recommending particular targets for the fishery; part of the function of the workshops with Industry members was to identify and select such targets.

In this present work the simulation framework will be used for three main investigations. The first is to examine the interactions between setting an LML and a TAC for a given geographical area. Since the introduction of explicit quota zones into Tasmania, starting in 2000, there has also been a number of changes to the LML imposed in different zones. There is invariably passionate discussion whenever the topic of changing an LML is raised. To examine how the fishery dynamics are altered by LML changes a simulation framework based on single populations was used (described in the methods). One outcome of introducing a legal minimum length is that it can take a number of years for a post-larval recruit into the stock to grow past the LML and recruit into the fishery. Such time-lags make interpreting the observable dyna; mics (of catch rates and other fishery performance measures) relatively difficult. This has led to discussion concerning the sense of making serial changes to the TAC from year to year without leaving time for the first change to have an effect. The second investigation using the MSE was to examine the effect of introducing delays between TAC changes. For this the full MSE framework was used with a simulation of 60 populations to examine the effects of making TAC changes every year, relative to changes every two, three, and four years. Finally, the third MSE use was to examine the effectiveness of a proposed new management regime. The current management of the Tasmanian abalone fishery (and that in many other jurisdictions in Australia) is relatively informal. With the aim of providing more defensible management advice in Tasmania a more formal harvest strategy has been developed using a multi-criteria decision analysis that can incorporate multiple performance measures from the fishery (Knuckey, 2015). Before implementing this new management strategy formally into the fishery, potential variants of the MCDA harvest strategy will be tested using the MSE framework to identify the properties of the harvest strategy and weed out any variants with unintended but unhelpful outcomes.

6.2 What is Management Strategy Evaluation?

One reason that working with MSE is relatively specialized is that the simulation framework used needs to be able to simulate a wide range of processes including the dynamics of the selected biological stock, the dynamics of the fishery imposed on the stock, the generation of simulated fishery data from the fishery, the stock assessment applied to that data, and the control rule used to modify the present management options (generally changing the TAC), which are fed back into the dynamics of the stock in a feedback loop within the modelling framework (**Figure 1**). The feedback loop is an essential part of what makes a simulation a management strategy evaluation (Punt *et al,* 2016).

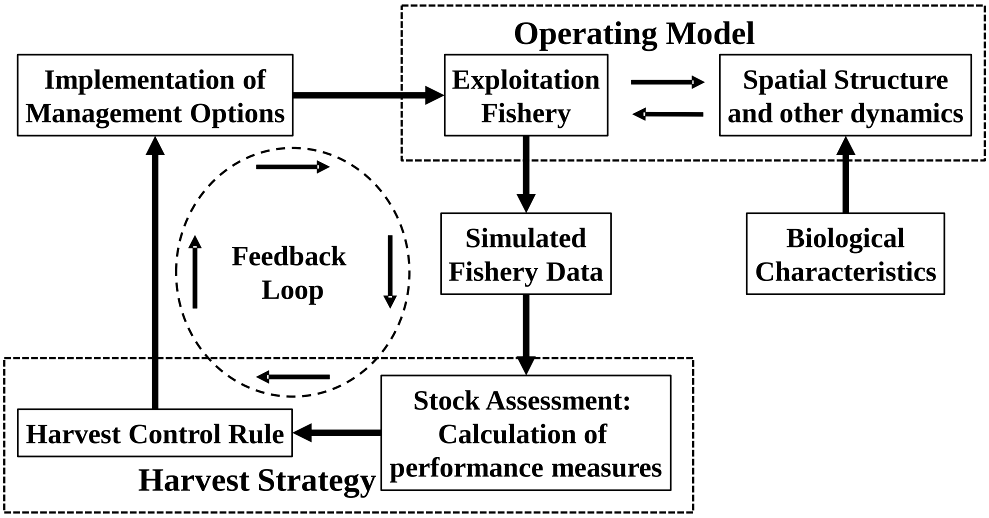

Figure 1. A diagrammatic representation of the main components of an MSE simulation framework such as used with abalone.

Because of the spatial complexity of real abalone stocks it is not possible to successfully fit the abalone MSE framework to the previously observed dynamics of an actual fished abalone zone. Instead, the biology of the populations simulated when generating a simulated zone can only be conditioned to be similar to observed properties as seen in some real world abalone fishery. It is possible, however, that this conditioning can include the use of simple assessment models, such as surplus production models, to estimate relative productivity (see below). This means we can only ever test the effectiveness of alternative management strategies upon simulated abalone zones that have biological properties that are only similar to known zones. By altering the recruitment dynamics within the framework we can also arrange to have the simulated zones have yields similar to those expressed in real abalone zones. However, the complex spatial heterogeneity of biological properties exhibited by abalone stocks means it remains impossible with the current information requirements to directly fit a simulated zone to the dynamics of a real zone.

The complexity of the simulation framework is why the production of the MSE is such specialized task. In an effort to simplify this for the future a start was made at putting the software code required to produce a simulation framework that could be conditioned on any abalone stock into a fully documented software package (R Core Team, 2016; Wickham, 2015). This was not part of the original project design and is a significant addition. Abalone zones can now be simulated with the R package 'AbMSE' but and subsequent MSE manipulation has still to be included in the package.

6.3 Conditioning the Abalone Operating Model

The application of management strategy evaluation (MSE) to compare alternative management scenarios for an abalone fishery requires a number of steps. The first is to ensure that the properties of the modelled abalone fishery reflect the real abalone fishery being modelled with sufficient realism that the simulation produces at least plausible dynamics when projected. 'Conditioning the operating model' within the MSE is the phrase used to describe the process of characterizing the properties of the fishery under study and translating them into the modelling framework. This translation can be considered adequate for purpose if the conditioning leads to the model exhibiting dynamics behaviours similar to the observed fishery. All models are abstractions that omit many details of the system being modelled (Haddon, 2011), which prompts the question: 'When conditioning an operating model what is sufficient to capture the dynamics of the modelled system?'

In situations where there is a great deal of information it is sometimes possible to fit an MSE operating model or parts of it to the available data as if it were a stock assessment model. If this is possible then the MSE testing would effectively be model projections that involve adaptive feedback via the harvest control rule. This approach would provide very detailed and specific advice with respect to the modelled fish stock, which has obvious advantages when answering specific questions with respect to a particular fishery (Punt *et al*., 2016). The abalone MSE, however, has been designed to reflect the hierarchical spatial structure of such fisheries; that is, each population is treated as having only very minor interactions biologically with their neighbours (Miller et al, 2009), while being treated as part of the whole stock in the fishery being imposed upon it. When the abalone MSE simulation framework was first developed (Haddon et al., 2013; Haddon and Helidoniotis, 2013) a hierarchical spatial structure was used to represent the relationships between the various populations (**Figure 2**).

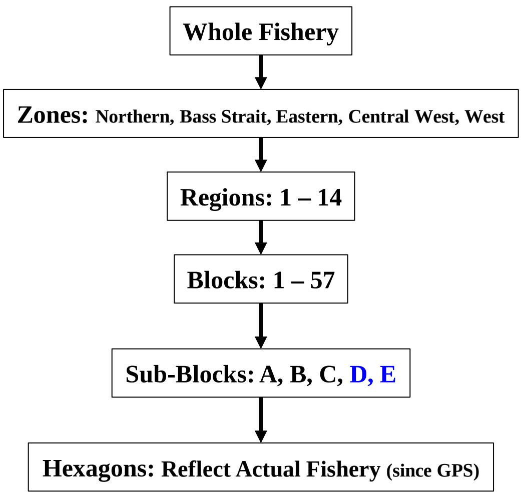

Figure 2. Spatial structure imposed on the Tasmanian abalone fishery. Zonation has been in place since 2000, at which time sub-blocks were developed. Some blocks have no sub-blocks, most have A – C, a few have up to five, A – E. The statistical reporting blocks have been in place since 1970, although reliable data is only available since about 1985; the year that individual transferable quotas were introduced. The hexagons have only been defined since the advent of the GPS data loggers in 2011.

6.3.1 Spatial design

Within the MSE the spatial design of the analyses are a simplified version of the hierarchical scheme used in the fishery (**Figure 2**). Thus, the simulations can refer to zones, which represent the quota or TAC area, the statistical blocks, which represent areas in which the populations have similar properties, and individual populations, which range in scale from sub-blocks down to a few 1 Ha hexagons, depending on the production ascribed to each population. Like many fisheries the organization of the spatial design is unbalanced. That is, each block can have a different number of populations each with different numbers of hexagons, and each zone can have a different number of blocks.

In addition, the amount of data available differs with respect to the geographical scale. For example the number of records in one zone (the largest spatial scale in the current modelling; **Table 1** and **Table 3**), may only be a fraction of that from another zone within the same fishery. Trends are likely to be less noisy at larger geographical scales as more data is available leading to a trade-off between information and variation i.e. the signal to noise ratio is likely to be lower at a population level than at a block level or at the zone level. Where there are variable amounts of data between units within a spatial scale (e.g. populations within a block), comparisons can be less reliable due to imbalances between the numbers of records. Obviously the amount of available data and numbers of records included needs to be considered when making comparisons. For the same reason it is also necessary to examine trends at different spatial scales when characterizing the dynamics of diver behavior.

Prior to developing of the GPS data logger system the spatial scale at which data could be collected in Tasmania was, at best, at the statistical sub-block scale. Now, with the GPS data logger system, information from the fishery relating to effort, fleet dynamics, and depth distribution is available at a very fine scale, which, for practical purposes can be summarized into one hectare hexagons around the coast of Tasmania (Mundy, 2011).

Clearly, such methods provide for very fine detailed information concerning the operation of the abalone fishery in Tasmania. Structurally similar data collection systems (Mundy, 2011), deriving from or assisted by the developments in Tasmania, have also been implemented in New South Wales, Victoria, South Australia, and New Zealand. As part of the development of more formal harvest strategies the utilization of this highly detailed spatial information opens many possibilities for improved monitoring of each stock's performance and status (Mundy, 2011; **Figure 3**).

6.3.2 Management Strategies

A management strategy (or harvest strategy) is made up of three components: 1) the monitoring data, 2) the assessment or estimation of performance measures, and 3) the harvest control rule(s) (**Figure 1**). However, when using empirical harvest strategies that entail no formal stock assessment, generally the performance measures themselves constitute the assessment/review of the relative stock condition and placing them within a harvest control rule both determines the stock's status and generates the required management advice. The fine-scale spatial information, implemented as a number of potential spatial performance measures, therefore enters the system in the form of monitoring data, but this is equivalent in empirical harvest strategies to being the performance measure or assessment (**Figure 3**).

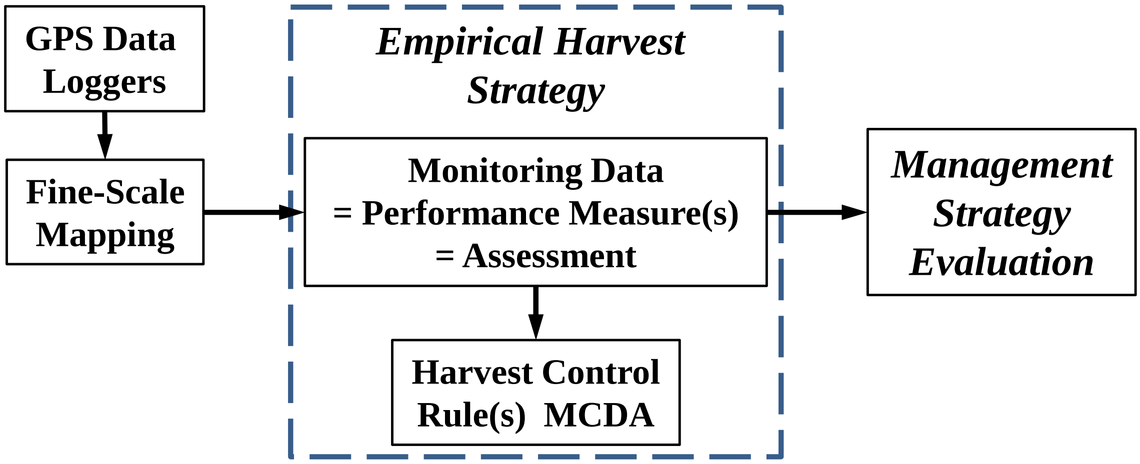

Figure 3. The use of GPS data loggers and personal depth loggers enables fine-scale mapping of effort and related catches. The information flowing from such a data source contributes to harvest strategies by enhancing spatial aspects of performance measures that can be used to monitor the status of the stock in relatively fine detail.

In order to reflect this increased resolution in data availability from the different fisheries, structural changes were needed to the MSE framework. Previously, its geographical structure was based around individual zones made up of *n* populations that all had somewhat different biological properties derived from the selected probability density functions characterized from each simulated zone (Haddon et al, 2013). These populations could be grouped, after the fact into Blocks or Region, as desired. To operate with and simulate the hexagon scale information two extra layers in the structural complexity have been added to the MSE framework (**Figure 2** and **Figure 4**).

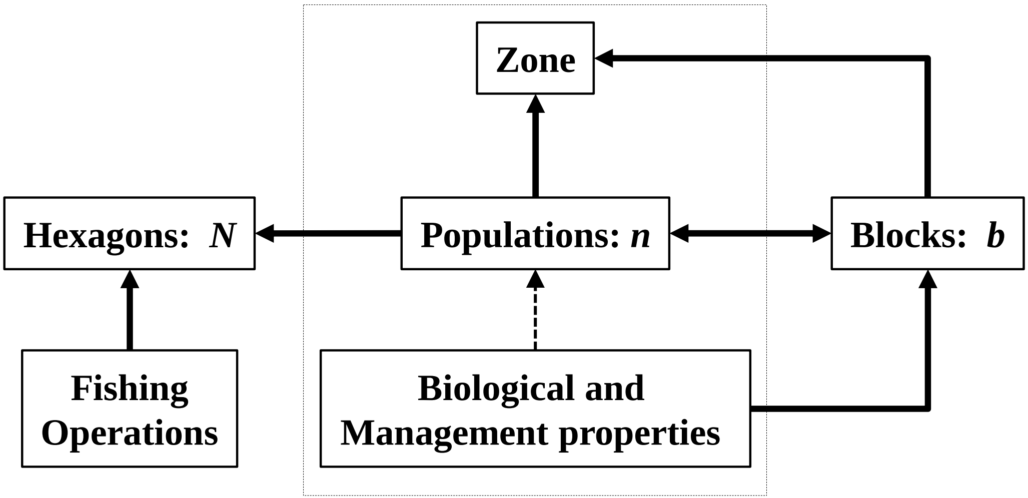

Figure 4. Fundamental structure within the MSE simulation framework used to represent spatial structure. The biological properties expressed within populations reflect the characteristics exhibited by the abalone within each of the blocks (statistical reporting areas) making up the zone and the management properties are those imposed by the fishery management agency responsible for looking after the stock. The previous MSE (Haddon et al., 2013) is represented by the fine box and dashed lines.

Zones are made up of blocks and, if these are conditioned on the biological properties exhibited within particular blocks it would then be possible to allocate populations to hexagons within blocks or hexagons to populations depending on the scale selected.. The fishable habitat differs markedly between blocks and subblocks, which becomes clear when one considers the number of unique hexagons that have been fished to date in each subblock (**Table 1**). For example, subblocks 08A and 08B) contain relatively few fished hexagons, whereas others, such as Block 11 and 12, contain relatively large numbers and thus presumably extensive abalone habitat. Fishing operations occur at the scale of the hexagons contained within populations (**Figure 4**).

Table 1. Example of the distribution of records, catches, and the number of unique hexagons visiting in 2012 and 2013 on the west coast of Tasmania.

	Records		Catch (t)		Unique Hexagons	
Subblock	2012	2013	2012	2013	2012	2013
06D	454	84	48.053	9.019	376	72
07A	137	98	19.576	9.707	125	78
07B	365	248	31.581	23.826	342	214
07C	143	87	13.358	7.541	136	79
08A	30	24	2.656	2.309	30	23
08B	36	26	4.994	3.001	36	25
09A	7	14	0.289	0.305	5	13
09B	424	433	46.651	40.038	396	406
09C	554	844	76.749	94.598	511	759
10A	200	374	18.009	31.125	179	325
10B	83	361	6.366	28.910	73	318
10C	211	430	25.836	41.621	190	373
10D	339	514	45.299	50.023	296	450
11A	459	745	51.721	64.976	419	682
11B	319	785	32.582	66.698	293	692
11C	699	748	74.354	56.358	627	659
11D	282	735	24.586	51.187	263	641
12A	236	414	27.286	40.777	215	381
12B	392	539	35.780	31.718	356	477
12C	361	520	54.068	66.926	327	433
12D	727	842	60.697	54.662	650	757
13A	175	216	14.187	15.172	139	196
13B	132	240	10.703	14.020	116	210

The MSE framework is currently designed to examine general ideas such as the trade-offs between applying different combinations of LML, TACs, and risk aversion and, as such, it does not require to be matched to a particular zone in relatively fine spatial detail. The important aspects of spatial heterogeneity of biological properties and production can be captured by the current structure. However, given a need to provide recommendations for specific fisheries concerning particular management options, then, in the absence of a detailed formal stock assessment model that could be used for risk assessment projections, the MSE would have to be conditioned at a finer spatial scale.

While the MSE framework remains too complex biologically and spatially for available data to be fitted to the model, the finer scale information derived from the GPS data loggers opens the possibility of conditioning the MSE to more closely match a given set of blocks or subblocks (although this is not required for the original objectives of this project). Now that production can be linked to actual fished area it becomes possible to condition the model at a finer geographical scale in relation to its production and subsequent catch. This suggests an extension to the initial plan for the structure of the MSE framework which modifies the conceptual structure of the MSE.

The original underlying structure relies on the biological and management properties of a zone to be characterized and the results of that used to condition the selected number of populations used to represent the fishery (**Figure 2**; **Figure 5**). Instead of characterizing a complete zone (defined as having uniform management) it is generally possible to characterize individual blocks or other sub-components making up a zone; especially now that the GPS data have permitted such a detailed characterization of the fishery. If the populations representing the fishery are then allocated using properties that reflect individual blocks rather than the whole zone combined, even more diversity of biology and management can be included in a single MSE simulation (**Figure 2** and **Figure 4**). Such a detailed conditioning would involve far more initial analysis and biological details may not be available over smaller sections of the coast so many assumptions are still required and the conditioning process can take much longer than previously. Nevertheless, utilizing the GPS logger data to aid in this conditioning greatly improves the resulting realism of simulations.

An example of a suitable area for simulation might be the south-west corner of Tasmania made up of statistical blocks 9 - 12 (**Figure 5**). In such a case the simulated zone would only be a subset of an actual zone in the fishery, the blocks are the real blocks 9 – 12, and the number of populations in each block vary roughly as a function of the productivity of the stock. Management has changed in that area with blocks 9 – 12 and 13A and B being a zone by itself for some years (see **Table 5**). This was then changed and has recently been changed again (Tarbath and Mundy, 2015). Here we have focussed only on blocks 9 – 12.

6.4 Details of Conditioning the Operating Model

Once the biological properties of the modelled blocks within the fishery are defined then the zone conditioning needs further refinement by searching for the average unfished recruitment levels that would give rise to the assumed productivity of each block. Sometimes it is possible to gain some notion of productivity by fitting a simple model (even a surplus-production model; Haddon 2011) to the coarse scale data for a zone or the individual blocks. However, if this is not available or possible then it is necessary to search for a level of recruitment that would at least provide sufficient productivity to allow for observed or known catches. This latter would be a form of stock reduction analysis. Once the populations within each block are parameterized and the zone as a whole conditioned on potential productivity within each block, it can then be used to simulate an unfished stock ready for MSE testing.

6.4.1 The MSE Objectives

Generally there are three stages to conducting an MSE model run to test the effectiveness of a particular empirical harvest strategy (eHS). The first stage is to set the desired state of initial depletion; this is required to determine whether the eHS is capable of recovering a depleted stock and of maintaining a stock at its target once that is achieved. It was considered unlikely that an abalone stock would be found that was not at least fully exploited so the capacity of the eHS to control a fish down from an elevated stock state was given a relatively low priority. The focus was thus on whether a given eHS could recover a depleted stock and how well it could maintain a stock in a desirable state once this was achieved.

6.4.2 Productivity from Surplus Production Models

The purpose of the operating model within an MSE simulation framework is to simulate a stock's dynamics; it thus represents the 'reality' against which it becomes possible to determine the relative management performance of different eHSs (e.g. an eHS may interpret data from the operating model and conclude that the stock is at target, but is it really?). If the aim of a study is to answer questions about a specific fishery then, ideally, it would be best to have the operating model express dynamics that are as close to those of a given real-world fishery as possible. Assuming that the operating model is structurally more complex than the available biological and fishery samples from the real fishery such over-parameterization means it can become impossible to fit the operating model to the available data as can usually be done with an assessment model. There is a spectrum of possibilities ranging from being able to fit a model to the available data, which it is assumed would provide the most complete reflection of real dynamics possible with the model structure adopted, down to an arbitrary representation based on properties that would be plausible for the species concerned (**Table 2**; Punt *et al.*, 2016). The intent of the abalone MSE is to attempt to answer some questions about some specific fisheries so it becomes necessary to condition the operating model so that its dynamics at least approximate those of the fishery zones to which it will be applied.

Table 2. A spectrum across the relationship between an operating model and a real-world fishery. The generic MSE is merely plausible, the Conditioned MSE relates to a given fishery, while a Specific MSE would need a great deal of data and should provide the best reflection of the actual fishery.

Property	Generic MSE	Conditioned MSE	Specific
Biological and fishery parameters	Plausible; like the species	Selected from probability density functions reflecting known properties	Fitted to data
Initial Depletion	Arbitrary	Most plausible; reject options that lead to implausible dynamics	Fitted to data
Historical trends	Decreasing, increasing, or stable	Fishery's known history imposed following initial depletion	Fitted to data

There are biological data relating to maturity and growth available for each of the blocks 9 – 12; this derives from samples collected by the Abalone Section from first the Marine Laboratories at Taroona, which became TAFI, and then IMAS. In addition there is detailed catch and standardized catch rate data available for these blocks. To obtain estimates of the productivity (MSY) and the unfished exploitable biomass, surplus production models can be fitted to the catch and CPUE data for each block. Such estimates are only made with a degree of uncertainty and the plausible bounds on these conditioning parameters can also be used to provide bounds on the dynamics of the simulation model used in the MSE.

6.4.3 Fitting Surplus Production Models to Block Data

There are complications with fitting a surplus production model to abalone data. In Tasmania the legal minimum length (LML) has been changed significantly a number of times, which directly affects the amount of exploitable biomass available to be fished, which, in turn, will affect the catch rates observed in the fishery. Hence, when fitting a surplus production model some means of accounting for these changes in LML and exploitable biomass need to be included in the model dynamics. In the model fitting process below the different LML periods of the fishery are delineated by using different closed form estimates of catchability over different blocks of years.

While the previous underlying structure of the MSE (Haddon *et al*., 2013) works well for the larger scale zones in Tasmania it is becoming less applicable to smaller zones elsewhere, which often have more complex management in terms of multiple areas with different legal minimum lengths mixed up within a zone (Victoria and New Zealand), despite having a single TAC spread across the zone. Such arrangements now occur in Tasmania (e.g. the Northern zone in the west of Tasmania) but generally the majority of the catch still comes from single management regions within the zones, which are best treated separately. Without these modifications the MSE framework would only be able to be applied to sub-regions within those zones with diverse management. This would be difficult in special cases such as the re-building fisheries in Victoria and in the north of the South Island in New Zealand (PAU 7). In those places multiple LML, which will also change through time are being put in place across zones with single TAC values. The new MSE structure allows such arrangements to be simulated as a complete zone so the dynamics associated with a specific TAC can be included in a realistic fashion. In the current project (2013/200) there is insufficient time or resources to apply the new structure anywhere except in Tasmania, nor is it necessary to meet the current project's objectives.

Surplus production models aim to predict the dynamics of the exploitable biomass. The exploitable biomass B_t at any one time t can be described by:

$$B_{t+1} = B_t + \frac{r}{p} B_t \left(1 - \left(\frac{B_t}{K} \right)^p \right) - C_t \tag{1}$$

where r, K¸B_0, and p are the parameters of the surplus production model. If p is set to 1.0, this is equivalent to the Schaefer production model and if p is set to a very small number (e.g. 1e-8) then it becomes equivalent to the Fox model (Haddon, 2011). The difference is that the peak of surplus production is at K/2 in the Schaefer model while it is skewed to a smaller biomass level in the Fox model. Here the Schaefer version of the model was used (although the difference in MSY estimate, a measure of productivity, is usually minor between the two models). To fit the model parameters to the theoretical dynamics a simple observation error approach was used that minimized the difference between the observed catch rates. I_t, and those predicted by the model, $\hat{I}_t$:

$$\hat{I}_t = q_t B_t e^{N(0,\sigma^2)}$$
$$SSQ = \sum \left[Ln(I_t) - Ln(\hat{I}_t) \right]^2 \quad (2)$$

where q_t is the catchability at time t, B_t is the exploitable biomass at time t, and $e^{N(0,\sigma 2)}$ implies log-normal random residual errors.

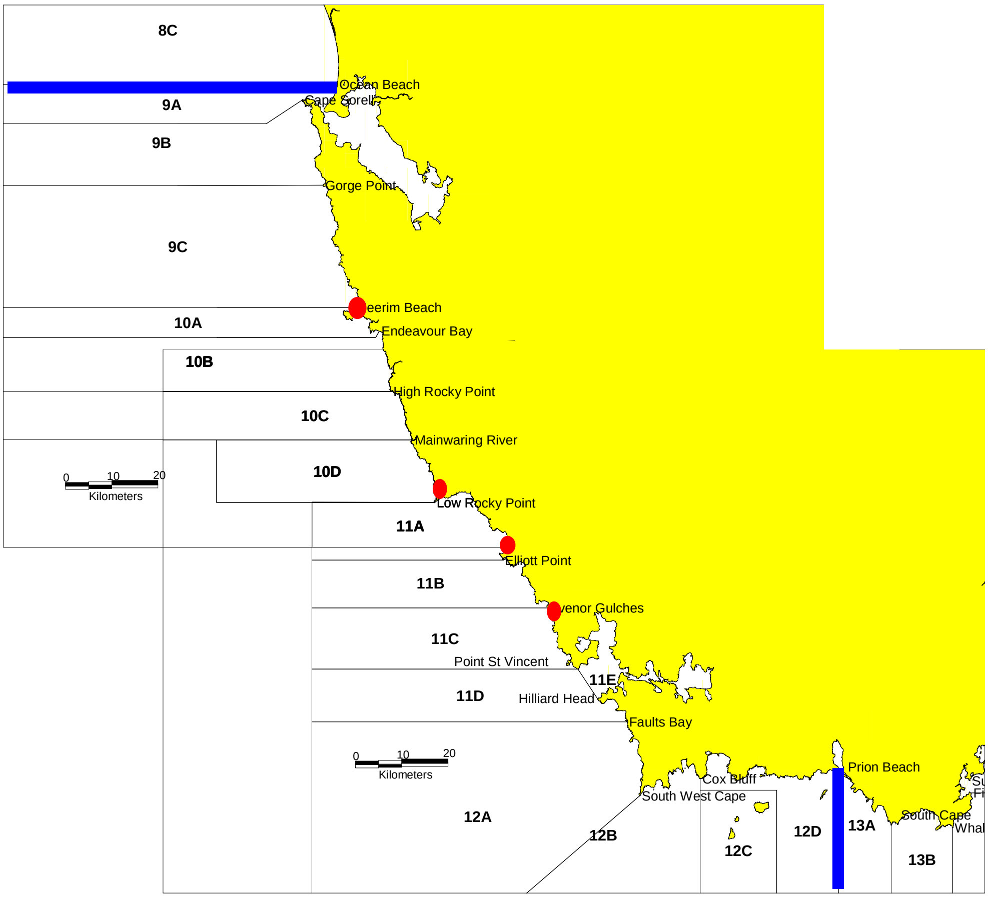

Figure 5. The southwest of Tasmania with blocks 9 – 12 being between the thick blue lines. The red dots depict the location of data used to define the growth characteristics.

The closed form estimation of the catchability for a given block of *n* years is:

$$\hat{q} = e^{\frac{1}{n}\sum \text{Ln}\left(\frac{I_t}{\hat{B}_t}\right)} \quad (3)$$

which is the simple geometric mean of the observed CPUE divided by the predicted biomass in each year. Because of LML changes on the west separate catchability values were estimated for 1986 – 1987 and 1988 – 2008. In addition, the character of the fishery appeared to change radically after 2008 so a separate catchability for 2009 – 2014 was also estimated. Without this extra catchability the models were incapable of capturing the uptick in CPUE in 2009 that occurred in all blocks. If maximum likelihood methods are used instead of least-squared residuals then an estimate of the variation of the CPUE through time can also be determined. Assuming the residual errors are multiplicative and lognormal with a constant variance [i.e., $I_t = qB_t e^{\varepsilon}$, where $\varepsilon = N(0; \sigma^2)$], then estimates of the model parameters (B_0, r, q, and K) are obtained by maximizing the log-normal likelihood function

$$L\left(\text{data}|B_0, r, K, q\right) = \prod_t \frac{1}{I_t\sqrt{2\pi}\hat{\sigma}} e^{\frac{-\left(\text{Ln}\, I_t - \text{Ln}\, \hat{I}_t\right)^2}{2\hat{\sigma}^2}} \tag{4}$$

where L(data|B_0,r,K,q) is the likelihood of the data given the parameters, the product is over all years (t) for which CPUE data are available and, where:

$$\hat{\sigma}^2 = \sum_t \frac{\left(\text{Ln}\, I_t - \text{Ln}\, \hat{I}_t\right)^2}{n} \tag{5}$$

and n is the number of observations (Haddon, 2011). The use of catch rate data implies that log-normal residuals are the most plausible. Equation (4) can be converted to a log-likelihood and greatly simplified (Haddon, 2011) so that

$$LL = -\frac{n}{2}\left(Ln\left(2\pi\right) + 2Ln\left(\hat{\sigma}\right) + 1\right) \tag{6}$$

where LL refers to log-likelihood, n is the number of observed catch rates, and σ is the square root of Eq. (5). The outcomes of fitting these surplus production models illustrates that the different blocks have very different productivity (**Table 3**; **Figure 6**). Once the model is fitted to the data the Maximum Sustainable Yield can be estimated using

$$MSY = \frac{\text{rK}}{\left(\text{p}+1\right)^{\frac{(p+1)}{p}}} \tag{7}$$

and the effort leading to MSY as

$$E_{MSY} = \frac{r}{q\left(p+1\right)} \tag{8}$$

which means that if the LML changes through time it is necessary to use the latest estimate of catchability in these estimates to capture the rapid changes seen, for example, in 2008/2009 (**Figure 6**).

Table 3. The result of fitting surplus production models to the catch and CPUE data from blocks 9 – 12 from the west coast of Tasmania. The current depletion is for 2015 while the mean catch is across the years 2000 – 2015. The relative area is derived from counting the number of unique 1 Ha grids visited across the years 2012 – 2015 by divers whose tenders carried GPS data-loggers (Mundy, 2011), see **Table 1** and **Figure 7**.

Parameter	Block 9	Block 10	Block 11	Block 12
r	0.661	0.299	0.396	0.378
B0 (t)	844.141	1796.682	2849.776	2456.903
B1986 (t)	383.792	516.795	1042.919	816.355
MSY (t)	139.469	134.222	282.072	232.414
Depletion	0.317	0.236	0.245	0.367
Mean Catch	147.678	160.416	302.507	260.838
Relative Area	1462	1974	3319	2506

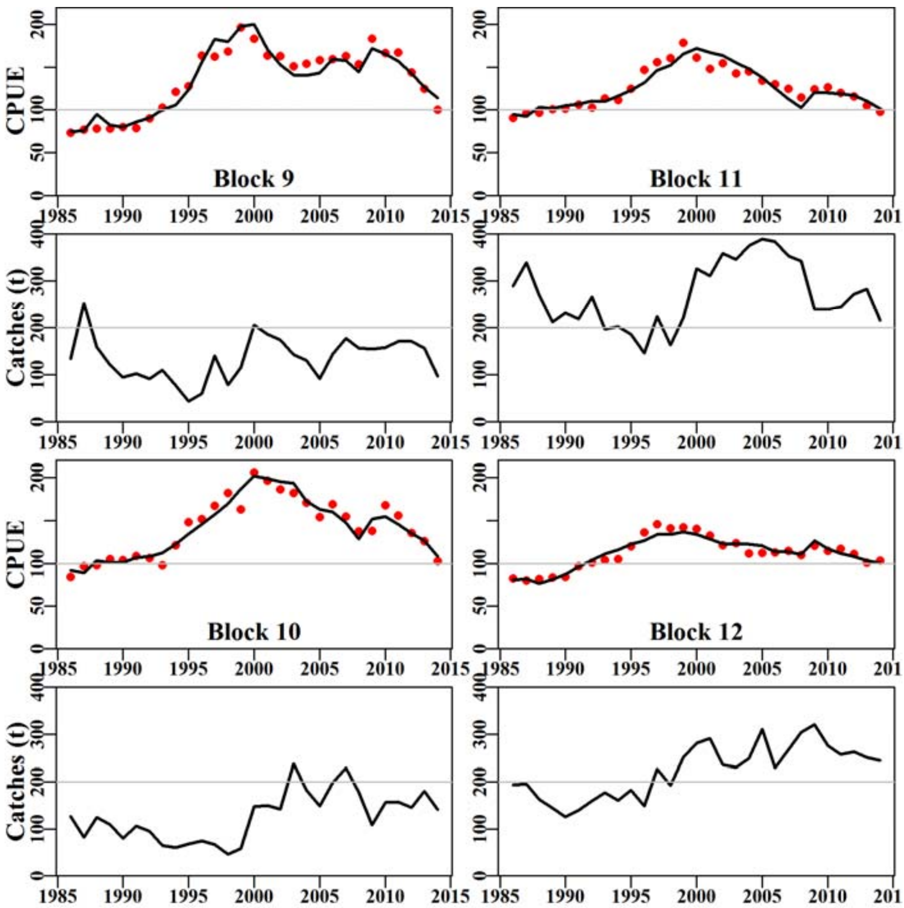

Figure 6. Surplus production models fitted to catch and CPUE data from the four western zone blocks 9, 10, 11, and 12. Standardized observed CPUE are shown as red dots, the predicted CPUE is the solid black line on each CPUE plot. Below each CPUE plot is the associated catches taken from the respective block (**Table 3**). Horizontal grey lines are for visual comparisons.

The productivity of each block is approximately linearly related to a measure of the total area of fishable reef (**Figure 7**) although there does not appear to be a relationship between the area or productivity and the relative depletion.

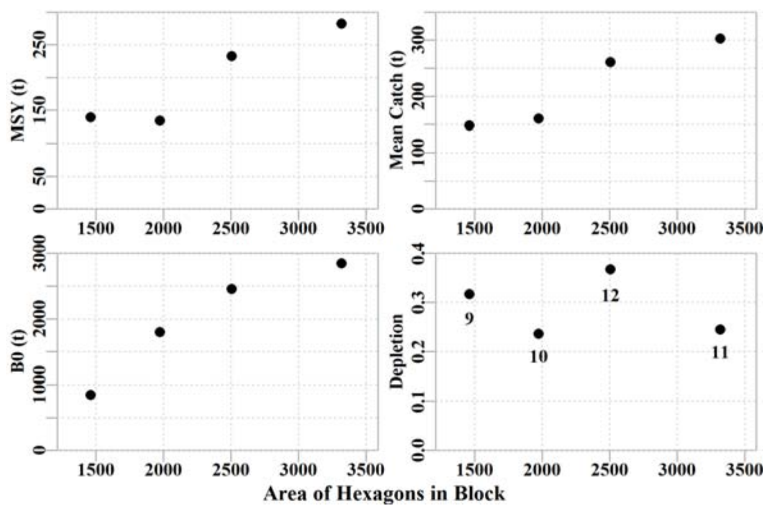

Figure 7. The outcome of fitting Schaefer surplus production models to the catch and CPUE data from blocks 9 – 12 (**Table 3**). The labels on the points in the last plot depict the relative order of the different blocks in all the plots.

6.4.4 Productivity from Stock Reduction

In circumstances where a surplus production model either fails to fit or there is not sufficient data available to obtain a plausible model fit, it is still possible to conduct a stock reduction analysis. This involves the more complex operating model itself, which is used to search for an unfished recruitment level or unfished biomass level that will enable all known catches to be taken and leave the stock in a plausible state, from which it is then possible to generate the unfished state (**Figure 8**).

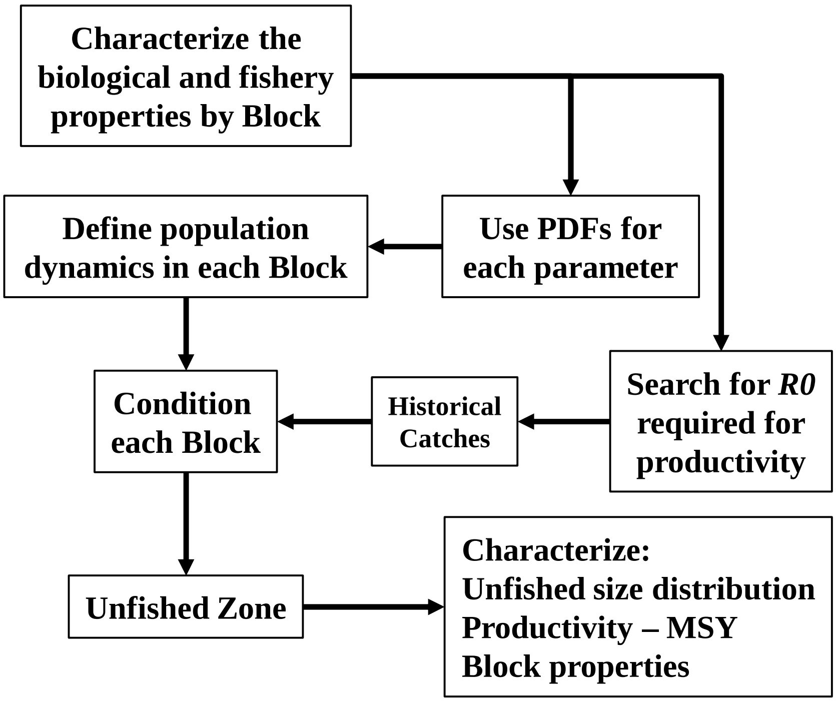

Figure 8. Schematic representation of the processes required to generate the operating model to produce the predicted unfished zone.

The biological properties relating to growth, maturity, natural mortality, size at emergence, weight at length, etc, are all parameterized by characterizing what is known about the populations in a particular fishery.

Biological properties are either randomly selected from their respective probability density functions defined in the data file (**Table 4**). Or are a function of other parameters constrained in a manner that captures the correlations between those parameters (Haddon and Helidoniotis, 2013). The steepness parameter of the stock recruitment curve (Francis, 1992) is defined for each population within a block by sampling from a given distribution, but the average unfished recruitment levels for each block needs to be defined separately (see ‘Chapter 7 The Uses of Legal Minimum Lengths’ for the importance of steepness to the productivity). The productivity of each block is determined by its growth form, by natural mortality, by the steepness, and by the average unfished recruitment level (R_0). Given the biological properties and the R_0, the unfished equilibrium size-structure for each population, and hence each block, can be determined, which in turn, defines the unfished spawning biomass (B_0).

For a given steepness, the selection of the R_0 for each block is a key step in the conditioning of any simulated zone. If they are set too low then the observed catches would either not be possible or would lead to severe over-depletion. If they are set too high then the fishery catches would have only minor effects on the stock. The strategy used to identify plausible values for each block's R_0 (that at least allow all the catches that have been reported without the stock being depleted to zero), is to assume a starting depletion level and then conduct a stock reduction analysis testing whether or not the predicted outcome reflects the observed dynamics in the fishery or not. This needs to be repeated many times, especially if the initial and final depletion levels are unknown.

6.4.5 The Stock Reduction Process

The stock reduction process which follows the initial parameterization of a simulated zone, involves five steps, which are repeated numerous times until sets of suitable R_0 values and the random seeds that give rise to them, are found. These processes are:

1. following parameterization, initial guesses at R_0 values are selected that at least lead to MSY values that should account for known catches,
2. the production curve for each block is generated so that the constant harvest rate that leads to a given equilibrium depletion level can be selected accurately.
3. each block is then depleted to its assumed initial depletion level,
4. the dynamics are run for as many years as there are known catches,
5. the predicted outcomes are compare with observations from the fishery (e.g. general CPUE trend, and length frequency distribution of catch, plus a plausible final depletion) and the relative plausibility of each run (combination of R_0, initial depletion level, and random seed) is assessed and compared.

This process is repeated until plausible R_0 values are discovered that can allow all the known catches at reasonable (< 0.4 for abalone) annual harvest rates across each block (higher levels are allowed occasionally within populations), and (if the CPUE data are available) at catch rates of the same magnitude (and ideally the same general trend) as those observed. These will lead to distributions of the current stock depletion, which are expected to be variable but should be within a narrow band of possibilities. Simulations conducted in this project demonstrate that annual harvest rates > 0.4 (implying 40% of all legal sized abalone are taken each year) cannot be sustained for more than 2 or 3 years at most before most stocks are depleted to low levels.

6.5 A Typical Conditioning Run

In all cases the simulated zone is first generated in an equilibrium unfished state, which involved conditioning it on the biological properties of particular statistical blocks as described previously. The task or questions being asked will influence the scale of the simulation adopted. For example, in the chapter considering the influence of the LML on sustainability and fishing dynamics only one population was simulated but in the other chapters a total of 60 populations spread unevenly across the blocks were used (**Table 4**).

Obtaining estimates of the various biological parameters is difficult because of the limited data available but this limited data means obtaining sensible estimates of the variation across each block for such parameters is more difficult. This is why there may be unique values attributed to the parameters but simplistic variance estimates used and shared across blocks (**Table 4**). Such difficulties from data limitations are a direct reflection of the spatial heterogeneity of biological properties. Obtaining sufficient data to fully parameterize such a spatially explicit model would involve an untenable level of cost.

Table 4. A selection of the constants used to define the simulation model based on values estimated from statistical blocks 9 – 12 on Tasmania's south-west coast. Those parameters beginning with a lower-case 's' are the standard deviations of the parameters immediately above them in the table. In a number of case identical values were used which reflects a lack of knowledge.

	Intent	AB09	AB10	AB11	AB12
Populations	Spatial Structure	10	11	21	18
MaxDL	Growth	38.5	37	37.75	36.5
sMaxDL	Growth	2.5	2.5	2.5	2.5
L50	Growth	125	124	121	120
sL50	Growth	5	5	5	5
L50inc	Growth	36	42	44	43
sL50inc	Growth	1	1	1	1
SigMax	Growth	4.581	4.581	4.581	4.581
sSigMax	Growth	0.1	0.1	0.1	0.1
LML	Management	140	140	140	140
Wtb	Weight-to-Length	3.161963	3.161963	3.161963	3.161963
sWtb	Weight-to-Length	0.148461	0.148461	0.148461	0.148461
Wtbtoa	Weight-to-Length	962.8098	962.8098	962.8098	962.8098
sWtbtoa	Weight-to-Length	-14.3526	-14.3526	-14.3526	-14.3526
Me	Natural Mortality	0.2	0.2	0.2	0.2
sMe	Natural Mortality	0.003	0.003	0.003	0.003
Mc	Natural Mortality	0.2	0.2	0.2	0.2
sMc	Natural Mortality	0.003	0.003	0.003	0.003
AvRec	Ln(Recruitment)	11.4	11.9	11.2	11.2
sAvRec	Recruitment	1	1	1	1
defsteep	Recruitment	0.6	0.6	0.6	0.6
sdefsteep	Recruitment	0.02	0.02	0.02	0.02
L50C	Emergence	126.4222	126.4222	126.4222	126.4222
sL50C	Emergence	0.5	0.5	0.5	0.5
L95C	Emergence	145.3749	145.3749	145.3749	145.3749
sL95C	Emergence	1	1	1	1
MaxCEpar	Unfished CPUE	0.37	0.37	0.38	0.38
sMaxCEpar	Unfished CPUE	0.02	0.02	0.02	0.02
selL50p	Selectivity	0	0.25	0	0.25
selL95p	Selectivity	1.5	1.75	1.5	1.75
SaMa	Maturity	-16	-16	-16	-16
L50Mat	Maturity	123.384	122.893	112.373	116.345
sL50Mat	Maturity	4	4	4	4

During the conditioning of the simulated stock, where biological and fishery data from the selected statistical blocks are used to direct the dynamics of the modelled stock to be like those in the real fishery (**Figure 6** and **Figure 9**), the productivity properties of the stock are also determined. Each simulation begins with the stock in an unfished state (**Table 4**; **Figure 10**) and this is then depleted to a selected level within each tested scenario by searching for the constant harvest rate that would produce the desired depletion. The selected depletion level is then maintained for an initial five years by removing the expected productivity as catch so as to allow the stock dynamics to stabilize relative to the new depletion level. The selected harvest control rule (HCR) is then applied such that subsequent catches are determined by the HCR. In each scenario the whole simulation was run at least 1000 times to enable estimates of the relative proportion of different outcomes to be tabulated.

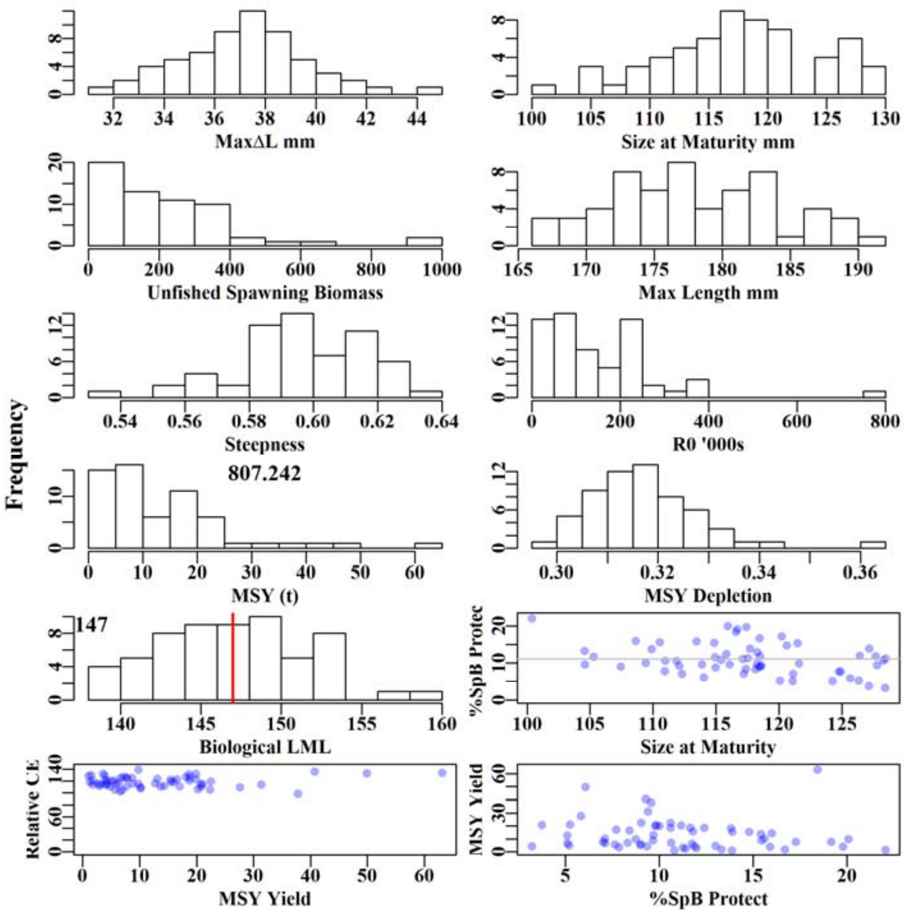

Figure 9. The properties of 60 abalone populations in a simulated zone generated using the properties as expressed in **Table 4**. In each case the histograms depict the distribution of each property as expressed in the 60 populations. For example, steepness ranges from 0.52 – 0.64 from an input mean of 0.6. The mean biological LML (size-at-maturity plus two year's growth) was 147 mm, while the LML is 140 mm. The maximum length is the length after 23 y of growth, MSY, maximum sustainable yield by block with 807.242 being the summed total (after Haddon and Helidoniotis, 2013).

The operating model represents reality in the simulation framework and each year that the dynamics are simulated forward from the starting point the model is used to generate simulated fisheries data. Each year such simulated data is then used to estimate the performance measures (CPUE) used by the HCR within the selected management strategy and the resulting management advice, the TAC, is imposed back onto the operating model dynamics, which in turn moves the stock dynamics forward. This feedback loop between the operating model and the HCR is an essential part of management strategy evaluation and differs from simply projection constant management settings forward in time (Punt *et al.*, 2016).

In each simulation three sources of variation are included in:

1) the recruitment variation,
2) the simulated catch rate estimates, and
3) the distribution of future effort across blocks and their populations.

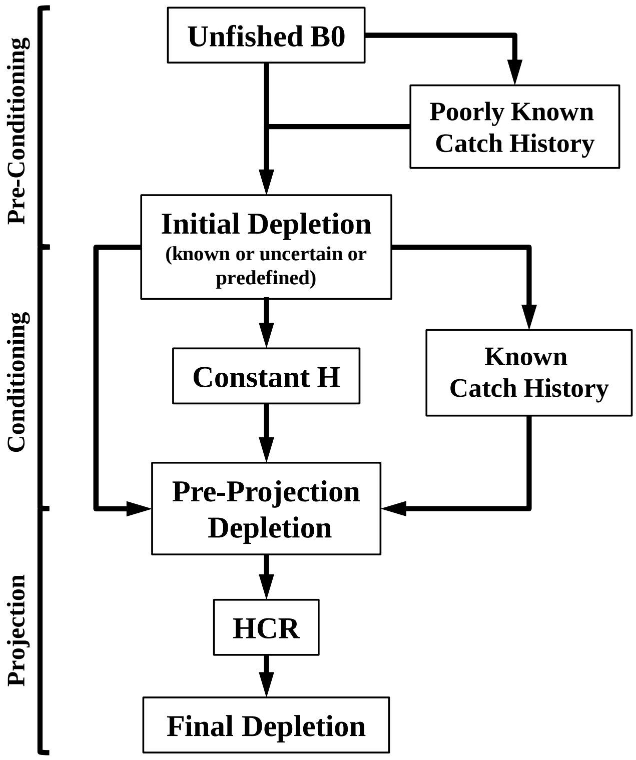

Figure 10. Schematic structure of the stages of conditioning and running an MSE. The pre-conditioning and conditioning of the MSE simulation framework is required to setup the initial conditions in the MSE before running the projections used to test the different harvest control rules (HCR). The MSE runs are those steps contained in the projections. The more information is known about the stock the more specific the conditioning can be.

Recruitment variability is clearly important in abalone fisheries and is found in all but the simplest stock assessment modelling. Catch rate data from fisheries always has associated uncertainties and so these are included in the simulated catch rates (which make up the three empirical fishery performance measures within the MCDA). Finally, each year, the divers make decisions with regard to where they will go fishing and this is generally based on their impressions of the state of each area, either from their own experience or from hearing other divers. Such decisions are also intrinsically uncertain so the proportional allocation of a TAC across a fished zone includes significant variation away from the ideal distribution.

6.6 Plausibility of the Conditioning

As described in section 6.3 (Conditioning the MSE Framework) it is first necessary to condition the MSE framework so that the simulated dynamics operate in a manner similar to a known fishery. Here, while separate surplus production models were fitted to each of the simulated blocks, 9 – 12, so as to obtain a direct estimate of the productivity expressed in each block (**Figure 6**; **Table 3**), this does not constitute fitting the 60 populations across the whole zone to the available data. Using surplus production models rather than a simpler stock reduction analysis should improve the conditioning as the productivity of the simulated blocks should more closely approximate that expressed in the real fishery. Nevertheless, there remain many assumptions concerning the spread of variation across the populations within each block (**Table 4**) so the application of aspects of the stock reduction analysis after the use of surplus production models can still provide greater insight into how well the simulation framework mimics the behaviour of the real fishery. The full model specification, along with details of the software implementation are given in 'Chapter 10 The Size-Based Operating Model'.

Before proceeding with the MSE comparisons of the various settings possible within the MCDA procedure it is best to document the properties of the simulation first to ensure they remain in the realm of the plausible.

6.6.1 Implications of the Conditioning

The production curve for each block defines its expected equilibrium yield at different spawning biomass depletion levels and different harvest rates (**Figure 11**). These are produced by essentially turning off recruitment variation and the variation associated with the distribution of catches so they are distributed across populations in direct proportion to the relative abundance of exploitable biomass. This removal of the variability alters the dynamics and fishing to become essentially deterministic. A constant harvest rate ranging from about 0.05 – 0.55 is applied sequentially and for as many years as required to achieve a stable spawning biomass depletion level to a precision of < 0.1%.

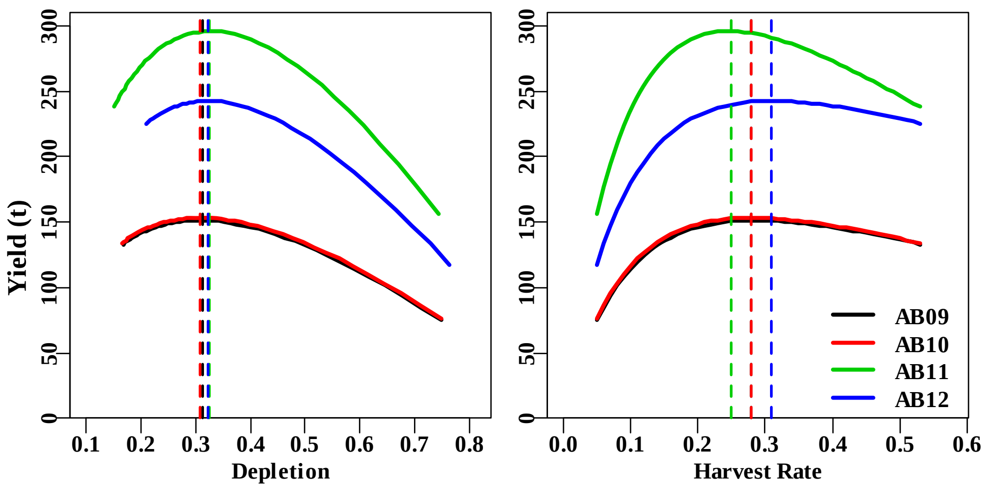

Figure 11. Production curves for a simulated zone conditioned approximately on the Tasmania west coast blocks 9 – 12. The vertical dashed lines indicate the MSY values for each block, with blocks 9 and 10 almost on top of each other (see **Table 3**).

This empirical search generates both the production curve and an estimate of the MSY for each block (**Figure 11**). In the case of blocks 9 – 12 on Tasmania's west coast, the block 9, 10, and 12 all have relatively flat production curves against harvest rates greater than 0.2, while block 11's curve is steeper. Those blocks with relatively flat production curves will allow harvest rates much higher than the optimum without a large loss in catch, which would lead to economically inefficient fishing with far more effort than required for the yield taken. Once the production curves are estimated then it is possible to determine the particular harvest rate to impose to obtain the selected initial depletion level. For example, if an initial depletion level of 25% were selected for the four blocks 9 – 12 in the west coast simulation this requires the four block level harvest rates to be 0.36, 0.36, 0.34, and 0.43 respectively to achieve the desired initial depletion level.

6.6.2 Implementing Initial Depletion Levels

Given that each block is likely to have a different production curve this implies that each block will need a slightly different constant harvest rate to achieve approximately the same depletion level. It is also important to find the harvest rate that leads to a stable depletion level so that when recruitment and spatial-catch allocation variation is included the mean block depletion is not greatly altered, although some change will be expected to happen (**Figure 12**).

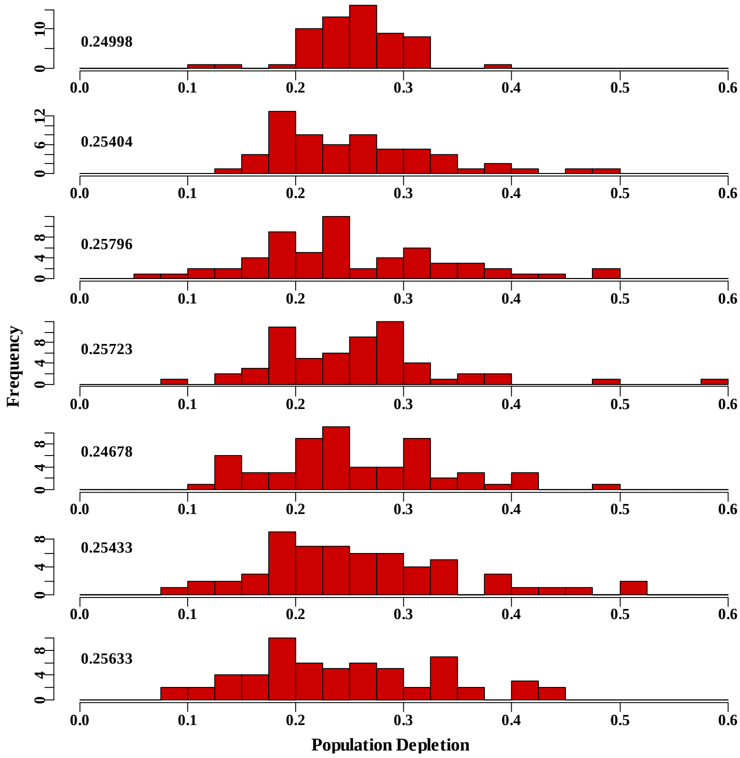

Figure 12. The effect of depleting an unfished zone of four blocks and a total of 60 populations down to a level of 25%B_0. The top panel is deterministic depletion while the other panels indicate the effect of six different applications of the required constant harvest rate with variability added to recruitment in each population and the distribution of catches among populations within blocks, both of which obviously influence the dynamics.

The inclusion of variation and uncertainty within the dynamics of an MSE is one of their characteristics and permits the examination of the effects of uncertainty on the effectiveness of different management strategies. So depleting the stock to a particular selected level needs to be done in a manner that retains the level of variation across the populations that would be expected in any fishery undergoing fishing. The productivity of each population within each block differs from one another and from those in different blocks. Thus, even if fishing at a given constant harvest rate is conducted in the absence of recruitment variation and in the absence of errors in the allocation of catch across the separate populations within a block, then given a mean block depletion level a range of depletions at the population level is expected (**Figure 12**). After initial deterministic depletion, once variation is included in recruitment and the distribution of catches then the variation of depletion among populations can be expected to increase although if the constant harvest rate is correct the block mean will not change greatly.

In the MSE this is implemented by first depleting the stock in a deterministic manner and then including variation for two more cycles of 50 years. The outcome varies in each model run, but generally two extra cycles of 50 years is sufficient for most of the variation to be expressed.

6.6.3 Testing Plausibility

Before any simulated projections are made it is possible to apply the history of catches taken from each block in the known fishery and examine the outcomes to determine their plausibility. These may be termed conditioning trial runs. Each conditioning trial run will give rise to a biomass trajectory and a final depletion level, it will also generate an expected CPUE time series, and an expected length frequency distribution for each year. If the final depletion level is too low to be realistic, or the CPUE time series differs markedly from those observed, the parameters giving rise to such outputs can be considered implausible and rejected. If the expected length frequency distributions differ markedly from those observed, it could be the selected R_0 or possibly the growth parameters would require modification. Such comparisons of the expected with the observed is analogous to fitting a model but in this case the operating model is so over-parameterized that it can only identify plausible parameter combinations.

6.6.4 Equilibrium Unfished Size Distribution

If the unfished equilibrium size distribution is smaller than the current size-composition data from the fishery or is rather larger than any of the fishers can remember this would constitute evidence that the conditioning (the parameters adopted) were implausible (Helidoniotis and Haddon, 2014b).

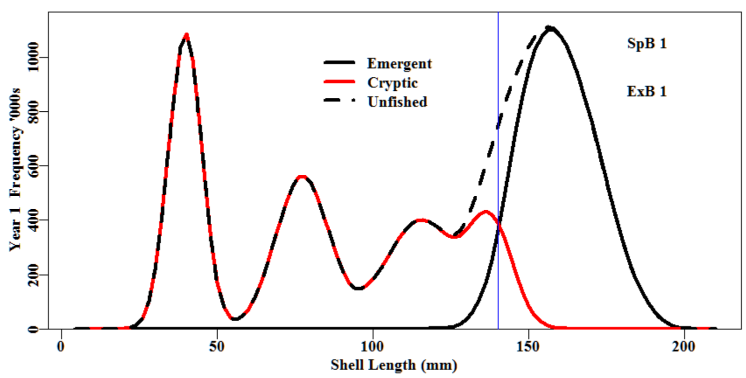

Figure 13. The unfished size-composition of the whole zone combined illustrating both the cryptic and emergent parts of the stock. The smallest post-larval animals are omitted to allow details of the larger animals to remain clearer.

7 The Uses of Legal Minimum Lengths

7.1 Introduction

7.1.1 Historical Uses of LML

The imposition of a minimum legal size is one of the oldest forms of regulation used in fisheries management. For example, in Australian fisheries legal minimum sizes have been used since the late 1800s. Hill (1992, p 9) stated: "…restrictions on the size of fish taken were introduced in Victoria in 1873 and in Queensland in 1877, apparently to produce marketable sizes".

Minimum sizes are generally introduced to achieve particular stated objectives but the primary objectives appear to have changed through time. Issues concerning sustainability of fished populations globally did not start being taken seriously until after the start of the 20th century (Huxley, 1884; Garstang, 1900). Minimum sizes were often justified in earlier times as ensuring that fish sold were of marketable size, rather than to meet sustainability objectives. In the 20th century ideas of growth-overfishing and recruitment-overfishing were developed within a yield-per-recruit framework (YPR; Russell, 1942; Beverton and Holt, 1957 and 1993). One aim of YPR analyses is to optimize yield from a fished stock by identifying the size or age at which to start fishing a species. Such analyses aim to balance the trade-offs between increases in biomass through somatic growth and losses to biomass through natural mortality and lead naturally to concepts such as minimum sizes and related gear regulations.

Hancock (1992) reported the outcome of a survey across different jurisdictions in Australia concerning the reasons for using minimum size limits in their fisheries. The dominant reasons given for using a minimum size (Table 2 in Hancock, 1992) were: 1) to protect immature animals, 2) to help control the harvest, and 3) to ensure an optimum market size. Controlling the harvest was usually taken to mean ensuring that effort was spread more widely into areas where larger fish were to be found. A common approach reported for the protection of immature animals was to set the minimum legal size either at the size at maturity (assumed to be defined by the size at 50% maturity; although see the Appendix to this chapter on estimating the size at maturity) or a set number of years after the size at maturity; this is equivalent to preserving some minimum proportion of mature biomass,.

7.1.2 Current Uses

Minimum legal sizes are common in many invertebrate fisheries, and this is the case in all rock lobster (e.g. *Jasus edwardsii*) and abalone (e.g. *Haliotis rubra*) fisheries in Australia (Mayfield et al., 2012) and New Zealand. About 50% of wild caught abalone in Australia are taken in Tasmania and there have been a number of changes to the legal minimum length (LML) imposed from the late 1980s to the present day (**Table 5**). The intention of such changes was to afford each stock greater protection for the immature animals and increase the chance of mature abalone having at least two years opportunity to reproduce (Helidoniotis and Haddon, 2014a; Tarbath and Mundy, 2015). Any change or suggested change to an LML engenders often heated debate among abalone fishery stakeholders in all jurisdictions. Some believe that each increase will preclude divers from parts of the fishery that only contain or are perceived to contain smaller abalone, effectively reducing the extent of fishing grounds. Other divers believe such increases will protect a greater proportion of mature biomass and hence will add insurance for a sustainable fishery especially when stocks have declined or appear stressed. The different intuitions that drive this on-going debate are about how different LMLs will affect the biological dynamics of a fished stock. A critical gap in knowledge, seemingly across all stakeholders, is the effect on long term production of alternate LML strategies that either provide access to all populations through smaller LMLs, or greater protection for the most productivity populations through higher LMLs. Despite disagreements about the need and the implications of LML change, the idea that a legal minimum size provides protection for immature animals or some minimum spawning biomass remains a common reason now cited behind setting up a minimum size regulation (Stewart, 2008; Mayfield *et al*, 2012).

Table 5. The changes to the LML (or MLS) in Tasmania from the start of the fishery in 1962 (Haddon *et al*., 2013; Tarbath and Mundy, 2015). Many years in which no changes were made are omitted. Footnotes indicate fine-scale modifications.

Year	13C-31A East	6D-13B Western	5D-6C Central West	5A-5C North	1A-5C; 31B 39-40; 47-49 North	41-46 Bass Strait	32-38 50-57	Zonation
1962	127	127	127	127	127	127	127	
1964	152	152	152	152	152	152	152	
1965	127	127	127	127	127	127	127	
1987	132	132	132	132	132	132	132	
1989	132	132	132	132	132	110	110	
1990	132	140	132	132	132	110	110	
1991	132	140	132	132	132	118	118	
1993	132	140	132	132	132	110	110	
1994	132	140	132	132	132	132	132	
1995	132	140	132	132	132	100/110[1]		
1996	132	140	132	132	132	132	132	
2000	132	140	132	132	132	132	132	East, West
2001	132	140	132	132	127	127	127	Northern
2002	136	140	132	132	127	127	127	
2003	136	140	136	132	127	114	114	Bass Strait
2006	136	140	136	132	127	110	114	
2007	138	140	136	132	127	110	114	
2008	138	140	136/132[2]	132/127[2]	127	110	114	
2009	138	140	136/132[2]	132/127[2]	127	110	114	Central West
2010	138[3]	140	136/132[2]	132/127[2]	127[4]	110	114	
2012	138	140	136/132[2]	132/127[2]	127[5]	110	114	
2013	138/145[6]	140	136/132[2]	132/127[2]	127[5]	110	114	
2014	138/145[6]	140	136/132[2]	132/127[2]	127[5]	110	114	

1 - Special fishery held in May and June Bass Strait with LML 110mm; another in November at LML 100mm.

2 - Controlled trial in blocks 5 and 6 to test the effect of decreasing LML and increasing the TAC, LML from 132 - 127mm in 5A-5C and 136 - 132mm in 5D - 6C. The Central Western Zone covered Blocks 6 – 8, while the new Western Zone was made up of blocks 9 – 13B.

3 - Permit fishing in Subblock 31A allowed at 132mm from July - Oct 2010

4 – In Blocks 47, 48, 49, LML reduced from 127mm to 125mm.

5 - In block 49, LML reduced from 125mm – 120mm on Hunter Island and Three Hummock Island; on Albatross Island it was increased from 125mm – 127mm.

6 - Catch capped on Freycinet Peninsula, 26B - 28B, LML increased to 145mm; Experimental fishing in 30B at 145mm

Because of their high value and strong market demand all abalone fisheries tend to be fished as intensely as permitted. Given the challenges associated with determining stock status, appropriate management is particularly critical. In the mid-1990s, Tasmania established a draft size limit policy known as the 'two-year rule' for abalone (Anon, 2000; page 51), which simply required "all abalone be protected for two breeding seasons" before entering the fishery. The policy document does not establish a rationale for the two year rule, or a procedure for determining an effective LML to achieve that policy objective. The lack of a rationale and a defined procedure means there is a risk that interpretation of this 'two-year-rule' will become *ad hoc*. Policies couched in such weak terms are unhelpful as they can lead to confusion over how such policies are to be implemented and if different operational procedures are adopted at different times this can lead to inconsistencies which can also confuse subsequent management; in addition it would likely lead to confusion among divers and potentially lead to reductions in compliance. In practice, determining the LML involves estimating the size-at-50%-maturity and then adding two year's growth (Tarbath et al 2001; Tarbath & Officer, 2003; Helidoniotis and Haddon, 2014a; and see appendix on size-at-maturity for alternative ways of operationalizing these processes). All other Australian States with abalone fisheries use an LML (or a minimum legal size, MLS) but their specification has no formal or explicit basis in their respective Management Plans. Certainty over the adequacy of the LML policy and implementation has been hampered by inadequate information on Blacklip Abalone reproductive biology. Consequently, it appears that, especially in the south-west of Tasmania, the current LML is below the two-year rule policy guideline at many sites (Helidoniotis and Haddon, 2014a; Tarbath and Mundy, 2015); whatever the case the end result is a complex framework of different LML by area with exceptions and minor changes imposed on top (**Table 5**). Despite the complexity, however, these recent attempts to set more local LML values to more closely match the local productivity conditions is an improvement over the state-wide use of 127mm, which was too large in a few places in the north of the State but far too small in many places more to the south.

7.2 Spawning Biomass Protection

7.2.1 The Geographical Scale of Protection

Abalone stocks in Australia are currently managed through a combination of setting total allowable catches for particular fishery zones, and identifying legal minimum lengths, which are sometimes set independent of zone boundaries. Importantly, while the spatial scale of implementation of these two management levers (TAC and LML) is large, the spatial scale at which they effect control on sustainability differs.

The third important aspect of abalone management are the spatial controls put in place within a fishing year in an effort to distribute catches across the stock; the spatial spreading of effort is especially important with species such as abalone whose stocks are spatially structured into numerous micro-stocks. In Tasmania the imposition of different types of within-year spatial management includes the allocation of local catch caps by area, but also explicitly includes spatial mechanisms such as seasonal closures or temporary changes in LML.

Such spatial structure and management is generally ignored or rather understated in the theory of classical fisheries population dynamics (Goethal *et al*., 2011). There is a class of models known as ‘dynamic pool’ models which sub-divide the population dynamics into four major processes of growth, recruitment, natural mortality, and fishing mortality, and each process can be broken down into multiple sub-processes (Pitcher and Hart, 1982; Haddon, 2011). A key aspect of these classical models is the notion that any of the processes that can affect the population will affect the whole population. This implicitly ignores any spatial structuring and effectively assumes a single stock or multiple sub-stocks whose dynamics are dependent or strongly linked. For example under the dynamic pool model, if fishing occurs in only one area then any impact of that fishing would affect the whole stock not just that which resides in the area where fishing occurred. Stated in this blunt fashion these assumptions appear to be completely implausible, especially over the large geographical distributions exhibited by some species in Australia, and especially for abalone species with their multitude of what can be termed micro-stocks. However, when working with a highly mobile scalefish and using a long enough time frame, such as a year (which is very common in fisheries), such an approach can form a plausible approximation to the continuous processes that a real population is undergoing. The approximation fails, sometimes badly, where there is significant spatial structuring of a population (even with mobile species such as with Blue-Eye Trevalla, *Hyperoglyphe antarctica*; Haddon, 2015), such that different parts of the exploited stock can exhibit different fishery and biological properties (somatic growth, depletion, morphometrics etc; Haddon and Willis, 1995).

The extent to which an exploited species departs from the dynamic single-pool model will depend on the nature of the ecological dynamics as well as the fishery dynamics. In the case of southern rock lobster (*Jasus edwardsii*), there is substantial regional variation in growth and fishing mortality, but there is strong connectivity among regions through an extended (~18 month) pelagic larval dispersal phase. For some Haliotids (*Haliotis rubra, H. laevigata)* connectivity among local populations is weak or non-existent, and demographic parameters may be homogenous over large spatial scales (10s of kilometres), or vary substantially over local scales (100s of meters) where conditions are marginal (Miller *et al*., 2009, 2011). If a dynamic pool model (most current stock assessment models) is used to describe either population type, this would imply that a process such as serial depletion would not be possible. Of course, once spatial structuring is included in a model then the localized depletion of sub-sets of a stock would be possible and progressive serial depletion of a stock becomes a possibility. Such serial depletion has been identified as contributing to the failure of a number of high profile abalone fisheries (Hobday *et al*, 2001). Unfortunately, the explicit inclusion of spatial structure into stock assessment models remains under-developed (Goethel *et al*., 2009; Punt *et al*., 2015; Punt *et al*., 2016). Currently, because of limited availability of biological data, particularly concerning growth, length-based stock assessment models can only be applied to abalone stocks over relatively large geographical scales by making generalizing assumptions about the biological properties (such as with the growth characteristics) of the stock (Fu, 2012).

When examining the efficacy of any management measure how it interacts with the spatial nature of the stock concerned is best considered explicitly. Mathematical models of the population dynamics involved in fisheries invariably operate at the relatively large geographical scale of the SMU or the zone. This may bias any conclusions concerning the effectiveness of a management measure if their operation at the scale of the fishing operation is not also considered. Here we will attempt to consider how the imposition of global TACs and LMLs might operate at both the larger geographic scale of zone and SMU as well as at the much smaller scale of the individual fishing operation.

7.2.2 The Effects of Depletion on Recruitment

The protection of spawning biomass and immature animals now remains the primary justification for the use of minimum sizes in Australian abalone fisheries. There is an intuition that appears to be held by many abalone divers and fishery managers, that the numbers of sub-legal animals would remain at the unfished level irrespective of whether or not the legal sized abalone were in a depleted state or not (**Figure 14**; see Knuckey, 2015, p36 for an example). This is an important assumption and influences many discussions around the setting of LML in different areas. A number of processes could affect the validity of this assumption, including properties of the stock recruitment relationship, the average size of available abalone (emergence in Haliotids), and the state of depletion of the legal sized stock. The effects of these processes can be explored by simulating an abalone population, applying a known catch history to it and comparing the impact when there are different levels of stock depletion, stock recruitment steepness, and different LML.

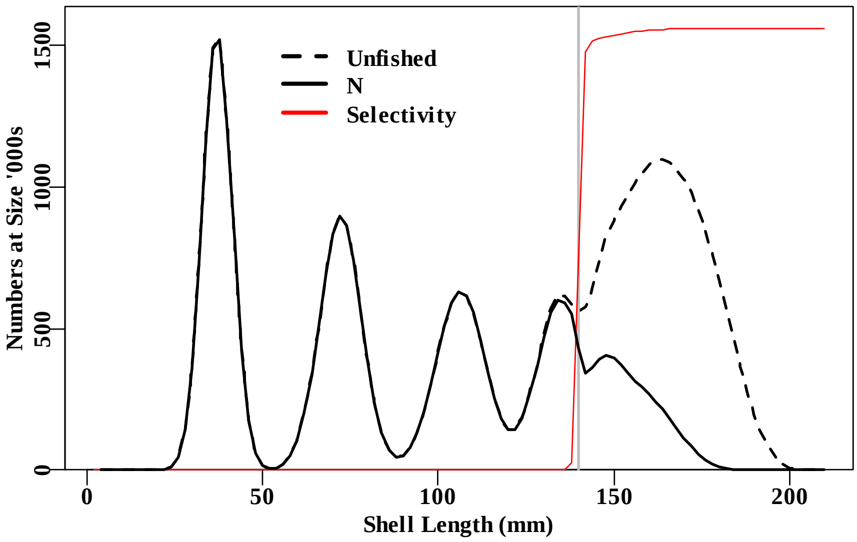

Figure 14. The predicted equilibrium numbers-at-size for an abalone population when unfished and when depleted to 30%B_0. The modal progression of cohorts is apparent although the earliest cohorts are omitted to allow the detail in the sizes of interest to be clear. Steepness in the stock recruitment relationship was set at 0.999 to mimic an absence of density-dependency in recruitment (i.e. no effective stock recruitment relationship). The red line represents the selectivity of the fishery with the vertical grey line identifying the LML.

Fishing a stock where gear, size-selectivity, or size-limits is effective at excluding sub-legal animals, should not directly affect the abundance of sub-legal animals at the time of fishing. However, if fishing leads to the stock being depleted significantly below the unfished state then the abundance of sub-legal animals will decline through time unless there is no density dependence within the spawning stock – subsequent recruitment relationship (**Figure 14**). If a stock-recruitment relationship includes density-dependence then as depletion becomes greater, recruitment production will also be reduced and the number of sub-legal animals will eventually decline. The presence of a legal minimum size and such density-dependence leads to time-lags between the occurrence of heavy fishing and the appearance of the stock becoming depleted because it can take several years for reduced numbers of recruits to enter the fishery and the decline in consequent biomass to be observable.

7.3 Objectives

7.3.1 Large Geographical Scale

This present work attempts to inform intuitions about the effectiveness of legal minimum lengths for the protection of sub-legal abalone (although the intuitions apply to any fishery with a legal minimum size). These attempts involved two approaches.

A size-structured population dynamics model was used to explore the interactions at an SMU or zone scale between stock depletion levels, the maximum potential yield, the legal minimum size, the stock – recruitment relationship, and finally the size at emergence. The stock depletion level is a result of the fishing mortality imposed with the depletion level being inversely related to the harvest rate. The stock-recruitment relationship is important because the degree of density dependence will influence how sensitive sub-legal abalone are to being depleted. Density-dependence in stock-recruitment relationships is well summarized using the concept of steepness (Francis, 1992).

By imposing an array of alternative scenarios of legal minimum length, constant harvest rates, and stock-recruitment steepness onto the size-structured model the influence of these different factors on the effectiveness of legal minimum lengths for the protection of immature and spawning biomass will be clarified. In addition, the interaction between the LML and the size of emergence from crypsis becomes important if the size at emergence overlaps the legal minimum size. A logistic curve is used to describe emergence from crypsis and if any of these curves overlaps the selectivity curve this will affect the abalone available for capture. This in turn will influence the size composition of the catches and hence has importance when attempting to assess abalone stocks.

Thus, in terms of the objectives of this work, the size-structured population model will be used to determine the implications of different scenarios of legal minimum length as they relate to different growth characteristics. In addition, how these implications are modified by 1) the level of stock depletion that might occur, 2) the steepness of the stock recruitment relationship, and 3) the form of the curve describing emergence of smaller abalone from crypsis.

7.3.2 Scale of Fishing Operations

Generally population models are designed to operate at relative large scales and involve very large numbers of individual animals. Here we attempt to simulate the dynamics on a set of very small areas representing relative small individual reefs so as to illustrate and illuminate how the dynamics at those scales may need to differ from larger scales to generate plausible or realistic outcomes. Because there is very little known about the dynamics of abalone populations at the scale of fishing operations an attempt will be made to generate a minimum specification for such a model of small geographical scale dynamics and also identify what kinds of evidence currently available may be able to inform questions concerning the dynamics.

7.3.3 Specific Objectives

- Demonstrate how, in an unfished population, the selected LML affects the initial expected exploitable biomass, the maximum sustainable yield, and the proportion of the spawning biomass that is protected at an SMU or zone scale.

- Demonstrate how, as the stock is depleted to different levels, the proportion of spawning biomass protected at an SMU or zone scale changes relative to the current spawning biomass and relative to the unfished spawning biomass.

- Demonstrate how any changes to the level of protection afforded a stock by an LML are affected by the steepness of the Beverton-Holt stock recruitment relationship.

- Demonstrate under what circumstances would the size-at-emergence from crypsis influence the protection at an SMU or zone scale afforded to the mature biomass.

- Draw conclusions about the protection afforded by an LML to the sub-legal biomass and stock at the scale of individual fishing operations?

7.4 Methods

7.4.1 The Simulation Model

A size-structured population dynamics model was constructed in R (Haddon and Helidoniotis, 2013; R Core Team, 2016) to contrast the effects of different LMLs on stock dynamics in both unfished equilibrium and fished states (see Appendix: The Size-Based Population Model for the model equations). While the basic form of the model derives from the model of Sullivan *et al*. (1990) as further developed by Punt *et al*. (1997), it differs from previous models through including the full size range of post-larval abalone with an initial size class of 1 – 3 mm having a central value of 2 mm, stepping in 105 × 2 mm classes up to a size class centred on 210 mm. Specifically, this structure differs from current abalone stock assessment models (Breen *et al*., 2003; Gorfine *et al*., 2005; Fu, 2012) which start the model dynamics in a size class representing three or four year old animals.

The previous use of a relatively large initial size class reflects the difficulties in modelling the growth of smaller size classes. The growth dynamics are captured here using the inverse logistic growth model (Haddon *et al*., 2008; Helidoniotis *et al*., 2011). The inclusion of these smaller size classes improves the modelled dynamics and avoids guesswork when trying to incorporate time lags between the post-larval and mature phase. Recent research (Haddon *et al*., 2013) shows it may take three to five years for an abalone to grow from the 2mm size class to the 70mm size class, and such time lags have important implications for recruitment dynamics (**Figure 14** and **Figure 18**).

7.4.2 The Scenarios Tested

The model dynamics were conditioned on the biology of Tasmanian west coast Blacklip Abalone (*Haliotis rubra*) with various constants relating to growth, maturity, and selectivity being defined (**Table 6**; **Figure 5**). Four sets of scenarios were examined (**Table 7**). First the simulated population was generated in the unfished state and the relative protection that would be achieved in an unfished population with different LML was tabulated. Second, a constant catch history was applied to the simulated population for 46 years until an approximate new equilibrium was achieved and the proportion of mature biomass protected (with respect to current mature biomass and also relative to unfished mature biomass) was tabulated. These projections were made for different combinations of LML, recruitment steepness, and unfished average recruitment; the level of harvest rates imposed were modified for each scenario to give rise to similar ranges of final depletion.

All scenarios were conducted with recruitment and other variation reduced to trivial levels so that the dynamics were essentially deterministic. When variation was included the median predicted values always remained close to the deterministic predictions.

Table 6. A selection of the constants used to define the simulation model based on values estimated from statistical blocks 9 – 12 on Tasmania's south-west coast.		
Description	Variable	Value
Maximum growth increment	MaxΔL	35.213
Length where the growth increment is 0.5MaxΔL	L50	126.270
Length where growth increment is 0.05MaxΔL	L95	172.319
maximum variation around the growth increments	$Max\sigma_L$	5
Width of the 105 size classes	LW	2
centre of maximum size class	LMax	210
centre of the minimum size class	LMin	2
Legal Minimum Length (varied)	LML	140
Length at 50% Maturity	Lm50	125
Difference between Lm50 and Lm95	δ_m	9.812
Weight at Length, intercept	Wta	5.62E-05
Weight at Length, gradient	Wtb	3.1792
Natural Mortality	M	0.2
Length at 50% Selectivity	Ls50	140
Difference between Ls50 and Ls95	δ_s	1.5
Length at 50% Emergence	L_E50	120.5
Difference between L_E50 and L_E95	δ_E	3
Average unfished recruitment level (varied)	AvRec	13000000
Steepness of the Beverton-Holt model (varied)	steepness	0.75
Standard deviation of recruitment residuals	sigmaR	0.0000001

Table 7. The sequence of scenarios considered in the population simulations.	
Scenario	Description
1) Unfished	Constant average recruitment, steepness 0.75, unfished, LML 127 – 166mm
2) Constant Catch History	Steepness: 0.6, 0.65, 0.7, 0.75, 0.8, and 0.9; Average recruitment varies by steepness to find values that lead to plausible depletion levels given the constant catch history.
3) Constant Depletion	Steepness: 0.6, 0.65, 0.7, 0.75, 0.8, and 0.9; Average recruitment changed to a level leading to depletion of $0.25B_0$ with the constant catch history.
4) Constant Average Recruitment	Steepness: 0.6, 0.65, 0.7, 0.75, 0.8, and 0.9; constant average recruitment, leading to constant B_0 and unfished exploitable biomass but different productivity or MSY.

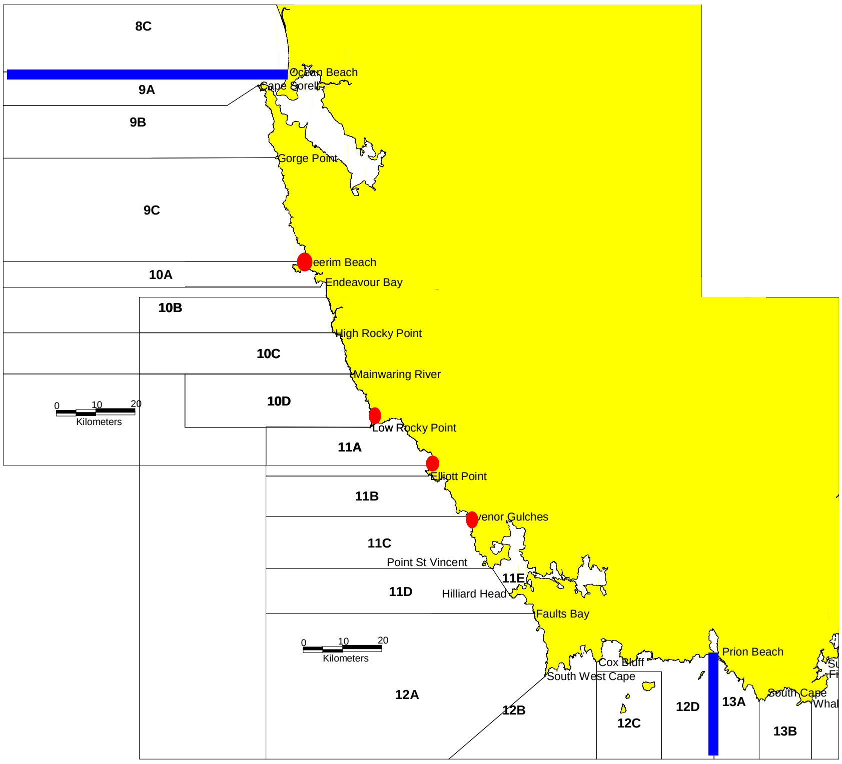

Figure 15. The southwest of Tasmania with blocks 9 – 12 being between the thick blue lines. The red dots depict the location of data used to define the growth characteristics.

7.4.3 Small Geographical Scale Processes

When considering small scale population dynamics the sized-based model was conditioned to represent only 10 individual reefs using biological parameters from blocks 9 and 10 on the Tasmanian west coast. All parameters were left the same as for the larger scale simulation but the average recruitment was reduced by two orders of magnitude so that the total productivity of the ten reefs (small-scale) was appropriately smaller. When simulating 60 populations (large-scale), then each population represents an array of the smaller-scale reefs, the predicted MSY (productivity) for each of the large-scale 60 populations varied from 1.0 t – 64 t, when conditioned to represent 10 small-scale individual reefs, which together might equate to a single large-scale population, the MSY per reef ranged from 0.011t – 0.121t (11 – 121kg). These are intended to represent the productivity of individual reefs that might form the focus of individual dive events. Such productivity levels imply relatively low levels of exploitable biomass. If classically estimated catchability values are used at the individual reef level (fishing operation level) then catches of less than a kilogram per reef would eventuate, which are implausibly low. A major difference between such small scales and the more classical larger scale would need to be in the fishing dynamics. This is an illustration that the MSE framework can be used across a wide range of geographical ranges with the large-scale possibly encompassing a whole zone while the small-scale covering only a few kilometres of coast.

A minimum specification for a model of small scale processes was developed in an effort to clarify the differences between a typical model designed for the large scale and one more suited to the small scale of an individual dive operation. The intent being to clarify the expected fishery dynamics when individual operations are considered and to illustrate the implications these have for sustainability.

7.4.4 Tasmanian One Hectare Hexagon Grid

In Tasmania, since 2012 regulations require that all abalone divers carry a depth-logger on their person and a GPS data-logger in the run-about they use when fishing. These enable precise and detailed data to be collected concerning actual diver effort and location information for each dive (Mundy, 2011). When attempting to examine small geographical scale processes (such as diver operations and fleet dynamics) such detailed data provides the only viable means currently available for such monitoring. All fishing activity in the region of interest can be summarised by quantifying effort (as dive time) within grid cells. Here we use a one hectare hexagonal grid (Mundy, 2011), with data pooled within the four years (2012 – 2015). Fishing intensity at local scales often varies among years (**Figure 16**), which suggests harvest rates at the local scale may not inherit the apparent stability observed when data are pooled at the much larger SMU or zone scale.

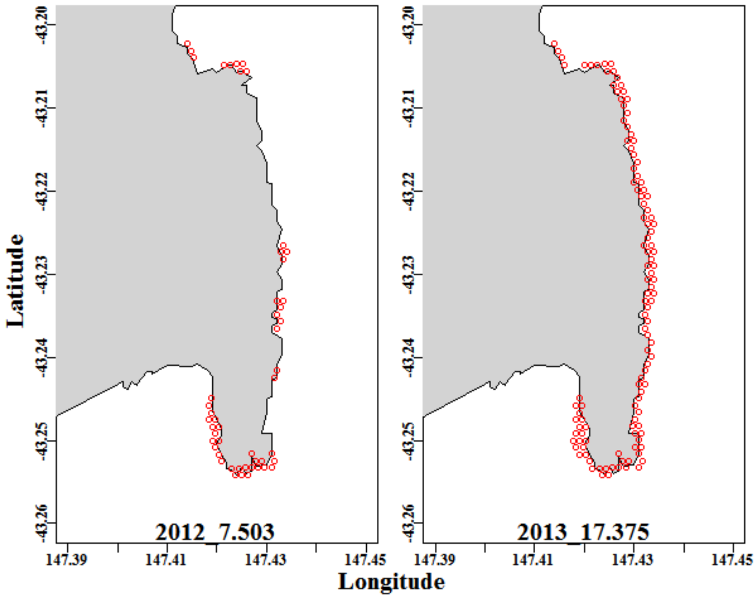

Figure 16. An example of the use of the one Ha grid of hexagons around Tasmania between 2012 and 2013. Only a small fraction of a particular block is illustrated with the total catch reported for that block (that is the catch associated with the GPS data-logger data for the whole block, not just the area illustrated) is also given. When catch more than doubled the number of hexagons visited also expanded greatly.

The hexagon grid can be used to summarize all the 10 second observations from all dives across all divers contained within each hexagon. Each hexagon has a unique identifier so the dynamics exhibited by the fishery within each hexagon, or set of hexagons, can be followed and analysed through time.

After four years of fine scale data collection the number of new unique hexagons being fished is now very few so that the total fished area in each statistical block (Spatial Management Unit – SMU) is almost completely defined (**Table 8**). The number of years required to determine the total fished reef area will depend in part on the state of the fishery. Estimates of total fished area for example in the Tasmanian Eastern zone with a current historic low TACC, may increase gradually over many years as depleted populations rebuild. With only four years of data any longer term variations in fishing behaviour are yet to be observed.

Table 8. The total number of one-hectare hexagons per statistical block with an average of 9 or more minutes of effort in the years in which it was fished, and the number fished in each of the four years 2012 – 2015. The standard deviation, mean, and CV are for the four years 2012 – 2015. The blocks are sorted in terms of the lowest CV.

Block	Hexagons	Y2012	Y2013	Y2014	Y2015	StDev	Mean	CV
13	2173	1817	1842	1851	1887	28.987	1849.3	0.016
39	406	318	309	323	317	5.795	316.8	0.018
6	1642	1228	1189	1261	1260	33.985	1234.5	0.028
22	793	730	727	714	684	21.014	713.8	0.029
9	1462	1041	1126	1080	1023	45.684	1067.5	0.043
5	1502	1085	1061	975	1029	47.564	1037.5	0.046
43	205	115	119	107	121	6.191	115.5	0.054
49	1777	1276	1127	1265	1222	67.796	1222.5	0.055
12	2506	1815	2114	1995	2058	129.781	1995.5	0.065
21	542	469	422	406	475	34.205	443.0	0.077
20	570	462	422	512	498	40.278	473.5	0.085
48	559	334	319	365	388	30.968	351.5	0.088
16	593	389	483	479	461	43.726	453.0	0.097
19	61	54	42	46	46	5.033	47.0	0.107
53	226	186	195	170	150	19.755	175.3	0.113
11	3319	2028	2539	2526	2659	279.813	2438.0	0.115
23	479	357	451	443	377	47.018	407.0	0.116
24	876	625	683	719	546	75.518	643.3	0.117
17	211	146	196	180	182	21.229	176.0	0.121
10	1974	1105	1525	1489	1462	195.213	1395.3	0.140
38	220	147	116	162	156	20.451	145.3	0.141
31	1394	1150	813	919	1045	146.882	981.8	0.150
3	1405	685	788	971	744	123.437	797.0	0.155
54	37	23	25	17	23	3.464	22.0	0.157
7	540	498	364	352	435	67.894	412.3	0.165
33	612	252	336	376	287	54.451	312.8	0.174
14	926	597	529	769	540	110.913	608.8	0.182
4	437	271	171	262	223	45.544	231.8	0.197
29	555	282	472	458	433	87.664	411.3	0.213
27	620	383	261	397	460	83.204	375.3	0.222
28	193	60	84	96	120	24.980	90.0	0.278
30	166	59	118	118	95	27.863	97.5	0.286
45	36	30	16	35	24	8.180	26.3	0.312
8	143	97	58	66	115	26.646	84.0	0.317
37	285	129	109	85	55	31.890	94.5	0.337
51	155	49	90	47	46	21.370	58.0	0.368
32	164	56	31	93	56	25.547	59.0	0.433
44	31	11	9	26	17	7.632	15.8	0.485
26	44	30	7	19	29	10.720	21.3	0.504
34	77	43	11	48	22	17.455	31.0	0.563

Table 8: Cont.								
Block	Hexagons	Y2012	Y2013	Y2014	Y2015	StDev	Mean	CV
1	480	46	194	269	355	131.039	216.0	0.607
2	309	117	29	153	233	84.601	133.0	0.636
41	41	16	0	23	29	12.517	17.0	0.736
46	41	35	19	16	0	14.341	17.5	0.819
35	304	50	69	259	42	103.289	105.0	0.984
56	49	38	0	0	35	21.109	18.3	1.157
36	45	8	2	31	4	13.401	11.3	1.191
18	5	3	2	0	0	1.500	1.3	1.200
25	1	0	0	1	0	0.500	0.3	2.000
42	5	0	0	0	5	2.500	1.3	2.000
52	8	0	0	8	0	4.000	2.0	2.000
57	2	0	0	2	0	1.000	0.5	2.000

Most blocks have similar numbers of hexagons visited each year although some are highly variable, with the most variable being those blocks with very low numbers of hexagons visited (**Table 8**; **Figure 17**).

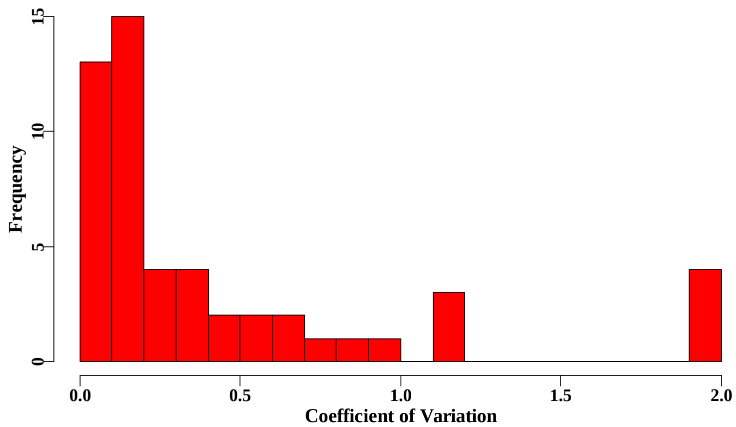

Figure 17. The coefficient of variation of the number of hexagons visited in each block across the four years of observations (see **Table 8**).

7.5 Results and Discussion

7.5.1 Unfished Equilibrium Population

The southwest of the Tasmanian coast holds a relatively productive stock of Blacklip Abalone (*Haliotis rubra*), which is an important component of the Tasmanian fishery (Tarbath and Mundy, 2015). Growth rates and maximum size are amongst the highest recorded for this species (Helidoniotis *et al*., 2011), and rapid early growth generates a relatively clear modal progression of cohorts up to reproductive maturation. After growing in relatively discrete modal groups for two to five years, with gradually increasing overlap and spread, the modal groups become far less distinguishable and eventually merge into a single broad mode containing numerous cohorts. Thus a mature unfished population will contain a large number of age-classes (cohorts) (**Figure 18**). South west Tasmanian abalone can take between 5 – 7 years to achieve the LML of 140mm. Given that the weight of abalone increases approximately as the cube of shell length, most of the mass of the unfished population is found above about 130mm and, in the west of Tasmania, only about 18% of all unfished biomass is predicted to be below the current LML of 140mm. As egg-production in Haliotids appears linearly related to body mass (Rogers-Bennett 2004, Bilbao et al 2010) this also means that animals above the current LML will contribute the majority of egg production **Figure 19**.

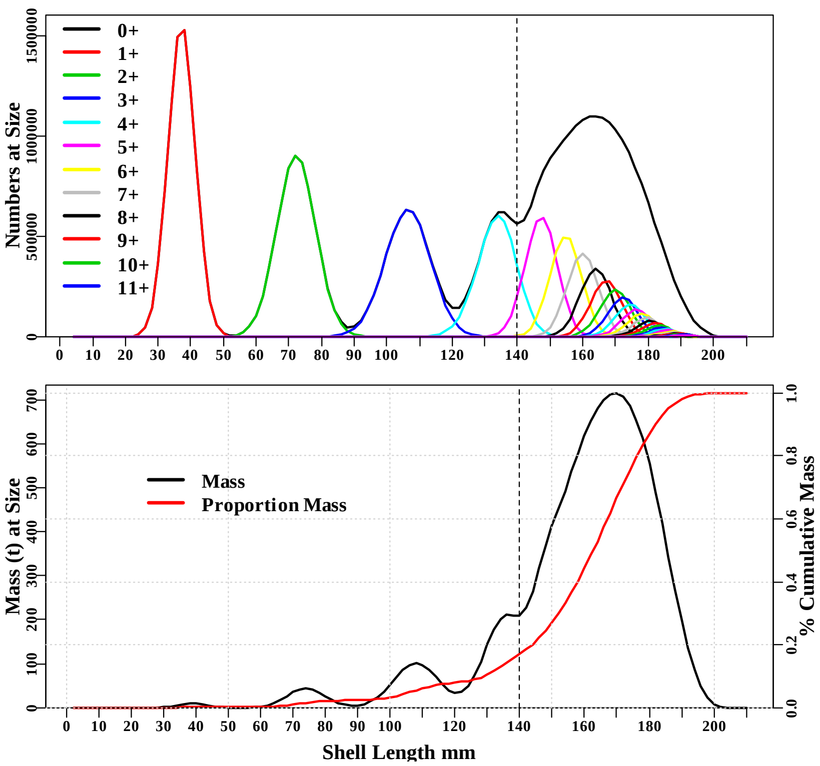

Figure 18. The unfished equilibrium numbers-at-size, mass-at-size, and predicted age-at-size for an abalone population model conditioned on the southwest Tasmanian stock (the 2mm size class is omitted for clarity). On the fast growing south west coast the abalone are predicted to take between 2 – 3 years to reach 70mm (first green line). Only 20 cohorts are illustrated. More than 80% of the mass of the unfished population lies above the current LML of 140mm. In slower growing areas the number of years to reach the LML would be greater.

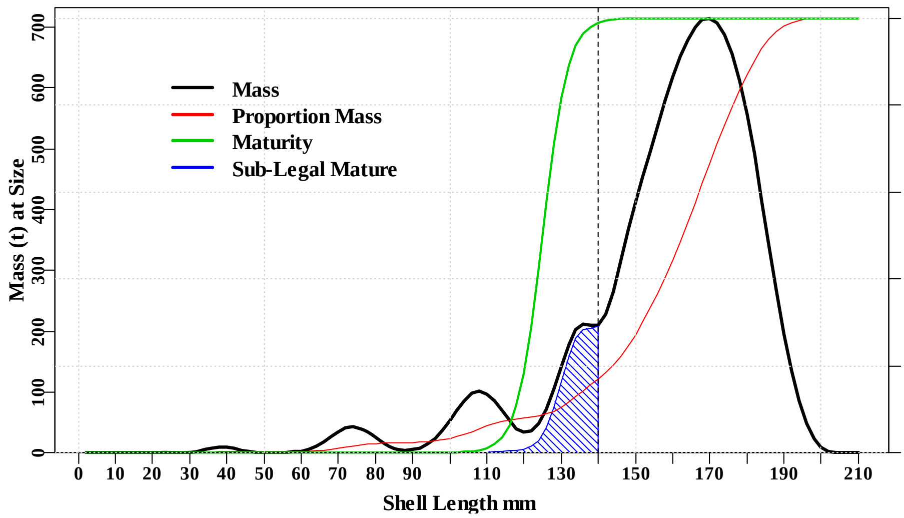

Figure 19. The mass-at-length from the simulation model at unfished equilibrium with a LML of 140mm and a length at 50% maturity of 125 mm. The blue shaded area makes up 8.1% of the total unfished mature biomass.

7.5.2Effect of Changing the LML on spawning biomass protection

Assuming the description of growth is a reasonable approximation for the areas considered then the original Tasmanian LML of 127 mm in place during the peak harvest period (1963 – 1985) provided minimal protection to mature biomass in southwest Tasmania and 132 mm was only slightly better (**Table 5**, **Table 9**; **Figure 20**, **Figure 21**).

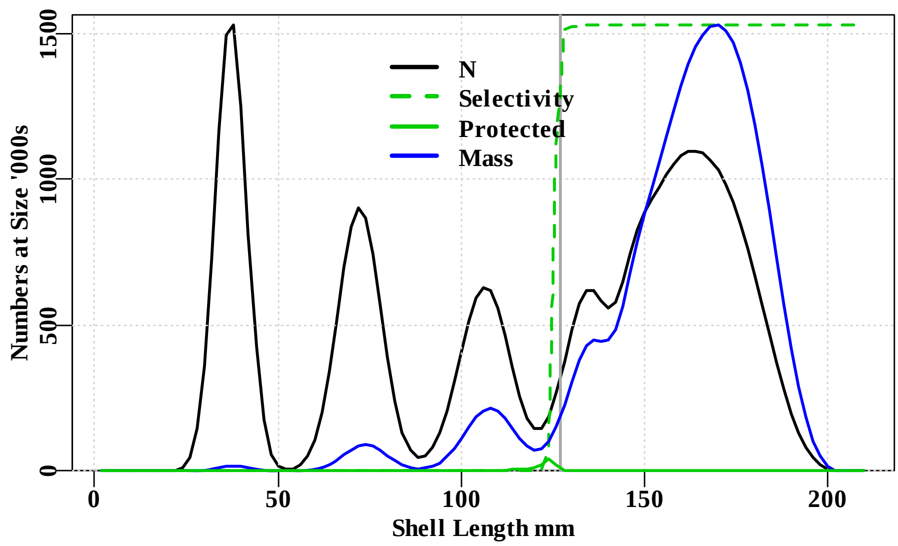

Figure 20. The size distribution as numbers at length, N (the black line), the selectivity curve (dashed green line), the LML (grey line), the amount of mature biomass protected by the LML (solid green), and the relative mass of the numbers at size (blue line) for an equilibrium population conditioned on the properties of abalone from the southwest of Tasmania (**Table 6**); LML = 127mm.

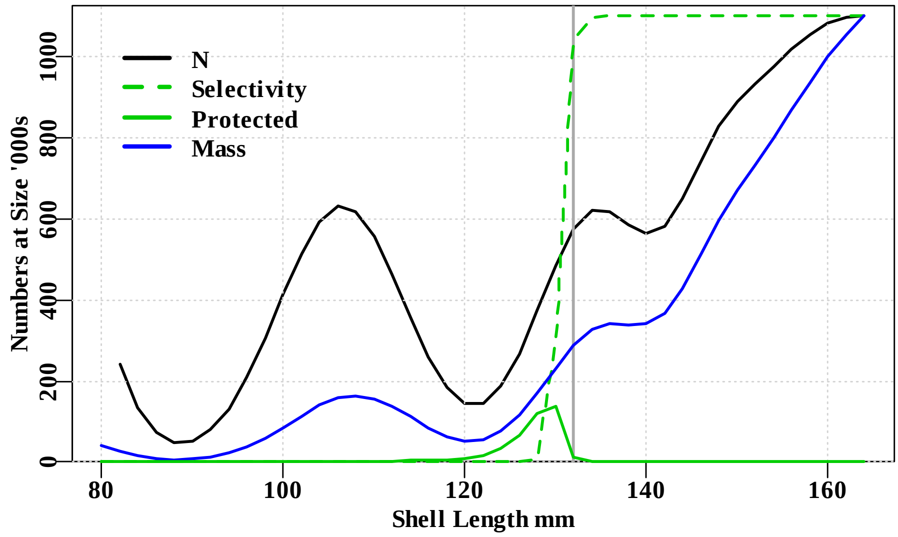

Figure 21. An expanded section of the same population as in **Figure 20** but with an LML = 132 mm, to provide a clearer view of the interactions between maturity, selectivity and protected spawning biomass with an LML of 132 mm.

By using the same hypothetical population structure, conditioned on the south-west of Tasmania, and applying different LML (127, 132, 140, and 150 mm) the proportion of the unfished mature biomass that was protected increases rapidly as the LML increases (**Figure 22**; **Table 9**). Given that most of the mass of the unfished abalone stock lies above 140mm it is not surprising that an LML of 127mm only protects 0.7% of the unfished spawning biomass, and even an LML of 140mm protects only 8.1%.

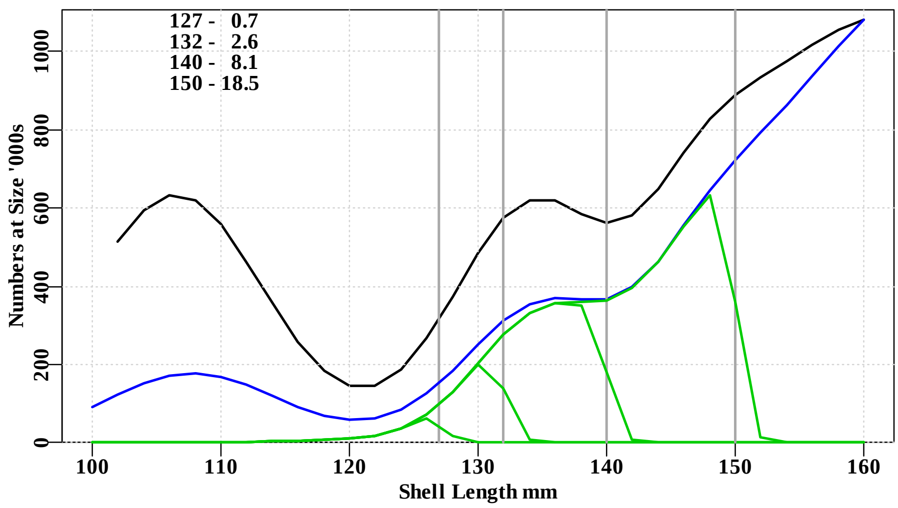

Figure 22. The interactions between maturity, selectivity and protected spawning biomass with LML 127, 132, 140, and 150 mm (steepness fixed at 0.75). In this case emergence was modelled as occurring at about 110mm and thus had no effect. The legend relates to the % of mature biomass protected at each LML. In each case the selectivity expressed around the LML leads to some protection beyond the LML, in addition, at this scale the 2mm size classes influence the appearance of the plot.

Table 9. Effect of different LML on the equilibrium, unfished population conditioned on abalone from the south west of Tasmania (with a steepness of 0.75). 'SpBProt' is the absolute amount of mature biomass protected, 'AboveLML' is the mature biomass above the LML, ExB is the exploitable biomass, exN is the number of exploitable abalone in millions, MSYDepl is the depletion level required to achieve MSY, bProt is the proportion of mature biomass under the LML and nProt is the proportion of the numbers of mature abalone below the LML. See **Figure 23** for plots of all LML options tested. LML with asterisks indicate LML that have been used on the west coast.

LML	SpBProt	AboveLML	ExB	exN 10^6	MSY	MSYDepl	bProt	nProt
127*	97.243	14108.244	14214.313	23.938	765.418	0.330	0.007	0.016
130	227.260	13978.227	14041.248	23.485	768.327	0.332	0.016	0.035
132*	364.579	13840.908	13881.274	23.033	770.177	0.336	0.026	0.053
135	633.290	13572.197	13590.589	22.198	771.825	0.343	0.045	0.088
140*	1143.870	13061.618	13066.597	20.753	773.012	0.356	0.081	0.147
145	1743.979	12461.508	12463.062	19.239	774.842	0.372	0.123	0.209
150	2629.789	11575.698	11576.153	17.240	777.639	0.392	0.185	0.291
155	3786.470	10419.017	10419.139	14.886	768.131	0.426	0.267	0.388
160	5205.519	8999.968	9000.000	12.281	734.517	0.474	0.366	0.495
165	6846.594	7358.894	7358.901	9.548	645.284	0.551	0.482	0.608

When the effect of LML on this simulated population is explored by applying LML from 127 – 166 mm it is possible to characterize the expected equilibrium outcomes. A larger proportion of mature numbers is protected by any given LML than mature biomass (**Figure 23**), which simply reflects the fact that the weight of an abalone increases as approximately the cube of length.

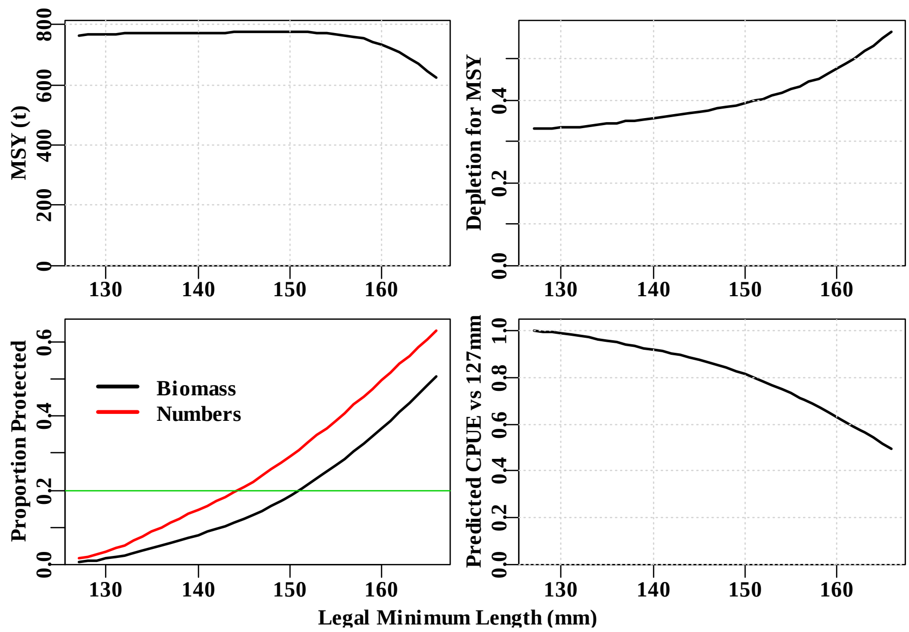

Figure 23. The effect of increasing the LML on the estimated MSY, the depletion of the stock required to generate the MSY at equilibrium, the proportion of the mature biomass protected by the LML in an unfished state, and the predicted effect on the predicted CPUE at the start of fishing. Steepness was set at 0.75. See **Table 9** for a selection of the data.

However, it is clear that the maximum sustainable yield is relatively stable across the LML from 127mm to just above 150mm, while beyond that the MSY begins to decline quite sharply. This is simply because with increasing biomass being below the LML the available biomass reduces accordingly. This, in turn, is reflected in the depletion level needed to attain the MSY increasing sharply, which also implies a steeply increasing harvest rate would be required. The extra effort required to make the required catches to achieve the MSY is also why the CPUE would be so reduced at these high LML levels. The trade-off to consider relative to the increase in mature biomass protected by increases in LML are these increases in the harvest rate required to maintain catches, the decrease in CPUE, and eventually, if LML is greatly increased, the reduced maximum sustainable yield.

7.5.3 Effects of Growth Rate

The equilibrium spawning biomass is greatly affected by the average recruitment but this does not alter the proportion protected by an LML. However, the results here are greatly influenced by the growth characteristics, especially the maximum growth increment. The effect of changing the maximum increment was more than linear such that a 30% reduction in the maximum increment led to a 63% increase in the spawning biomass protected by the 140mm LML (**Table 10**). The faster a population's growth rate the lower the proportion of a stock will be protected by an LML simply because the animals will grow through any LML more quickly. Uncertainty with regard to the growth characteristics could therefore be a major influence on both stock assessments and in any determination of the effectiveness of a given LML.

Table 10. The influence of decreasing only the maximum growth increment by 10, 20, and 30% on the proportion of spawning biomass protected by an LML of 140mm. In this series the starting MaxDL was set at 35mm

Parameter	-30%	-20%	-10%	0
MaxΔL	24.5	28	31.5	35
B0	9021	10798	12486	14116
%Protect	14.45	11.96	9.87	8.86
%ΔProt	1.631	1.350	1.114	1.000

It is possible to set an LML that provides a great deal of protection to the spawning biomass but that would, if set high enough, reduce the sustainable yield from a fishery and require fishers to apply a great deal more effort to catch that sustainable yield than they would at a smaller LML (consider the graph of relative CPUE in **Figure 23**). This reflects the increased exploitable biomass initially available with smaller LML, or conversely the fact that as the LML is increased the amount of exploitable biomass will decrease, with a concomitant reduction in expected CPUE and a greater level of depletion of available biomass for the same level of catch (**Figure 23**; **Table 9**). The trade-off to be considered when changing the LML is the level of protection increase against the CPUE reductions and the increased effort required to take the catch.

7.5.4 Steepness – Stock Recruitment Relationship

The steepness of the spawning stock – recruitment relationship is highly influential because it directly affects the productivity of the population concerned (**Figure 24**). If the unfished average recruitment is set constant along with all the other biological properties of growth and maturity then differences brought about by the spawning stock – subsequent recruitment relationship can be clarified (**Figure 24**). This ignores any potential effects brought about by abalone fertilization biology requiring some minimum local biomass for successful spawning to occur (depensation).

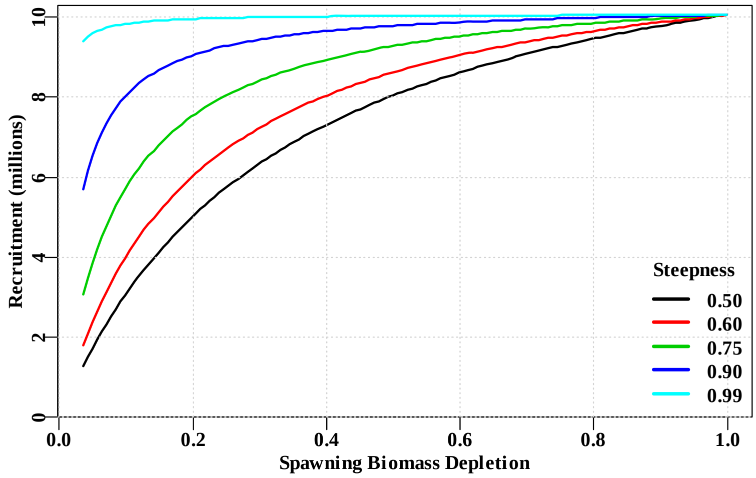

Figure 24. The Beverton-Holt spawning stock – subsequent recruitment relationship used in the modelling with five different values of steepness. Steepness is defined as the relative recruitment at a depletion level of 20%B_0. Hence, a steepness of 0.5 and 0.9 imply the recruitment level at 0.2B_0 would be 0.5 and 0.9 times the maximum, respectively. A steepness of 0.2 would be a straight line from zero to the maximum recruitment.

7.5.5 Unfished Recruitment, Steepness, and Productivity

In the modelling, the reduced productivity of populations with lower steepness can be offset by the average unfished recruitment levels being increased. Holding everything else constant in the population model but with different levels of steepness for the same catch history to achieve the same degree of depletion then in each case different levels of unfished average recruitment are required (**Figure 25**).

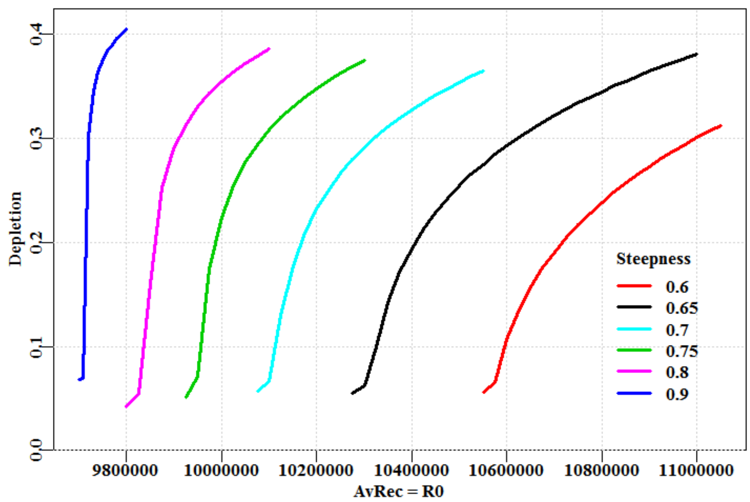

Figure 25. The modelled population with different levels of steepness and average unfished recruitment (R_0) when the same catch history from the simulated blocks 9 – 12 is applied. The kinks at the end of each contour indicates where the dynamics break down and the applied catches cannot be fully taken.

The effects of steepness and average recruitment have implications for the parameterization of stock assessment models and their respective outputs. The higher the assumed level of steepness the more sensitive any analysis will be to the estimate of average recruitment. As the steepness increases the modelled dynamics become much more sensitive to the average recruitment level, which is illustrated by the narrowing of the range of viable average recruitment levels as steepness increased. While the model may become more sensitive to changes in the estimate of average recruitment, an important implication for any stock is the strong relationship between steepness and productivity. This can be seen in the increasing MSY with increasing steepness (**Table 11**). The correlation between steepness and predicted MSY is very strong (a regression of the six points in **Table 11** has an $R^2 = 0.9996$), which illustrates the strong relationship between productivity (MSY) and the steepness parameter and the unfished recruitment levels.

7.5.6 The Effects of Depletion Level

The results from the unfished equilibrium population obviously do not provide direct insights into expectations for what will occur when the population is fished and depleted away from the unfished state. By setting up simulations that take the unfished equilibrium population and applying a known and constant catch time series to the population it is possible to vary different model parameters (steepness, LML, R_0 – average unfished recruitment) and determine the effects.

By searching for and then applying the average unfished recruitment (R_0) required to achieve a depletion of $0.25B_0$ for each of an array of steepness values the impact of such depletion on the numbers-at-size for sub-legal abalone, with an LML of 140mm can be determined (**Figure 26**; **Table 11**). The increasing productivity as steepness increases is demonstrated by the increasing MSY values despite the average recruitment declining (**Table 11**).

Table 11. The population outcomes when all biological properties are held the same and different combinations of steepness and R_0 are applied. These gave rise to different productivity levels exhibited by the different B_0 and MSY values. Applying an identical catch history to each population then led to it depleting to approximately $0.25B_0$ (**Figure 26**).

Steepness	R0	B0	MSY	Depletion
0.60	10,830,000	15303.935	722.652	0.2500
0.65	10,491,000	14825.302	739.700	0.2501
0.70	10,225,000	14449.406	755.241	0.2508
0.75	10,020,000	14159.711	769.897	0.2499
0.80	9,874,000	13953.392	784.756	0.2505
0.90	9,716,100	13730.257	815.585	0.2491

The different biological properties needed to attain the same degree of depletion with the same catch history means that the unfished spawning biomass was smaller for a steepness (h) of 0.9 relative to one of 0.6 (**Table 11**) although because the larger steepness population is more productive the MSY for the h = 0.9 population is greater than that for the h = 0.6 population (**Table 11**). The difference between the depleted numbers-at-size and the unfished numbers-at-size is greater for an h = 0.6 population than for an h = 0.9 population (**Figure 27**), especially for sub-legal sizes (that is, in **Figure 26** the blue lines are closer together than the red lines).

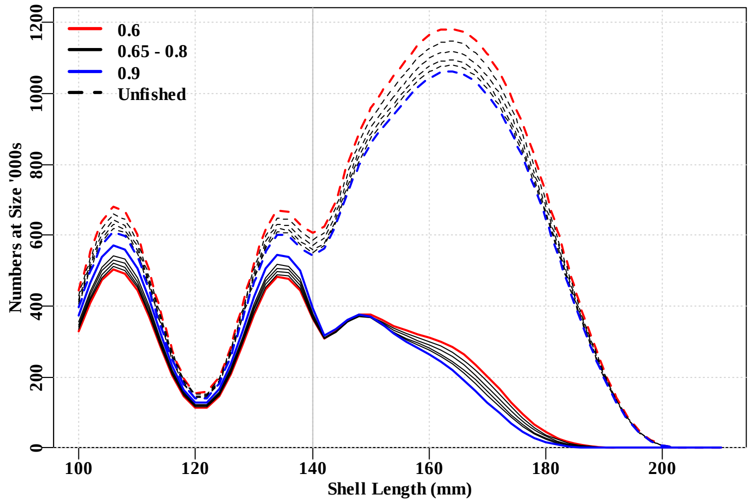

Figure 26. The predicted equilibrium numbers-at-size (lower lines) and their respective unfished levels (upper dashed lines) for populations with different combinations of R_0 and steepness to which the same catch history has been applied to obtain the same degree of depletion.

If this is considered in proportional terms (**Figure 27**) then the increased depletion in the sub-legal population with h = 0.6 is clearly apparent. In the sub-legal sizes when the stock is depleted to 0.25B_0 then the sub-legal population (at equilibrium assuming constant recruitment) is only about 75% of the unfished levels. Hence the mature biomass protected relative to unfished levels declines with steepness.

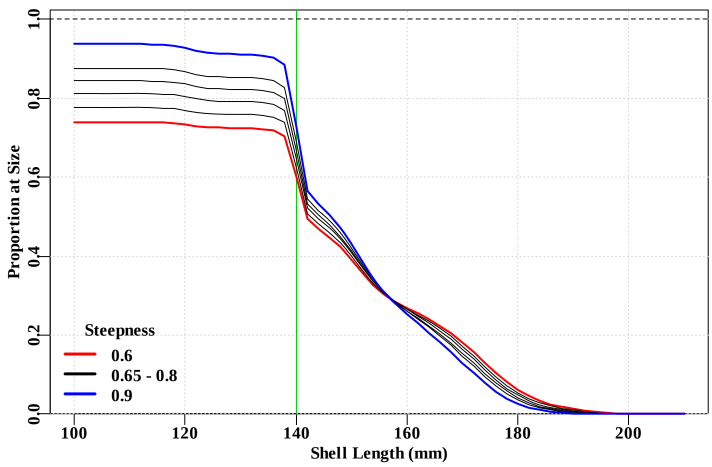

Figure 27. The predicted equilibrium proportion-at-size relative to the unfished levels for populations with different combinations of R0 and steepness to which the same catch history has been applied to obtain the same degree of depletion.

7.5.7The Effect of Steepness

In the previous analysis the depletion level wrought by the constant catches was brought about by adjusting the average recruitment to make up for the altered productivity brought about by the changes in steepness. If the average recruitment and catches are held constant then the depletion wrought by the catches changes but a clearer view of the effect of steepness on productivity is obtained (**Figure 28**). The relationship between MSY and steepness is approximately linear over the range 0.6 – 0.95, although the effect on depletion level from constant catches is much more variable (**Figure 28**; **Table 12**).

In previous stock assessments (e.g. Breen *et al*., 2003; Gorfine *et al*., 2005; Fu, 2012) steepness levels of 0.7 - 0.75 are typically assumed. This remains, however, a very important assumption as can be seen from the linear relationship between productivity (MSY) and steepness (**Figure 28**).

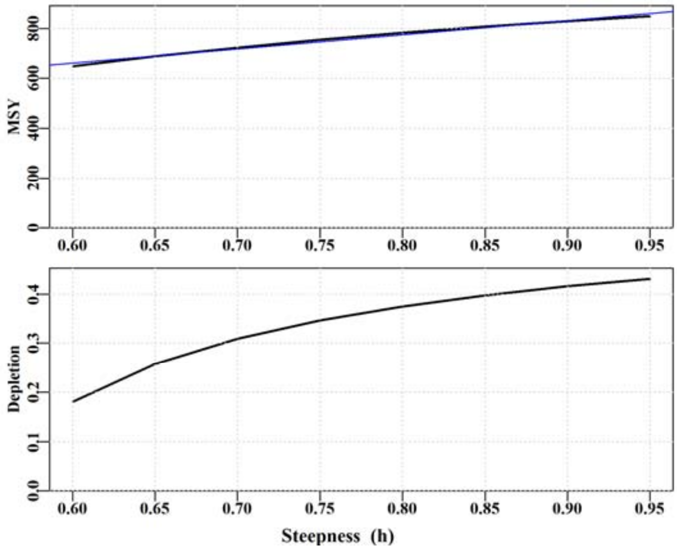

Figure 28. The effect on the predicted MSY and depletion level of altering the steepness while holding average recruitment and the catches removed constant. The thin blue line in the top plot is a linear regression of MSY against steepness.

All other variables being the same, lower values of steepness lead to lower productivity and this has the side effect of increasing the proportion of the remaining mature biomass protected by the LML. This occurs because the total biomass above the LML declines more than that below the LML so the proportion protected by that LML increases (**Table 12**).

Table 12. The effects on MSY and depletion of holding average recruitment (*R0*) and the catches applied constant while changing the steepness. The LML in all cases was 140mm, the *B0* was also constant in each case. 'Protection' is the proportion of mature biomass provided protection by the LML and the MSYDepl is the depletion level required to achieve the MSY.

Steepness	Depletion	Protection	MSY (t)	MSYDepl
0.60	0.180	0.306	648.915	0.370
0.65	0.257	0.236	687.837	0.361
0.70	0.309	0.210	722.833	0.355
0.75	0.346	0.196	754.120	0.348
0.80	0.375	0.187	781.995	0.344
0.85	0.398	0.180	806.807	0.341
0.90	0.416	0.176	828.935	0.337
0.95	0.431	0.172	848.750	0.336

7.6 The Potential Effect of Emergence

7.6.1 Selectivity and Emergence Size relative to the LML

If all abalone are emergent below the LML then there can be no effect of emergence on the proportion of the stock protected by a given LML. However, in some of the faster and larger growing areas where the abalone also mature at large sizes, it is possible for the logistic ogive describing emergence to overlap with the LML and the selectivity of fishing (**Figure 29**).

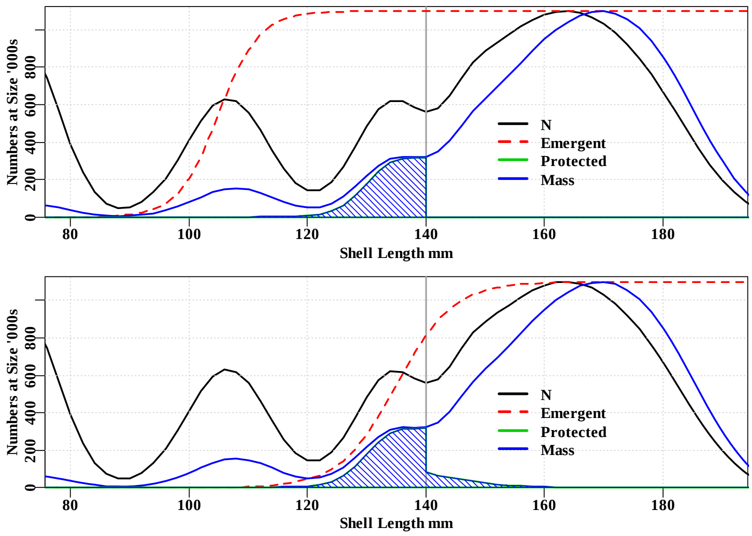

Figure 29. A comparison of the mature biomass protected by an LML of 140mm with and without emergence occurring near the LML.

When emergence occurs at a relatively large size then, of course, the LML is not the only mechanism that protects mature biomass and some can remain in crypsis. Below the LML whether an animal is in crypsis or not does not affect its protection from fishing however, above the LML it would mean that not all mature biomass above the LML is available to fishers.

However, the effect of crypsis on spawning biomass protection remains minor, with the increase in protection in the illustrated example being only about an extra 1.5% in the unfished stock; this would be expected to decline as the legal sized stock was depleted.

7.7 Effects of LML at the Scale of Fishing Operations

7.7.1 Zone or Block Scale versus Local Scale

Fishing operations in the Tasmanian abalone fishery occur at the scale of individual reefs and often cover between 100 – 200 m of reef (e.g. see Fig. 18 in Mundy, 2011). Such small areas may contain only relatively few animals, possibly as few as only 10s – 100s of legal sized animals, although some may contain very many more. At such scales the mass of legal sized abalone on an individual reef, or at least over the area of an individual dive, will also vary from 10s – 100s of kilograms. Such small amounts of abalone imply that the TAC for the zone in which the reef exists is effectively irrelevant in terms of managing catch on a reef scale; this assumes that individual divers visiting the reef have access to sufficient quota to cover the total available, which would very often be the case (**Figure 30**). In such cases, it would be possible mechanically for a diver to totally remove all animals at and above the legal minimum length, leaving only sub-legal animals on the particular reef. Of course this would require that none were in crypsis and that visibility was such that all legal abalone could be found, which would likely not be the case, although this would undoubtedly vary depending on the weather conditions, the water clarity, the reef habitat, and the physical complexity of the reef. Clearly the description of fishing at a reef level should differ from that at a zone or block (SMU) level.

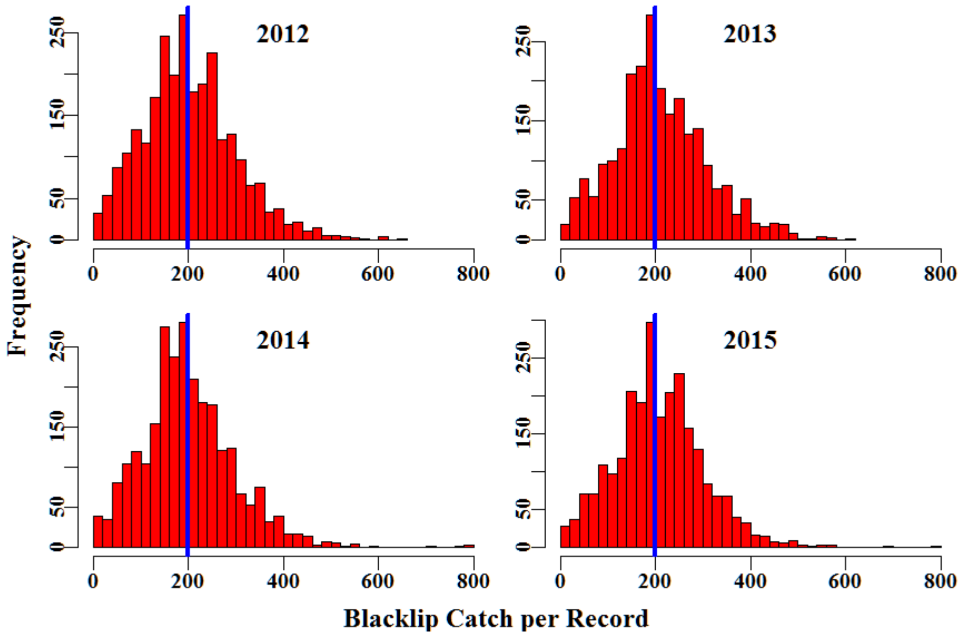

Figure 30. The observed Blacklip Abalone catch (kg) per record from the Tasmanian eastern zone for the years 2012 – 2015. The vertical blue line in each case illustrates the 200kg mark.

7.7.2The Concept of Catchability at Different Scales

The fisheries concept of catchability can be used to illustrate the difference between fishing at a zone or SMU level and fishing at an individual operation or reef level. Catchability is usually defined in terms of the proportion of the available biomass taken as catch for one unit of effort:

$$C_t = qE_tB_t \tag{9}$$

where q is the catchability, C_t is the catch at time t, E_t is the effort to time t, and B_t is the exploitable biomass at time t. At the scale of a zone, this implies that X hours of effort will lead to the proportion of the exploitable biomass being taken as catch equalling qX. If, across a complete statistical block there were, for example, 500 t of legal sized abalone and 5 hours effort yielded 250 kg, the catchability would be defined within 0.25 = q × 5 × 500, and so the catchability (q) will be 0.25/2500 = 0.0001, which is obviously only a small fraction of 1.0. This would imply that the stock as a whole could be depleted gradually down in a continuous and potentially well controlled fashion as the effort applied in the block increased through time. However, if such a catchability also operated at a reef level, where there might only be 250 kg of legal sized abalone in total, a catchability of 0.0001 would only yield 0.025kg/hr, which is totally implausible. Thus, as indicated previously, at a reef by reef level, the catchability could be as high as 1.0 or at least some relatively large fraction of 1.0. This implies that depletion of individual reefs could occur in a patchy and sequential fashion across any set of relatively independent reefs. At the extreme such depletion would be equivalent to serial depletion (Hobday *et al*., 2001).

In reality, some reefs are very open, flat with little weed cover, and no apparent cryptic habitat while others can have a complex physical structure, lots of cryptic habitat, and plenty of seaweed. At the same time these reefs can be fished in conditions varying from flat calm and clear water to an appreciable swell and high turbidity. These combined extremes attempt to bracket the potential spectrum of reef types and conditions that can be found in the day-to-day fishery. Catch rate standardization can be regarded as a disarticulation of the notion of catchability so that catch rates become a function not just of effort but of all the factors deemed important in a fishery (who is fishing, where they are fishing, when they are fishing, etc). Such factors will affect CPUE at both a zone and a reef level and should not affect the general notion that catchability at a large scale will be a much smaller number than at a small scale.

The spectrum of reef types and conditions suggests that catchability at a reef scale might also be expected to exhibit a spectrum from a maximum of 1.0 down to some fraction of 1.0 (although still appreciably large relative to 0.0001). This, in turn, implies that one might expect some reefs (those with relatively high catchability) to be visited only infrequently by divers (because each visit can remove most legal sized abalone), while others (those more complex reefs with relatively low catchability) will be expected to be visited by divers more often (as legal sized abalone would remain despite repeated visits). The assumption is made that divers will only continue to visit particular reefs for any amount of time if their CPUE remains worthwhile. The relationship between reef and habitat type and catchability would not be simple as it would also be greatly affected by the relative productivity of each reef. An additional complexity is the number of fishers in the fleet and the extent to which knowledge is shared. Typically, there is good communication across small clusters of fishers within the fleet, but rarely is information shared globally. Thus decisions by individual fishers to fish on reefs that can support single or multiple visits annually are made with a limited knowledge of the entire fleet activity.

Prior to the advent of GPS and depth loggers for the Tasmanian abalone fishery (Mundy, 2011) diving activity could only be inferred at the block or sub-block scale. This implied, for any analyses based on such data, that fishing was effectively homogeneously distributed across that area. Now, however, much more precise estimates of activity can be obtained. Using the 1Ha grid that has been used to examine the individual dive events demonstrates that individual 1Ha hexagons within a given area can experience, in any given year, a limited range of visits from divers. Fishing is certainly not evenly spread over the reefs containing abalone (**Figure 31**).

7.7.3 Serial Depletion or Serial Fishing

The spatially explicit evidence now available (e.g. **Figure 31**) makes it clear that intuitions about the patchy nature of abalone fishing and the potential for serial depletion are certainly plausible. However, while the availability of the spatial data clearly illustrates the patchy nature of abalone fishing something more is required to demonstrate whether or not unrecoverable depletion is occurring. The notion of serial depletion (Hobday et al, 2001) is usually taken to imply that a stock will become severely depleted through fishing but while it was happening this would be undetectable in terms of catch-rates at a larger scale, because divers move from patch to patch (or reef to reef) maintaining their catch-rates until they run out of patches.

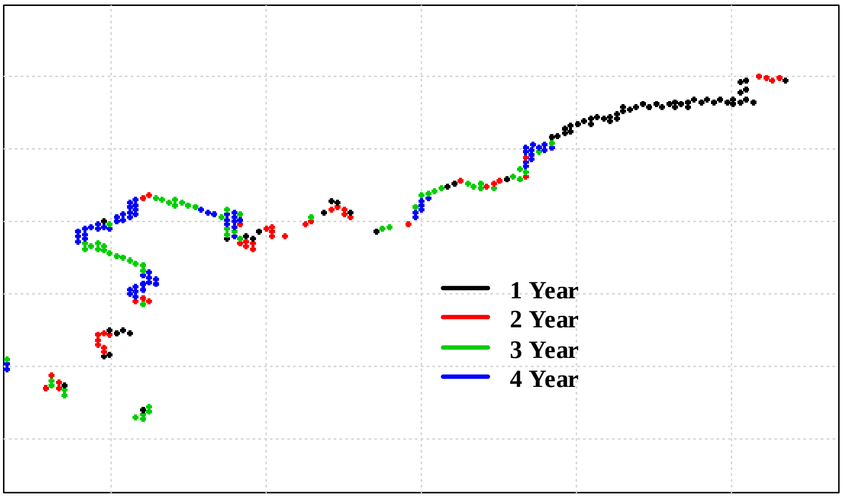

Figure 31. An example of the patchiness of fishing in the Tasmanian abalone fishery. The relative location (reconfigured for reasons of confidentiality) of hexagons in which catches from 2012 – 2015 were taken in only a single year, in two years, in three years, or in all fours year. Total catches per hexagon were not necessarily related to how often a hexagon was visited across the years.

If catchability at the smallest scales really is much higher than when considering the wider more dispersed stock, then the expectation might be that at an individual reef level, fishing would only occur on a limited number of days in any one year, irrespective of the stock size. This would be expected because given a relatively high catchability only a limited number of visits would be required to deplete the legal sized abalone available in a small area down to levels where catch-rates would no longer be sufficiently attractive for divers to stay for any length of time. This would be made somewhat more complex because through the year, especially during the season of maximum growth, some sub-legal animals would grow through into the legal sized sub-set of the population. This in itself would also be variable depending on changes in settlement into the post-larval stages a number of years previous. Despite this dynamic, however, there would still only be a limited number of days expected in any single hexagon, with only the most productive or most structurally complex having many days. The number of days a hexagon is fished is not necessarily the same as the number of visits from divers as more than one diver could visit in a day, but nevertheless it does provide a reasonable approximation.

Using the 1Ha grid data once again, each with its own unique identifier, it is possible to count the number of days each hexagon in a SMU is visited (**Figure 32**); remembering the minimum time of 9 minutes used to remove accidental and very minor incursions). In Block 14, catches from 16.4 – 20.9 t (in 2012, 2013, and 2015) involved about 1170 days with visits to about 550 hexagons, whereas in 2014, taking 29.6 t required 1869 days with visits to 769 hexagons.

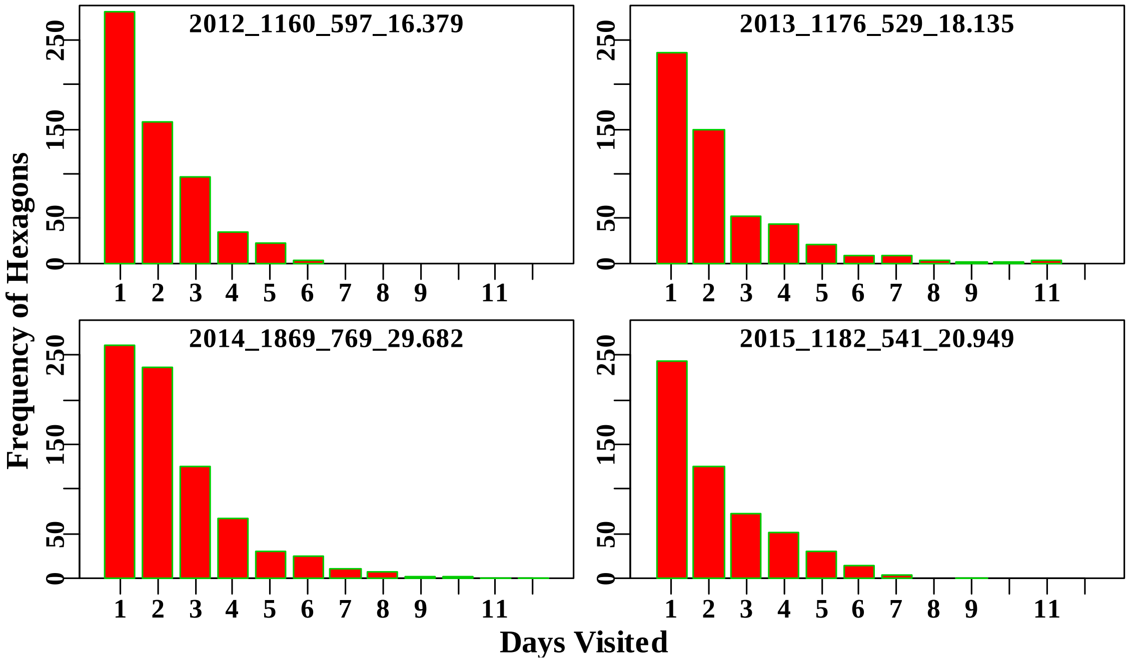

Figure 32. In Block 14, the frequency of hexagons visited for differing numbers of dive-days in each of the four years of observations. The headings in each case are the year, the total numbers of dive-days reported, the number of unique hexagons visited, and the total catch in tonnes in Block 14 reported in association with the GPS data-loggers.

With a total number of hexagons in Block 14 being 926 to date (**Table 8**) it becomes clear that not all previously visited hexagons are visited every year, although generally the more catch is taken from hexagons that are frequently visited.

7.7.4 The Importance of Geographical Scale

The catchability of legal sized abalone must change at the different geographical scales of operation and this has implications for the relative importance of the TAC and LML as management tools for abalone stocks, and for the predictive capacity of population dynamic models. At the zone and SMU scale, the LML is only of peripheral interest because most of the spawning biomass should always reside above the LML, and the key management tool to ensure sustainability would therefore be the TAC. The objective being to set the TAC at a level that would enable the stock to retain a high proportion of itself above the LML and thereby have a large breeding population to support on-going fishing. On the other hand, at the local fishing operation scale it is the TAC which becomes of peripheral interest and the key management tool for supporting sustainability will be the LML. At the large scale the residual biomass above the LML should always be more than that below the LML and so the significance for on-going reproduction of the sub-legal sized mature animals protected by the LML will only be minor. However, at the smaller scale of fishing operations, there may only be the sub-legal animals left to reproduce so the LML is essential if those local areas are to remain viable populations in their own right. For this reason, the proportion of the spawning biomass directly protected by the LML for an SMU becomes very important if it fails to protect a sufficient proportion of each local population from fishing pressure.

7.8 Further Discussion and Conclusions

7.8.1 Productivity

In fisheries the term 'productivity' has been applied to a number of different concepts or ideas, including the potential yield from a stock, the growth of individuals, and the recruitment of new animals to the stock, and combinations of growth and recruitment. Formally, mathematical equations from population dynamics can be used to define 'productivity' in terms of numbers-at-size, weight-at-size, growth of individuals, and the spawning stock –subsequent recruitment relationship. The key components to productivity are the growth of individuals and the number of recruits to the smallest sizes a stock can produce (Haddon, 2011). Such formal definitions can assist in understanding the relative contributions of different components. Thus, if two populations have exactly the same growth and natural mortality characteristics then the population that can produce more recruits on average from the same level of spawning biomass will generally be more productive. To be more productive implies a stock could be fished more intensely and yet be depleted to the same degree as a less productive and less heavily fished stock. As a general rule, all other things being equal, the higher the steepness, the more productive a stock.

7.8.2The Effect of Steepness

The effects of steepness on the stock recruitment model are important to the effectiveness of any LML applied to a stock. Assuming a steepness of 1.0 is implausible for abalone (and most species) although deciding on a realistic value for steepness is difficult (He *et al.* 2006). Values of 0.7 or 0.75 have previously been assumed for abalone (Breen *et al.* 2003). Whatever value is used, with *h* values < 1.0 sub-legal abalone deplete along with the legal sized abalone, although the extent of sub-legal depletion depends directly on steepness. This sub-legal depletion implies that the degree of protection afforded an abalone population will become less as depletion progresses. In addition to this effect, the fact that most of the spawning biomass is found in animals greater than the LML also implies that it is primarily the residual biomass left above the LML that provides most of the recruitment potential. At a large geographical scale the LML does provide some protection (which declines as depletion proceeds) but most egg production generally comes from legal sized animals. The conclusion from this is that while the LML is important, especially in depleted stocks, an objective of management should be to maintain significant proportions of biomass above the LML as this is where most of the recruitment comes from. The only way to avoid serious depletion is to match the catches to the productivity of the stock through time, thus it appears that most attention needs to be paid to setting a sustainable TAC. This becomes even more difficult if the productivity of stocks change or if there are depensation effects that require a minimum stock size for effective egg production to occur. At a small scale, however, the emphasis changes. Because individual reefs, at the scale of individual fishing operations, can potentially have a large proportion of their legal sized abalone removed, then it is only the LML which can act to preserve the mature biomass required to make the stock on that reef self-sustaining. Thus, overall, both the TAC and the LML have important roles to play in the management of abalone. If the TAC is set too high then the overall depletion levels will become worse and leave less residual biomass to reproduce for following years. In addition, the incentive to fish at the individual reef level will increase and the likelihood of removing all legal sized animals will also increase. Thus, the LML become especially important when a stock is heavily depleted.

If an LML is increased when a stock is already depleted the expectation will be that, all other things being equal, the available exploitable biomass will be reduced and as a consequence CPUE will decrease. Thus, while increasing the LML when a stock is depleted would be beneficial it will also have large impacts on CPUE. Decisions should only be made in the face of understanding the implications of such decisions.

In fisheries management every regulation should be justifiable through each being established to achieve explicit objectives, however, it is not unknown for such justifications to be imprecise and vague. This vagueness applies especially to the imposition of legal minimum lengths (LML; or MLS as minimum legal size), the justifications for which appear to have relied on intuitions rather than an appreciation of the implications of different LML for the population dynamics of the managed species. An improved understanding of what each of the management tools is doing should help managers produce sensible justifications for their regulations. The generally contentious nature of setting size-based management tools means that not relying on intuitions leads to more defensible decisions.

7.9 Appendix: Size at Maturity

Estimating the Protection Afforded by the Size at Maturity Plus Two Year's Growth

In Tasmania the management of the abalone fishery uses a number of regulatory instruments, including 1) it is necessary to have an abalone divers licence to fish for abalone in Tasmania, 2) a Total Allowable Catch (TAC) is allocated as individually transferable quota within four Blacklip Abalone (*Haliotis rubra*) zones around the coast plus a separate Greenlip Abalone (*H. laevigata*) TAC, 3) this spatial management is articulated further by hard caps on catches being placed on some of the statistical reporting blocks within zones; these caps are effectively competitive TACs , finally 4) each zone has at least one legal minimum length (LML), although blocks and sub-blocks within a zone may have a different LML if the biology of the abalone stocks makes that desirable (this is only implemented in a few cases owing to difficulties with ensuring compliance). The spatial management measures and the different LML in different parts of the State aim to distribute the catch in a manner that avoids local depletion and preserve some minimum level of spawning biomass away from fishing mortality.

The LML in any zone is determined by sampling the populations of abalone to determine the size at maturity and then adding on two years' growth to allow for some protection of the spawning biomass. This is only a guideline and no similar rule is used in any of the other Australian states where abalone are fished. Application of the guideline is made more complex by the existence of a great deal of spatial heterogeneity among separate populations of abalone in terms of their biological properties relating to growth and maturity. Any LML selected for large geographical areas (like a zone) is always a compromise between providing more than two years protection to the relatively slow growing populations and less than two years protection to the faster growing, potentially more productive populations.

A major issue with this approach is that the notion of size at maturity is a relatively loose concept. In general it is typically taken to imply the size/length at which 50% of a representative sample is found to be mature. Maturity at size j, m_j, is usually described using a logistic curve defined using two parameters L_m50 and δ_m:

$$m_j = \frac{1}{1+e^{-Ln(19)(L_j - L_m50)/\delta_m}} \tag{10}$$

a common alternative formulation uses parameters a and b:

$$m_j = \frac{e^{a+bj}}{1+e^{a+bj}} \tag{11}$$

An advantage of the latter formulation is that in addition to the $L_m50 = -a/b$, it is possible to estimate the interquartile distance directly using $IQ_m = 2\times Ln(3)/b$.

With data in the form of length versus maturity status it is possible to fit the logistic curve (ogive) using a binomial general linear model.

Table 13. The simple format of a data file for input to a binomial GLM. A real data set would contain hundreds of observations and should contain the maturity status across a wide range of shell lengths.

sex	length	maturity
M	142	1
M	163	1
I	118	0
F	152	1
M	160	1
F	162	1
M	150	1
F	168	1
I	115	0
M	143	1
F	144	1
…	…	…

If the data set is named 'ab4' then using the statistical programming language R:

```
# Example R code to conduct such a calculation
reps <- 1000
results <- matrix(0,nrow=reps, ncol=11)
colnames(results) <- c("a","b","SaM","IQ")
rownames(results) <- 1:reps
nobs <- dim(ab4)[1]
model <- glm(ab4$maturity ~ ab4$length, family=binomial)
summary(model)
origa <- model$coef[1]
origb <- model$coef[2]
origSaM <- -a/b
origIQ <- 2*log(3)/b
for (i in 1:reps) {
	pick <- sample.int(nobs,replace=TRUE)
	model <- glm(ab4$maturity[pick] ~ ab4$length[pick],family=binomial)
	summary(model)
	a <- model$coef[1]
	b <- model$coef[2]
	results[i,] <- c(a, b, -a/b, 2*log(3)/b)
}
```

will generate the required optimum statistics and 1000 bootstrap samples around the original maturity and length data (**Figure 33**). The bootstrap samples are used to estimate the uncertainty around the parameter estimates (an alternative to using the asymptotic approximation; Venables and Ripley, 2002, p 193). Once these have been obtained for a site (or Block, or whatever sample scale one uses) then the original solution, the bootstrap values, the original maturity data and histograms of the distributions of the bootstrap estimates can be plotted (**Figure 33**):

```
# Example R code to plot the output as in Figure 33
if (!("windows" %in% unlist(.Devices))) windows(width=7,height=6)  # define window
par(mfrow=c(1,1),mai=c(0.45,0.45,0.1,0.05),oma=c(0,0,0,0),cex=0.85)
par(mgp=c(1.35,0.35,0),font.axis=7,font=7,font.lab=7)
layout(rbind(c(1,1),c(2,3)),heights=c(2,1))
layout.show(n=3)
x <- seq(40,200,1)
origy <- (exp(origa+origb*x)/(1+exp(origa+origb*x)))
plot(x,origy,type="l",xlab="",ylab="",ylim=c(0,1.1))
title(ylab=list("Proportion Mature", cex=1.1, col=1, font=7),
    xlab=list("Shell Length (mm)", cex=1.1, col=1, font=7))
for (i in 1:reps) {
  a <- results[i,"a"]; b <- results[i,"b"]
  y <- (exp(a+b*x)/(1+exp(a+b*x)))
  lines(x,y,lwd=1,col="grey")
}
points(xdat,ydat,pch=16,col=2)   # plot the data points
lines(x,origy,lwd=3,col=4)          # plot the original logistic fit
abline(h=0.5,col=1,lty=2)           # identify the Lm50
abline(v=(-origa/origb),col=1,lty=2)
label <- paste(ab4$block[1],site,year,round(-origa/origb,3),round(2*log(3)/origb,3),
[count,8],sep="  ")
mtext(label, side=3,line=-1.0,outer=F, font=7,cex=1.0)
hist(results[,"SaM"],main="",xlab="",col=2)
abline(v=(-origa/origb),col=1,lwd=3)
title(xlab=list("Size 50% Maturity (mm)", cex=1.0, col=1, font=7))
hist(results[,"IQ"],main="",xlab="",col=2)
abline(v=(2*log(3)/origb),col=1,lwd=3)
title(xlab=list("Inter-Quartile Distance (mm)", cex=1.0, col=1, font=7))
```

The maturity logistic curve itself is symmetrical around the L_m50 value. Thus it is possible to obtain an estimate even if data in the lower part of the curve is missing but in general it is best estimated when there are maturity estimates for a number of replicates across the full size range in which maturity develops in the population.

7.9.1 The Size at Maturity

Abalone within a single population can be observed to mature across a relatively wide range of sizes (**Figure 33**; from about 112 - 139), which might stretch over a number of year classes (**Figure 18**). When this is observed it can raise the question of whether or not the L_m50 provides an adequate representation of the size at maturity. This can appear to be especially an issue if the intent of the two year rule is to allow abalone at least two years of reproduction before exposure to fishing mortality. In the illustrated population (**Figure 33**), which comes from the Tasmanian west coast and an LML of 140mm, at least the animals that mature above the 75th percentile (> 130mm) will obtain less than two years protection, with those maturing at the largest sizes gaining almost no protection at all from the LML.

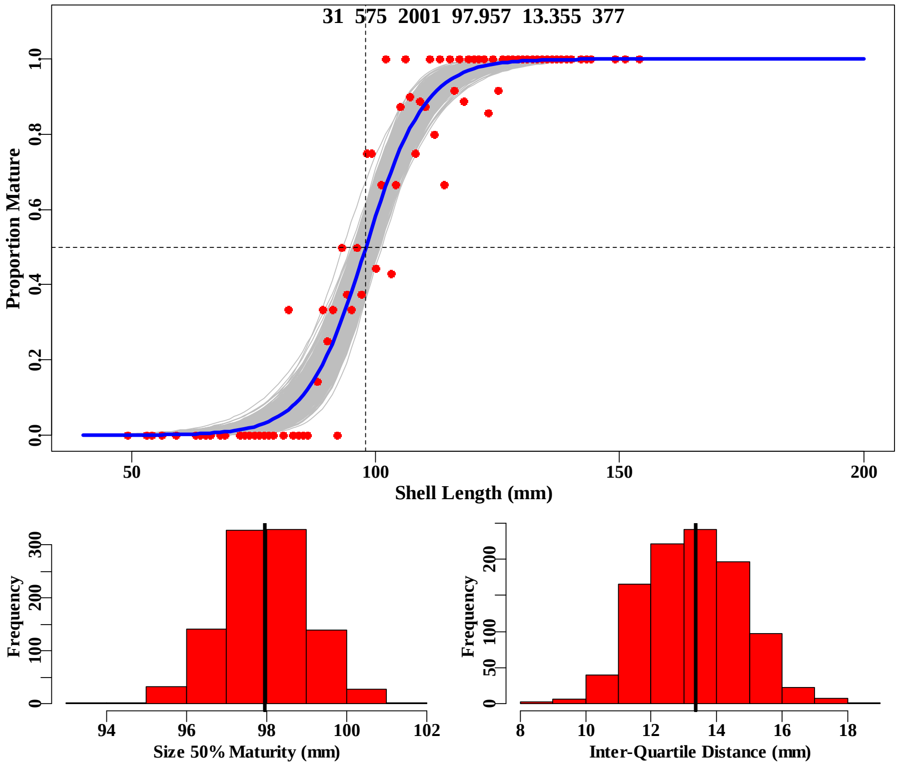

Figure 33. An example of the output from a binomial GLM applied to maturity data (blue line) from a Tasmanian abalone population which has then been bootstrapped 1000 times (the grey lines). The red dots are the mean maturity for each length, the dashed are the L_m50 (97.95). The histograms are the size-at-maturity and the inter-quartile distance bootstrap outcomes with the black liens representing the optimum solutions. This is for site 575 in Block 31 with the sample taken in 2001 with a sample size of 377 an size-at-maturity of 97.96 and inter-quartile distance of 13.35.

However, while these later maturing animals obtain little to no protection the earlier maturing animals at lengths less than the L_m50 will obtain more than two years protection from the LML and, as the maturity ogive is symmetric, this implies that, if two year's growth has been added to the L_m50, then the population as a whole will obtain, on average, the designated two years protection from fishing pressure. It is reasonable, therefore, rather than some arbitrary larger size, to retain the L_m50 as the index of maturation for any given population to which two year's growth should be added. The question should rather be what proportion of the population needs to be preserved from fishing mortality to ensure its own maintenance? On top of that how best to describe the two-years' growth can also add uncertainty and potentially bias.

7.9.2 Estimating the LML for Two-Years Protection

Given estimates of the maturity ogive and the growth characteristics in an area, there are a number of ways to estimate the LML required to meet the two-year rule, that is to calculate the 'empirical LML' or *eLML* (Helidoniotis and Haddon, 2014a).

7.9.2.1 *Deterministic Calculation*

The simplest approach would be to use the length at 50% maturity, L_m50, and then deterministically calculate the expected growth increment for one year's growth from the L_m50 (ΔL_{Lm50}), and then add the expected one year's growth from that shell length:

$$eLML = \left(Lm50 + \Delta L_{Lm50}\right) + \Delta L_{Lm50+\Delta L_{Lm50}} \tag{12}$$

```
# Example R code to conduct such a calculation using inverse logistic growth
invlog <- function(x,y,z,L) {   # calculates the expected growth increment for length L
  ans <- x/(1+exp(log(19)*(L-y)/(z-y)))
  return(ans)
}
param <- c(26.0,120.0,170.0,4.0)  # MaxDL, L50, L95, SigMax
Lm50 <- 116                        # estimated size at 50% maturity
oneyear <- Lm50 + invlog(param[1], param[2], param[3], Lm50)
eLML <- oneyear + invlog(param[1], param[2], param[3], oneyear)
print(eLML)                        # deterministic empirical LML
```

This example as listed generates an empirical LML of 139.620 mm

7.9.2.2 *Use of a Growth Transition Matrix*

The deterministic approach in Equ (12) provides an acceptable approximation but, clearly, ignores variation in growth and the potential spread of maturation within a population around the Lm50 (**Figure 34**). One way of attempting to capture the variation in growth is to use a growth transition matrix as a means of projecting the expected growth forwards from the size at maturity (see section '10.2.2 The Growth Transition Matrix'). In this case one might place 1000 animals into the size class closest to the Lm50 within a vector of zeros and then multiply that vector of numbers-at-size by the growth transition matrix twice, which would lead to a spread of sizes and identify the median length of the final distribution.

$$eLML = \mathbf{G}(\mathbf{GNt}) \qquad (13)$$

Where **G** is the growth transition matrix and **Nt** is the vector of numbers-at-size with 1000 in the size class nearest the Lm50. eLML, in this case, would be a vector of numbers at size, the median of which would be used as the empirical LML.

```
# Example R code to conduct such a calculation using a size transition matrix
STM <- function(p,mids) {
      n <- length(mids)
      G <- matrix(0,nrow=n, ncol=n, dimnames=list(mids, mids))
      cw <- mids[2] - mids[1]
      SigL  <- p[4]/((1+exp(log(19.0) * (mids - p[3])/(mids[n] - p[3]))))
      MeanL <- mids + (p[1]/((1 + exp(log(19.0)*(mids - p[2])/(p[3] - p[2])))))
      for (j in 1:n) {
        for (i in 1:n) {
              Prob <- (1-pnorm(mids[i]+cw/2.0,MeanL[j],SigL[j],FALSE))
              if (i < j)  { G[i,j] <- 0.0 }
              if (i == j) { G[i,j] <- Prob }
              if (i > j)  { G[i,j] <- Prob - (1-pnorm(mids[i-1]+cw/2.0,MeanL[j],SigL[j],FALSE)) }
        }
      }
      G[n,] <- G[n,]+ (1-colSums(G)) # plus group rather than distributing the excess across all
      return(G)
}
findmedL <- function(x) { # A function to find the median length from a vector of frequencies
  pick <- which(x > 0)
  Len <- midpts[pick]  # midpts is a global variable and hence available in the function
  x <- x[pick]
```

```
  n <- length(x)
  y <- x
  for (i in 2:n) y[i] <- y[(i-1)] + x[i]
  midx <- max(y)/2
  upper <- which(y > midx)[1]
  propdiff <- (midx - y[(upper-1)])/(y[upper] - y[(upper-1)])
  eLML <- Len[(upper-1)] + propdiff * (Len[upper] - Len[(upper-1)])
  return(eLML)
}
param <- c(26.0,120.0,170.0,4.0)
Lm50 <- 116
midpts <- seq(2,210,2)
G <- STM(param,midpts)
Nt <- numeric(105)
Nt[trunc(Lm50/2)] <- 1000
Nt1 <- G %*% (G %*% Nt)
print(findmedL(Nt1))
```

This example as listed generates an empirical LML of 138.686 mm while using the same Lm50 and growth parameters as the deterministic example. Further alternative methods could be developed, for example, grow animals using the transition matrix from the first post-larval size class (1 - 3 mm) out until the cohorts mean was on the estimated Lm50 so as to capture the variation within the cohort, and then project that cohort by two years. However, as long as a consistent method of describing and estimating the size at maturity and growth is used this should lead to repeatable and hence defensible results.

7.9.3 The Protection Afforded by the LML

The common objective now for imposing a LML would be the protection of a minimum proportion of mature or spawning biomass and the protection of very small, immature or low value individuals. While this objective appears to be intuitively reasonable, the explicit benefit of the LML imposed on a particular species is generally unknown. There is currently no standard method for estimating the degree of protection afforded to a population. Given growth and maturity, it remains unclear how best to estimate the degree of protection thus afforded the population.

This is an issue because the size at maturity is L_m50 and so the proportion protected can be calculated in a number of ways. Should it be measured as years protected or % of spawning biomass protected? The average years of protection does not provide a usable measure of the protection but even if the proportion of biomass or mature biomass protected by an LML is used there remains more than one way of calculating that (the terms mature and spawning biomass are used here interchangeably). These methods require the development of a model of the stock dynamics. Even if this is of little use in stock assessment because it could really only be applied at very small scales, if it can be conditioned on the growth and maturity of local populations it can be used for estimating the proportion of protection given by an LML. Using P^B as the proportion of biomass protected, B^T as total biomass, B^{Ex} as exploitable biomass, and B^{Sp} as spawning biomass; $N_{L,0}^{E}$ as the numbers at size L in the unfished emergent population (year 0), similarly $N_{L,0}^{C}$ as the numbers at size L in the unfished cryptic population; W_L as the weight at length L, and m_L as the proportion mature at length L then:

- The ratio of the total biomass above the LML to the total biomass above the size-at-maturity; which treats the size at 50% maturity as a knife edge maturation threshold and the LML as knife-edged selection.

$$B^T = \sum_{L=Lm_{50}}^{\max} W_L N_{L,0}^E + \sum_{L=Lm_{50}}^{\max} W_L N_{L,0}^C \tag{14}$$

$$B^{Ex} = \sum_{L=LML}^{\max} W_L N_{L,0}^E \tag{15}$$

$$P^B = \left(B^T - B^{Ex}\right) / B^T \tag{16}$$

- Alternatively the exact proportion that are mature could be used by including the logistic curve describing maturity at length in the calculations. This avoids the assumption that all abalone above the LML are mature:

$$B^{Sp} = \sum_{L=1}^{\max} m_L W_L N_{L,0}^E + \sum_{L=1}^{\max} m_L W_L N_{L,0}^C \tag{17}$$

$$B_{LML}^{Sp} = \sum_{L=LML}^{\max} m_L W_L N_{L,0}^E \tag{18}$$

$$P^B = \left(B^{Sp} - B_{LML}^{Sp}\right) / B^{Sp} \tag{19}$$

- Finally, equation (18) can be modified by including selectivity (s_L) explicitly instead of assuming knife edge selectivity at the LML when calculating the mature biomass above the LML:

$$B_{LML}^{Sp} = \sum_{L=1}^{\max} s_L m_L W_L N_{L,0}^E \tag{20}$$

$$P^B = \left(B^{Sp} - B_{LML}^{Sp}\right) / B^{Sp} \tag{21}$$

It is important to use the unfished state as the proportions will change dramatically once depletion has occurred with the proportion of available mature biomass protected increasing with depletion although the proportion of unfished protected will decline.

Generally, the best practice would be to use equations (17), (20), and (21), because this provides direct estimates of the effect of the LML on the mature or spawning biomass, and it is the reproductive biomass that is of most direct interest when considering sustainability. In addition, this approach (algorithm) also provides for estimates as depletion of a stock continues and thereby provides a clear indication of the implications of depletion.

7.10 Biological Variability

Using the methods described in 'Section 7.9 Appendix: Size at Maturity' on page 68 the maturity ogives at sites sampled in all fished blocks were examined to illustrate the variation possible around Tasmania. Data is available from years of taking size at maturity samples through the Abalone section at the Marine Laboratories Taroona, then TAFI, and now IMAS. When those samples that have acceptable coverage of the size range are analysed the range of variation at different sites across Tasmania is apparent (**Figure 34**, **Figure 35**, and **Figure 36**). Such variability illustrates the difficulty in setting a single LML appropriate to every location. In addition the variety among the plots illustrates the broad range of interquartile ranges that exist in many areas. For example, in **Figure 34** while the Lm50 in Block 4 varies markedly among samples the gradient and implied inter-quartile distance appears very similar. A similar range of Lm50, albeit at a larger size, is apparent in Block 12 but there is a wide range of different gradients apparent in the plots of the samples from Block 12.

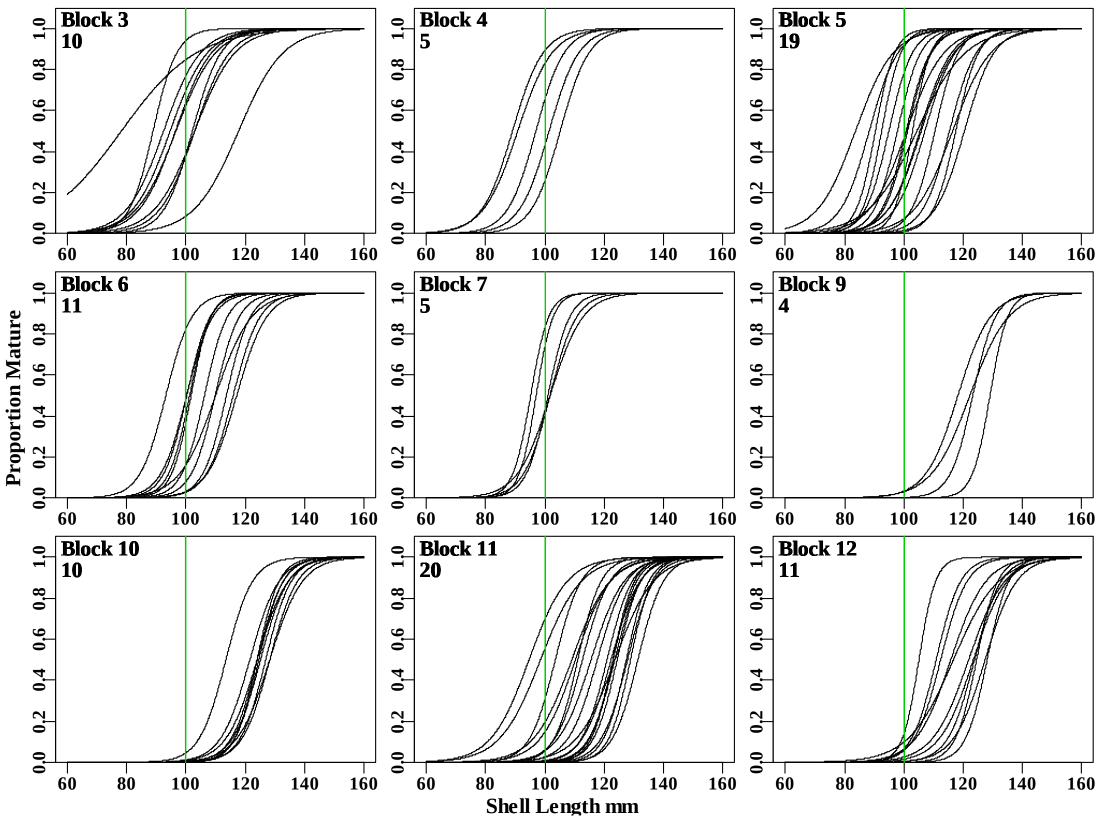

Figure 34. Size at maturity for an array of different sites in each statistical block on the south west coast of Tasmania. The vertical line at 100m is simply for reference between plots.

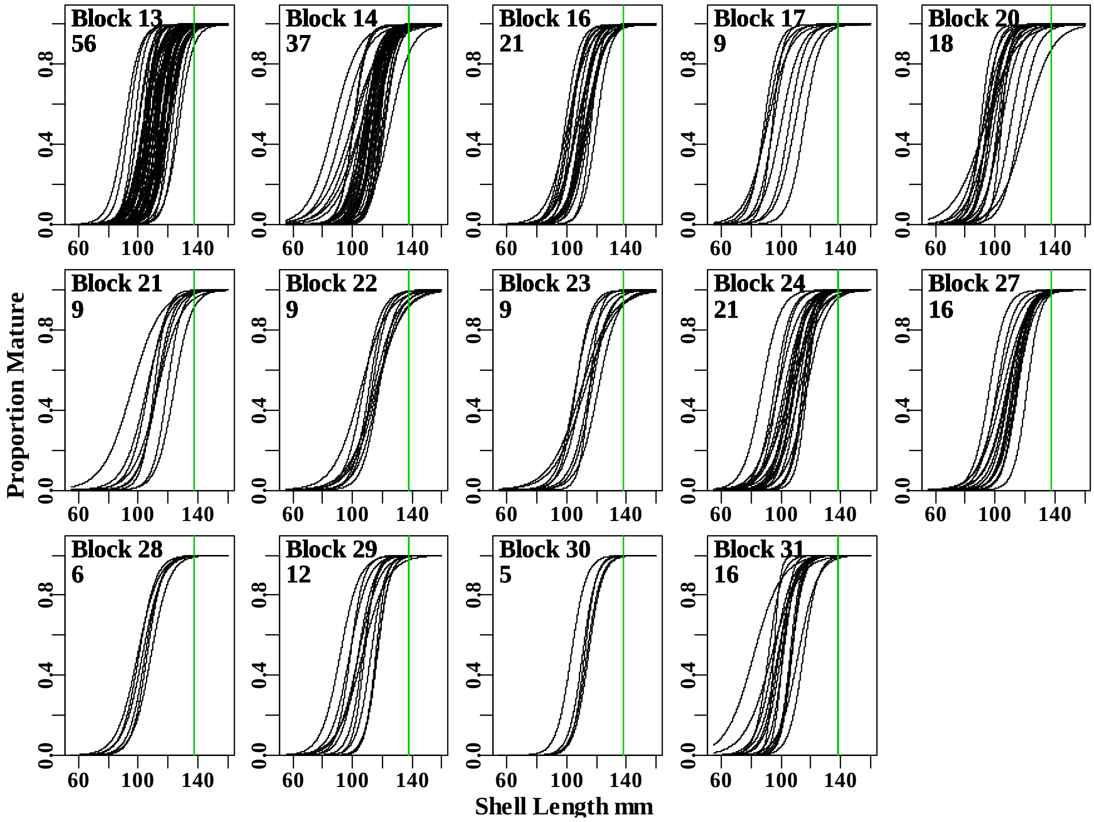

Figure 35. Size at maturity for an array of different sites in each statistical block on the east coast of Tasmania. The green line is at 138mm, the current LML.

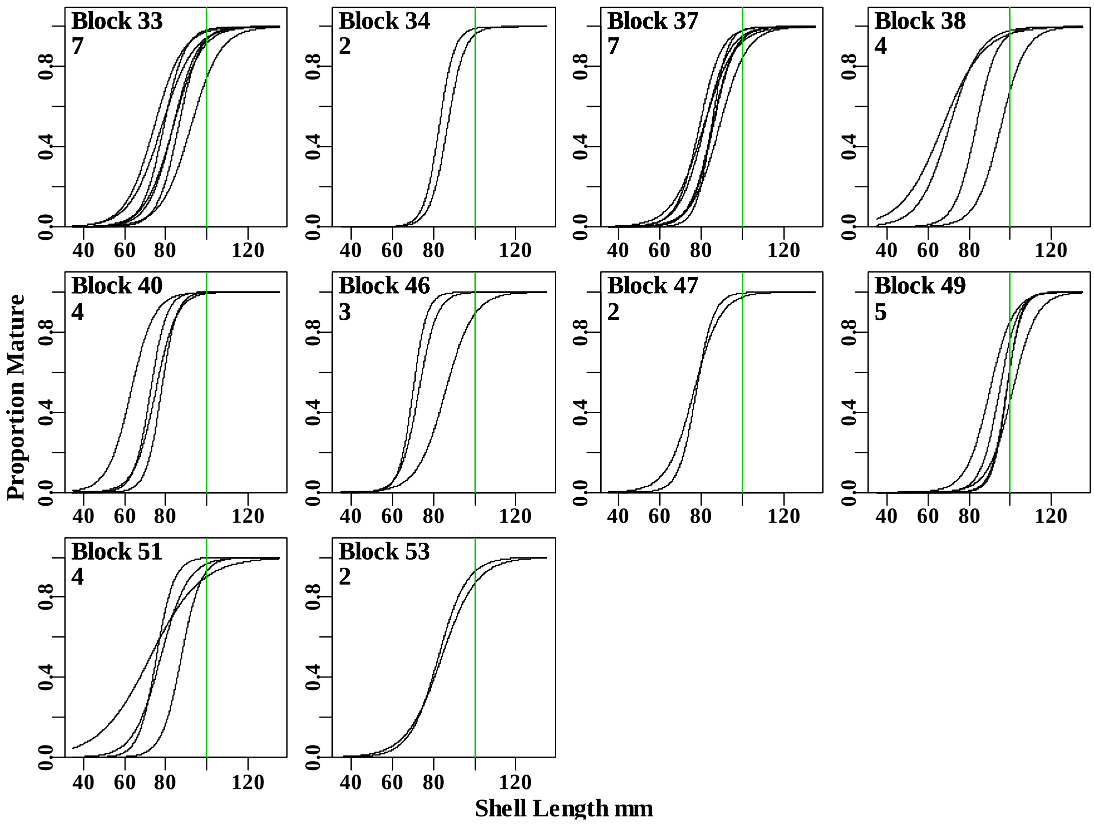

Figure 36. Size at maturity for an array of different sites in each statistical block on the north coast of Tasmania and in Bass Strait.

8 Frequency of Management Intervention

8.1 Introduction

Every year, abalone fisheries in Australia usually undergo a stock assessment process which potentially leads to changes being recommended to total allowable catches (TAC). This annual degree of attention reflects the relatively high value of these fisheries. However, within the Tasmanian abalone fishery annual recommendations to change TACs for the different zones in a series of years led to questions being raised as to whether sufficient time was being allowed to pass to permit the effects of previous changes in TAC to be observable.

One effect of imposing a legal minimum length (LML) on abalone stocks is that a number of years pass between post-larval settlement and the appearance of new entrants into a fishery. Such effects introduce time-lags into the fishery and stock dynamics such that the recruitment of post-larvae in a particular year is related more to the stock size a number of years beforehand than to the size of the stock in the year of recruitment (care is needed here to distinguish discussion of the recruitment of post-larval forms from the recruitment of animals through the LML into the fishery, although both suffer time-lags). These time-lags can also mean that an abalone fishery will exhibit delayed responses to any management changes to the TAC or the LML. For this reason it is prudent to question whether stock assessments or at least their related management advice and changes should occur every year or less frequently.

Answering the question of whether there is an optimum frequency with which to assess and manage the TAC within abalone fisheries will involve examining trade-offs occurring between competing management objectives. For example, if a given harvest control rule (HCR) is introduced into the management of a depleted stock there may be a wish for the stock to recover quickly but at the same time, a wish for any impact on total catches to be minimal. Such management objectives are intrinsically in conflict (maximum recovery rate should occur by shutting the fishery), so the question becomes what are the predicted outcomes given different weighting applied to each of the objectives.

How the frequency of assessment and TAC revision is expected to alter the balance of competing objectives can be answered using management strategy evaluation (MSE). Which balance of outcomes is considered optimum will depend upon which objective is given most weight. The MSE simulation framework used here is a further articulation and development (see appendix) of that originally produced in FRDC 2007/020 '*Identification and Evaluation of Performance Indicators for Abalone Fisheries*.' (Haddon *et al*., 2013; Haddon and Helidoniotis, 2013). Selection of an optimum management approach can rarely be automated because in addition to balancing a set of competing management objectives some management arrangements may give rise to undesirable fishery behaviour in a qualitative sense. How best to balance the predicted implications of management are more properly the scope of policy decisions regarding the particular objectives towards which a fishery should be managed towards. Thus, instead of selecting a single 'optimum' management arrangement the outcomes from the MSE will be tabulated and illustrated in a manner that simplifies the selection by managers (and possibly other stakeholders) of a management strategy to apply into the future.

The objective for this current work is therefore to compare the implications of assessing and modifying the TAC at different yearly intervals so that a decision can be made whether to alter the current practice of repeating the assessment and management routine every year.

8.2 Methods

8.2.1 The Simulation Model

A size-structured population dynamics model was constructed in R (R Core Team, 2016) that could be conditioned to be similar in its dynamics to known fisheries (see the 'Chapter 10 The Size-Based Operating Model' from page 153 onwards for a full description of the model structure and equations). The operating model used derives from the models of Sullivan *et al*. (1990) as further developed by Punt *et al*. (1997). However, it differs from previous models in a number of ways, particularly where it includes the full size range of post-larval abalone with an initial size class of 1 – 3 mm with a central value of 2 mm, stepping in 105 × 2 mm classes up to a size class centred on 210 mm. This contrasts with current abalone stock assessment models (Breen *et al*., 2003; Gorfine *et al*., 2005; Fu, 2012) which start the model dynamics in a size class representing three or four year old animals. The use of a relatively large initial size appears to be a result of difficulties in modelling the growth of the early size classes. The growth dynamics here are modelled using the inverse logistic growth model, which has been demonstrated to provide an accurate description of Blacklip Abalone growth across the full range of sizes (Haddon *et al*., 2008; Helidoniotis *et al*., 2011). The inclusion of the smaller size classes improves the modelled dynamics by explicitly including any time lags introduced into the dynamics by the time it takes the post-larval abalone to grow into the legal size classes. It can take two to four years for an abalone to grow from the 2mm size class to the 70mm size class (approximately the size at which other abalone size-based model begin their dynamics) and such lags have important implications for the recruitment dynamics (**Figure 37**).

Such time-lags can be very influential on the potential response time the stock can make to any management changes. For example, with respect to the south-west coast of Tasmania there can be five cohorts of under-sized abalone still to enter the fishery before the effects of management changes on recruitment dynamics can begin to have any effects. Thus, such time-lags can be between 4 – 6 years or more in duration.

8.2.2 The Scenarios Tested

12 scenarios were examined (**Table 14**) so as to explore the implication of the different assessment intervals when applied at different starting conditions of stock depletion.

The model dynamics were conditioned on the biology of Tasmanian west coast Blacklip Abalone (*Haliotis rubra*) with various constants relating to growth, maturity, and selectivity being defined (**Table 15**; **Figure 38**). The conditioning needed to be conducted for each statistical block in the south-west (**Figure 38**). This involved fitting a surplus production model (Haddon, 2011) to the data from each block independently

8.2.3 The Simulation Procedure

Management Strategy Evaluation uses simulation modelling to evaluate the relative performance of different 'management strategies' (combinations of data collection schemes, stock assessment methods, and harvest control rules). Each simulation replicate run applies a candidate management strategy (often also called a harvest strategy) to data sampled from an 'operating model', where the operating model is a representation of an actual stock under management. The dynamics of the model are conditioned using biological and fishery data from the stock in question. The management actions (in this case setting a TAC; a catch limit) are used each year to update the stock dynamics underlying the operating model (Punt *et al*. 2016). Outputs from an MSE are typically performance metrics that attempt to quantify how well each candidate management strategy is able to achieve the management goals (they are termed performance metrics to distinguish MSE outputs from performance measures relating to the fishery). In the case of Tasmanian abalone, however, there are currently no quantified management goals and so for the purposes of this study CPUE targets and other catch constraints are introduced so that relative performance can be judged.

Table 14. The combinations of scenarios considered in the zone simulations.

Scenario	Description
Assessment Intervals (years)	1, 2, 3, and 4
Initial Depletion	0.26, 0.33, and 0.47
LML	140, 145
Harvest Control Rule	Multi-Criteria Decision Analysis of CPUE performance measures.
Weight on Grad4 : TargCE : Rate1	0.25 : 0.5 : 0.25
TAC Adjustment Schedule 0 - 10	-25, -20, -15, -10, -5, 0, 5, 10, 15, 20, 25

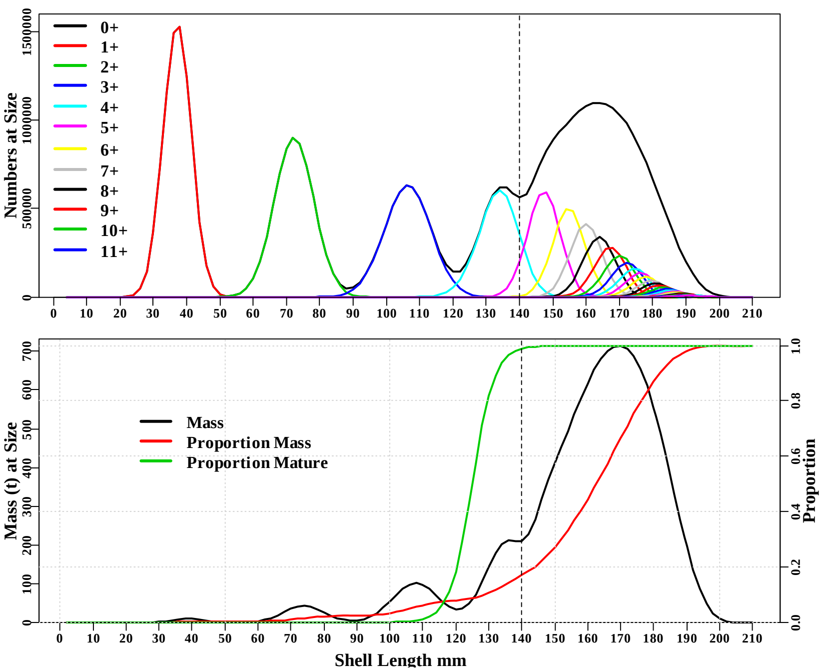

Figure 37. The unfished equilibrium numbers-at-size, mass-at-size, and predicted age-at-size for an abalone population model conditioned on the southwest Tasmanian stock (the first 2mm size class. 1 – 3 mm, has very large numbers and is omitted for clarity). On the fast growing south west coast the abalone are predicted to take between 2 – 3 years to reach 70mm (first green line). Only 20 cohorts are illustrated. More than 80% of the mass of the unfished population lies above the current LML of 140mm. The spike of 0+ animals less than 10mm in length are omitted to retain detail in the other cohorts.

First the simulated zone was generated in an equilibrium unfished state, which involved conditioning it on the four statistical blocks in the area using 60 populations spread unevenly across the blocks (**Table 15**).

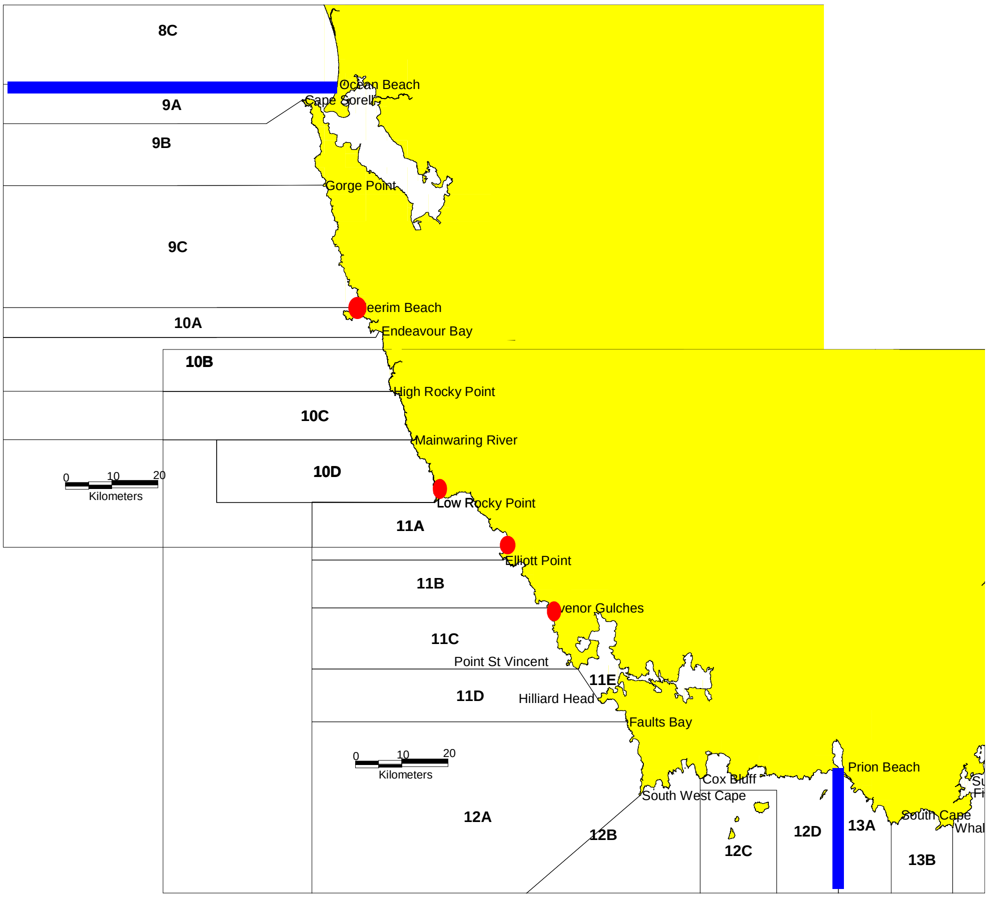

Figure 38. The southwest of Tasmania with blocks 9 – 12 being between the thick blue lines. The red dots depict the location of data used to define the growth characteristics.

During the conditioning of the simulated stock, where biological and fishery data from the selected statistical blocks are used to direct the dynamics of the modelled stock to be like those in the real fishery (**Figure 39**), the productivity properties of the stock are also determined. Each simulation begins with the stock in an unfished state and this is then depleted to a selected level (**Table 14**) by searching for the constant harvest rate that would produce the desired depletion. The selected depletion level is then maintained for an initial five years by removing the expected productivity as catch so as to allow the stock dynamics to stabilize relative to the new depletion level. The selected harvest control rule (HCR) is then applied such that subsequent catches are determined by the HCR. With the whole simulation being run 1000 times to enable estimates of the relative likelihood of different outcomes to be tabulated.

The operating model represents reality in the simulation framework and each year that the dynamics are simulated forward from the starting point the model is used to generate simulated fisheries data. Each year such simulated data is then used to estimate the performance measures (CPUE) used by the HCR within the selected management strategy and the resulting management advice, the TAC, is imposed back onto the operating model dynamics, which in turn moves the stock dynamics forward. This feedback loop between the operating model and the HCR is an essential part of management strategy evaluation and differs from simply projection constant management settings forward in time.

Table 15. A selection of the constants used to define the simulation model based on values estimated from statistical blocks 9 – 12 on Tasmania's south-west coast. Those parameters beginning with a lower-case 's' are the standard deviations of the parameters immediately above them in the table. In a number of case identical values were used which reflects a lack of knowledge.

	Intent	AB09	AB10	AB11	AB12
Populations	Spatial Structure	10	11	21	18
MaxDL	Growth	38.5	37	37.75	36.5
sMaxDL	Growth	2.5	2.5	2.5	2.5
L50	Growth	125	124	121	120
sL50	Growth	5	5	5	5
L50inc	Growth	36	42	44	43
sL50inc	Growth	1	1	1	1
SigMax	Growth	4.581	4.581	4.581	4.581
sSigMax	Growth	0.1	0.1	0.1	0.1
LML	Management	140	140	140	140
Wtb	Weight-to-Length	3.161963	3.161963	3.161963	3.161963
sWtb	Weight-to-Length	0.148461	0.148461	0.148461	0.148461
Wtbtoa	Weight-to-Length	962.8098	962.8098	962.8098	962.8098
sWtbtoa	Weight-to-Length	-14.3526	-14.3526	-14.3526	-14.3526
Me	Natural Mortality	0.2	0.2	0.2	0.2
sMe	Natural Mortality	0.003	0.003	0.003	0.003
Mc	Natural Mortality	0.2	0.2	0.2	0.2
sMc	Natural Mortality	0.003	0.003	0.003	0.003
AvRec	Ln(Recruitment)	11.4	11.9	11.2	11.2
sAvRec	Recruitment	1	1	1	1
defsteep	Recruitment	0.6	0.6	0.6	0.6
sdefsteep	Recruitment	0.02	0.02	0.02	0.02
L50C	Emergence	126.4222	126.4222	126.4222	126.4222
sL50C	Emergence	0.5	0.5	0.5	0.5
L95C	Emergence	145.3749	145.3749	145.3749	145.3749
sL95C	Emergence	1	1	1	1
MaxCEpar	Unfished CPUE	0.37	0.37	0.38	0.38
sMaxCEpar	Unfished CPUE	0.02	0.02	0.02	0.02
selL50p	Selectivity	0	0.25	0	0.25
selL95p	Selectivity	1.5	1.75	1.5	1.75
SaMa	Maturity	-16	-16	-16	-16
L50Mat	Maturity	123.384	122.893	112.373	116.345
sL50Mat	Maturity	4	4	4	4

Three sources of variation are included in the simulations: 1) recruitment variation, 2) the simulated catch rate estimates, and 3) in the distribution of future effort across blocks and their populations. Recruitment variability is clearly important in abalone fisheries and is found in all but the simplest stock assessment modelling. Catch rate data from fisheries always has associated uncertainties and so these are included in the simulated catch rates (which make up the empirical fishery performance measures within the MCDA). Finally, each year the divers make decisions with regard to where they will go fishing. This is generally based on their impressions of the state of each area, either from their own experience or from hearing other divers. Such decisions are also intrinsically uncertain so the proportional allocation of a TAC across a fished zone includes significant variation away from the ideal distribution.

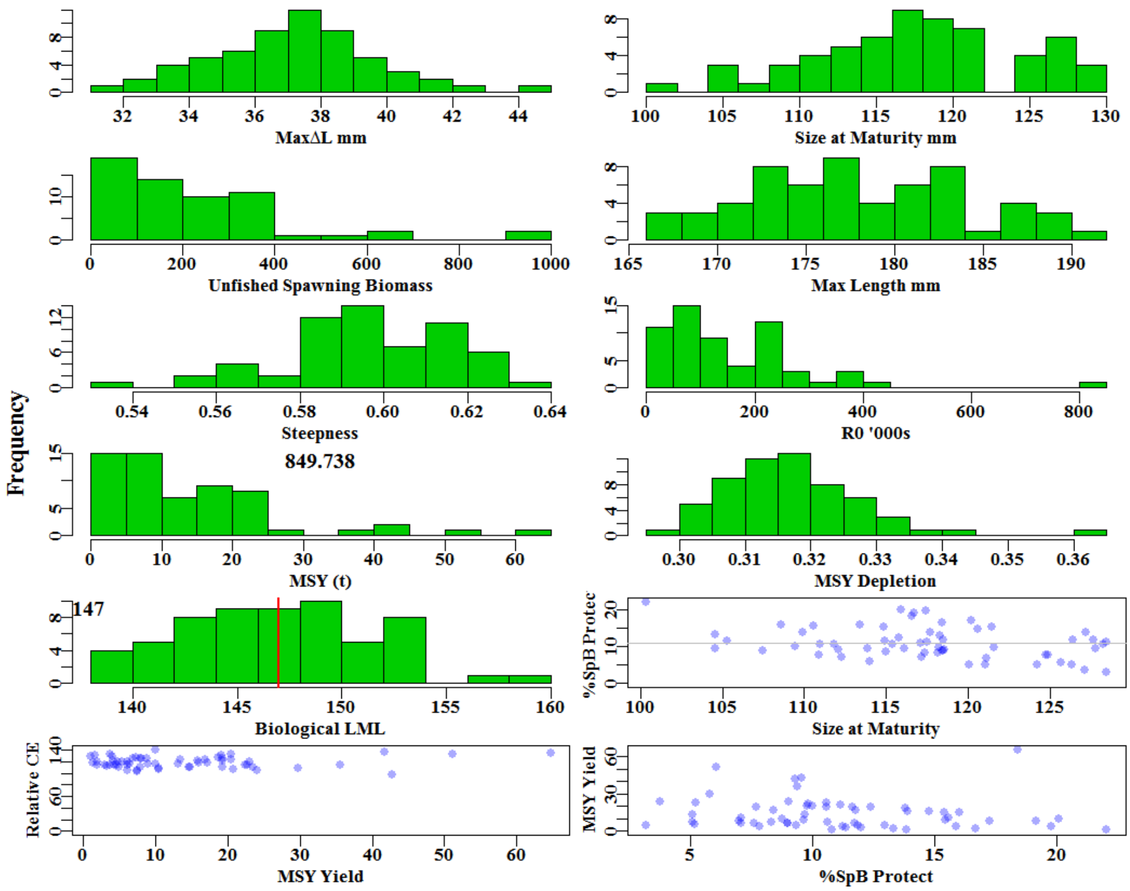

Figure 39. The properties of the 60 populations making up the operating model illustrating the variation exhibited across populations. The overall average in each case does not necessarily represent the whole.

8.2.4 Management Strategy Performance Metrics

The common performance metrics used with MSE studies attempt to quantify the degree to which each candidate management strategy attain the specific management goals of the fishery concerned (Punt *et al*., 2016). For many fisheries, this metric is expressed as some fraction of B_0, although this has the implicit expectation that a reliable estimate of B is available. With abalone there are currently no specific quantified management goals, such as $0.4B_0$ or even proxies such as a target CPUE of 100kg/hr, which can currently be used to assess the relative performance of alternative management strategies.

For this study, an arbitrary CPUE target of 100kg/hr will be trialled along with other constraints on change rates to TAC and upper and lower limits to the TAC values. Currently, for the western zone upon which the operating model is conditioned there is discussion and an intent to increase the legal minimum length (LML) from 140mm to 145mm and possibly larger. Hence their inclusion in the scenarios considered (**Table 14**).

Numerous management related performance metrics have been devised and used in MSE studies (Punt et al., 2016). The Tasmanian abalone fishery is prone to large scale cycles of CPUE and presumably abundance (e.g. **Figure 42**). These oscillations in abundance are a reflection of the time-lags introduced into management actions by the number of years it takes for animals to grow from post-larval settlement up until they enter the fishery above the LML. In the projections such oscillations also occur so simply presenting the average spawning biomass level after X years is unlikely to provide a useful representation of how each management strategy performs. Oscillations will also distort the estimates of average annual variation in catches (AAV). As a result of the expected oscillations the projections were made over a 50 year period although because the initial depletion level is maintained for five years the useable projection years extend from year 6 – 50. For each scenario at least some projections will need to be plotted to illustrate whether or not oscillations are indeed occurring in a particular scenario. In addition, the following performance metrics can be calculated for every 11 years (6 – 16, 17 – 27, 28 – 38, 39 – 49) to gain a better grasp of events, plotting up those that illustrate the changes and advantages and disadvantages best.

The metrics calculated here include:

- The number of years passing before the CPUE target is first reached
- The average catch over the projection years
- The proportion of trials when the CPUE is above the target CPUE in any year
- The proportion of trials when the CPUE is below a limit reference point for CPUE
- The average annual variation in catch:

$$\mathrm{AAV} = \sum_{y=2}^{projyr} \left| C_y - C_{y-1} \right| / \sum_{y=2}^{projyr} C_y \tag{22}$$

Where C_y is the catch in year y and *projyr* is the number of years of projection being used.

- The spawning biomass depletion level
- The expected CPUE
- The average length in the catch.

Except for the first, all these metrics can be calculated for the whole time series of projected years and for the four sub-sets, as well as for the whole zone and the separate blocks.

8.2.5 Standard Graphical Outputs

Communicating the results of a management strategy evaluation that compares a number of alternative harvest strategies is often made difficult from the very large amount of information it is possible to generate with each scenario run. With the option to alter the initial depletion, the number of years between management intervention, the LML, and many other parameters and variables, there can be a very large number of different scenarios. Presenting the results in an unbiased fashion generally means many tables and figures, which do not lend themselves to easy reading.

In this case except for the initial depletion and the years between assessments all other parameters and variables are assumed to remain constant. This will simplify being able to concentrate only on the effect of changing the initial depletion and the management cycle.

8.3 Results

8.3.1 Unfished Equilibrium Population

The southwest of the Tasmanian coast holds a relatively productive stock of Blacklip Abalone (*Haliotis rubra*), which is an important component of the Tasmanian fishery (Tarbath and Mundy, 2015). The abalone in the southwest can grow to a relatively large maximum size (Helidoniotis *et al*., 2011). Rapid early growth generates a relatively clear modal progression of cohorts in the first few years. After growing in relatively discrete modal groups for three to four years, with gradually increasing overlap and spread, the modal groups become far less distinguishable and eventually merge into a single mode containing numerous cohorts. South west abalone can take between 5 – 6 years to achieve the LML of 140mm and, in an unfished population, there can be a wide range of age-classes (cohorts) present in the population (**Figure 37**). Given that the weight of abalone increases approximately as the cube of length (*Wtb* in **Table 15**) most of the mass of the unfished population is found above about 130mm and there is only about 18% of all unfished biomass below the LML of 140mm. As the egg-production is more linearly related to body mass than shell length this also means that most of the egg-production will be from animals above the current LML even though the animals can become mature below the legal minimum length (**Figure 37**).

8.3.2 The Effects of Assessment Interval on Blocks

An immediate and not unexpected effect of altering the frequency of the assessment round would be that the management trajectory of catches and other fishery statistics becomes more step-like (**Figure 40** and **Figure 41**).

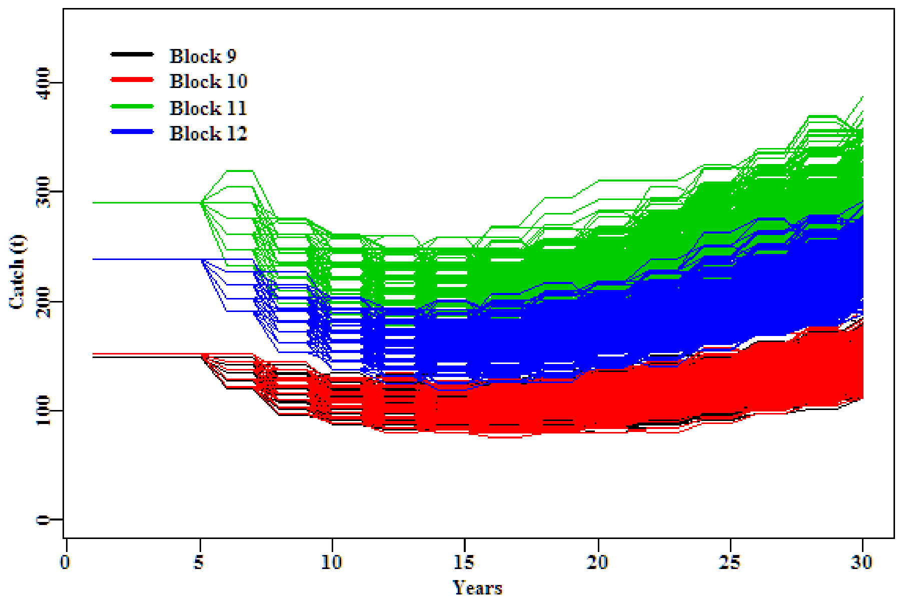

Figure 40. The predicted catch (TAC) expected to be taken from each of the simulated south-West statistical blocks across 1000 replicate runs. Block 9's data (black lines) lie mostly under block 10 (red lines). In this case the simulation started at a depletion level in each block of $0.26B_0$ and the assessment period was set every two years.

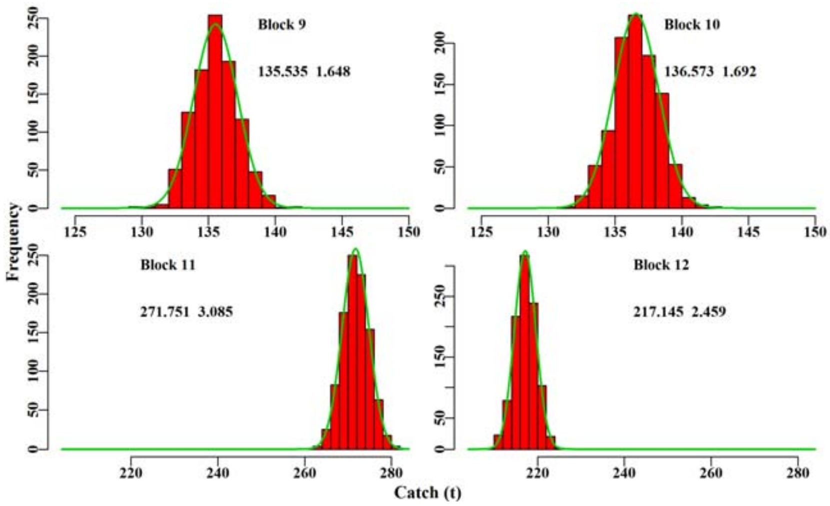

Figure 41. The distribution of average annual catches from the simulated years 5 – 50 within each block for scenario 0.26_1; implying an initial depletion to 26%B_0 and an assessment interval of one year. In each panel the histogram is topped by a fitted normal distribution and the mean and standard deviation is given below the block number. The scales differ between plots.

8.3.3 The Effects of Assessment Interval at the Zone Level

Considering the whole simulated zone simplifies the comparison of the different management strategies (focussing here only on the assessment interval). The stable catches in the first five years are clear. Given the 0.26B_0 state of the stock the MCDA HCR obviously recommends a drop of the TAC over the first 5 – 6 years when changes can occur every year. When changes are made every two years this initial period extends over the first ten years, and even occur after 12 years when changes are every four years (**Figure 42**). The effect upon the median total catch over the same periods is also markedly different, although the effects are smoothed in CPUE and spawning biomass.

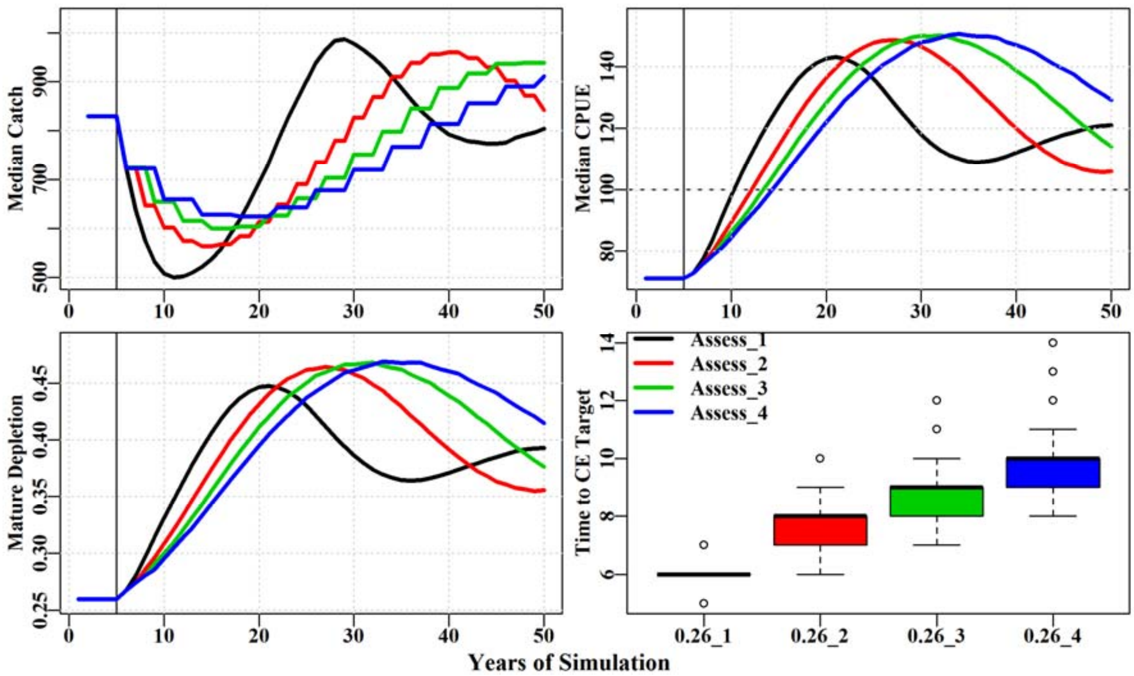

Figure 42. The median trajectory of total zone catches, CPUE, and spawning biomass depletion, plus years to meet the CPUE target of 100 kg/hr from 1000 simulations starting at a stock depletion level of 0.26B_0 and using the MCDA harvest strategy applied every 1, 2, 3, or 4 years. 'Time to CE Target' uses CE instead of CPUE to save space.

8.3.4 The Effects of Depletion Level

Different initial conditions of depletion have large effects upon the outcome of applying the MCDA HCR (**Figure 42**, **Figure 43**, and **Figure 44**).

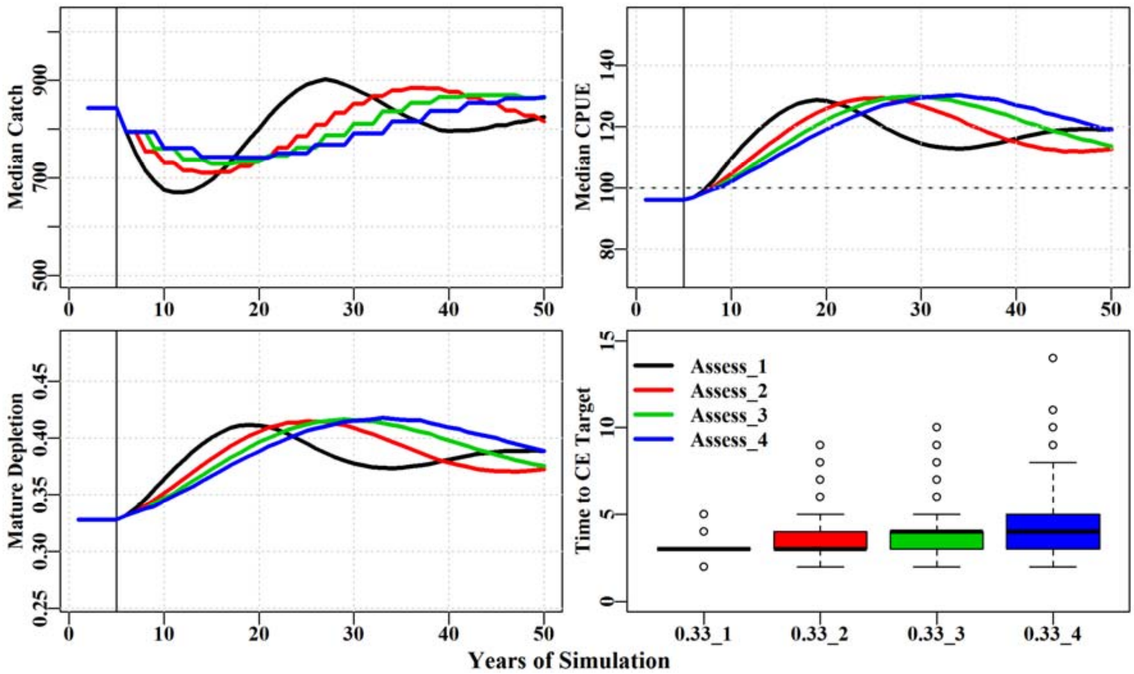

Figure 43. The median trajectory of total zone catches, CPUE, and spawning biomass depletion, plus years to meet the CPUE target of 100 kg/hr from 1000 simulations starting at a stock depletion level of $0.33B_0$ and using the MCDA harvest strategy applied every 1, 2, 3, or 4 years.

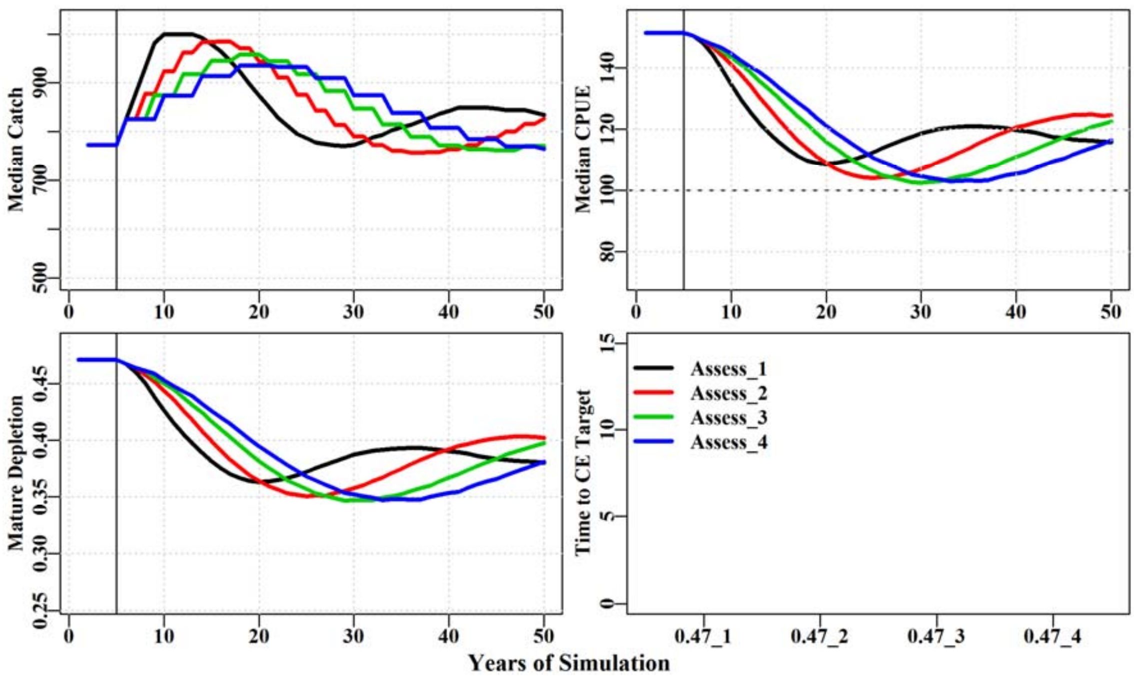

Figure 44. The median trajectory of total zone catches, CPUE, and spawning biomass depletion, plus years to meet the CPUE target of 100 kg/hr from 1000 simulations starting at a stock depletion level of $0.45B_0$ and using the MCDA harvest strategy applied every 1, 2, 3, or 4 years. All scenarios meet the CPUE target in year 0.

Not surprisingly the smaller the degree of depletion the more rapidly the target CPUE is attained, although at 0.45B_0 the simulation starts well above the target CPUE and stays that way throughout the simulation and so boxplots of time to target would indicate a negative value. When initially depleted to 0.33B_0 the time to the target CPUE is only half that when initial depletion is 0.26B_0 (**Figure 42**, **Figure 43**, and **Figure 44**).

8.3.5 Relative Change in Metrics vs Assessment Interval

By scaling each trajectory for Catch, CPUE, the spawning biomass depletion and the exploitable biomass to a mean of one (divide each trajectory by its average) their relative changes with respect to different assessment intervals and initial depletion states can be made clear (see **Figure 45**, **Figure 46**, and **Figure 47**).

Catches appear to be the most sensitive to the MCDA HCR and the CPUE trajectory, as expected, closely follows that of the exploitable biomass trajectory. The greater the level of depletion the more dramatic the changes are to the trajectories in catch, depletion, and CPUE. In addition, the greater the level of depletion the longer it would appear to take to achieve a new equilibrium. Thus with a starting depletion of 0.47B_0 the trajectories appear to converge on a relatively stable outcome almost within the 45 years of projection whereas with a starting depletion of 0.26B_0 relatively strong oscillations are still underway at the end. The impression is gained that the end point of the oscillations will be different depending on the starting conditions but this could only be tested correctly by extending the projections out much further.

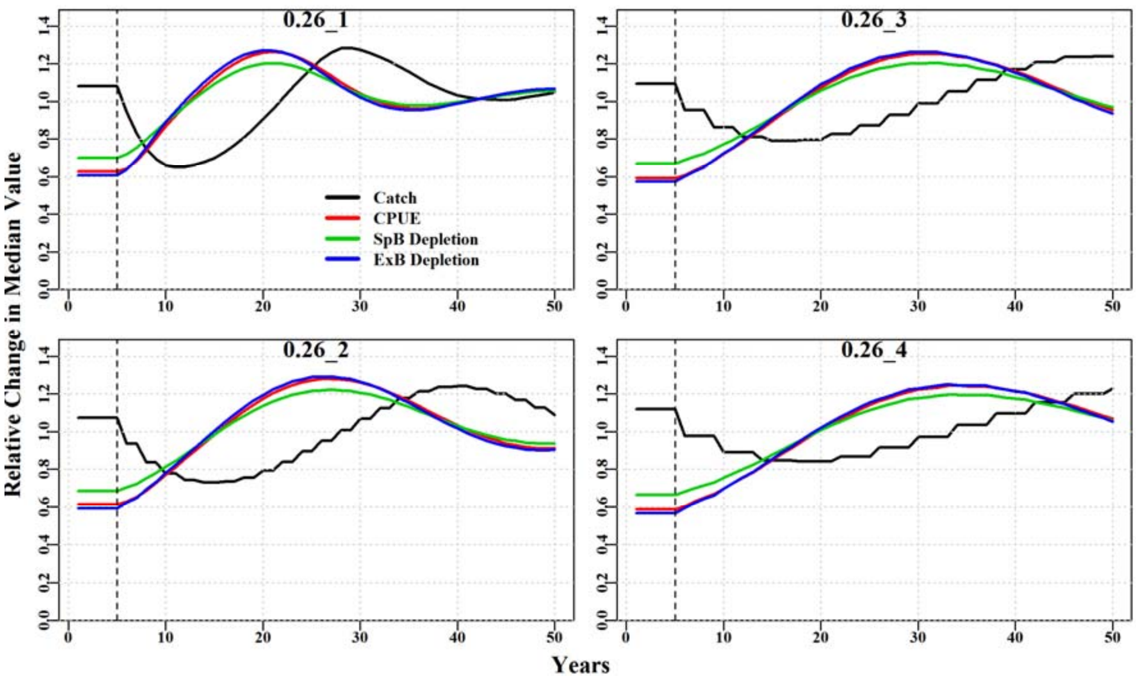

Figure 45. The median trajectories of catch, CPUE, spawning biomass depletion, and exploitable biomass depletion for simulations starting at 0.26B_0 and with management changes occurring at 1, 2, 3, and 4 year intervals, as denoted by each panel's title.

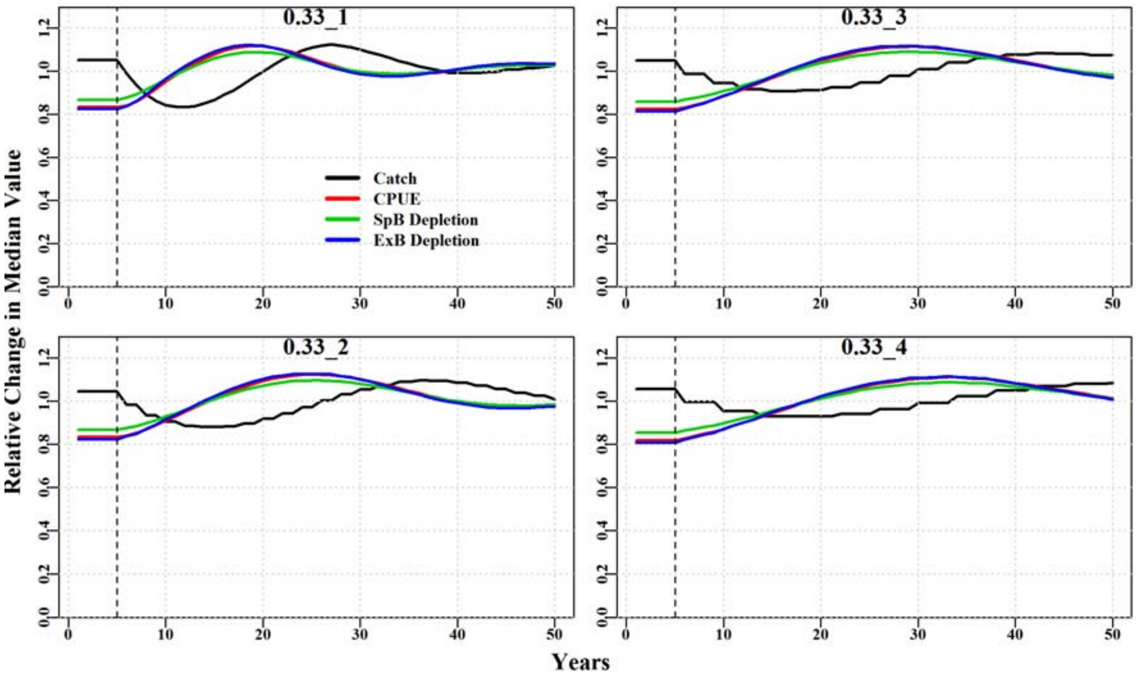

Figure 46. The median trajectories of catch, CPUE, spawning biomass depletion, and exploitable biomass depletion for simulations starting at $0.33B_0$ and with management changes occurring at 1, 2, 3, and 4 year intervals, as denoted by each panel's title.

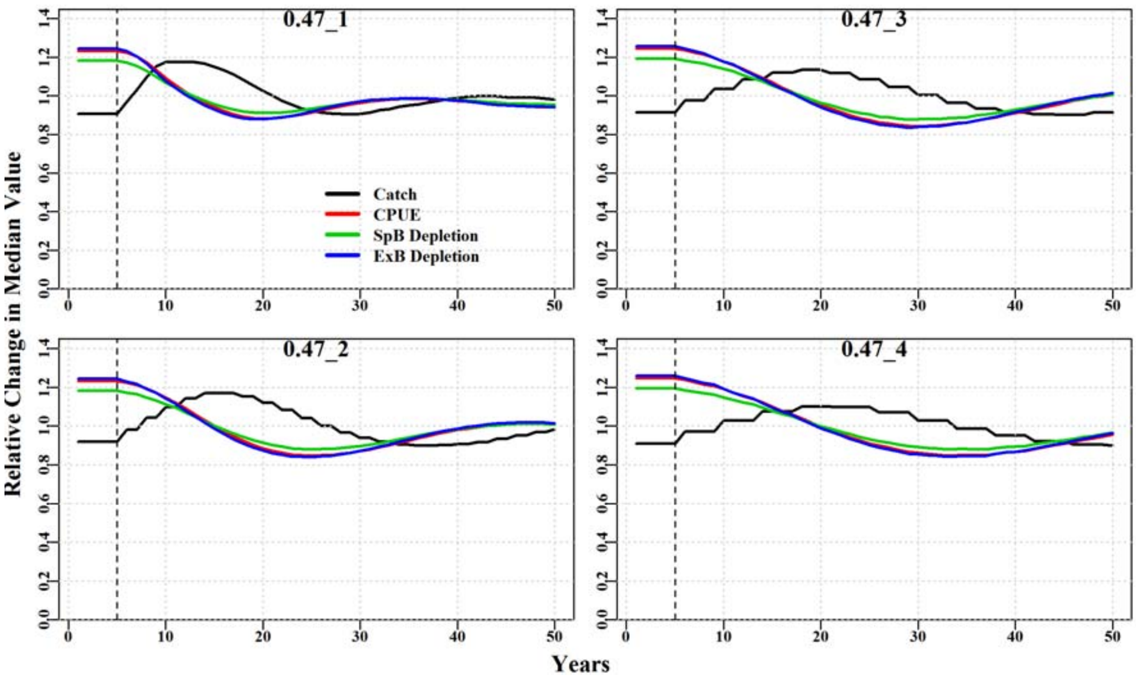

Figure 47. The median trajectories of catch, CPUE, spawning biomass depletion, and exploitable biomass depletion for simulations starting at $0.47B_0$ and with management changes occurring at 1, 2, 3, and 4 year intervals, as denoted by each panel's title.

8.3.6 Interaction between Assessment Interval and Initial Depletion

Changes in the intensity of any effects and the timing of those effects are made clear by plotting the different scenarios either together or above one another to make visual comparisons simpler (**Figure 48**). The ordering of the time delays brought about by the different assessment intervals (longer delays associated with longer assessment intervals) remain the same irrespective of the state of initial depletion. However, the closer the initial depletion is to the depletion level that would give rise to the maximum productivity then the more rapid are the changes to catches, CPUE, and spawning biomass depletion, although the differences are only minor (of the order of 1 – 3 years). If the initial depletion is reduced so that the simulated stock begins in a state above the biomass that gives rise to maximum productivity then any oscillations are inverted with peaks instead of troughs and troughs instead of peaks.

Not surprisingly the maximum delays to management responses are brought about by the four-year assessment interval (**Figure 49**). This certainly stabilizes the fishery but keeps catches low for longer although at not such low levels as the one-year assessment interval. For that reason the spawning biomass also takes the longest to recover to more resilient levels (**Figure 48**).

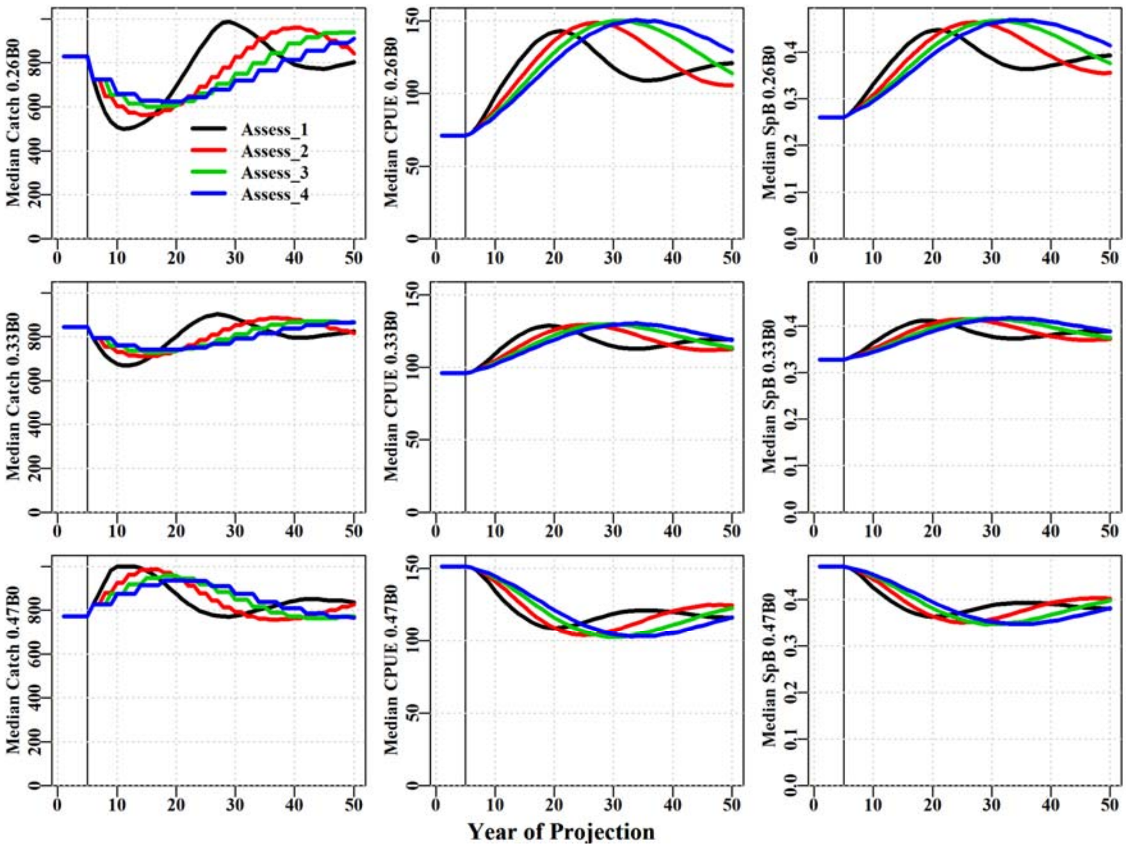

Figure 48. The median trajectories of catch, CPUE, and spawning biomass depletion for each initial depletion level and each assessment interval. Within each column the vertical axis retains the same scale.

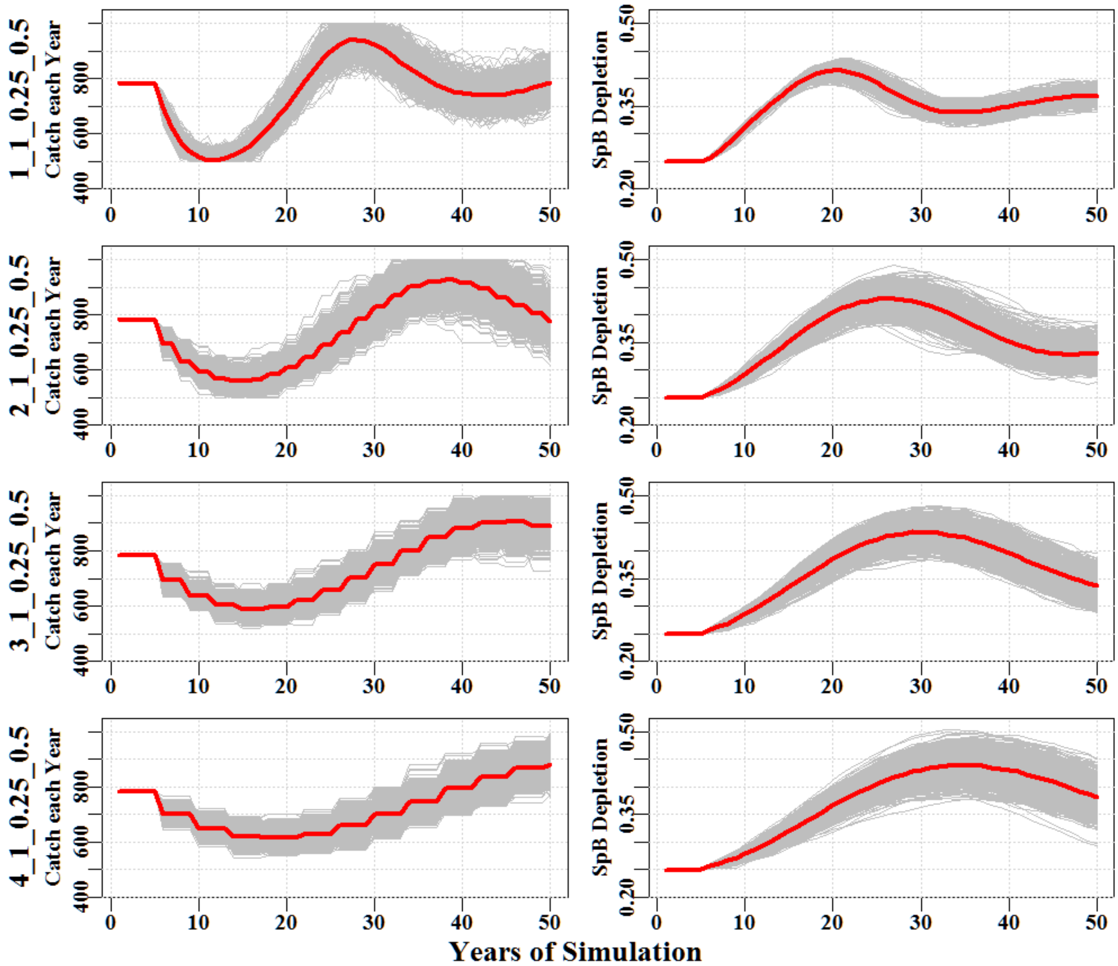

Figure 49. Some example scenarios illustrating the increasing time-delays brought about by assessment intervals of different duration. The progression of the location of the mode of the upper levels of catch and of spawning biomass depletion levels with increasing assessment interval is clear from the top to the bottom panels. The minimum catch allowed by this example harvest strategy was 500 t.

8.4 Discussion

8.4.1 Selection of an Assessment Interval

There are clear differences brought about in the simulated stock and fishery dynamics brought about by the interaction of the assessment interval with the time-lags inherent in the population dynamics of abalone stocks being fished using a legal minimum length. The delays brought about by assessment intervals of three or four years are quite marked and yet the benefits in stability and reduced disturbance to fishing practices seem relatively small.

Across all metrics, there is a pattern of extending required TACC reductions over a long time period and a longer time to recovery as the Assessment Interval increases. Either one-year or two-year assessment intervals might be reasonable choices depending on the management objectives that are given most emphasis. The assessment interval may also vary depending on whether the fishery is in a rebuilding phase or maintenance phase. However, such a choice does have consequences for both the fishery and the stock and thus, should really be directed through consultation informed by the outcomes of this MSE.

Further analysis (see the next ‘Chapter 9 Testing the MCDA Harvest Strategy’) where alternatives to the relative weights of the different performance measures as well as an alternative TAC adjustment schedule are considered will illustrate the relative utility of combinations of MCDA settings, including whether assessment intervals of 1 or 2 generate the best outcomes.

9 Testing the MCDA Harvest Strategy

9.1 The Adoption of a Formal Harvest Strategy

An implicit objective when attempting to manage abalone stocks in Australia would appear to be to maximize the allowable catch each year while minimizing the risk to the sustainability of the stock. This combination of two objectives leads to a trade-off or a conflict between the two aspects of exploitation and stock maintenance (balancing catch against productivity) when trying to manage the stocks most effectively. Empirically, when dealing with highly valuable fish stocks, such trade-offs are difficult to balance and there have been troubling failures with an array of abalone fisheries around the world (Hobday et al., 2001). To examine this trade-off we use management strategy evaluation (MSE) to explore alternative harvest strategies for their relative performance in terms of management advice and management outcomes.

9.1.1 The Current TAC Setting Approach

In the process of setting sustainable total allowable catches for abalone fisheries there can be multiple data streams (catches, catch rates, length composition of catch, fine-scale spatial location of the catch, etc) that can be informative about the state of a fished stock. The current process of examining available information and then recommending TACs in Tasmania is highly collaborative. The process involves four formal meetings each year of the Fishery Resource Advisory Group (FRAG) to obtain industry observations and interpretations of summarized fisheries data at the level of individual statistical blocks (and sometimes finer). In this semi-quantitative manner catch recommendations for each block are produced, which are then summed to generate a recommended TAC for each fished zone. The FRAG is an Industry forum and comprises the Tasmanian Abalone Council board members, management, and scientists, and the meetings are open to all industry members and other interested parties should they wish to attend. The meetings also consider issues relating to spatial management (spatial caps), minimum legal sizes, and other matters relating to the state of the stocks and the fishery. The data considered by the FRAG in relation to setting catch level advice is provided by scientists from the Institute of Antarctic and Marine Studies (IMAS; part of the University of Tasmania) and constitutes catches, catch rates, sometimes length composition data, and any other information relevant to spatial aspects of the fishery. The recommendations arising from the FRAG process are delivered to the Abalone Council AGM and forms the basis of the Industry position on management changes for the coming fishing year. The Tasmanian Abalone Council may not approve the FRAG recommendations, but to date generally they follow these recommendations. The report is also provided to the Fishery Advisory Committee (FAC; a ministerially appointed collection of people). The FAC produces a recommendation to the Minister. Since the introduction of the FRAG process, there has been a high level of agreement between the FRAG and FAC recommendations, but the Abalone Council may make a separate representation to the Minister. The fisheries manager has input into both groups and in the Departmental brief to the Minister.

There is what can be termed a harvest strategy already in place but at best it could only be called informal. The collaborative approach has the advantage of being open and consultative, although it is often difficult to get complete agreement across the wide range of opinions amongst divers and quota holders. Detailed analysis of the overlap of individual dive events between divers within blocks indicates that much of the time they are fishing is rather different areas to each other, so the lack of general agreement among divers should not be surprising. Nevertheless, there are a number of weaknesses to the current system.

The use of a legal minimum size means that there can be a number of years between the occurrence of large or small successful settlement events and these then becoming apparent in catches and catch-rates. Such time-lags mean that events in the fishery (e.g. rises and falls in catch-rates) are not an immediate indication of events in the stock (rises and falls in exploitable biomass will be due to events between 4 – 8 years previously). This has previously led to declines in CPUE being given too little emphasis when they occur, which has led to significant declines (Tarbath and Mundy, 2015). In addition, sometimes great weight is given to opinion concerning what may have influenced catch-rates when such effects should ideally be quantified.

While multiple factors or fishery performance measures are considered (catches, catch-rates, diver opinion) there is no explicit weighting given to any of these information sources. And while there are some ad-hoc guidelines such as approximate bounds around the historical catch histories for each block there are no explicit biological fishery reference points (neither targets nor limits). Finally, while a record is kept of the decisions the justifications and reasoning behind each decision is only weakly referred to, if at all, which means given the same fishery information it might be very difficult to obtain exactly the same result. If different people were in the room it might even lead to a completely different result. This lack of repeatability weakens the defensibility of any management advice deriving from the process because of the uncertainty that it injects into the outcomes.

9.1.2 The Introduction of a Formal Harvest Strategy

In past years, for example, during 2000 – 2010, what became IMAS was asked, perhaps surprisingly, not to provide explicit advice on what might constitute sustainable catch levels for different zones within the fishery. This restriction has now changed so there is now an urgent need to be able to provide defensible and repeatable management advice that explicitly includes proposed sustainable catch levels. Generating such advice is difficult in the absence of explicit, specific, and operational fishery objectives and currently the draft management plan for abalone in Tasmania only contains generic fishery objectives. Nevertheless, the introduction of a formal harvest strategy, with reference points, decision rules, and a published structure at least provides for increased discussion and involvement with industry members, who are now actively contributing to decisions concerning potential reference points and related matters.

A management or harvest strategy is made up of at least three components: 1) the monitoring data, 2) the assessment or empirical performance measures (PMs), and 3) the harvest control rule or rules (Smith *et al*., 2008; Haddon et al., 2014). In addition, there may be pre-agreed responses to what may be termed ‘exceptional circumstances not envisaged in the formal harvest strategy (for example a mortality event brought about perhaps by a warm water event). Also there may be meta-rules developed that may be used to temper the strict application of a harvest control rule should it unintentionally lead to highly disruptive management advice. In some abalone fisheries a formal mathematical integrated stock assessment model of a fishery’s dynamics has been produced in attempts to understand the current state of the stock (Worthington *et al*., 1999; Gorfine *et* *al*., 2005; Fu, 2012). However, such stock assessment models are known to be weak at capturing the details of spatial structuring in any population (Punt *et al*., 2015; Punt *et al*., 2016) and the extreme spatial structure exhibited in abalone fisheries has yet to be captured appropriately in any stock assessment model that has been applied to a large geographical area. At best they provide an approximation to the stock dynamics simply because they summarize across the large amounts of variation present in any extensive area of an abalone fishery. Instead of developing such a stock assessment model for Tasmania it was instead decided to adopt the use of multi-criteria decision analysis (MCDA), which is an approach that derives from operations research. MCDA is often used where there are multiple sources of information that need to be integrated when making decisions that involve possibly conflicting objectives. Within fisheries management, the use of MCDA is a tool used to apply a harvest strategy rather than it itself being a specific harvest strategy (Mundy *et al*. 2015). Currently, the proposed abalone harvest strategy in Tasmania is being trialled in parallel with the current approach to providing management advice on abalone TAC setting.

9.2 The Use of Proxies

In the mid-1990s a number of highly influential documents for fisheries management were published by the FAO, including: the *Code of Conduct for Responsible Fisheries* (FAO, 1995), the *Precautionary Approach to Capture Fisheries* (FAO, 1996), and *Fisheries Management* (FAO, 1997); these latter two documents being parts of the *Technical Guidelines for Responsible Fisheries* series. The *Guidelines* appear to be some of the first documents to describe the components of what are now referred to as Harvest Strategies (Haddon et al., 2015). The need for *targets*, described as the desired outcomes (or desirable state) for a fishery, *limits*, described as undesirable outcomes that are to be avoided, and *harvest control rules* which specify in advance what action(s) should be taken when specified deviations from the operational targets and limits are observed, were all identified explicitly (FAO, 1996; Caddy and Mahon, 1995; Caddy and McGarvey, 1996). The most common approach to the definition of formal harvest strategies can be traced back to work by Serchuk et al. (1997) and Restrepo et al. (1998) who used harvest control rule diagrams that have spawning stock biomass on the x-axis and some measure of fishing mortality on the y-axis. These documents were the origins of using spawning or mature biomass and fishing mortality as the fishery performance measures of choice and for setting limit and target reference points (Smith et al, 2008).

As previously discussed the use of formal, integrated stock assessment models can only provide approximate estimates of the current state of a stock if at all. Their use can provide inappropriate levels of confidence that the current state is known. The relatively extreme spatial heterogeneity exhibited by abalone populations and abalone fisheries means that most abalone fisheries are effectively data-poor even if a large amount of information is available. What this means is that insisting on the use of spawning biomass or fishing mortality as the basis for reference points is only likely to lead to disappointment and errors because such things can only be estimates, if at all, with a great deal of uncertainty. Instead, there is a need to develop suitable proxies to stand in for both stock biomass and fishing mortality. This is where the use of empirical performance measures enters the assessment and management process.

When direct estimates of changes in stock biomass and in fishing mortality are not available or feasible then the implications of such changes need to be considered. Changes in biomass and mortality are normally reflected in aspects of the fishery which can be observed. For example, there are implications for the size composition of catches, for the localized geographical distribution of catches, and for the catch-rates, among other properties of the fisheries. Not only are there changes to the absolute values of some of these measures but also their rates of change when measured consistently through the years. Thus, for example, if catch-rates are considered to be a plausible index of relative abundance through time then if a time-series of CPUE is increasing or decreasing slowly or rapidly not only would the actual value of CPUE be suggestive of the relative stock biomass (compared to some other period) but the rate of change of that CPUE would provide an indication of how fishing mortality was changing through time. Thus, if CPUE was increasing rapidly and it was a reasonable index of relative abundance then one could conclude that fishing mortality must have been reducing. It may be the case that instead of the actual rate of change of fishing mortality only the direction of change would be known, nevertheless, this is better informed than only having anecdotal information about the stock. It is possible to develop criteria to aid in the identification of potential empirical performance measure that might be suitable to act as a potential replacement or proxy for the more classical sources of reference points (**Table 16**).

Table 16. Possible criteria for the identification of performance measures that can potentially act as proxies for stock biomass or fishing mortality

With regard to proxies for stock biomass (either exploitable or spawning biomass):

- The performance measure needs to exhibit contrast across different stock levels
- The performance measure needs to exhibit consistent changes through time in how it reflects stock changes.
- There needs to be a strong relationship between the level of a performance measure and the state of the stock.

With regard to proxies for fishing mortality:

- The performance measure or its rate of change across years needs to reflect changes made to the fishery and its management.
- The performance measure needs to exhibit consistent changes through time in how it reflects changes in exploitation rate.

Such proxies can be used in the same way as the more classical spawning biomass and fishing mortality performance measures, however, as proxies they require further articulation. Thus, there has been extensive debate over what level of spawning biomass to accept as a target and limit reference point; these are termed biological reference points for this reason. Proxy performance measures are fishery reference points that are only correlated with the biological reference points. If one selects a CPUE target and limit reference point and CPUE is an acceptable index of relative abundance for the species concerned then the fishery reference points will behave just as well as true biological reference points. But they can be no guarantee that a CPUE target reference point exactly matches a particular biological reference point that might be defined in a harvest strategy policy (DAFF, 2007; Haddon, 2014; Haddon et al, 2015).

An excellent way of illustrating the current state and status of a stock is to plot the trajectory through time of the estimated performance measure selected for use as a proxy for stock biomass against the trajectory of the proxy for fishing mortality. In the case of CPUE, and or perhaps the total MCDA score for abalone, some measure of the rate of change of the biomass proxy performance measure in response to changes in fishing intensity could be used as a form of proxy for the impact of fishing mortality. As stated before, if catches rise and CPUE declines this implies that fishing mortality is too high (and vice versa). This suggests that if CPUE changes or the gradient of CPUE changes are negative then the stock is declining due to mortality being too high; and visa-versa if CPUE is rising consistently then fishing mortality is presumably reduced and the stock size is increasing. By defining a limit reference point and using the change rate in the performance measure as a different proxy a phase plot can be produced that captures the dynamics of the stock's status over time (**Figure 50**).

This is a simple way of illustrating where a stock stands and whether it is headed in the right direction (Haddon and Penney, 2016).

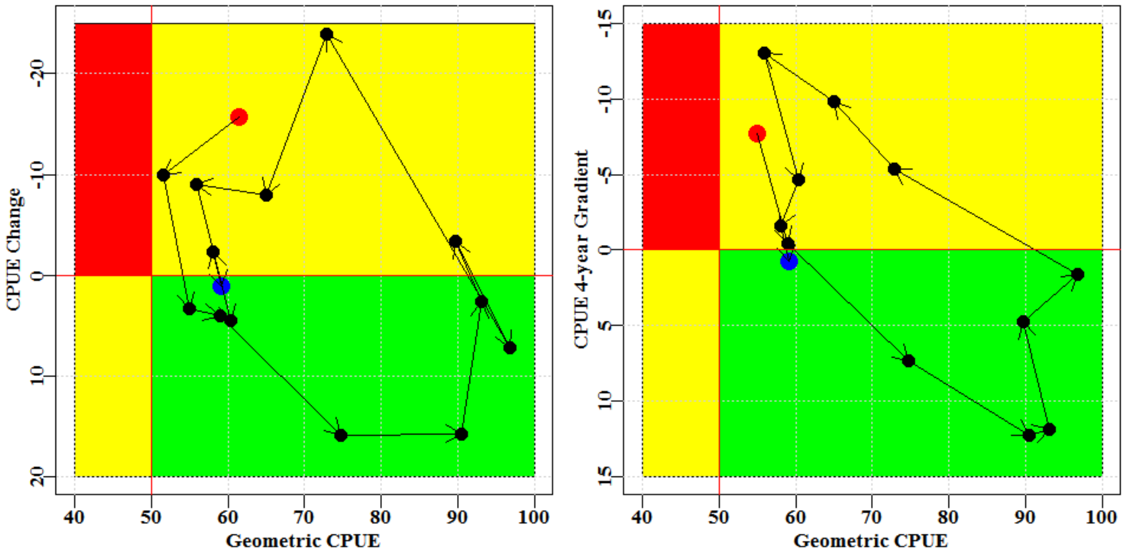

Figure 50. Alternative ways of representing the phase plot of stock status when using, for example, geometric mean CPUE as a proxy (only the y-axis differs). The red dots are the starting years (2001 and 2003 left and right) and the blue are the end years, 2015 in both cases. The left hand panel has the absolute change in CPUE as the y-axis acting as a proxy for fishing mortality, or the impact of fishing mortality, while the right hand panel uses a 4-year moving gradient of CPUE through time. Both produce qualitatively the same outcome (data relate to an abalone zone in Tasmania).

9.3 Management or Harvest Strategies

A formal management or harvest strategy is made up of at least three components: 1) the monitoring data, 2) the assessment or empirical performance measures (PMs), and 3) the harvest control rule(s). When using empirical harvest strategies (eHS), that entail no formal stock assessment, generally the performance measures themselves constitute the assessment of the relative stock condition and placing them directly into a harvest control rule determines the current state of the stock (**Figure 51**; we use the phrase 'current state of the stock' because the phrase 'stock status' has come to mean something else relating to pre-defined states of the stock; Flood et al., 2014; Patterson et al., 2015). The use of the MCDA means that the empirical harvest strategy can combine an array of time-series of specified fishery performance measures into a single total fishery performance score. For example, classical CPUE data or the fine-scale spatial information from the GPS data-loggers, implemented as a number of potential spatially explicit fishery performance measures, can be included into the system in the form of stock or fishery monitoring data.

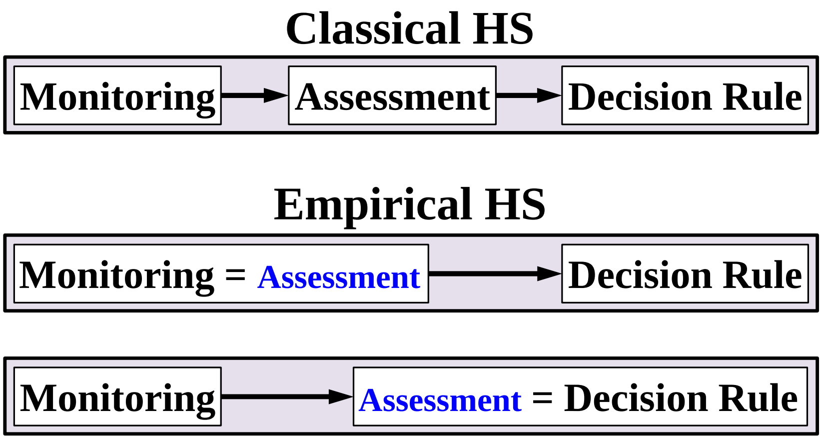

Figure 51. A simple structural comparison of a classical or three part harvest strategy (HS) with the analogous empirical HS (eHS).

In the simulation framework within the MSE the eHS is implemented using a multi-criteria decision analysis (MCDA) and for the initial testing three different performance measures (PMs) were implemented and combined by the MCDA to generate a single state of the stock score, which is then translated using a harvest control rule to provide advice on the specific expected catches per block within a zone. As with the current approach, the recommended zonal TAC then becomes the sum of the proposed expected block catches.

A harvest strategy (HS) within the context of the MCDA consists of the Performance Measure(s) (PM; equals the time series of data with empirical HSs), the assessment (a score determination for each PM, which are then combined in the MCDA into a single total score), and the Harvest Control Rule (HCR; translation of the score to an expected catch or the expected catch adjustment for each block). The use of the MCDA allows the use of multiple empirical performance measures by combining their separate scores (based on an array of different scales and measurement units) into a single final MCDA score for the current state of the stock. The combination of the different performance measures provides an opportunity to give each performance measure a different weight so as to place different emphasis on each (this includes a weight of zero, which would effectively turn off that PM). Once the final score is obtained for each block it is used in a harvest control rule (HCR), which, in this case, is simply a tabulation of the final MCDA score against a schedule of TAC adjustments relative to the expected catch obtained from each block. In this way if a block performs poorly then the expected catch from that block will be reduced and visa-versa if he block performs well. Once this process is applied to all blocks within a zone then the sum of the adjusted expected catches across all blocks makes up the TAC for a given zone.

This project uses the simulation model (see Chapter 10.3 The Size-Based Operating Model at page 159) to compare the relative performance of combinations of different performance measures, different weights applied to those performance measures, and finally different TAC adjustment schedules used with the final scores. By characterizing the behaviour of the possible empirical harvest strategies at very least those combinations that give rise to ineffective or highly variable outcomes can be avoided, while at best those combinations that appear to optimize outcomes relative to different objectives can be identified prior to deciding which to adopt.

9.4 Block Based Performance Measures

9.4.1 Introduction

Each block within a zone can be expected to have different long term productivity and each zone-wide TAC is made up of the recommended or expected catch to be taken from each of the zone's blocks. The catch taken each year from each block is adjusted using the harvest control rule based on the Multi-Criteria Decision Analysis (MCDA), which currently uses three different performance measures. The adjusted catches are then summed and this leads to a new TAC recommendation each year (or however often the assessment process is conducted). A question arises about exactly what catch from the block should be modified: the catch expected to be taken (that is the catch expected when the TAC was set) or should it be the actual catch taken in a given year? Past experience demonstrates that the actual catch can be rather different from the expected catch. Both options can be explored but initially efforts will focus on applying the TAC adjustment coming out of the MCDA analysis to the catch expected to be taken in each block in each year. This approach would reduce the TAC by levels more appropriate to any over-exploitation within a block. If, for example, the catch taken from a block were more than double that which was expected and this was reflected in poorer performance, then the proportional reduction would be on the expected catch rather than that which was actually taken. Thus, if the expected catch were 50 tonnes but 100 t were taken and this led to a recommendation of a 20% reduction then the effect would be that the expected catch would reduce to 40t. If the actual catch was used, with the TAC adjustment to set the next years' expected block catch it would in fact increase to 80t. This is not an arbitrary example, in 2015 during the process of closing block 11, which takes at least two weeks, the block was fished beyond its expected catch by 100 tonnes; which also illustrates the potential fishing capacity of the Tasmanian fleet.

Each of the performance measures used are designed to generate scores between 0 – 10. These are combined by multiplying each PM by a relative weight and summing the combined scores. The weights for each performance measure need to sum to 1.0; thus, for example, if given equal weight these weights could be 0.333, 0.334, and 0.333.

9.4.2 Rate1: Proportional CPUE change between Successive Years

The objective of the scoring function based on this performance measure is to recommend positive increases in the TAC if there are rapid increases in CPUE between pairs of years and conversely recommend decreases in the TAC if there are rapid decreases in CPUE. This was developed because such rapid changes are occasionally seen in the real fishery. Setting $CE_{b,y}$ as the CPUE in block b in year y, this is used to calculate the performance measure rate1:

$$rate1 = \left(\frac{CE_{b,y}}{CE_{b,y-1}} - 1 \right) \qquad (23)$$

The output is designed to provide a score between 0 – 10, so assuming a symmetric distribution of scores around the changes in CPUE (**Figure 52**), given an expected maximum percentage increase or decrease of *a* or –*a* between years, this can be translated to a score as:

$$score = \frac{5}{a} \times rate1 + 5 \qquad (24)$$

Limits constrain the score between 0 – 10 but if these limits are often reached then the range of potential changes (*a* to -*a*) would need to expand. Initially a range of changes from -40% – 40% will be used. This makes it equivalent to the CPUE gradient HCR score calculations but based over a single year.

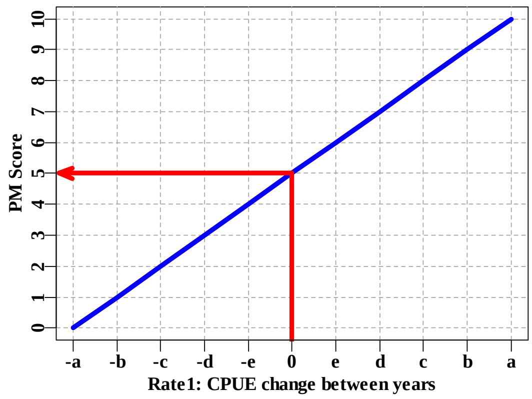

Figure 52. Illustration of the translation of a rate1 value (inter-annual change in CPUE) into an MCDA score. This is general for a range of rate1 changes from a maximum of *a* to a minimum of -*a*. The typical range of CPUE will vary depending on where the fishing occurs.

With all of the performance measures it is important to match the scale (range of expected values) of the performance measure against those observed in the real fishery, or at least to select the range to reflect acceptable values. If inappropriate values for the x-axis scale are selected then the resulting score could become uninformative. For example, if too wide a scale were used relative to that which actually occurs then observations will tend to fall mainly in the middle of the distribution and scores varying around 5 will occur. If the scale used is too narrow then the scores expected will tend to hit the bounds up at 10 and down at 0 too often.

9.4.3 Grad4: CPUE Gradient HCR

The objective of this scoring function is to recommend positive increases in the TAC if the gradient of CPUE against a given number of years increases and conversely it recommends decreases in the TAC if that CPUE gradient becomes negative. The assumption is that CPUE reflects the relative stock abundance so that changes in CPUE through time need to be converted to proportional changes through time otherwise areas of different productivity would be treated differently.

$CE_{b,y}$ is the CPUE in block b in year y, and $pCE_{b,y:z}$ is the proportional change of CPUE in year y relative to year z. If w years are used as the comparative period then $z = y_0 - w - 1$, where y_0 is the current year, thus if w is four years $z = y_0 - 3$.

$$pCE_{b,y-x:z} = CE_{b,y-x} / CE_{b,z} \quad x = 0..w-1 \tag{25}$$

The performance measure is the gradient of the linear regression between the $pCE_{b,y}$ and the sequence 1..w:

$$pCE_{b,y} = const + grad \times y \tag{26}$$

Once again the output is to provide a score between 0 – 10, so assuming a symmetric distribution of scores around the changes in CPUE (**Figure 53**), given an expected maximum percentage increase or decrease of a or $-a$ between years, this can be translated to a score as:

$$score = \frac{5}{a} \times grad + 5 \tag{27}$$

Limits constrain the score between 0 – 10 but if these limits are often reached then the range of potential changes (a to $-a$) would need to expand. Initially a range of gradients from -0.2 – +0.2 was used (i.e. $a = 0.2$).

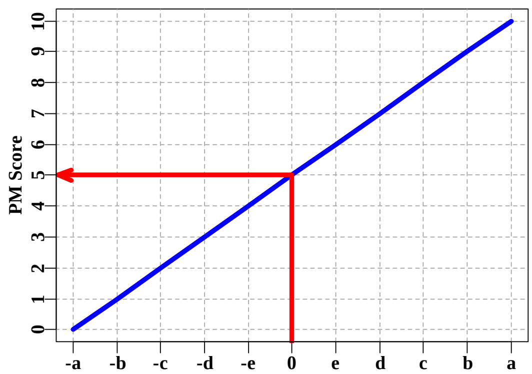

Figure 53. Illustration of the translation of CPUE gradient across four year into an MCDA score. Empirically, in Tasmania, for separate blocks this ranges from a maximum of +0.2 to a minimum of -0.2.

As with Rate1 the scale of the x-axis needs to reflect the real fishery so that a distribution of values is expected rather than being centred tightly around 5 or clustered up and down at 10 or 0. Of course, after application of a harvest strategy for long enough the expectation is that the fishery would achieve some approximate balanced equilibrium and at the point one would expect the scores to centre, hopefully tightly, around 5.

9.4.4 TargCE: CPUE Target

The objective of this scoring function is to recommend positive increases in the TAC if the CPUE in a year is greater than the pre-defined target and conversely to recommend decreases in the TAC if the CPUE is below the target.

$CE_{b,T}$ is the target CPUE in block *b*, and ΔCE, when added or subtracted from $CE_{b,T}$ is the upper and lower bounds of CPUE expected in block *b* in the fishery. Thus if the $CE_{b,T}$ = 110kg/hr with a ΔCE of 50kg/hr the range of CPUE for which scores are defined would be between 60 – 160 kg/hr. Given $CE_{b,y}$ is the CPUE in block *b* in year *y* then:

$$score = \left(\frac{5}{\Delta CE}\right) CE_{b,y} + \left(5 - \frac{5}{\Delta CE} CE_{bT}\right) \tag{28}$$

It is important to note the difference between the actual CPUE in a year, $CE_{b,y}$, and the target CPUE, $CE_{b,T}$. When the two are the same then, as designed, the score would be 5. This is a general relationship for all combinations of target CPUE and ΔCE, given the assumptions that $CE_{b,T} > \Delta CE$, and that both are always positive.

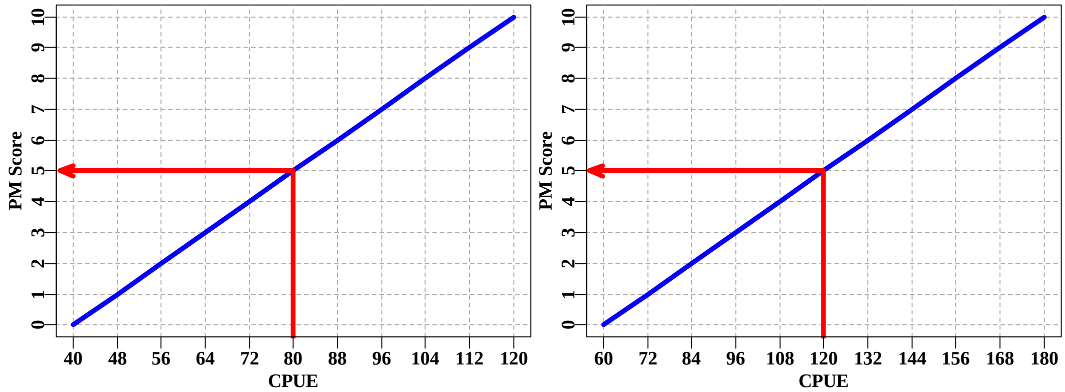

Figure 54. Illustration of the translation of an observed CPUE relative to a defined target CPUE into an MCDA score. Two instances are shown, the $CE_{b,T}$ are 80 and 120 kg/hr and the ΔCE are 40 and 60 kg/hr respectively.

Just as with the Grad4 and Rate1 PMs, the scale of the x-axis needs to reflect the real fishery so that a distribution of values is expected rather than being centred tightly around 5 or clustered up and down at 10 or 0. An effect of the relative weights attributed to the different performance measures is to alter the frequency of the different scores in any sequence of, for example, 1000 simulation runs (**Figure 55**). Using a weight of 0.5 on the TargCE PM leads to fewer scores above 5 than with a weight of 0.25. The effect of changing the Grad4 weight from 0.25 to 0.5 was far less. Of course, after application of a harvest strategy for long enough the expectation is that the fishery would achieve some approximate balanced equilibrium and at that point one would expect the scores to centre, hopefully tightly, around 5.

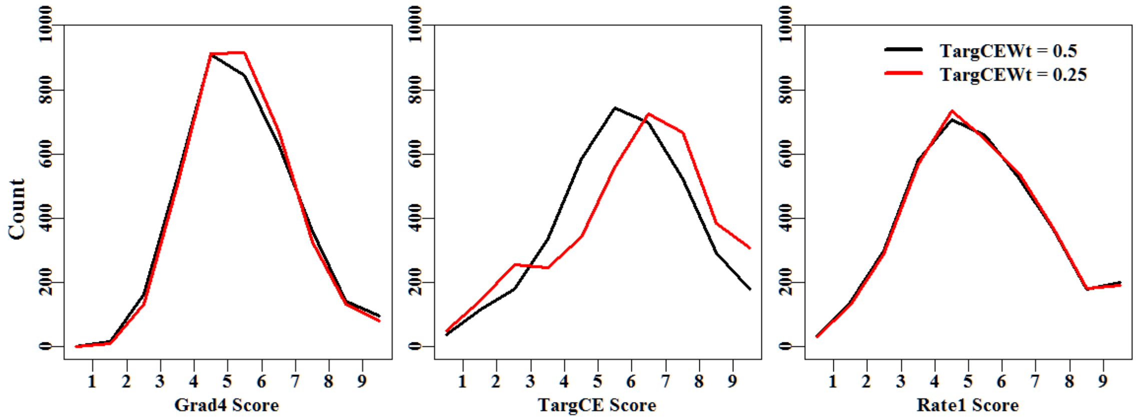

Figure 55. A comparison of the relative frequency of different scores from 1000 iterations of each scenario reflecting the different trajectories taken on by giving the different performance measures the weight Grad4 = 0.25, TargCE = 0.5, and Rate1 = 0.25 or Grad4 = 0.5, TargCE = 0.25, and Rate1 = 0.25. The difference being the weights attributed to the Grad4 and TargCE PMs. In this case the range on the Grad4 x-axis was from -0.2 to 0.2, on the TargCE x-axis was from 55 – 145 centred on 100, and on the Rate 1 x-axis a gradient range from -0.4 to 0.4. These values were used in all subsequent scenarios.

9.4.5 Relative Weightings

The MCDA procedure provides a means of combining estimates of multiple performance measures (PMs) relating to a particular fishery to produce a single combined score that would work within a single harvest control rule (HCR). Each scoring function described above relates to a different (though in this case related) performance measure. By combining them into a single score different facets of CPUE can be treated as different PMs and a more complete understanding of how stock changes affect CPUE can be obtained. Combining the various PMs adds an extra level of flexibility because the different PMs can be given different weightings (**Table 17**). Given 2 different assessment intervals (every 1 or 2 years; see Chapter 8 Frequency of Management Intervention for explorations involving 1, 2, 3, or 4 years) and two different TAC adjustment schedules a total of 56 scenarios were fully investigated. Many more scenarios were explored to provide a guide for where to place emphasis. For example, a preliminary analysis of an array of combinations of weights were used where one or other of the three performance measures was effectively omitted by setting its weight to zero. This quickly led to a conclusion that a target CPUE was required to prevent an on-going decline in catches and increase in spawning and exploitable biomass. Only abbreviated aspects of that work are presented here as we focus on combinations that are of potential value (**Table 17** and **Table 18**).

9.4.6 Converting the Overall Score to a TAC

The outcome of the MCDA is a final combined score across the three performance measures. To be applied to the management of a stock this final score needs to be converted into management advice concerning potential changes to the expected catch in each block, the modified values of which would be summed to obtain the final TAC recommendation. The combined score is a weighted mean of the three separate scores (as many scores as there are performance measures; in this case three), with the weights being tested by MSE and agreed by the fishery resource assessment group. The final score always lies between 1 – 10 and is converted into a catch adjustment multiplier using an agreed upon scale. Thus the scores are classified into categories and different percentage changes to the expected catch from each block are then recommended (**Table 18**). The process can be conducted each year, or relative to any selected time frame over which the performance measures might operate (**Figure 58**).

9.4.7 Meta-Rules

It should be noted that, in Tasmania, there are also meta-rules under discussion which would act as modifiers to some of the mechanics of the harvest control rules. For example, between 2009 and 2012, a sharp and extreme decline in CPUE and annual catch was observed in Block 27 in the Freycinet region (**Figure 56**), prompting consideration to close this area to commercial fishing. While it was acknowledged that severe action was warranted, the Industry preference was to substantially reduce fishing pressure, but allow some fishing to gauge recovery. This view led to a management decision as follows for the area of concern;

1) An increase in the LML from 138mm to 145mm.
2) A reduction in catch to 5t (approximately 90%).

This concept has since been coined the 'Freycinet Principal' and is perhaps the best illustration of industry recognition that severe action was required when a conceptual lower limit in the fishery was reached. Subsequent development in the MCDA Harvest Strategy and the need to have defined limits and actions was facilitated by this recent experience.

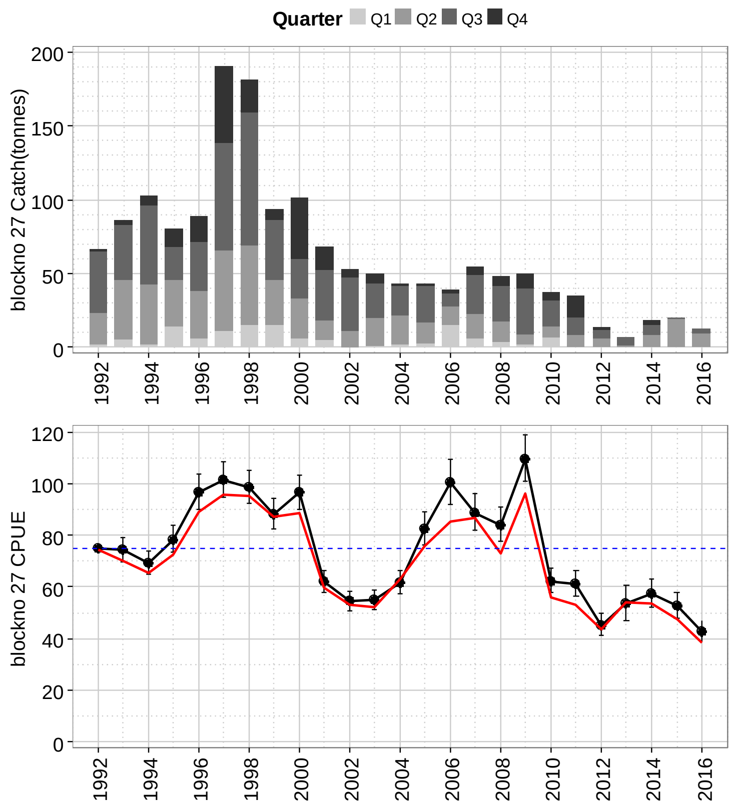

Figure 56. Catch and catch rate history for Eastern Zone Block 27. Shaded bars in the top figure represent catches across quarters of the year. Red line represents bias-corrected geometric mean CPUE and the black line represents standardised CPUE.

Table 17. 56 scenarios of different combinations of weights for the three performance measures combined with assessment intervals of 1 or 2 and block catch adjustment schedules 1 or 2 (see **Table 18**); many other scenarios were considered but these were illustrated. The performance measures are the CPUE gradient over four years, the target CPUE, and the Rate1 is the CPUE gradient between two consecutive years.

initDepl	AssessInt	Schedule	Grad4	Targ	Rate1	initDepl	AssessInt	Schedule	Grad4	Targ	Rate1
0.25	1	1	0.5	0	0.5	0.25	2	1	0.5	0	0.5
0.25	1	2	0.5	0	0.5	0.25	2	2	0.5	0	0.5
0.25	1	1	0.98	0.01	0.01	0.25	2	1	0.98	0.01	0.01
0.25	1	2	0.98	0.01	0.01	0.25	2	2	0.98	0.01	0.01
0.25	1	1	0.6	0.1	0.3	0.25	2	1	0.6	0.1	0.3
0.25	1	1	0.3	0.1	0.6	0.25	2	1	0.3	0.1	0.6
0.25	1	2	0.6	0.1	0.3	0.25	2	2	0.6	0.1	0.3
0.25	1	2	0.3	0.1	0.6	0.25	2	2	0.3	0.1	0.6
0.25	1	1	0.6	0.2	0.2	0.25	2	1	0.6	0.2	0.2
0.25	1	2	0.6	0.2	0.2	0.25	2	2	0.6	0.2	0.2
0.25	1	1	0.5	0.25	0.25	0.25	2	1	0.5	0.25	0.25
0.25	1	1	0.25	0.25	0.5	0.25	2	1	0.25	0.25	0.5
0.25	1	2	0.5	0.25	0.25	0.25	2	2	0.5	0.25	0.25
0.25	1	2	0.25	0.25	0.5	0.25	2	2	0.25	0.25	0.5
0.25	1	1	0.6	0.3	0.1	0.25	2	1	0.6	0.3	0.1
0.25	1	2	0.6	0.3	0.1	0.25	2	2	0.6	0.3	0.1
0.25	1	1	0.25	0.5	0.25	0.25	2	1	0.25	0.5	0.25
0.25	1	1	0.4	0.5	0.1	0.25	2	1	0.4	0.5	0.1
0.25	1	2	0.25	0.5	0.25	0.25	2	2	0.25	0.5	0.25
0.25	1	2	0.4	0.5	0.1	0.25	2	2	0.4	0.5	0.1
0.25	1	1	0.2	0.7	0.1	0.25	2	1	0.2	0.7	0.1
0.25	1	1	0.1	0.7	0.2	0.25	2	1	0.1	0.7	0.2
0.25	1	2	0.2	0.7	0.1	0.25	2	2	0.2	0.7	0.1
0.25	1	2	0.1	0.7	0.2	0.25	2	2	0.1	0.7	0.2
0.4	1	1	0.5	0.25	0.25	0.55	1	1	0.5	0.25	0.25
0.4	1	2	0.5	0.25	0.25	0.55	1	2	0.5	0.25	0.25
0.4	2	1	0.5	0.25	0.25	0.55	2	1	0.5	0.25	0.25
0.4	2	2	0.5	0.25	0.25	0.55	2	2	0.5	0.25	0.25

Table 18. The two expected catch adjustment schedules for translating the combined MCDA scores from all performance measures into expected catch multipliers for each block. The catch multiplier is applied to the expected catch from each block and the total for a zone summed to generate the new TAC (**Figure 58**). Option 2 is asymmetric in the TAC adjustment levels as well as having fewer and sometimes larger jumps.

Score Opt 1	< 0.5	0.5–1.5	1.5–2.5	2.5–3.5	3.5–4.5	4.5–5.5	5.5–6.5	6.5–7.5	7.5–8.5	8.5–9.5	> 9.5
Expected Catch Multiplier	0.75	0.8	0.85	0.9	0.95	1	1.05	1.1	1.15	1.2	1.25
%Change	-25	-20	-15	-10	-5	0	5	10	15	20	25
Score Opt 2		<1	1 – 2	2 – 3	3 – 4	4 – 6	6 – 7	7 – 8	8 – 9	> 9	
Expected Catch Multiplier		0.25	0.8	0.85	0.9	1	1.05	1.1	1.15	1.2	
%Change		-75	-20	-15	-10	0	5	10	15	20	

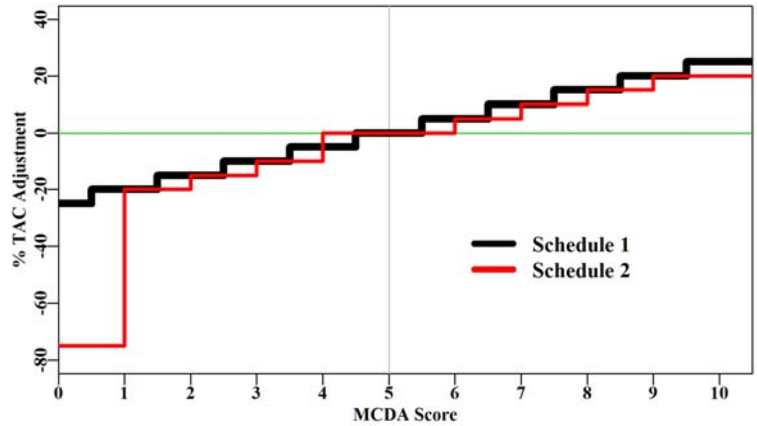

Figure 57. A visual depiction of the two expected-Catch Adjustment Schedules. They are staggered relative to each other because schedule 1 is calculated through truncating the final combined score plus 0.5 so that the block catch adjustment is centred on unit scores, while Schedule 2 directly truncates the final combined score and so changes at the unit scores.

9.5 Fishing a Simulated Abalone Zone

The essence of the management strategy evaluation is that a simulated abalone zone can be manipulated into different initial conditions of depletion and then fished for a given number of years under those different initial conditions along with different management arrangements (harvest strategies) in place. Each combination of zone parameters, initial depletion status, monitoring data, performance measures, control rules, initial TAC, and LML constitutes a single scenario. The simulations are repeated many times for each scenario chosen (generally 1000 times) and in this way comparisons of the distributions of outcomes of interest can be compared.

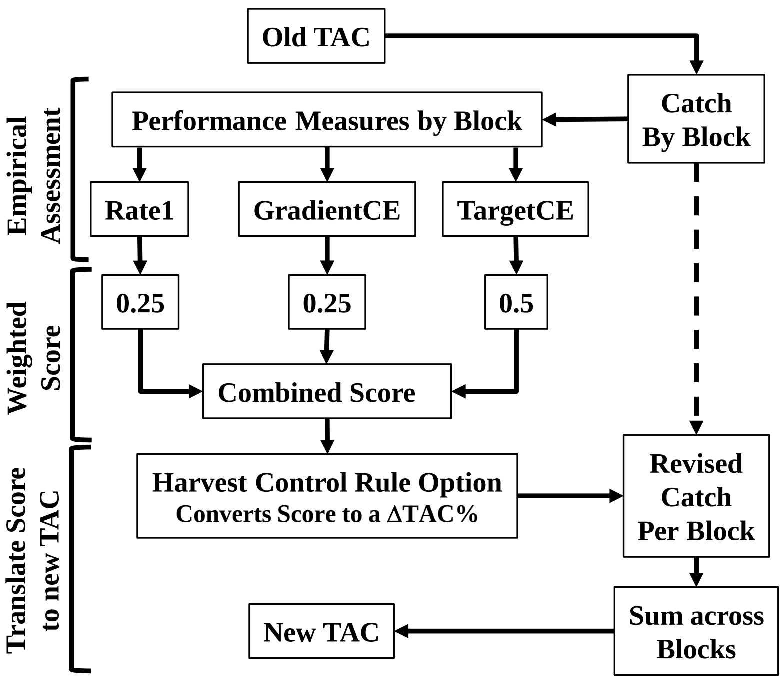

Figure 58. The process employed when applying the MCDA analysis of the three performance measures from each block. The different weights applied to the score from each performance measure are just an example but the important thing is that they all add to 1.0. The Catches per Block can be the expected or the observed catches; in the following the observed catches were used.

9.5.1 Sources of Variability

An essential part of the MSE process is to include variation in the dynamics being modelled. In this present case, the variation expected in observed catch rates and how catch rates are expected to vary relative to exploitable biomass, equation (29), the inherent variability of how catches are distributed among separate areas, equation (30), and the inherent variability in the recruitment, equation (31) all need to be pre-defined. In addition, it is possible to vary such things as the linearity or otherwise (λ) of the relationship between exploitable biomass and catch rates.

In the Tasmanian abalone fishery a linear relationship between catch-rates and catches, and hence with effort, is often observed (Haddon *et al*, 2013). Because of this, and the fact that when catches increase in an area CPUE eventually decreases, and when catches decrease CPUE eventually increases, catch rates are assumed to have some influence over the distribution of catches among areas. Observed catch rates (*CE*) would naturally be expected to be variable and so are modelled as:

$$CE = q_{t,a} B_{t,a}^{\lambda} e^{N(0,\sigma_q)} \tag{29}$$

where $q_{t,a}$ is the catchability coefficient exhibited in year *t* in area *a*, $B_{t,a}^{\lambda}$ is the exploitable biomass in area *a* at time *t*, with a non-linearity coefficient of λ, $e^{N(0,\sigma_q)}$ is a log-normal random deviate, and σ_q is the standard deviation of the catchability coefficient *q*; if λ is set equal to one then the relationship between catch rates and exploitable biomass is linear; this is the standard assumption in this work and alternatives have yet to be investigated.

Given a TAC then in any given year catches will be distributed as expected catches among the different blocks in the zone. Catch rates are often assumed to provide an index of relative abundance and thus, previous catch rates may be considered able to serve as a guide to where to fish in subsequent years. This is a reasonable assumption if the fishery regularly leaves behind a significant proportion of the legal sized animals. However, catch rates in one year do not give any indication of the availability of undersized animals that are expected to grow into the fishery. In abalone fisheries that are being fully exploited, which includes all of them, the advent of new recruits will be an important component of each year's fishery. Fortunately, the abalone fishery depends on divers literally handling their catch and this automatically provides them with an opportunity to identify those areas that would be expected to be productive in the next year and also those areas that would be expected to become less productive. Their own observations would be made with some error and discussions among divers would also rarely be precise. Such diver expectations give an indication of exploitable biomass and the expected variation is included in an algorithm for distributing catches by block:

$$C_{t,a} = TAC \frac{B_{t,a} e^{N(0,\sigma_b)}}{\sum_{a=1}^{n} B_{t,a} e^{N(0,\sigma_b)}} \tag{30}$$

where $C_{t,a}$ is the expected catch in block *a* in year *t*, TAC is the total allowable catch, and σ_b is the standard deviation of the catchability interpreted as the diver's observations on available biomass in the *n* areas assessed within the year in question.

The approach of first calculating the estimated biomass with error and then scaling it to the total ensures that the TAC is sub-divided among the blocks in direct proportion to those estimates made with error included. This reflects the system adopted in Dichmont *et al* (1999) and by Dichmont and Brown (2010) for distributing a TAC among areas. Their approach was related directly to catch rates (despite their equation implying a catchability coefficient of 1.0), however, the exploitable biomass is directly related to catch rates and so, especially with the random noise added to the biomass values this can adequately drive the distribution of catches.

As these proxies are for the diver perception of relative abundance they automatically include their knowledge of catches and catch rates from previous years. This approach can be used directly on the separate populations or, more in line with how the zones are managed, to collections of populations, known as statistical reporting blocks in Tasmania or Spatial Assessment Units (SAUs) more generally. It would be expected that as σ_b increased, the ability of divers to appropriately distribute catches between areas would decline which would, in turn, be expected to lead to poor outcomes for the fishery in terms of depletion levels within blocks.

Finally, recruitment variation is included here and indeed is important in all fisheries. Abalone populations around Tasmania certainly exhibit recruitment variability but there have also been observed occasional exceptionally large recruitment events. One such was observed on post-larval settlement plates in April 1991 where the count was approximately 1915 per m^2 rather than values between 10 – 80 m^2 (Nash *et al.*, 1995). Despite such exceptional events, recruitment variability in the operating model used steepness, *h*, the estimate unfished recruitment levels, R_0, and the current mature biomass, B_t^M (Haltuch et al., 2008), and expressed variation as:

$$N_{t,0} = \frac{4hR_0B_t^M}{(1-h)B_0 + (5h-1)B_t^M} e^{\varepsilon_t - \sigma_R^2/2} \tag{31}$$

The $\varepsilon - \sigma_R^2/2$ term is there to allow for bias in the log-normal relationship so that the simulated recruitments relate to the median of the distribution rather than the mode (see chapter 10 The Size-Based Operating Model). The option of including exceptional events was also coded and could occur between 0 – 5 % of the time as, empirically, in Tasmania, exceptional zone to State wide recruitment events have occurred about once every 25 years of so. But for the main runs of the MSE the assumption was made that such exceptional events did not occur in the projections.

9.6 Initiating the Analyses

The primary objective of the MSE is to compare the relative effectiveness of alternative combinations of management options and this is done by projecting the population forward with catches controlled by each alternative management strategy in turn. An important consideration is in what stock condition to begin the projections (**Figure 59**). The pre-projection state of the stock can be depleted or unfished so the MSE frameworks may be initiated to begin from the unfished state or possibly from a given depletion level. The latter may be used to determine how each harvest control rule (HCR) performs if the stock begins in a depleted state, at the target, or above the target. With abalone, however, it was deemed unlikely that any stock would ever be only lightly fished so the option of determining how well the different harvest strategies would control a fish down from only a lightly depleted state was omitted here.

9.7 Measuring Harvest Control Rule Performance

The simulations give rise to 1000 replicate population trajectories through the simulation time period. The total period used is fifty years with the first five years fished at about the constant catch that should leave the stock in the same state as it is initiated (**Figure 12** and **Figure 60**). The Harvest Strategy (HS) is the set of fishery Performance Measures used as well as their respective weights within the MCDA and the schedule of TAC adjustment multipliers used to translate the MCDA score into a TAC change; no change is thus a deliberate decision. In each alternative scenario the HS is first applied in year 6 and continues for the next 45 years. In reality, it is not expected that any HS introduced in the immediate coming years will still be used unchanged after the first review of actual performance (until more is known it is suggested that a review be conducted at least every five years). Even so, it is useful to examine the dynamics over a longer period because this makes it clear that large changes can take decades to come about in abalone stocks. While the long term behaviour is of interest, measuring the relative performance of the different HSs may be more relevant to current management if focused on shorter term changes. Six statistics were considered 1) The total catch over years 6 – 20, 2) zone-wide CPUE in year 20, 3) spawning biomass depletion in year 20, 4) the number of years to reach the CPUE target, 5) the proportion of replicates breaching TAC limits, and 6) the proportion of replicates reaching the CPUE target.

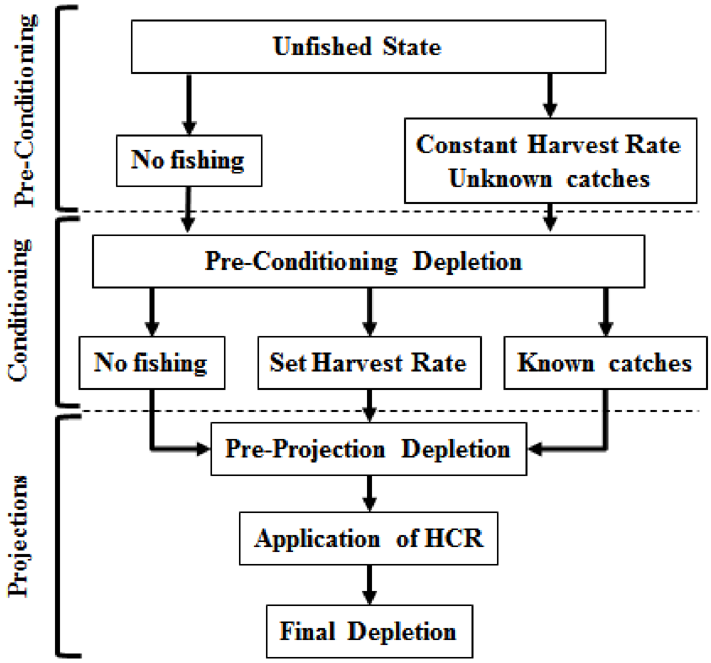

Figure 59. Diagrammatic representation of the generalized pathway through running an MSE. This includes options where the pre-projection depletion is the unfished state, a pre-determined depletion state, or the end result of known historical catches. The last two states derived from a pre-conditioning depletion state that was either in the unfished state or had experienced unknown historical catches represented by a selected harvest rate.

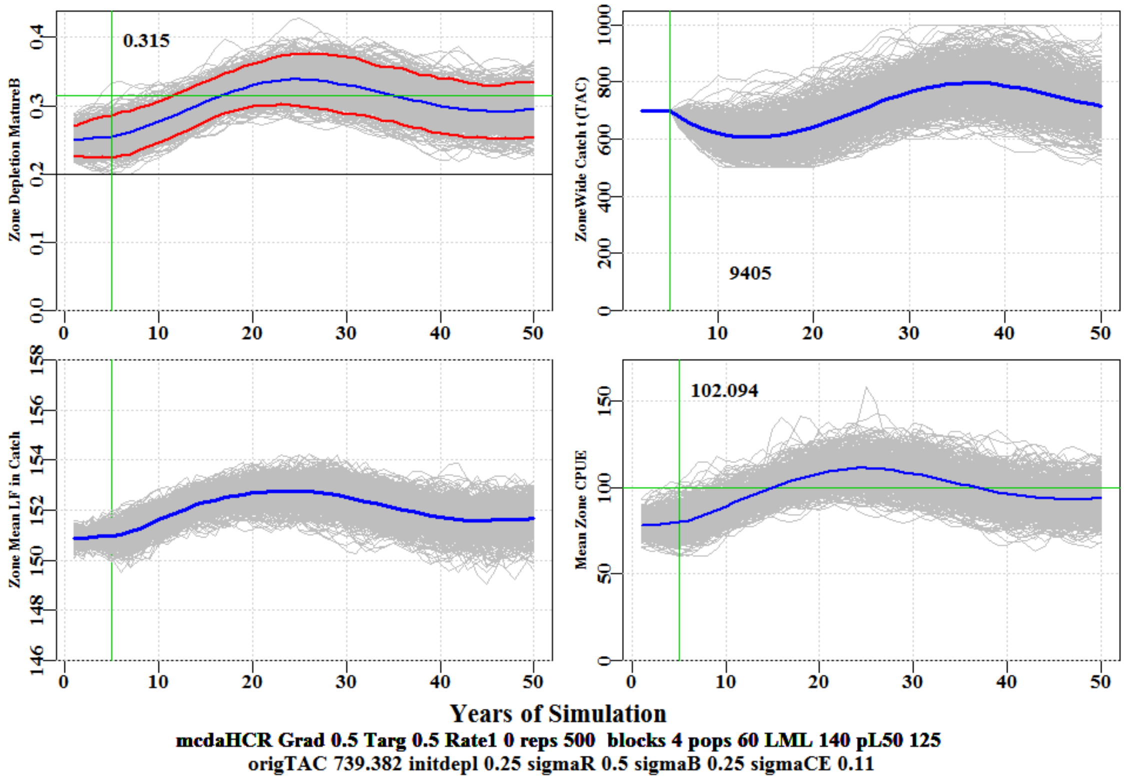

Figure 60. An example of a set of trajectory plots. Each consists of 500 replicates trajectories in grey, with the median values in blue, and the inner 90% of the zone depletion levels in red. The vertical green line indicates year 5 after which the HS comes into action. This case illustrates a weighting of 0.5 to the gradient CPUE and 0.5 to the Target CPUE (zero for the Rate1 PM).

9.7.1 Total Catch years 6 – 20

This is the total zonal catch over the first 15 years of applying the HS for each replicate:

$$Catch = \sum_{b=1}^{nblock} \sum_{y=6}^{20} C_{y,b} \tag{0.32}$$

where $C_{y,b}$ is the catch from block *b* in the simulated fishery in each year *y* in a fishery having *nblock* separate geographical blocks.

9.7.2 Zone-wide CPUE in Year 20

This is the observed block-catch-weighted CPUE for the simulated zone in year 20, which is 15 years after the introduction of the new harvest strategy:

$$\begin{aligned} totalC &= \sum_{b=1}^{nblock} C_{20,b} \\ CE_{Z,20} &= \sum_{b=1}^{nblock} \left[C_{20,b} / totalC \right] . CE_{20,b} \end{aligned} \tag{0.33}$$

where $C_{20,b}$ is the catch from block *b* in the simulated fishery in year 20, $CE_{Z,20}$ is the zone-wide catch-weighted catch-rate in year 20, and $CE_{20,b}$ is the catch rate observed from the fishery in block *b* in year 20.

9.7.3 Spawning Biomass Depletion in Year 20

As long as the LML remains constant there is also a stable relationship between spawning biomass and exploitable biomass; the latter is more important in fisheries where an LML is used. Year 20 is after 15 years of application of the HS.

$$SpB_D = \sum_{b=1}^{nblock} SpB_{D,20,b} \tag{0.34}$$

where $SpB_{D,20,b}$ is the spawning biomass depletion in year 20 from block *b* from the operating model.

9.7.4 Years to Reach CPUE Target

The rate of recovery relates both to the state of initial depletion as well as the particular details of the HS used; this is estimated by selecting the first year in which the observed zonal CPUE is ≥ the target CPUE, failing to reach the target returns a null result:

$$\begin{matrix} CE_{Z,1..50} \geq CE_{\text{Targ}} & Time = \min(year) \\ CE_{Z,1..50} < CE_{\text{Targ}} & Time = NA \end{matrix} \tag{0.35}$$

where $CE_{Z,1..50}$ is the CPUE observed across years 1 – 50 and min(*year*) is the first year the target is reached. In addition, the number of replicates that reach the target is recorded, which also provides the number of replicates that fail to achieve the target. The harvest strategy is only introduced after the first 5 years.

9.7.5 Proportion of Replicates Breaching TAC Limits

A meta-rule included in the HS is to have a minimum TAC below which it cannot go and, symmetrically, an upper TAC limit above which it is not allowed to go. These two statistics are merely a count of the number of replicates that meet these limits divided by the number of replicates. With the simulated zone here these limits were arbitrarily set at 500t and 1000t but in a real fishery they would need to be calibrated and decided upon if included as a meta-rule in the harvest strategy. Here they serve a secondary purpose of identifying when relatively extreme management actions are forthcoming from a harvest strategy. Breaches of the upper limit, if they occurred tended to occur beyond year 20 and it is expected that the empirical harvest strategy would be reviewed and adapted to changing conditions before then.

9.7.6 Proportion of Replicates Reaching the CPUE Target

The estimate of the time taken to achieve the CPUE target includes the possibility that a given replicate within a particular scenario might not reach the target throughout its 50 year trajectory. This statistic is simply a count of the number of replicates that reach the target divided by the number of replicates.

9.7.7 Graphical and Tabular Presentation

Each of the six measures of HS performance are plotted up as boxplots to illustrate differences between the scenarios considered (e.g. **Figure 63** and **Figure 65**). In addition, the trajectories of zone-wide catch, zone-wide CPUE, and spawning biomass depletion levels can be presented for individual scenarios (**Figure 60**; these present every replicate with the median illustrating the general trend). A much more limited number of randomly selected trajectories can also be plotted to illustrate the expected changes in the fishery as a contrast to the smooth trajectory predicted by the medians (e.g. **Figure 64**).

9.8 Results

9.8.1 Scenarios and Catches

There are four sets of variables that can have an effect on the predicted outcomes when applying the different harvest strategy scenarios. These are 1) the weighting given to the TargetCE PM, 2) the relative weights given to the Grad4 and Rate 1 PMs, 3) the assessment interval, and 4) the TAC adjustment schedule used; and some of these can interact. The relative weights given to the Grad4 and Rate1 PMs have less overall effect than that allocated to the targetCE. The targetCE weight was much more influential on the outcomes than the CPUE gradient weights. TargetCE weights were trialled across values of 0.7 down to 0.0 (the effect of zero weight on targetCE is illustrated in section 9.8.3 Omission of the TargetCE Performance Measure' from page 117). The larger the weight on the targetCE PM the greater and more rapid the effect of deviating from the target. At its strongest the targetCE PM would lead to oscillatory dynamics where catches and depletions levels would bounce above and below the equilibrium level. The quickest drop in catches and subsequent rise occurred with a weighting of 0.7, while with a weight of 0.1 on the targetCE the slowest declines occurred with minor increases above the minimum only occurring with the assessment interval of 1 year. Thus the dynamics moved from under-compensation to over-compensation. With assessment intervals of 2 years or with schedule 2, once catches were down they tended to remain down. So a weight of 0.1 was only a slight improvement over omitting the targetCE PM. Nevertheless, any weight on the targetCE from 0.2 upwards led to increases in catch following an initial decline, with the larger weights (0.5 and 0.7) leading to strong oscillatory behaviour and more extreme fishery changes (**Figure 67** and **Figure 70**). TargetCE weights from 0.2 to 0.3 led to predicted median catch trajectories which were intermediate between the extremes of 0.1 and 0.7 (and 0.5).

When the assessment interval was increased from 1 to 2 years, not surprisingly the effect was to slow the management responses down so that rates of decline and rises in catches and associated changes in spawning biomass were slower as the interval increased. This is visually apparent from the peaks in the oscillations occurring in later years as assessment interval increased (compare **Figure 67** with **Figure 70**).

The general trends and patterns in the predicted median catches were similar between the two TAC adjustment schedules but schedule 2 appeared to slow management intervention down. This is apparent in that the modes of the various oscillations are somewhat later with schedule 2 but also the duration of low catches early on is prolonged (**Figure 68** and **Figure 69**).

The primary trade-off being considered here is between maximizing catches and maximizing stock rebuilding (which also reflected changes in expected CPUE). Thus to obtain the full reflection of the implications of these different harvest strategy scenarios the effects on spawning biomass depletion need to be considered.

9.8.2 Fishing Down a Lightly Fished Stock

Instead of depleting the initial stock down to 25%B_0 the simulation framework can just as easily be depleted to 55%B_0 or 40%B_0 (**Figure 61** and **Figure 62**) so as to mimic a lightly depleted stock. The 55%B_0 is well above the 30-37%B_0 predicted to generate the maximum sustainable yield (**Figure 9**) while 40%B_0 is much closer to that level. These initial conditions would not require any rebuilding but the question remains whether or not the MCDA could control the fish down or maintain the stock at the target CPUE in a manner that led to relatively stable management (**Figure 61**).

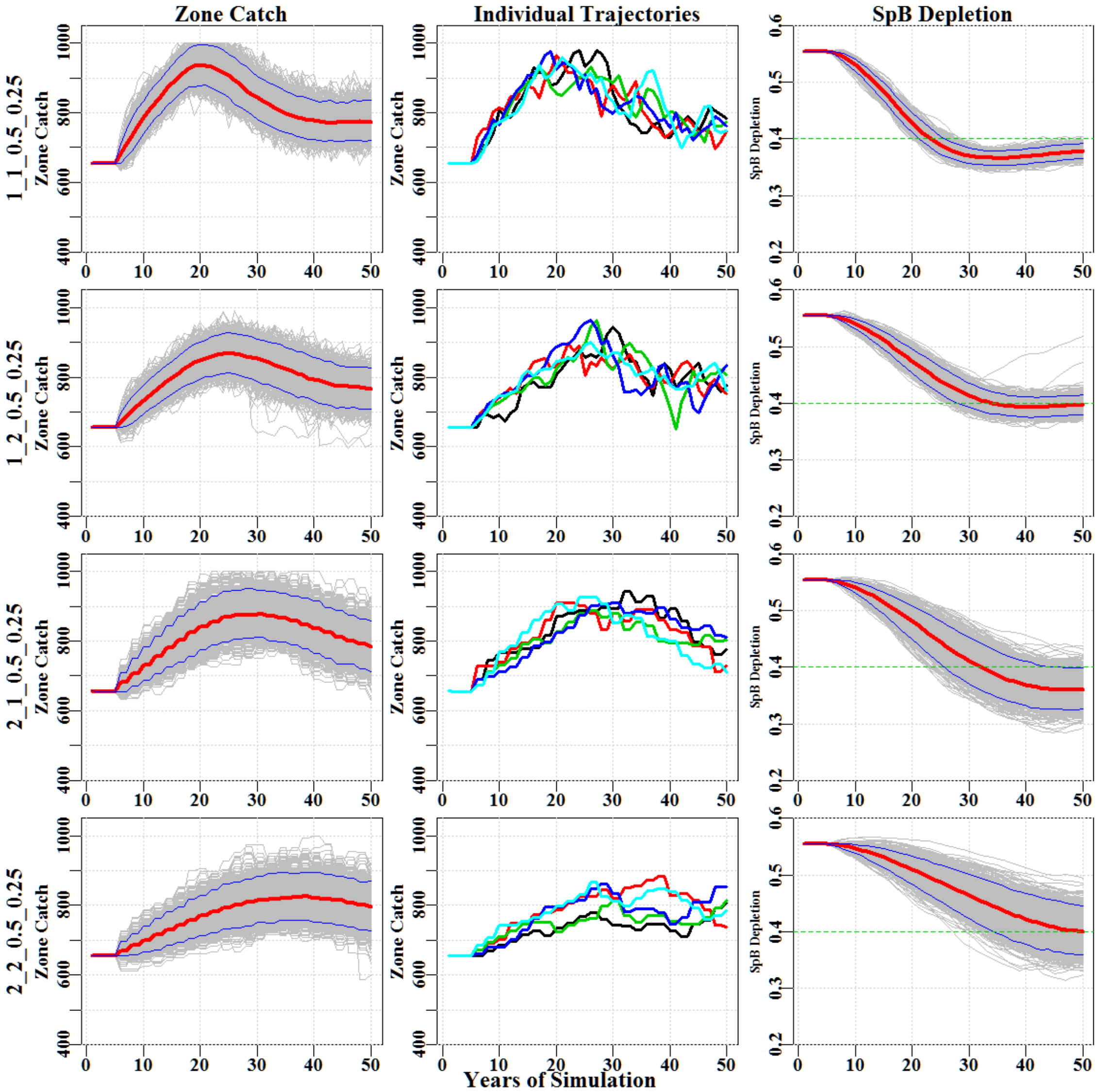

Figure 61. A comparison of the 1000 replicates for four harvest strategy scenarios that all start at 55%B_0 and have a weight of 0.25 on the targetCE and 0.5 on the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines and the inner 90% bounds around the medians. The axes are the same in comparable graphs. The central plots illustrate five individual replicates each with a different colour to indicate typical variation within each replicate.

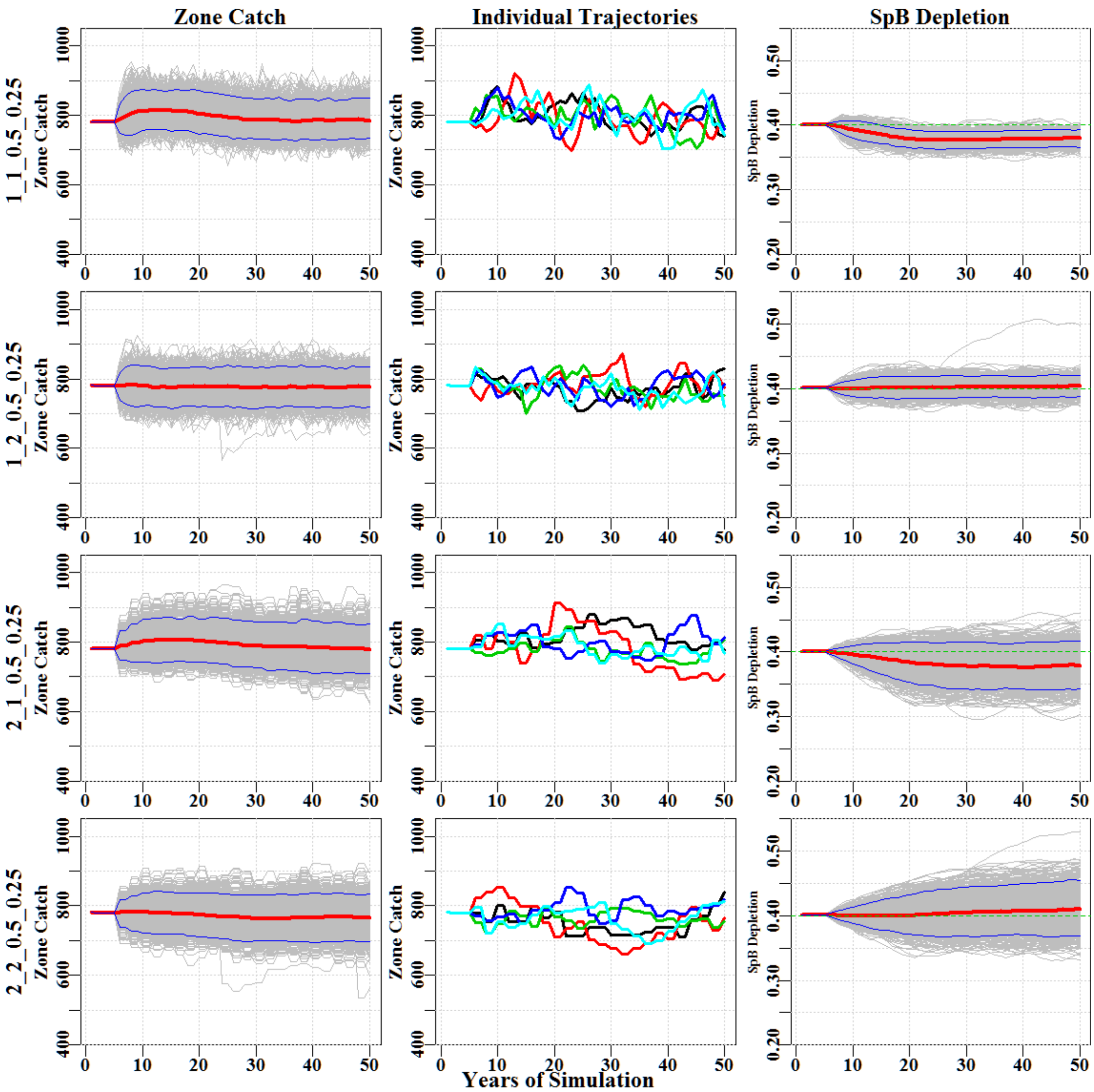

Figure 62. A comparison of the 1000 replicates for four harvest strategy scenarios that all start at 40%B_0 and have a weight of 0.25 on the targetCE and 0.5 on the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs. The central plots illustrate five individual replicates each with a different colour to indicate typical variation within each replicate.

The predicted trajectories (**Figure 61** and **Figure 62**) illustrate that for initial depletion levels of 55% and 40%B_0 respectively, the MCDA, with the settings used in these scenarios (a weight of 0.25 on the targetCE PM and 0.5 on the Grad4 PM), was able to provide sensible management advice that either fished the stock down towards the target CPUE or kept the stock at and around the target CPUE and related catch level. This occurred in all cases, although there were some differences between the combinations of assessment interval and TAC adjustment schedule. In all cases the two year assessment interval led to more variable outcomes than the one year assessment interval. With the one year assessment interval, schedule 2 led to slightly more variation than schedule 1.

Despite this increased variation the slight time-lag introduced with the two-year interval the initial depletion of 55%B_0 scenario declined more slowly to the target and avoided dipping slightly below the target, which occurred with the one-year interval and schedule 1 (**Figure 61**). The two-year interval with schedule 1 follows a similar trajectory to the one-year interval with schedule 2, although it achieves the target slightly slower and rather more variation is expressed in both catches and spawning biomass depletion. The time-lag induced by the two-year assessment interval is apparent in the longer term trajectories (**Figure 61**), so that the two-year assessment with schedule 2 takes the longest to achieve the target CPUE and associated catch. There are interactions between these factors in that the median trajectory followed by the one-year assessment interval with schedule 2 follows approximately the same trajectory as the two-year assessment interval with schedule 1, although the latter exhibits greater variation (**Table 19**).

With the stock starting at 40%B_0 each scenario essentially stayed stable with the median trajectories only exhibiting slight variations. The flattest and least variable of the four was the one-year interval with schedule 2. It appears as if the one-year interval with schedule 1 was more sensitive and able to fine tune the final state achieved although this only led to slightly more catch and a slightly deeper level of depletion. Similarly, the two-year interval with schedule 2 was flatter that the two-year interval with schedule 1, but both were far more variable in outcomes than with assessment interval 1 (**Figure 62**).

Table 19. Estimates for the median and central 90% quantiles for the cumulative catch from year 6 – 20, and the CPUE and spawning biomass depletion levels in year 20, 15 years after the introduction of the harvest strategy. All scenarios began at 55% depletion with a Grad4 weight of 0.5 and a TargCE weight of 0.25. The scenario legends then indicate the assessment interval and then the TAC adjustment schedule. These scenarios all began above the CPUE target so that performance measure is not given. With assessment interval of 1 year approximately stable states are achieved after about 25 years with assessment interval 2 years this takes approximately 35 years (**Figure 61**).

Performance Measure	0.25_1_1	0.25_1_2	0.25_2_1	0.25_2_2
Catch5%	12123	11067	10810	10275
Catch50%	12530	11545	11413	10794
Catch95%	12924	12005	12101	11378
CPUE5%	128.0	144.7	142.6	156.4
CPUE50%	134.8	153.0	155.0	166.8
CPUE95%	141.8	161.5	166.2	176.1
Depletion5%	0.412	0.454	0.449	0.484
Depletion50%	0.428	0.474	0.481	0.510
Depletion95%	0.446	0.496	0.509	0.533

9.8.3 Omission of the TargetCE Performance Measure

Using the gradient of CPUE over a fixed number of years as a performance measure by itself has already been demonstrated generally to maintain the status quo under given circumstances and thus not to provide a useful way of managing an abalone stock in the long term (Haddon *et al.*, 2013). However, the gradient CPUE PMs used here differ in that time periods of both one and four years are used along with a different harvest control rule. To determine whether the new combination remains of limited use the two CPUE gradient PMs (the one year and the four year) were first considered without the TargetCE being included (**Table 17**; **Figure 63**).

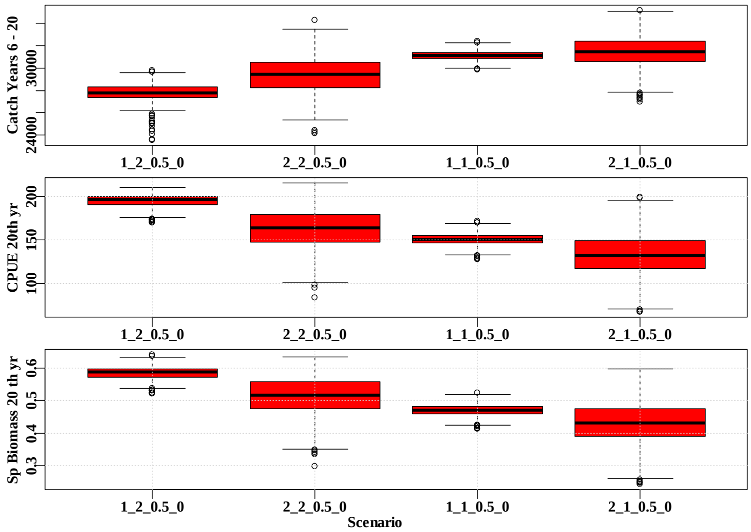

Figure 63. Box plots illustrating the different performance after setting the weight on the targetCE to zero. The spawning biomass depletion level and the CPUE are illustrated in the 15th year while the total catch is across the first 15 years after introducing the HS. The scenario labels combine the assessment interval (1 or 2 years), the TAC adjustment schedule (1 or 2; see **Table 18**), and the weight given to the Grad4 and TargCE performance measures i.e. zero.

All scenarios began at a spawning biomass depletion level of 25% B_0. The Grad4 and Rate1 performance measures were given equal weight in the four scenarios without a TargetCE performance measure so that any contrast in their outcomes relates to the differences in the assessment interval and the TAC adjustment schedule. The primary trade-off would appear to be between the total catch taken over the first 15 years of the HS and the level of recovery in spawning biomass achieved, which is closely correlated with the CPUE in the same year. Given the differences between the outcomes it is clear that the new combination can no longer be deemed to be one of relative status quo even in the relatively short term. Both the assessment interval and the TAC adjustment schedule influence the outcome with the least recovery of spawning biomass but the most total catch deriving from the two year assessment interval and the first TAC adjustment schedule. Across these outputs the 1 year assessment interval and the second TAC adjustment schedule appears most conservative in terms of spawning biomass and lead to the least total catch although the recovery in spawning biomass is much greater across all scenarios relative to any that include a TargetCE PM (see later). At the same time the assessment interval of 2 years leads to greater variation in all harvest strategy performance metrics. However, it is only by considering the complete projection trajectories that the properties of these harvest strategies can be fully determined (**Figure 64** and **Figure 65**). Plots of the 1000 trajectories are provided in section '**9.10.3 TargetCE Weight = 0.0**', in the Supplementary Results.

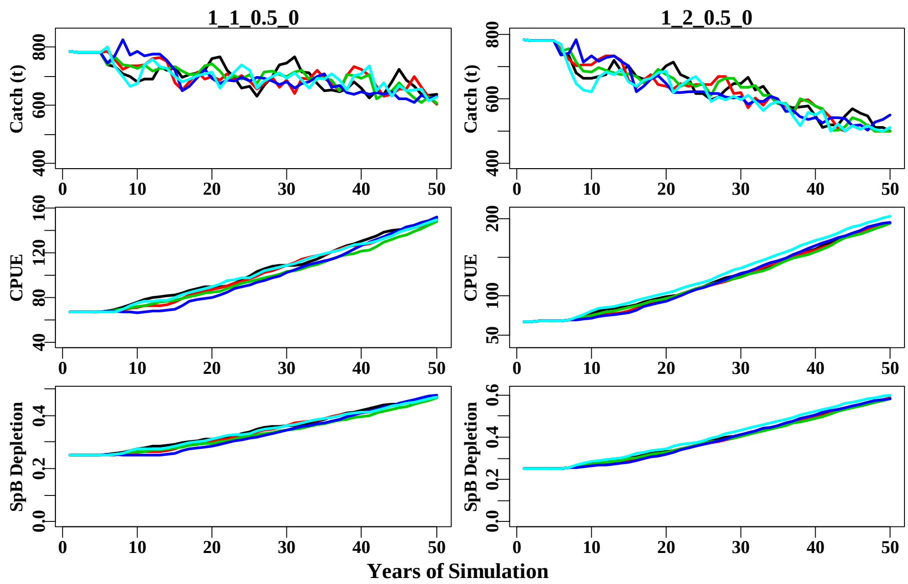

Figure 64. Five randomly chosen trajectories from two of the scenarios where the TargetCE weight was set to 0.0.

While the harvest strategy made up of these performance measure combinations no longer leads to a status quo outcome the management advice behaviour from all four alternative scenarios is pathological as a result of a positive gradient in CPUE always being scored as a positive result. This means that all the scenarios trialled lead to an on-going decline in catches that, in turn, leads to an increase in biomass, which leads to increases in CPUE. This leads to run-away behaviour where the catches are decreased until they bump up against the lower limit of 500 t, but this is the only thing slowing the decline in catches and the recovery of the spawning biomass.

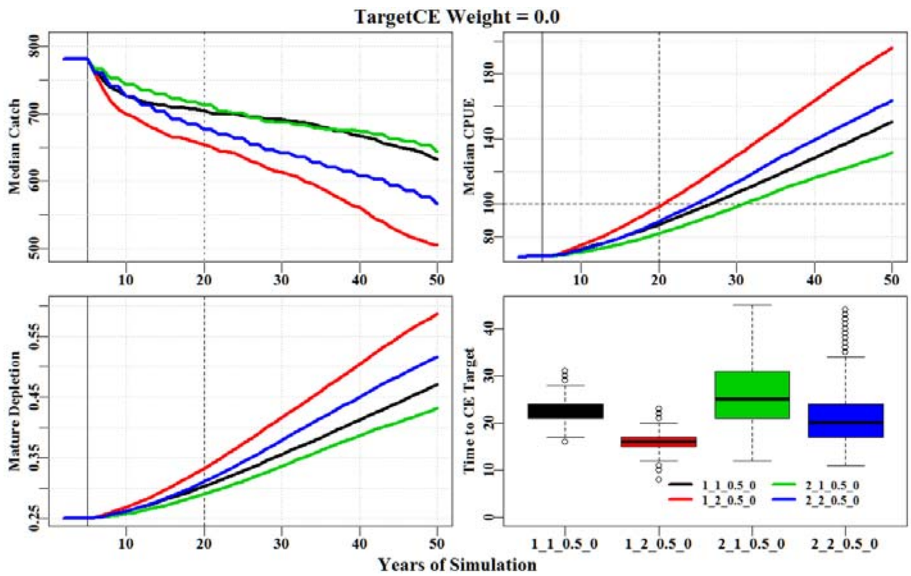

Figure 65. Median trajectories of the four scenarios considered where the TargetCE weight was set to 0.0. Except for the boxplot of time to achieve the target CPUE the x-axis relates to the years of simulation. Dashed vertical lines reflect the timing of the box plots in **Figure 63**.

9.8.4 Inclusion of the TargetCE Performance Measure

Given the results from the previous MSE study of abalone stocks and harvests (Haddon *et al.,* 2013) it was expected that the inclusion of the TargetCE performance measure would provide the ability for harvest strategies to manage each fishery towards a given level; although this required confirmation. In addition, the targetCE's interaction and relationship with the new gradient performance measures, the new control rules, and the different assessment intervals and TAC adjustment schedules needed clarification. The previous work operated at a zone wide level while the current work more closely reflects the current approach in Tasmania of setting expected catches each year at a statistical block (SMU) or other scale smaller than a zone level and then combining them into a single zone TAC. With the empirical harvest strategies implemented using the MCDA process, alternative harvest strategies are comprised of different combinations of performance measures, along with different weights allocated to each performance measure and then, finally, different TAC adjustment schedules for translating the MCDA scores into management advice on changes to expected block catch levels. The variants considered were described in the conditioning section (page 99; '9.4 Block Based Performance Measures').

The MSE simulations predict very different outcomes from the 1000 replicates of each of the 56 alternative scenarios (**Table 17**). Only the outcomes for the expected catch and the spawning biomass depletion level are illustrated. Those for the expected CPUE are generally omitted because, not surprisingly, there is a strong relationship between the expected CPUE and the expected spawning biomass depletion level (**Figure 66**).

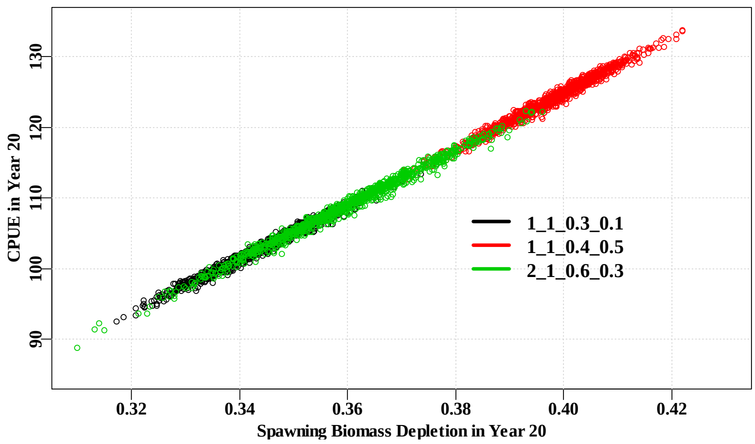

Figure 66. The relationship between the CPUE in year 20 (15 years after the introduction of each harvest strategy) and the spawning biomass depletion level in year 20 for three of the scenarios. The legend labels are the assessment interval, the block catch adjustment schedule, and the weights attributed to Grad4 and TargetCE performance measures.

9.8.5 Assessment Interval 1 with Catch Adjustment Schedule 1

As with all Management Strategy Evaluation studies the Abalone MSE (AbMSE) generates an enormous amount of output with the dynamics of all 50 years by 1000 replicates for each block with each zone being summarized and saved. An example comparison provides a plot of the time series of predicted zone-wide catches, zone-wide spawning biomass depletion and random selections of individual zone-wide catch trajectories (e.g. **Figure 67** and **Figure 70**). In the case of assessment interval 1 year and block-catch adjustment schedule 1 this enables a visual comparison of the effect of changing the weight on the different performance measures across a broad range (**Figure 61**). Of course, these trajectories apply the same weights to the same performance measures for 45 years and the suggestion is that the harvest strategy be reviewed after only five years, which may lead to changes as more is learned about the harvest strategy's performance in reality. Details of all scenarios considered for the performance metrics are provided in (**Table 24**).

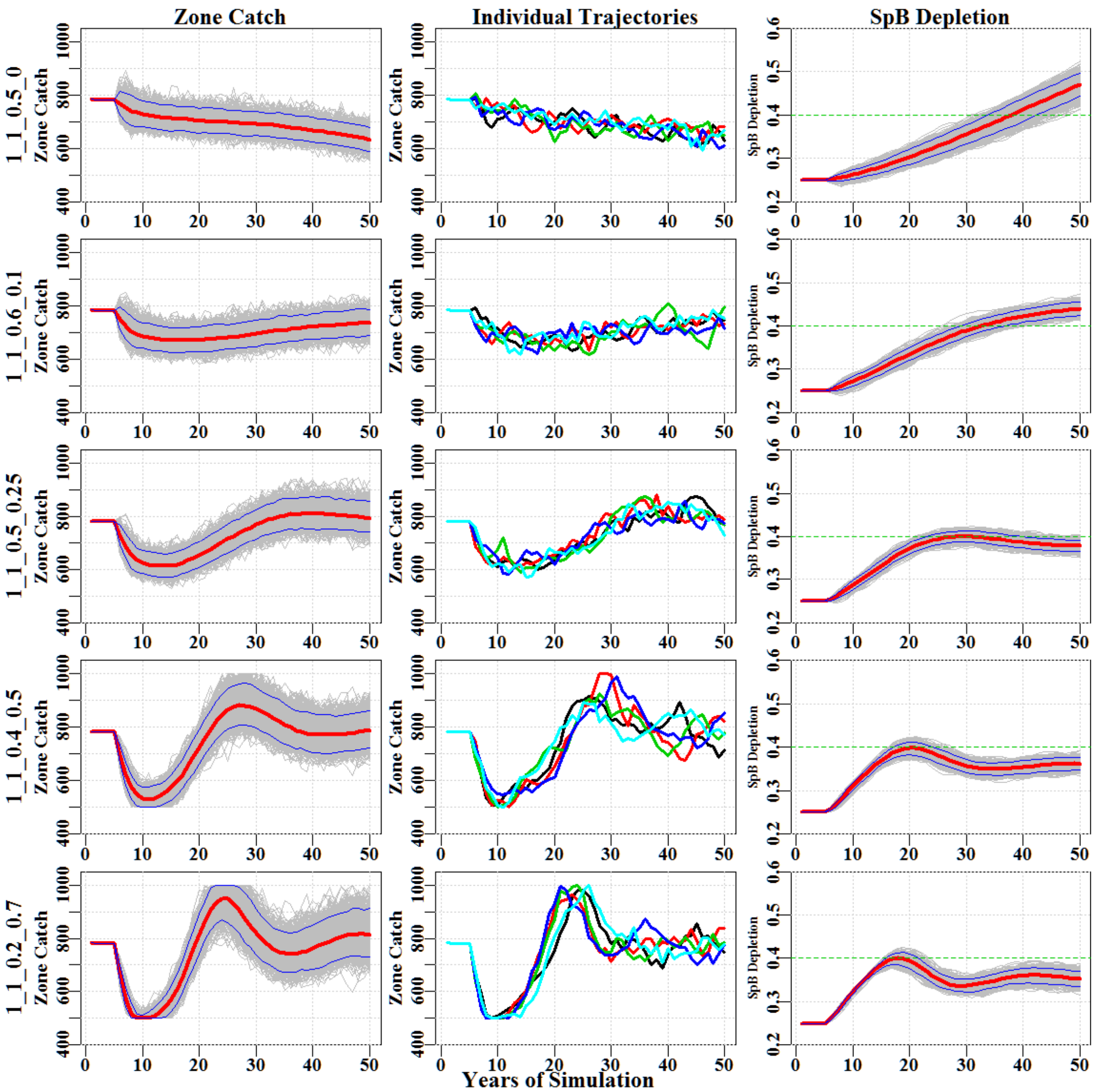

Figure 67. A comparison of the 1000 replicates for five harvest strategy scenarios that all start at 25%B_0 and have different weights on the targetCE and the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs.

Considering the performance metrics and visual comparisons (**Table 24**; **Figure 67**, **Figure 68**, and **Figure 69**) The full range of dynamic behaviour is exhibited ranging from the long term recovery of the stock and decline in catches obtained by omitting the targetCE PM to the strong oscillatory behaviour of both catches and spawning biomass depletion when the weight on the targetCE PM is set at 0.5 and 0.7. Low levels of weight in the targetCE (0.0, 0.01, and 0.1) lead either to no long term stability or a very slow onset of catch and stock depletion control. Weight levels on the targetCE of between 0.2 and 0.3 lead to relatively smooth management towards a more stable eventual outcome without dramatic changes being introduced.

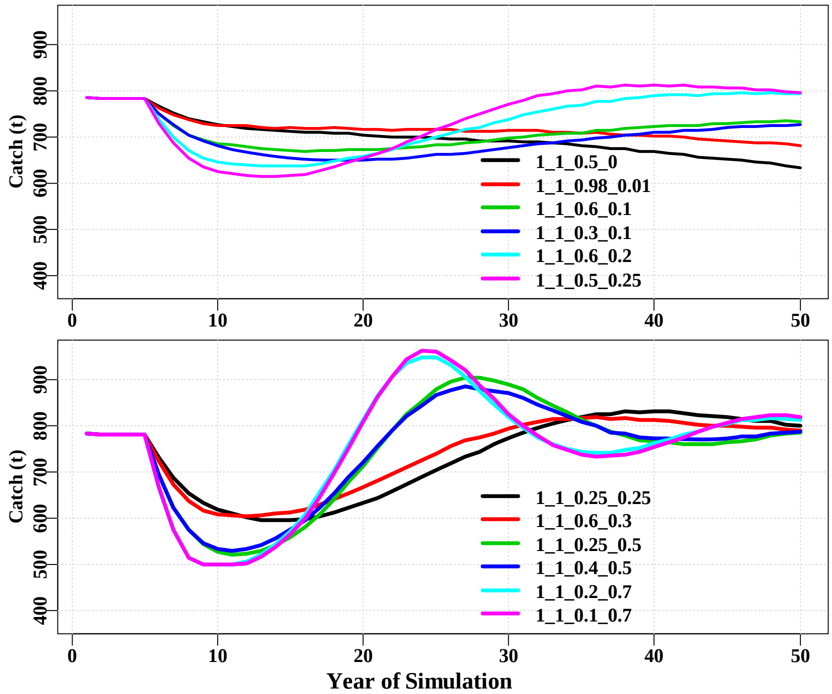

Figure 68. The 12 median trajectories of predicted catch for scenarios using Assessment Interval and Catch Adjustment Schedule 1. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs. The trajectories vary from effectively no compensation (the first four in the top panel) to over-compensation (the last four in the bottom panel).

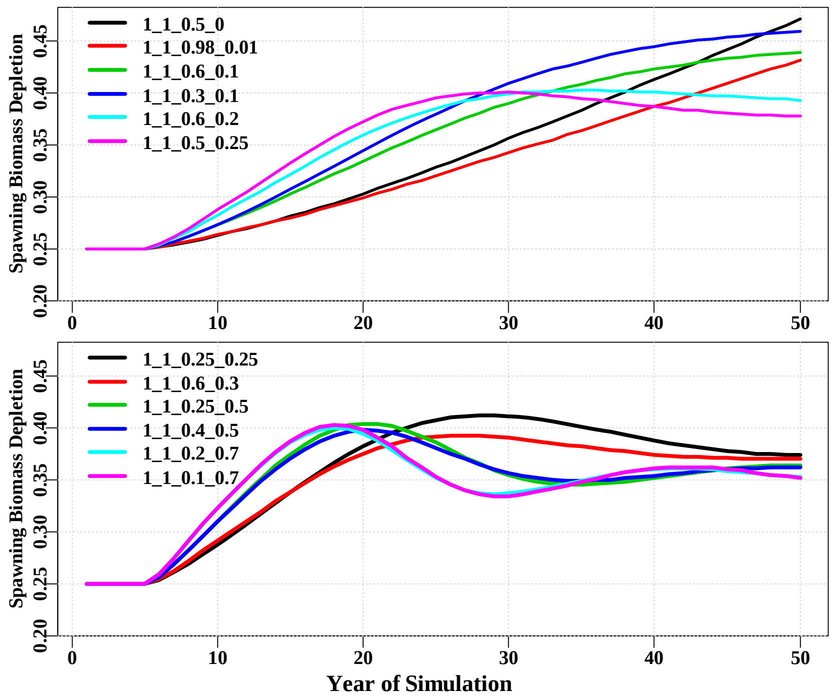

Figure 69. The 12 median trajectories of spawning biomass depletion for scenarios using Assessment Interval and Catch Adjustment Schedule 1. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

9.8.6 Assessment Interval 1 with Catch Adjustment Schedule 2

With an assessment interval of 1 year but using schedule 2, once again the lower weights on the TargetCE PM were ineffective at managing catches but weights between 0.2 – 0.3 led to targets being achieved reasonably smoothly. Higher weights (0.5 – 0.7), irrespective of the weights applied to the Grad4 and Rate1 PMs each led to relative dramatic changes in catches and related recovery rates (**Table 24**; **Figure 70**, **Figure 71**, and **Figure 72**). The key point is that alternative predicted trajectories should be possible to arrange depending upon what objective is given most emphasis.

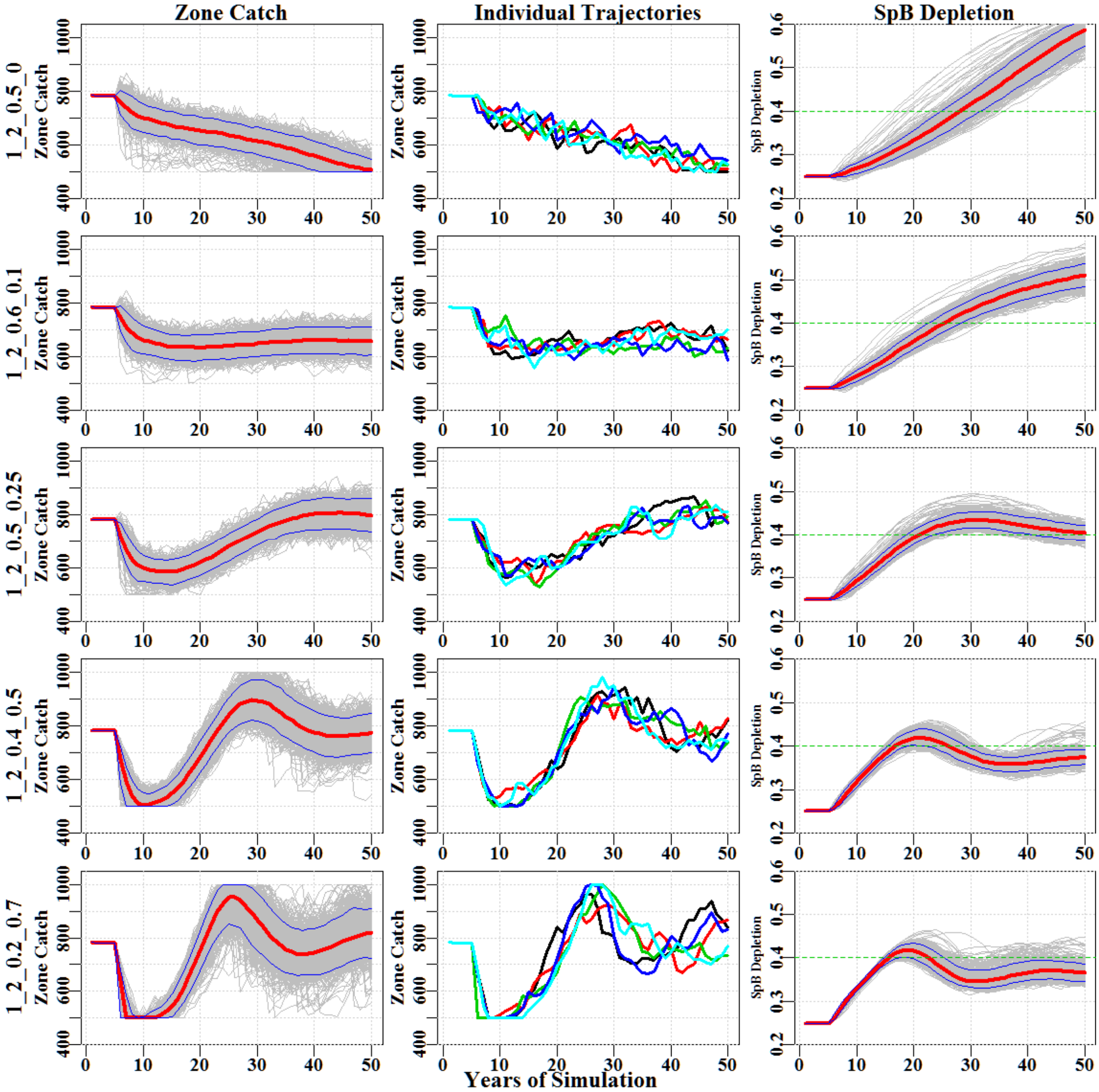

Figure 70. A comparison of the 1000 replicates for five harvest strategy scenarios that all start at 25%B_0 and have different weights on the targetCE and the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs. The lower and upper limits on catches in the illustrated harvest strategy were 500 t and 1000 t respectively.

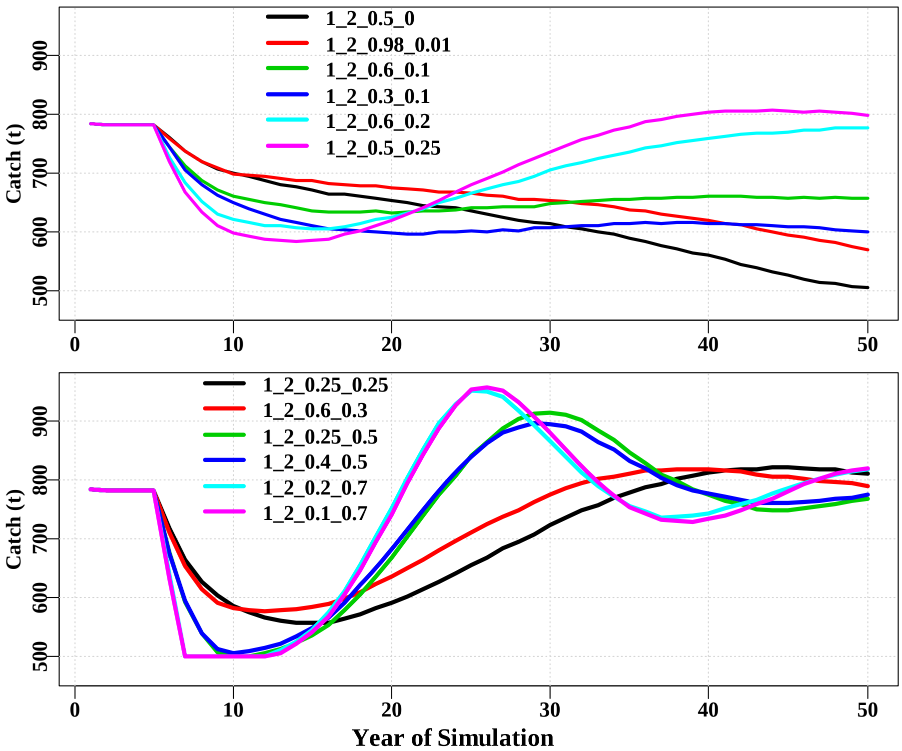

Figure 71. The 12 median trajectories of predicted catch for scenarios with Assessment Interval 1 and Catch Adjustment Schedule 2. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

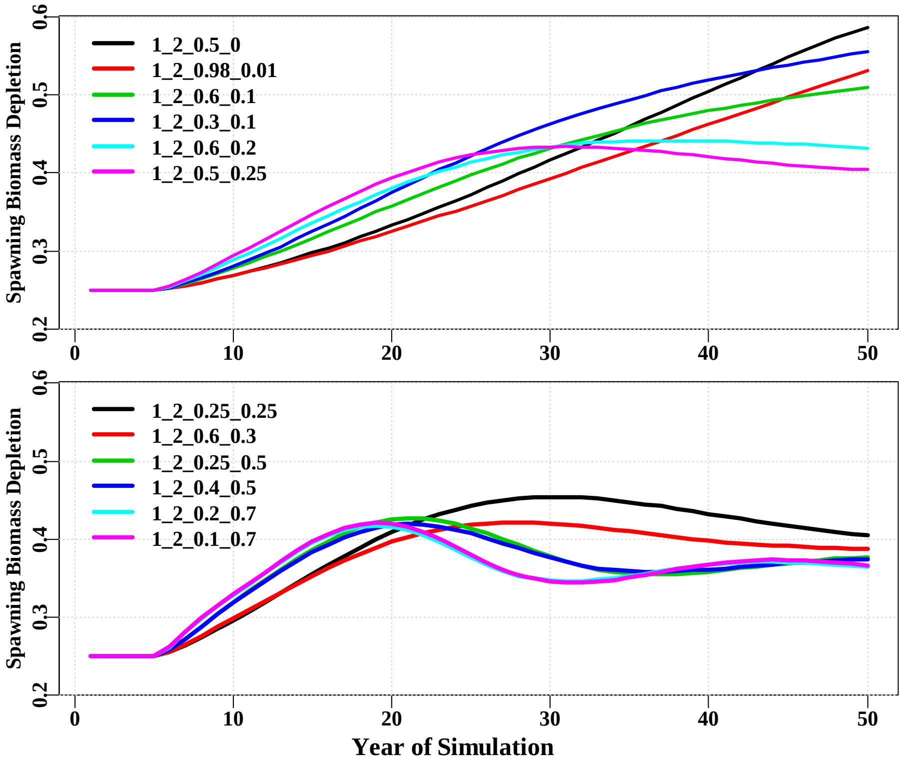

Figure 72. The 12 median trajectories of spawning biomass depletion for scenarios with Assessment Interval 1 and Catch Adjustment Schedule 2. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

9.8.7 Assessment Interval 2 with Catch Adjustment Schedule 1

Using an assessment interval of 2 years with catch adjustment schedule 1 (scenario 2_1) produced trajectories (**Table 24**; **Figure 73**, **Figure 74**, and **Figure 75**) similar to those from the assessment interval 1 Schedule 1 combination. They differed from the earlier trajectories (**Figure 68** and **Figure 69**) in being more variable around the median trajectories but also with the key dynamics being somewhat delayed relative to the 1_1 scenario. Thus the peak mode in catches in the most extreme oscillations (weight on TargetCE = 0.7) occurs about years 33 – 34 with scenario 2_1 while it occurs at about year 23 – 24 in scenario 1_1 (compare **Figure 73** with **Figure 67**).

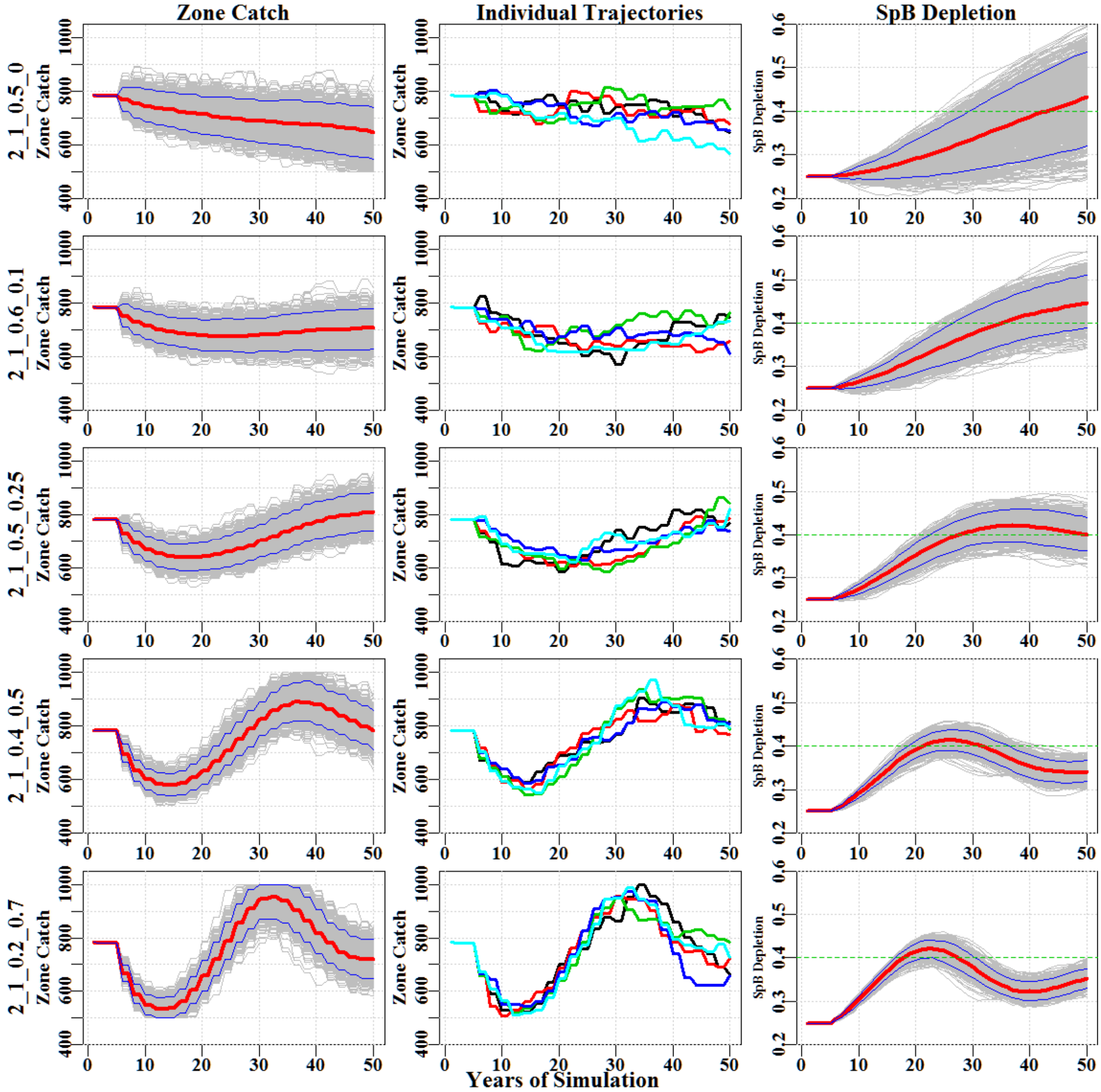

Figure 73. A comparison of the 1000 replicates for five harvest strategy scenarios that all start at 25%B_0 and have different weights on the targetCE and the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs. The lower and upper limits on catches in the illustrated harvest strategy were 500 t and 1000 t respectively.

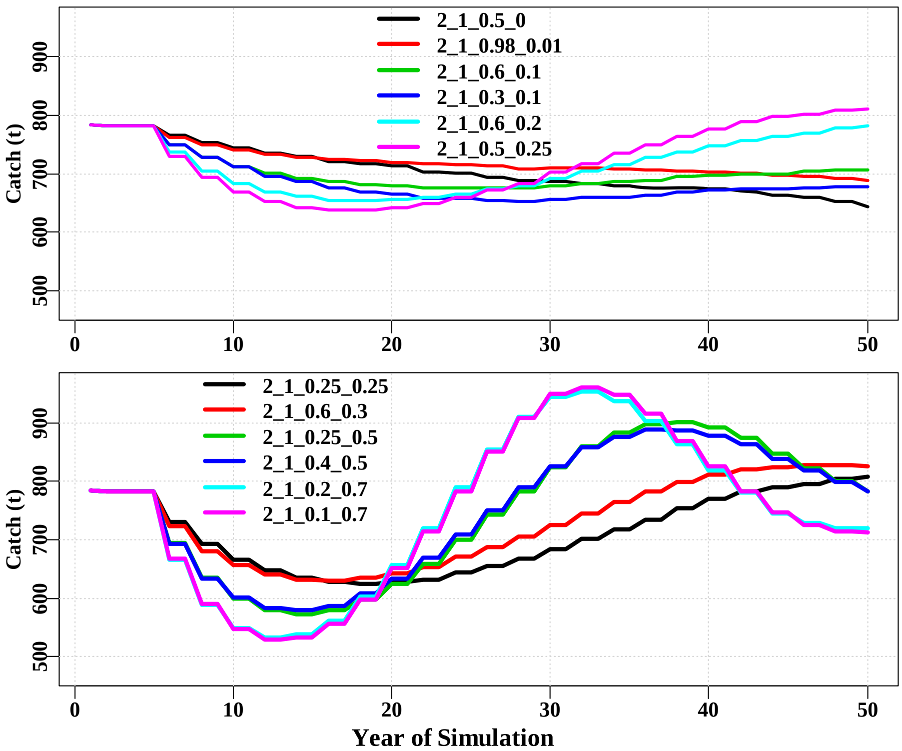

Figure 74. The 12 median trajectories of predicted catch for scenarios with Assessment Interval 2 and Catch Adjustment Schedule 1. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

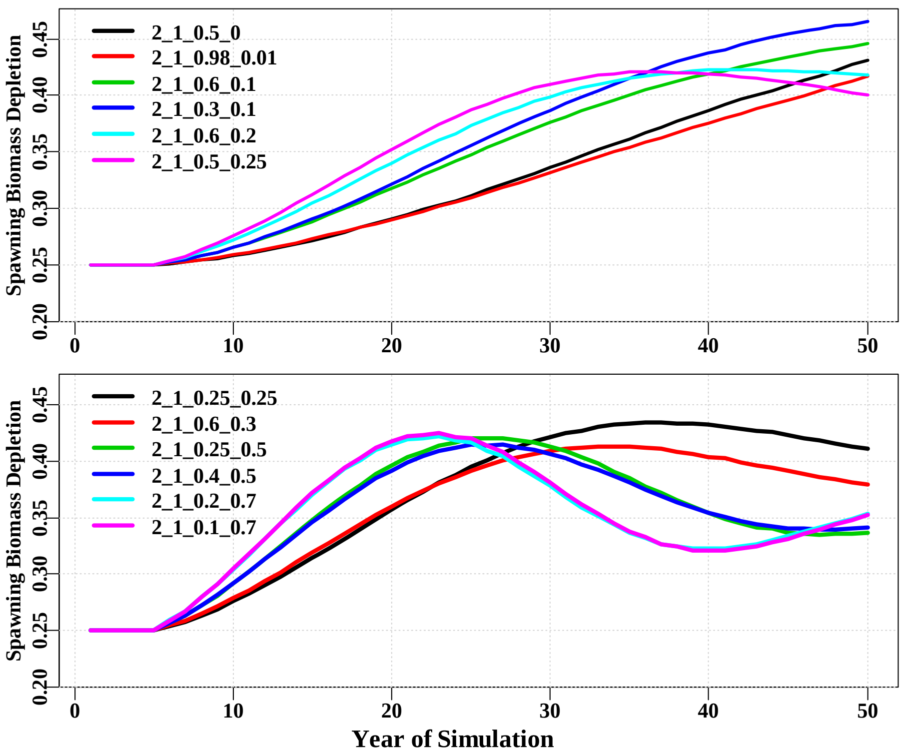

Figure 75. The 12 median trajectories of predicted spawning biomass depletion for scenarios with Assessment Interval 2 and Catch Adjustment Schedule 1. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

9.8.8 Assessment Interval 2 with Catch Adjustment Schedule 2

The final combination of assessment interval and catch adjustment schedule was 2_2. This led to outcomes as variable as scenario 2_1 but with rather greater extremes of result (**Table 24**; **Figure 76**, **Figure 77**, and **Figure 78**). Thus, the final rebuilding of spawning biomass when the targCE PM weight was set to 0.0 was greater than the 2_1 scenario, which reflected the increased incidence of reduced catches in the 2_2 scenario. These more extreme outcomes are reflected in all the other weights attributed to the targCE PM (compare **Figure 76** with **Figure 73**). The time lags are longer in scenario 2_2 than the other scenarios of assessment interval and catch adjustment schedule, with the modes of oscillations occurring later than in other scenarios.

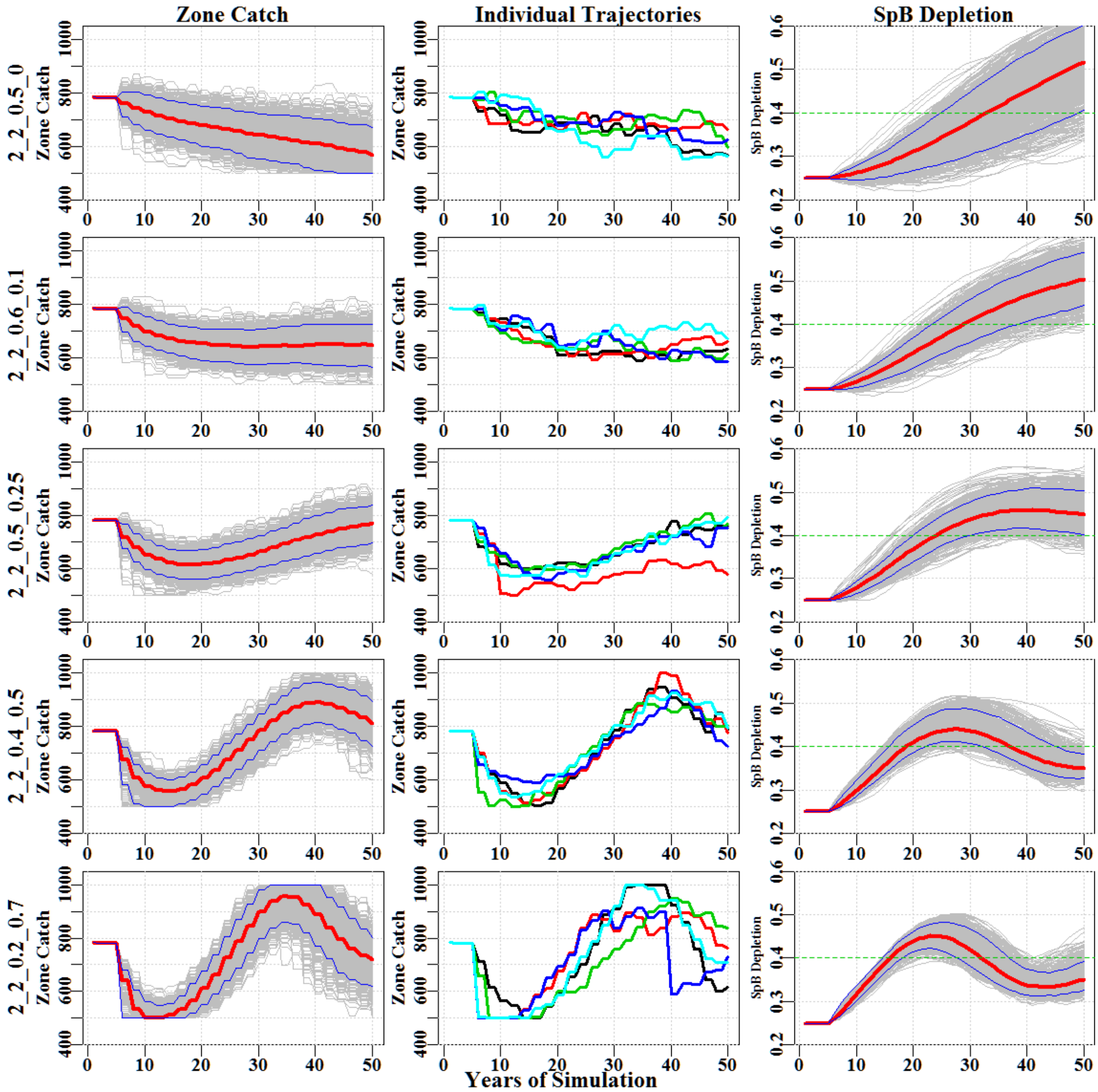

Figure 76. A comparison of the 1000 replicates for five harvest strategy scenarios that all start at 25%B_0 and have different weights on the targetCE and the Grad4 performance measures. The scenario legend in each case denotes the assessment interval, the TAC Adjustment Schedule followed by the weights. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs. The lower and upper limits on catches in the illustrated harvest strategy were 500 t and 1000 t respectively.

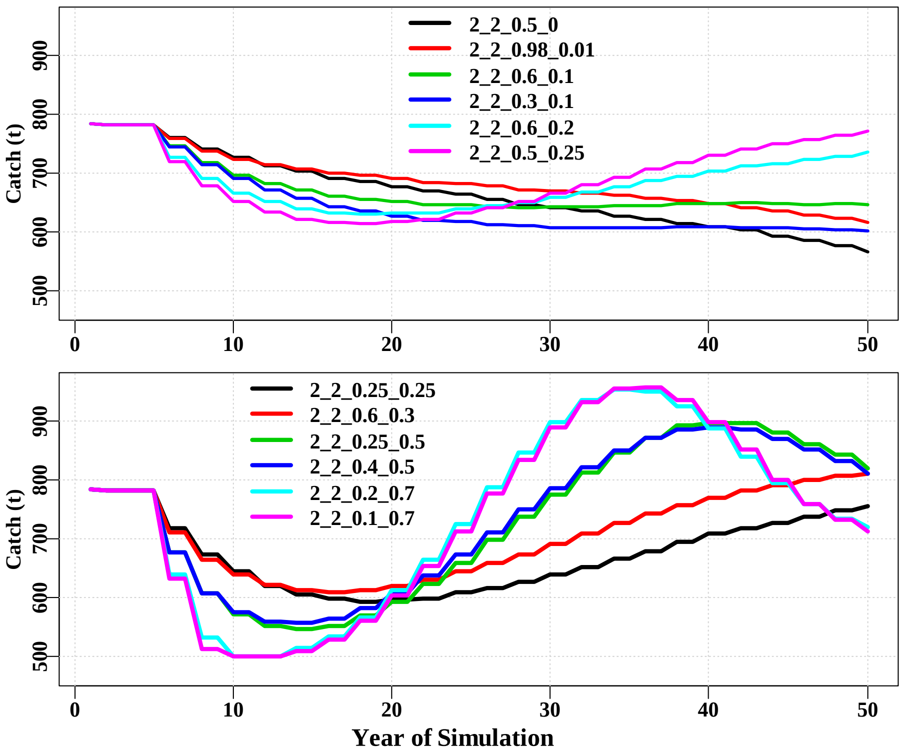

Figure 77. The 12 median trajectories of predicted catch for scenarios with Assessment Interval 2 and Catch Adjustment Schedule 2. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

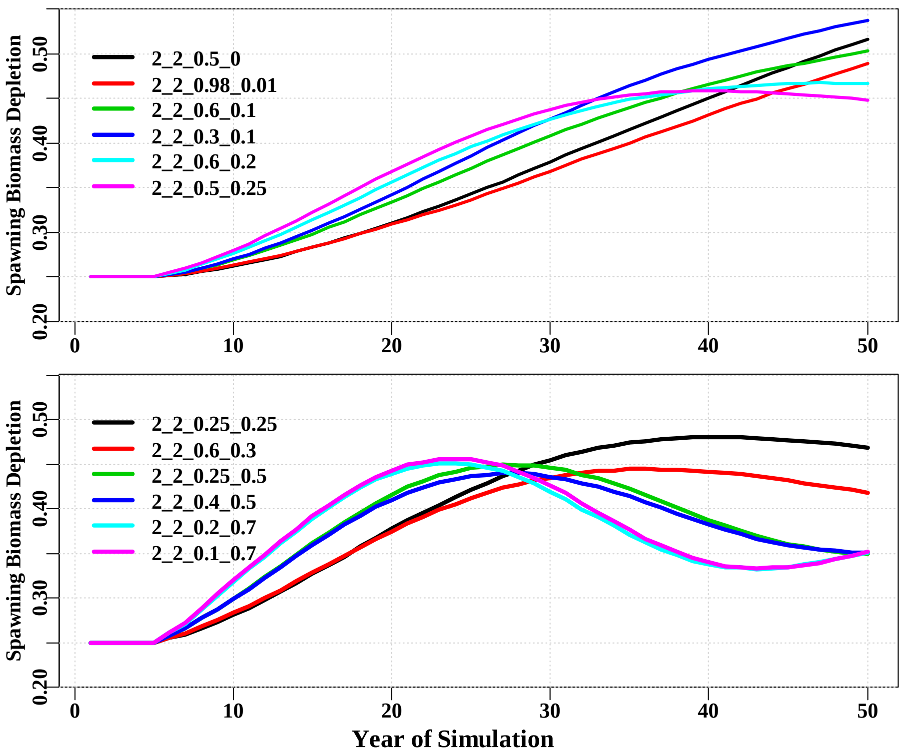

Figure 78. The 12 median trajectories of predicted spawning biomass depletion for scenarios with Assessment Interval 2 and Catch Adjustment Schedule 2. The legend in each case is the assessment interval, the schedule of block catch adjustment, and the weights on the Grad4 and the TargCE PMs.

9.8.9 Scenarios and Spawning Biomass depletion

Total catches and spawning biomass depletion recovery are almost in opposition, hence the trade-off, and this is reflected in the diagrams of the predicted median spawning biomass depletion levels relative to the catches that give rise to any recovery (e.g. **Figure 67** to **Figure 78**). In the case of the spawning biomass recovery when the targetCE weight is low (0.0 to 0.1) then the stock recovery is maximized with the median achieving greater than 45%B_0 with schedule 1 and greater than 50%B_0 with schedule 2. Schedule 2 led to the relative weight given to the Grad4 PM having much greater effects on the outcome, while with schedule 1 the Grad4 weight had relatively little effect. S high stock level may appear to be beneficial because it would add to stock resilience and generate high catch rates. However, when the properties of the original simulated zone are considered (**Figure 9**; page 34) the depletion levels that give rise to the hypothetical maximum sustainable yield ranged from about 30%B_0 - 37%B_0 so while elevated spawning biomass levels may increase resilience they would also be less productive.

The effect of the targetCE performance measure is to manage the stock towards the target CPUE, although generally the outcome is biased high relative to the arbitrarily selected target of 100kg/hr (**Figure 79**). The higher the weight on the targetCE PM the closer to the selected CPUE target the MCDA harvest strategy manages to get; although note the double oscillation when the targetCE weight is set to 0.95. The effect of the gradient performance measures is to temper the effect of the targetCE and biases the final theoretical equilibrium CPUE high (i.e. above the target).

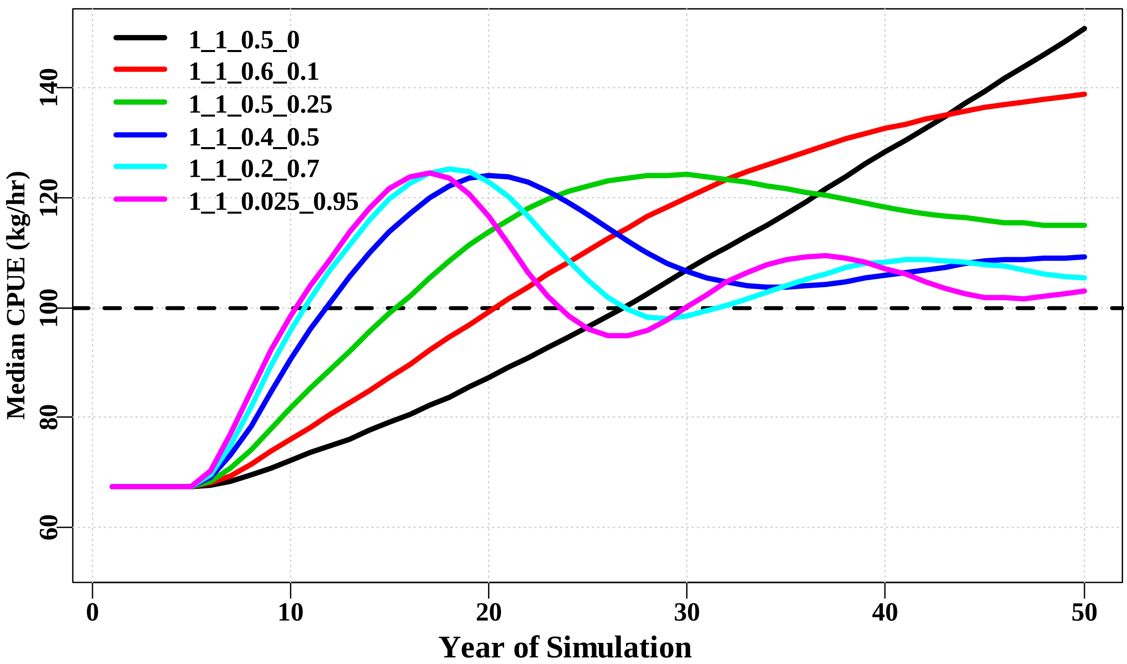

Figure 79. The median predicted CPUE for the 6 scenarios relating to the assessment interval of 1 year using schedule 1 and including the targetCE performance measure. The horizontal dashed black line is the arbitrarily selected 100kg/hr target. Note if a long term equilibrium CPUE appears to be present then the larger the weight on the targetCE, the closer to the selected target it achieves.

In a manner complementary to the most rapid changes in catch, the fastest biomass recovery times are associated with the largest targetCE weights, which is also associated with the fastest time to reach the target CPUE (**Figure 80** and **Figure 81**), The delays in the stock and fishery responses brought about by using different assessment intervals are clearer with the spawning biomass depletion plots as, with both schedules, the trajectories have lower initial gradients of recovery, and are spread over longer periods as the assessment interval increases.

When the median trajectories are considered over the full time series the delays brought about by the assessment intervals also slow the increases in catches and consequent changes in biomass depletion so the return to the hypothetical equilibrium is also delayed. The differences in the effect of the two TAC adjustment schedules is also quite marked in that schedule 2 leads to the stock achieving much higher levels of spawning biomass than schedule 1 (and hence lower total catches; **Table 24**). The median trajectories in schedule 1 scenarios top out at about 45%B_0 whereas with schedule 2 they stay higher for longer and some achieve as much as 50%B_0 and are more widely spread (e.g. **Figure 70** and **Figure 76**)

9.8.10 Time to CPUE Target and Extreme TACs

In addition to the total catch from years 6 - 20, CPUE in year 20, and spawning biomass depletion in year 20, the other performance metrics for the different scenarios are the time it takes to attain the target CPUE, and the proportion of replicates that breach lower and upper limits on the TAC. A full table of the median, 5% and 95% quantiles, and the mean and standard deviation of the first four of these metrics for all scenarios is provided in **Table 24** at the back of section '9.10 Supplementary Results' on page 150.

However, a visual representation of the last three performance metrics also aids in the interpretation and selection of the most useful harvest strategy scenarios (**Figure 80** and **Figure 81**). With TAC adjustment schedule 1 the time to reach the Target CPUE decreases almost linearly with the weight applied to the targetCE PM. In addition, the variation associated with those times increases as the targetCE weight decreases. With schedule 2 the decline in time to targetCE is similar to that in schedule 1 except in the targetCE weights of 0.1. In schedule 2 the variation of the higher weights is also greater, although it remains small relative to the smaller weights.

The proportion of replicates that breach the lower and upper TAC limits (500t and 1000t respectively) varies by assessment interval. Delays introduced by the longer assessment intervals reduce the number of replicates that breach the limits (**Figure 80** and **Figure 81**).

With schedule 1, the assessment interval 1 led to the greatest number of replicates breaching both the lower and upper limits, but only when the targetCE weight was greater than 0.34 (i.e. 0.5 or 0.7), which reflects the rapidity and extent of TAC changes seen when these weights are used (**Figure 80**). Somewhat fewer replicates breach the upper limit than the lower. With assessment intervals of 2 or 3 then the number of breaches reduced in those scenarios with targetCE weights of 0.5, although those with weights of 0.1 and the lowest Grad4 weights exhibited some breaches of the lower TAC limit. In almost all cases scenarios with targetCE weights of 0.7 or that with Grad4 = 0.0, and TargetCE = 0.5, exhibited high proportions of replicates that breach both the lower and upper TAC limits.

With schedule 2 a similar pattern to that seen with schedule 1 was exhibited except the proportion of replicates involved with breaches of both lower and upper TAC limits tended to be higher (**Figure 81**). The average time to the targetCE tended to be a couple of years earlier for the scenarios with lower weights on targetCE. The time to targetCE increased in both schedules with assessment interval, which is a reflection of the delaying effect of the increased assessment intervals on all the responses.

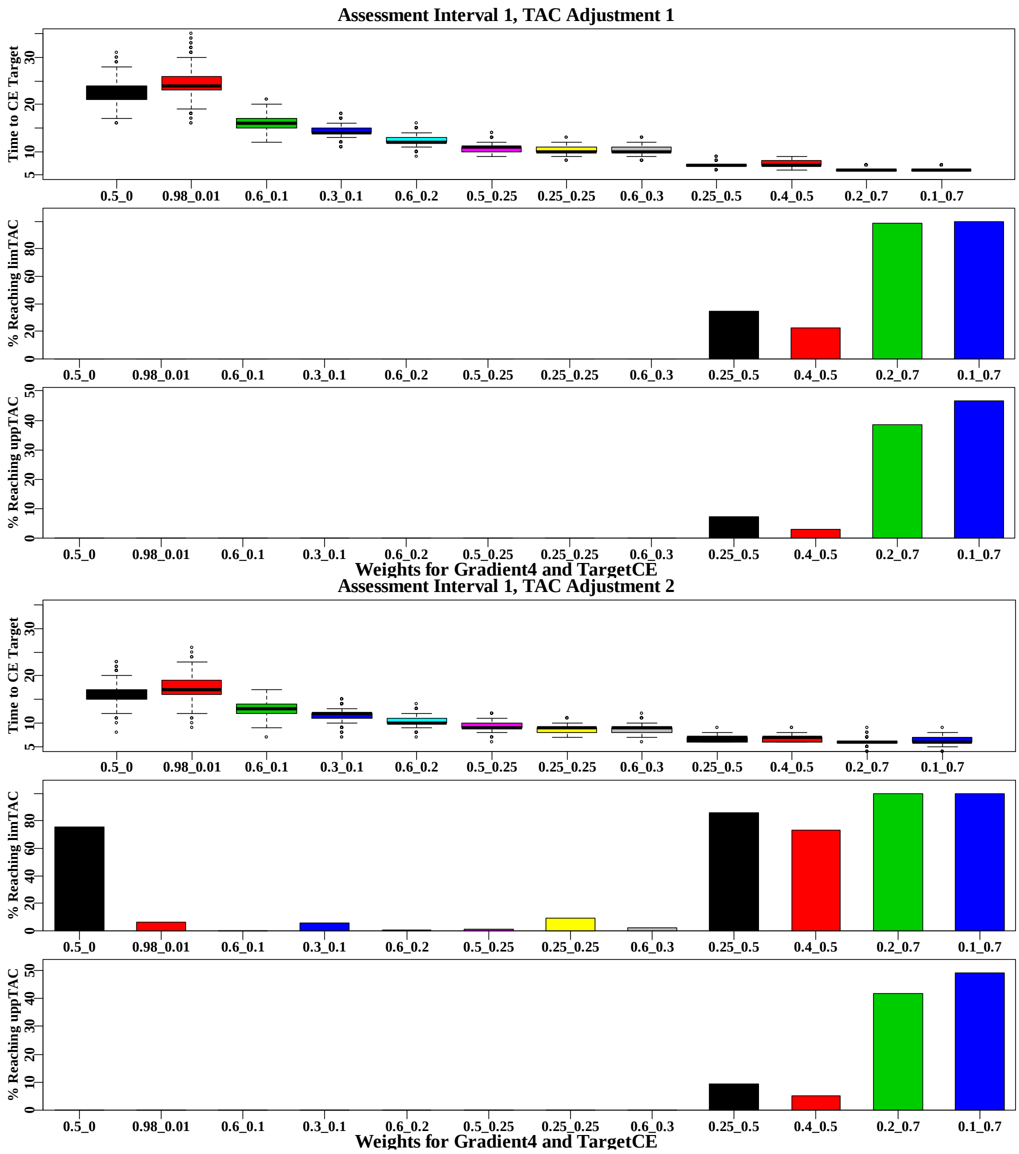

Figure 80. The time to first attain the CPUE target, and the percent of replicates breaching the lower and upper limits on the TAC for scenarios with assessment interval of 1 using Schedules 1 and 2 for the TAC adjustments. The label under each case is the weight on the Grad4 PM, followed by the weight on the TargCE PM.

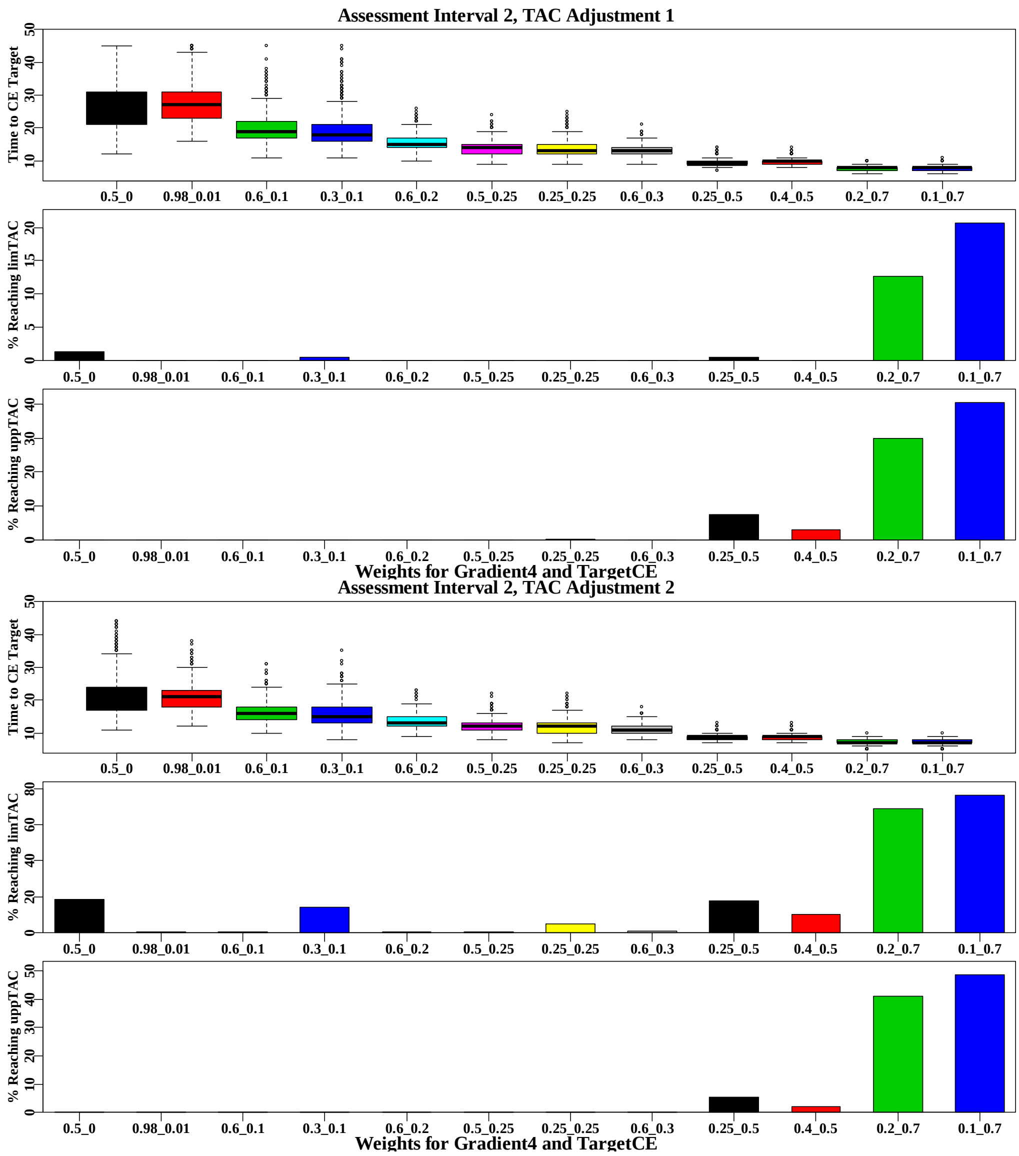

Figure 81. The time to first attain the CPUE target, and the percent of replicates breaching the lower and upper limits on the TAC for each assessment interval within scenarios using Schedule 2 for the TAC adjustments. The label under each case is the weight on the Grad4 PM, and the weight on the TargCE PM.

9.8.11 The Effect of TargetCE Weight on Catch Levels.

When producing the final score in the MCDA, the weight allocated to the targetCE PM is directly related to the predicted median cumulative catch over the first 15 years of application of the harvest strategy in each scenario (**Figure 82**). While the dominant factor is the targetCE weight the assessment interval and the catch adjustment schedule are also influential. Finally the relative weight attributed to the Grad4 and the Rate1 performance measures makes some finer scale changes. The patterns exhibited in the relative catches between scenarios are inverted when the spawning biomass depletion levels are considered (**Figure 82** and **Figure 83**).

Except where the targetCE weight was 0.7 the two year assessment interval with schedule 1 exhibited the greatest catches for a given targetCE weight. The catches exhibited by scenarios 1_1 and 2_1 (assessment interval and schedule) gave mixed results for total catches between years 6 – 20, in those instances the relative weight attributed to the Grad4 and Rate1 PMs made a difference. In all cases however, the outcomes from using an assessment interval of 2 years led to greater levels of variation about the median values (**Figure 83**). The outcomes for spawning biomass depletion were effectively a mirror image of the outcomes for total catches. The outcomes with a targetCE weight of 0.7 differed markedly from the rest primarily as a result of the lower catch boundary of 500 tonnes, which modified the operation of the control rules. Such meta-rules can have a large influence on the outcome of a management strategy. However, in Tasmania no single set of meta-rules have yet to be adopted, though a number of under discussion.

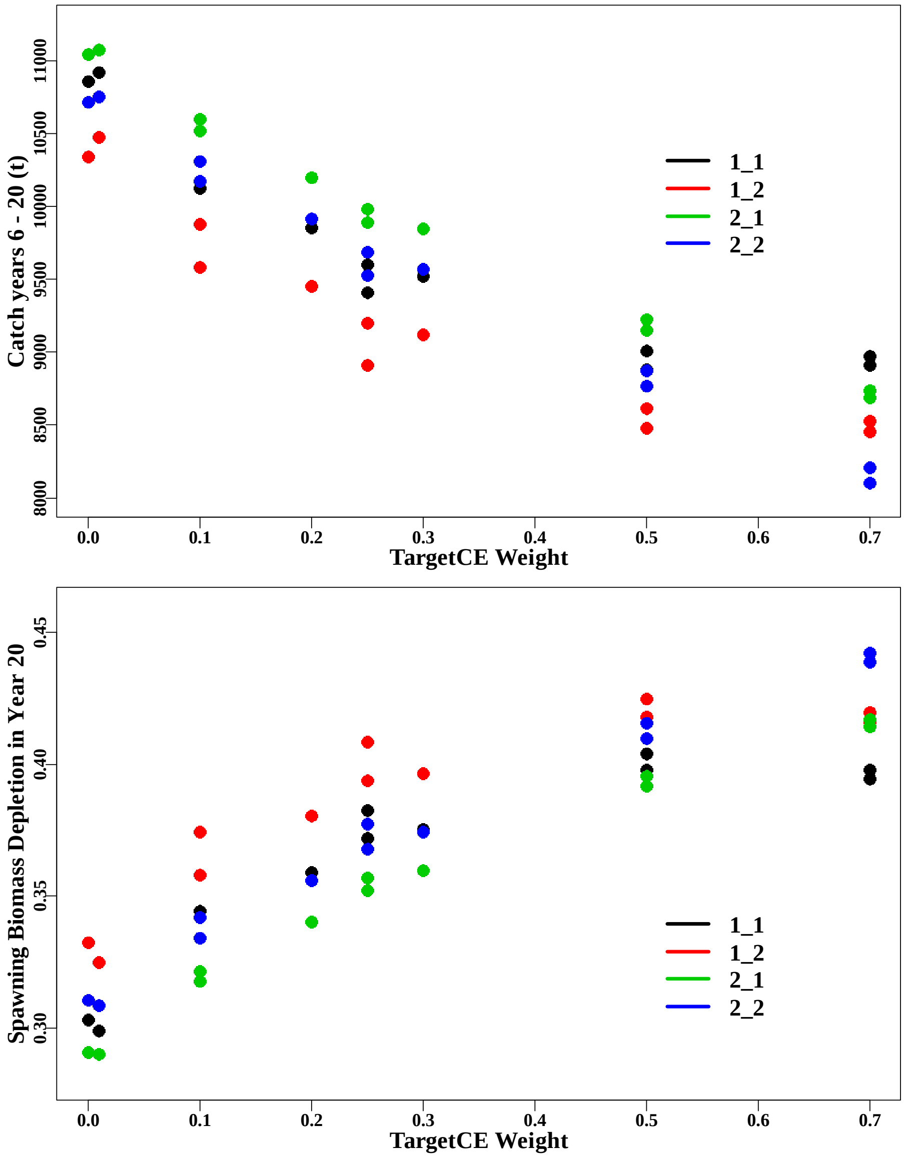

Figure 82. The median cumulative catch taken across the first 15 years of the application of the harvest strategy in different scenarios relative to the weight given to the TargetCE performance measure. The upper panel relates to the TAC adjustment schedule 1 and the lower panel schedule 2 (**Table 18**). The scales are identical in both panels.

9.8.12 Catch and CPUE vs Assessment Interval and TAC Adjustment

Maximum catches over the first 15 years of each harvest strategy occur with the lowest weights on the targetCE PM (**Figure 82**). The total catch achieved is inversely proportional to the median CPUE expected in year 20 (15 years after introducing each HS; **Figure 83**; which also reflects changes in the spawning biomass depletion). In addition, with catch adjustment schedule 1, the variability exhibited during the 1000 replicates of each harvest strategy scenario in terms of both cumulative-catch and CPUE in year 20 was generally greater the lower the weight on the targetCE (the higher the cumulative catch). However, there was also an interaction with the assessment interval with greater variability occurring with the longer assessment interval (year 2; see **Figure 83** and **Table 24**). With catch adjustment schedule 2 there was still a strong linear relationship between cumulative-catch and CPUE, although on average the cumulative-catches were lower and the CPUE in year 20 was higher for the equivalent scenario. The variation in the CPUE estimates was similar to that from catch adjustment schedule 1 but the cumulative-catches were more variable, and sometimes much more variable (**Figure 83**).

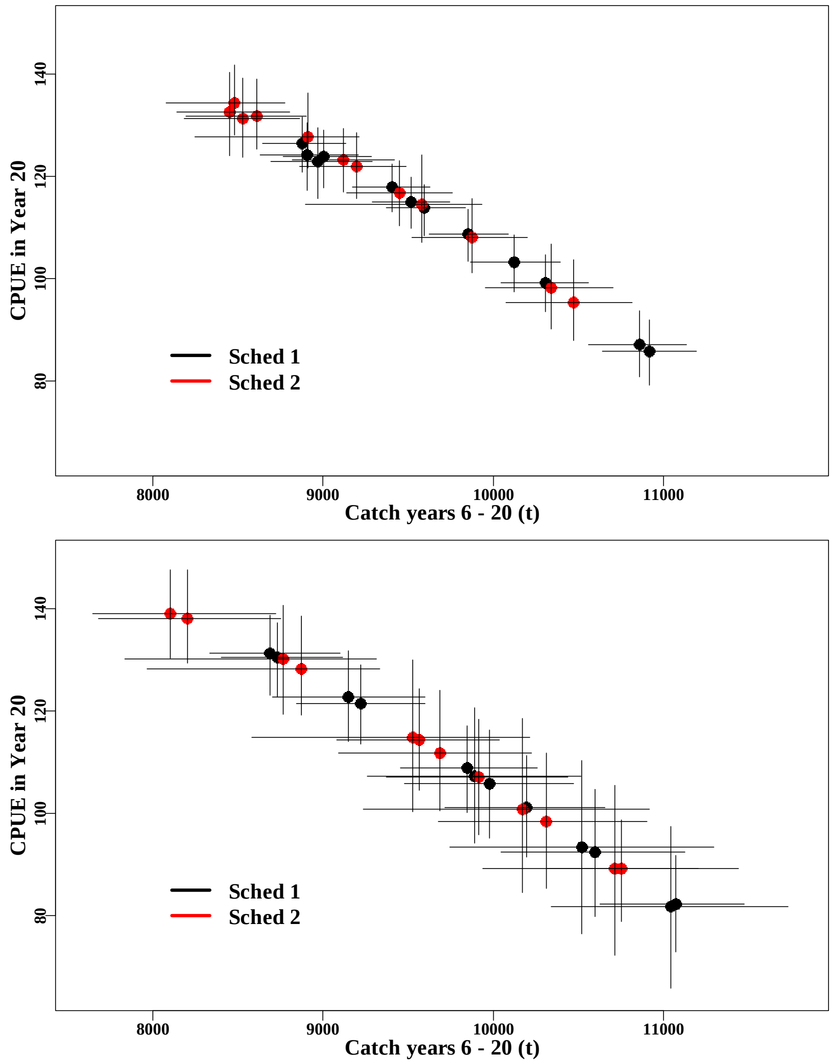

Figure 83. The median CPUE expected in year 20 relative to the cumulative catch taken across the first 15 years of the application of the harvest strategy using the same data as used in **Figure 82**. The upper panel relates to an assessment interval of 1 and the lower panel to an interval of 2. The scales are identical in both panels. The vertical and horizontal lines for each point are the 5% and 95% percentiles from the 1000 replicate runs.

9.8.13 Spawning Biomass vs Assess Interval and TargetCE Weight

The larger the cumulative-catches over the first 15 years of each harvest strategy (the lower the targetCE weight), the lower the predicted recovery of spawning biomass (**Figure 84**). For specific targetCE weights below 0.5 the longer the assessment interval the lower the recovery of spawning biomass after 15 years of applying each harvest strategy scenario. Once again, the effect of the weight attributed to the Grad4 and Rate1 performance measures only led to different median levels of recovery being expressed under TAC adjustment schedule 2; in **Figure 84** black circles (Schedule 1) tend to be on top of each other while red circles (Schedule 2) tend to separate. With targetCE weights less than 0.5 and 0.7 there appears to be an approximate linear relationship between recovery level and targetCE weight. However, when a second order polynomial curve is fitted to each combination of assessment interval and TAC adjustment schedule then the curvilinear nature of all relationships is more clearly apparent (**Figure 84**). The drop off in the spawning biomass depletion when the weight on the targetCE PM is 0.7 occurs because catches are increased faster once the CPUE is above the target, which occurs most quickly with a weighting of 0.7 after bumping up against the lower catch limit of 500 tonnes (**Figure 80** and **Figure 81**).

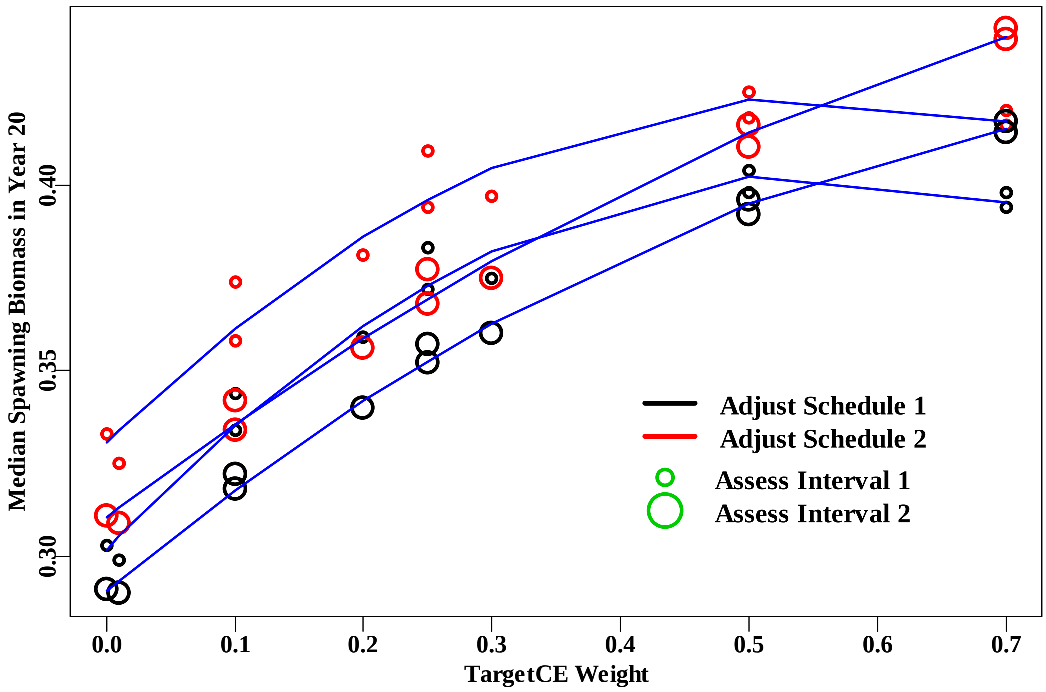

Figure 84. The predicted median spawning biomass depletion level in year 20 relative to the weight given to the targetCE performance measure in the MCDA. The TAC adjustment schedule is denoted by colour and the assessment interval by the size of the symbol used. Each fine blue line is a second order polynomial depicting the trajectory of medians for the six combinations of assessment interval and TAC adjustment schedule.

The differences between the alternative strategies can appear to be relatively minor (**Table 20**) although the maximum difference between cumulative catch for the first 15 years in the scenarios illustrated in **Figure 85** and **Figure 86** was 10598 – 8735 (1863 t); the maximum across all scenarios (**Table 24**) was 11071 – 8103 (2968 t). However, a consideration of the trajectories taken to reach these values (**Figure 85** and **Figure 86**) indicates that they are derived from fisheries having very different characteristics.

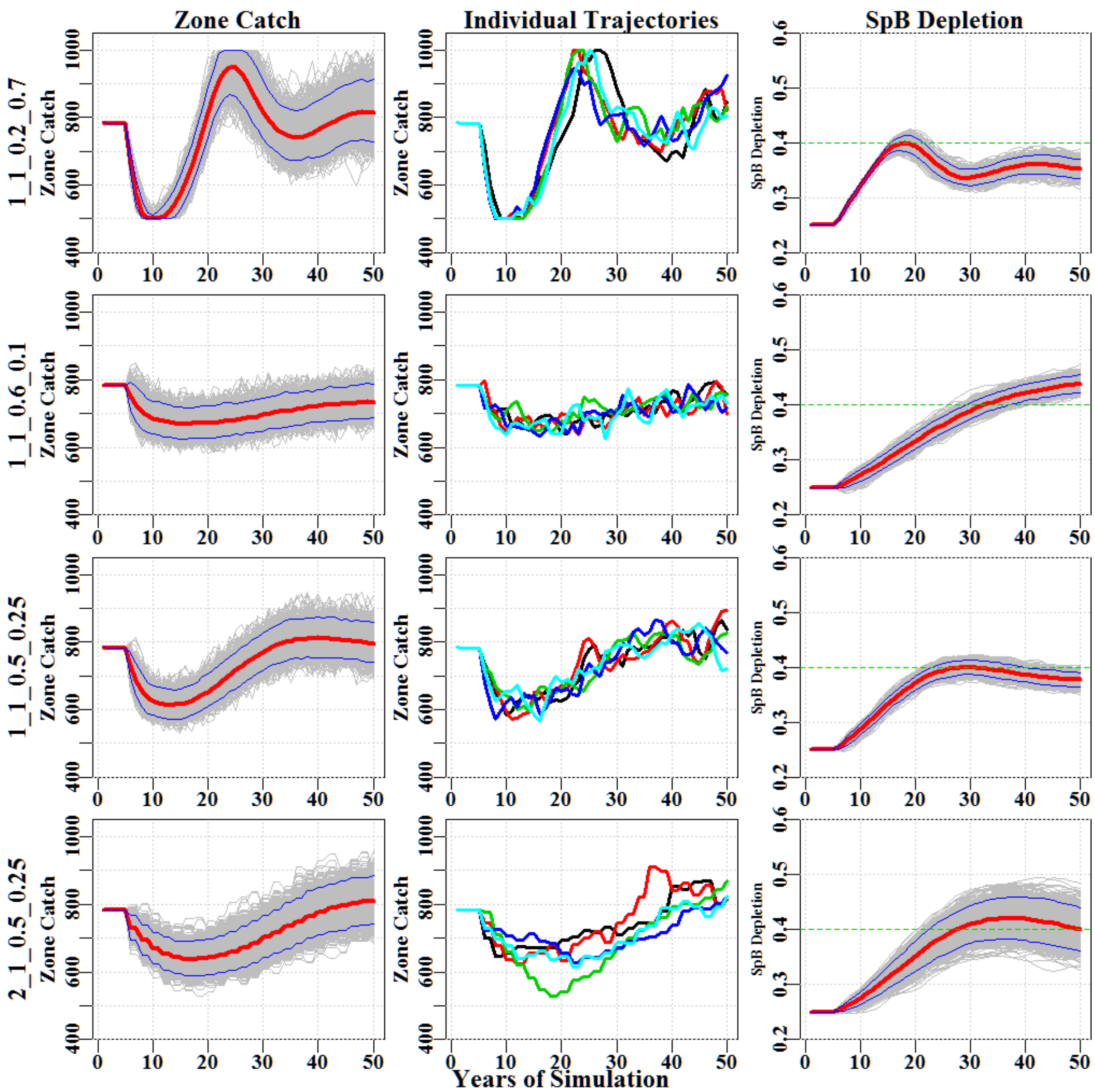

Figure 85. A comparison of the 1000 replicates for four contrasting harvest strategy scenarios: all use catch adjustment schedule 1, three have assessment intervals of 1 year and the fourth of 2 years, and one has a targetCE weight of 0.7, one has 0.1, and the other two have 0.25. The left hand plots are of catch each year, the middle plots are five random selected individual trajectories, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines 90th percentiles are blue lines.

TargetCE weights of 0.7 lead to relatively dramatic and rapid changes in catches and stock recovery such that the oscillatory behaviour of catches and spawning biomass depletion is clearly apparent, with numerous trajectories attempting to breach the lower and upper TAC limits. Such characteristics are greatly damped with a targetCE weight of only 0.25 with the opposite extreme dynamics when using a targetCE weight of 0.1 (**Figure 85** and **Figure 86**). The time lags introduced by catch adjustment schedule 2 lead to more trajectories bumping up against at least the lower TAC limit, although the two year assessment interval acts to prevent such events (**Figure 86**), which is apparent in the panel relating to the weight of 0.7 on targetCE.

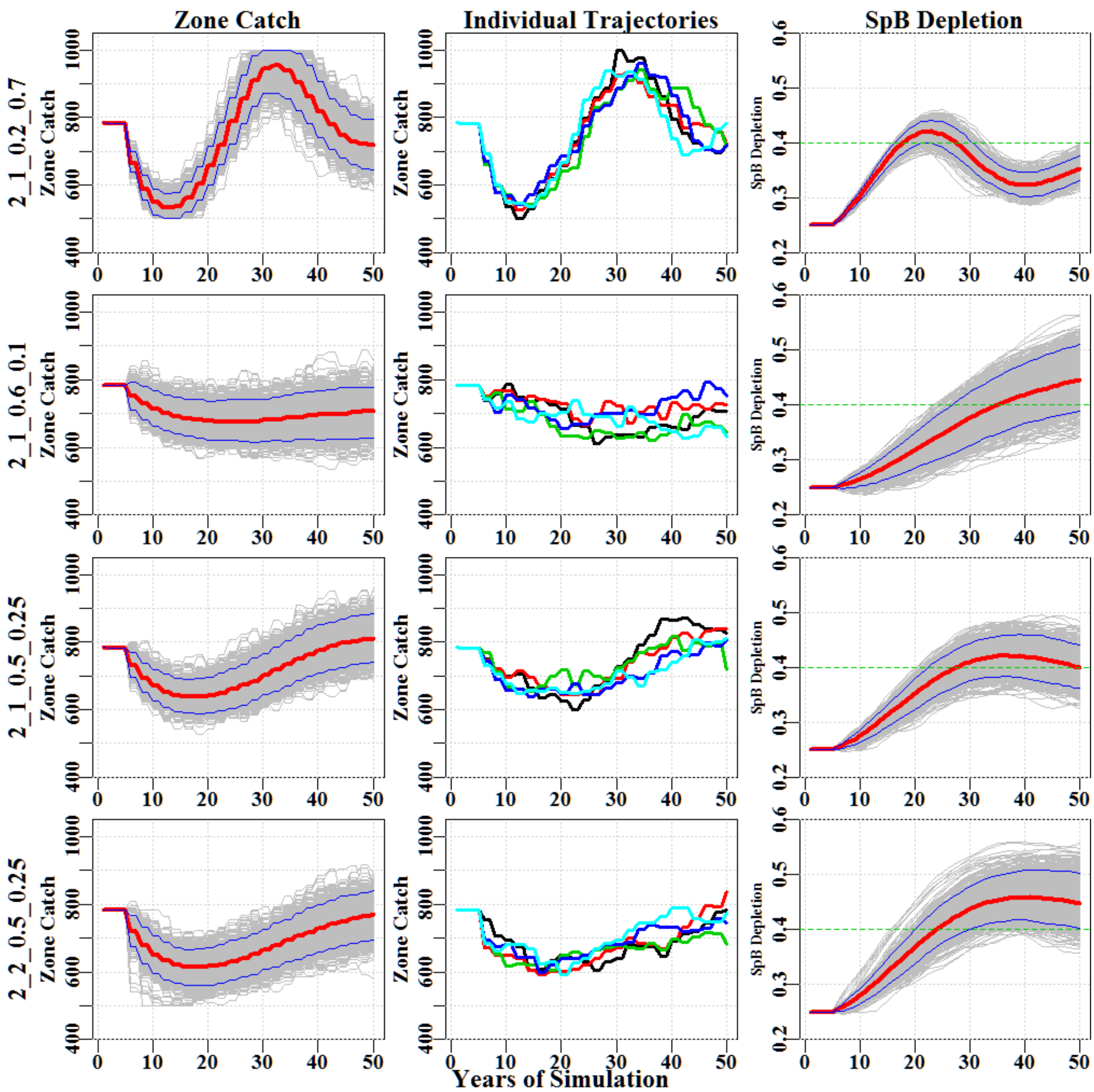

Figure 86. A comparison of the 1000 replicates for four contrasting harvest strategy scenarios: They all have assessment intervals of 2 years, three use the catch adjustment schedule 1 and the fourth schedule 2, and one has a targetCE weight of 0.7, one has 0.1, and the other two have 0.25. The left hand plots are of catch each year, the middle plots are five random selected individual trajectories, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines 90th percentiles are blue lines.

Table 20. The median Cumulative-Catch for years 6 – 20 and spawning biomass depletion in year 20 for each harvest strategy for the comparisons made in **Figure 85** and **Figure 86**. The columns are both the targetCE weight and the assessment interval while the rows are the two catch adjustment schedules.

TargetCE Wt	0.7	0.1	0.25	0.25
	AssessInt 1	AssessInt 1	AssessInt 1	AssessInt 2
Schedule 1: Catch	8970	10308	9597	9978
Schedule 1: Depletion	0.394	0.334	0.372	0.352
Schedule 2: Catch	8735	10598	9978	9688
Schedule 2: Depletion	0.414	0.318	0.352	0.368

9.8.14 Comparison of Initially Preferred Settings with Alternatives

Examining the changes suggested by applying the MCDA to each year to the fisheries in the individual zone through the history of the fishery it was possible for the Tasmanian FRAG to make initial selections with regard to the settings used in a proposed harvest strategy for Tasmania. This led to the FRAG suggesting a targetCE weight of 0.5, an assessment interval of 2 years and the use of the catch adjustment schedule 2 would be an acceptable group of settings for a first trial of the harvest strategy using the MCDA. In each case, starting at a depletion level of 25%B_0, the effect of the weight applied to the Grad4 and Rate1 PMs had little effect except where the Grad4 PM was given a weight of 0.0 (see **Figure 95** in the Supplementary Results). By comparing these general results with alternatives across the assessment intervals and catch adjustment Schedules for similar weight settings and others (see **Figure 87** and **Table 21**). Two things are apparent: 1) the more rapid response with more extreme events occurring and oscillatory dynamics with a weight of 0.5 and above relative to a weight of 0.25 on the targetCE; and 2) the slower response given schedule 2 relative to schedule 1 leading to more lower catches and consequently higher levels of spawning biomass depletion.

Table 21. Estimates for the median and central 90% quantiles for the cumulative catch from year 6 – 20, and the CPUE and spawning biomass depletion levels in year 20, 15 years after the introduction of the harvest strategy. The scenario legends indicate the assessment interval, the catch adjustment schedule, and the Grad4 and targetCE weights. The right-most column represents the current settings being trialled in Tasmania.

Performance Measure	2_1_0.5_0.25	2_1_0.25_0.5	2_2_0.5_0.25	2_2_0.25_0.5
Catch5%	9479	8705	9089	7840
Catch50%	9978	9148	9688	8769
Catch95%	10473	9599	10225	9314
CPUE5%	95.2	114.0	100.5	119.5
CPUE50%	105.9	122.8	111.7	130.1
CPUE95%	116.3	131.8	124.0	140.7
Depletion5%	0.324	0.372	0.338	0.387
Depletion50%	0.352	0.396	0.368	0.416
Depletion95%	0.380	0.419	0.401	0.455
MeetCE5%	16	13	15	12
MeetCE50%	19	14	17	14
MeetCE95%	23	16	20	15

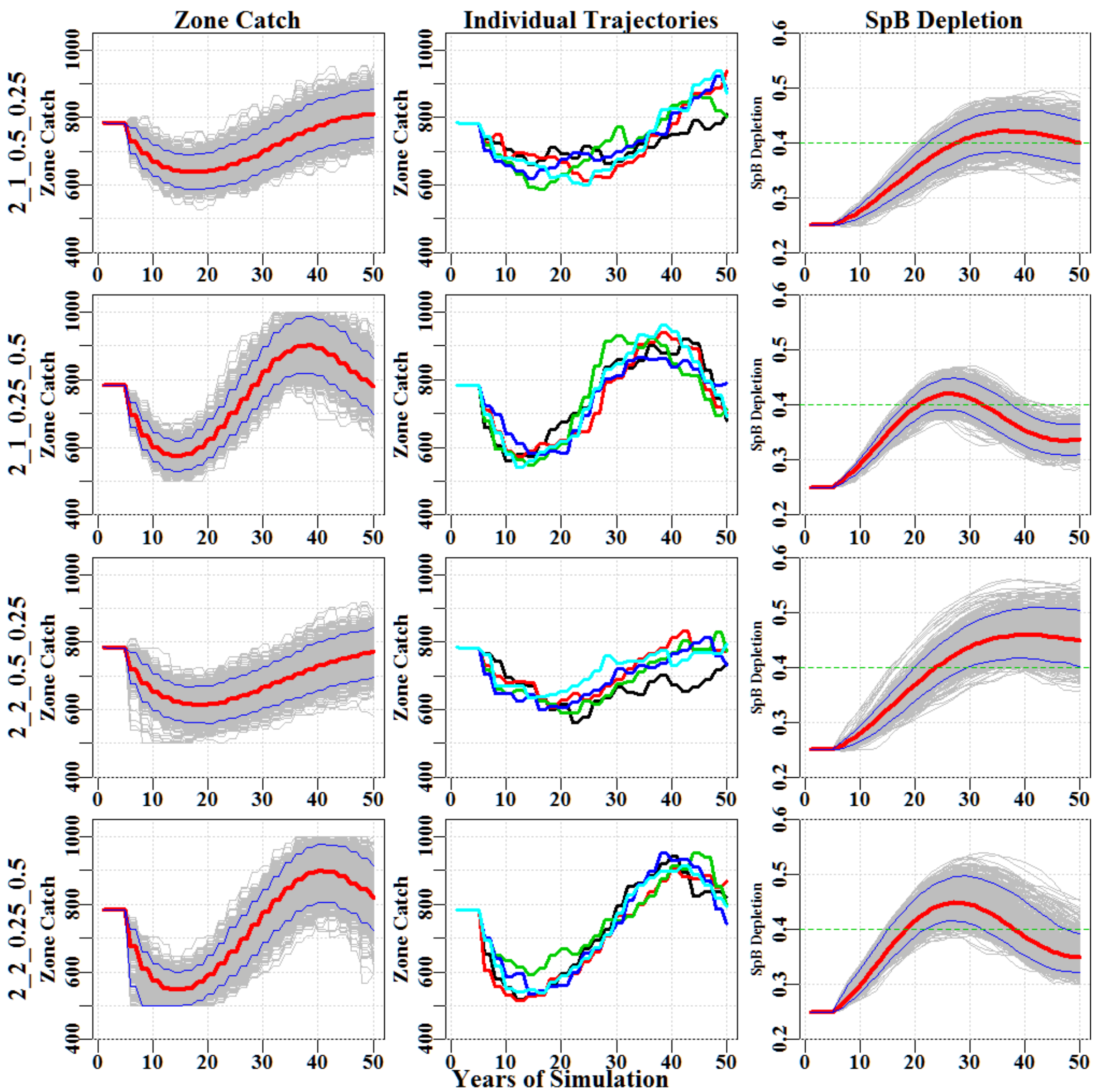

Figure 87. A comparison of the 1000 replicates for four harvest strategy scenarios: all use an assessment intervals of two-years. The other have combinations of a targetCE weight of 0.5 or 0.25 and using TAC adjustment schedule 1 or 2. The left hand plots are of catch each year, and the right hand plots are of spawning biomass depletion. The 1000 replicates are illustrated as fine grey lines with the medians as thick red lines. The axes are the same in comparable graphs.

The current settings lead to predictions of more extreme fishery dynamics than other combinations of settings within each harvest strategy with assessment intervals of 2 years. Without policy guidance on what outcomes are preferable (that is what are the explicit operational objectives for the fishery), then it is not possible to select a specific harvest strategy among those trialled.

9.9 Discussion

9.9.1 The Management of Abalone Fisheries

Like all commercial fisheries a key problem for the sustainable management of abalone stocks is to maximize catch levels taken from a stock while maintaining the ability of the stock to continue producing those same catch levels. All fisheries have this problem of balancing catches against productivity. However, because abalone have an exceptionally high monetary value there are clear short term incentives to keep catches high and a risk exists that these short term incentives will outweigh the longer term, and sometimes more difficult to perceive and to estimate, sustainability requirements.

Another major problem that makes the management of abalone exceptionally difficult is that abalone populations exhibit very complex spatial structuring. There is only weak connectivity between abalone populations, even those that are geographically close. Populations of Blacklip Abalone (*Haliotis rubra*) that are at distances ≤ 10km apart can be almost genetically isolated with only low levels of inter-population settlement success (Miller *et al*., 2009). Thus, if a population were to go locally extinct in an area it might take decades to re-establish, if ever. Oral history of divers fishing during the late 1970s and early 1980s at an LML of 127mm suggests this has occurred in the Tasmanian Eastern Zone (page 47, Frusher et al FRDC Project 2004-013). So sustainability is a more difficult issue for abalone fisheries and requires a finer spatial control of catches.

The estimation of what should be a sustainable catch for a fished zone is not as difficult a problem as ensuring that whatever catch level is agreed upon is spread out across a fished zone in a manner that matches how the total catch was estimated. Ideally, the total allowable catch (TAC) for a zone would be estimated by determining the local distribution of available biomass, agreeing on what proportion can safely be taken without compromising the following years' production capacity, and then summing those locally agreed catches. This is an approximate description of what currently occurs when meetings are held in more than one Australian jurisdiction to decide the following years' TAC. In Tasmania, the spatial scale of such decisions is now the statistical block (examples of such blocks can be seen in the map within **Figure 5** on page 28). However, it is not uncommon for expected catches to be identified for various blocks but then the catches become concentrated in other blocks when they are taken, which is clearly a failure of the intent to spread the catches in proportion to the available biomass. When more catch is taken within a year than was allocated during the FRAG assessment process, it is effectively a local TACC increase, but can be of a magnitude significantly larger than would have been accepted if proposed during the FRAG process.

Implementing a formal harvest strategy within the Tasmanian abalone fishery is one means of attempting to solve both these major issues. One outcome of steadily applying the MCDA application, even with a range of settings, would be to balance expected catches across the blocks in response to how each performs. There are possibilities for these rules to become confused (if, for example, catches expected from one block are taken in other blocks, this may lead to the original block appearing to perform well but in practice performing well when few catches are taken despite expectations, has not occurred). Rather than simply selecting an array of settings and applying the MCDA based harvest strategy, for Tasmania it was decided to test alternative harvest strategies using a management strategy evaluation to select the most effective before its implementation.

9.9.2 The Management Strategy Evaluation

The purpose of applying management strategy evaluation in this study was to identify which harvest strategy scenarios were capable of leading to a balance between maintaining catches while maintaining the stock size at the same time. This balance between scale and distribution of catch and sustainability of stock is the primary trade-off between potentially conflicting objectives that constitute the source of the difficulty in managing abalone fisheries. In addition, the promotion of greater stability within the fishery, in terms of catches and CPUE was deemed a better alternative to the oscillatory fishery behaviour exhibited, for example, on the east coast of Tasmania since the late 1990s. The issue of spatial structure was addressed by conducting the application of the empirical performance measures at the statistical block scale rather than using the whole of zone approach. A workable harvest strategy was defined as one which could find any balance and it was certainly the case that some combinations of performance measures failed to be 'workable'.

Importantly and fortunately, it was found that the Multi-Criteria Decision Analysis was able to be successful at combining alternative performance measures to produce management advice in terms of block catches and a resulting total allowable catch. In the simulations some but not all of the variations in empirical harvest strategies explored (different weightings, assessment intervals etc) were able to rebuild depleted stocks, control the fish down of only lightly harvest stocks, and finally to maintain a fishery at equilibrium once that equilibrium was achieved. This illustrates the importance of reviewing interactions between components of an empirical harvest strategy framework. Not only was it able to be put into an operational framework it was also possible to set up that operational framework so as to accept and include completely new performance measures into the empirical assessment process.

The different performance measures are not all equally influential (the targetCE is the most influential and the Rate1 the least influential) but their individual effects are greatly influenced by their relative weights, and by interactions that occur between the performance measures, the assessment intervals, and the block-catch adjustment schedule used as the basis for generating management advice.

9.9.3 Interactions between Performance Measures, Assessment Interval and Catch Adjustment Schedule

When only the CPUE gradient performance measures (Grad4 and Rate1) were used (by setting the weight on the targetCE PM to zero) the management outcomes were pathological in that they were unidirectional. They continually reduced catches which increased spawning biomass with no factor encouraging a balance between objectives (see **Figure 63** to **Figure 65**; and **Figure 91** to **Figure 94** in the supplementary results). This is a surprising outcome as the Grad4 performance measure should act to increase catches if the gradient is positive. However, what happens is that the catches in individual blocks do go up and down quite markedly in response to interactions between the Rate1 and Grad4 performance measures (**Figure 88**). The absence of balance makes this strategy unworkable, although with a depleted stock it could be used, at least for a few years, to get the stock started on a recovery path. However, such an approach would only be useful for a few years after which some more balanced strategy might be introduced that would be capable of achieving efficient exploitation as well as effective conservation of the resource. Even if it were used in this way the variation in catches within blocks would be a disadvantage.

Out of the three performance measures included in the current MCDA process the targetCE performance measure is required if eventually a balance is to be struck between changes in the catches and changes in the spawning biomass depletion levels. As the weight attributed to the targetCE PM increases, catches over the first 15 years of each harvest strategy scenario decrease while the recovery in spawning biomass across the zone increases. The inclusion of a lower limit on the TAC alters the relationship between targetCE weight and both catch and spawning biomass depletion level (see **Figure 82** to **Figure 84**). This inclusion was made to highlight exceptionally low catches and CPUE and is neither recommended or rejected for inclusion in the harvest strategy eventually adopted in the real fishery. As the weight on the targetCE declines and the weights of the other performance measures increases, the eventual long term equilibrium CPUE achieved becomes more and more biased high above the target. Conversely, as the weight on the targetCE approaches 1.0 the final equilibrium CPUE also approaches the selected target (see **Figure 79**).

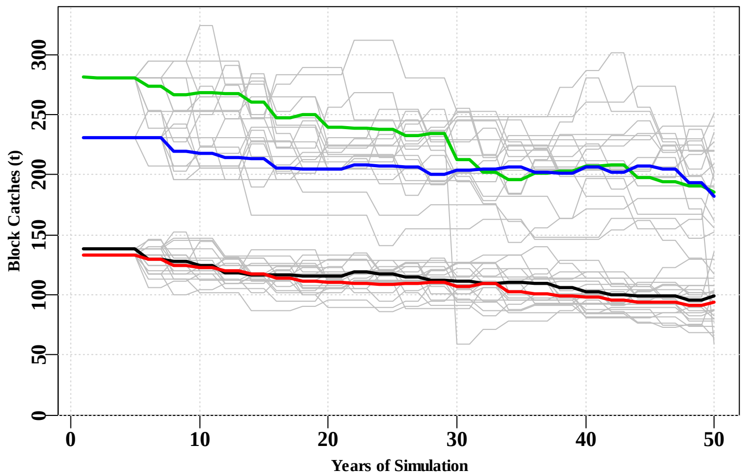

Figure 88. Ten replicate runs depicting the catch per block when the targetCE weight is set to zero. The Rate1 and Grad4 performance measures interact to increase the variation in catches between years. The approximate reduction in catches of about 20% leads to an approximate doubling of CPUE. The four colours identify the performance of the four simulated blocks.

There is a very strong positive linear relationship between the level of spawning stock depletion in year 20 and the expected CPUE in year 20 (see **Figure 66**). For the lower targetCE weights (0.5 and lower) there is also an approximately linear relationship between the targetCE performance measure weight and the spawning biomass in year 20; so the lower targetCE weights will also be strongly related to the expected CPUE in year 20.

As the targetCE PM weight increases the wave length of any oscillatory dynamics in catch, CPUE, and spawning biomass depletion levels becomes shorter, which implies changes occur more rapidly. This is also reflected in the time taken to achieve the target

CPUE which had an inverse relationship with the targetCE weight (see **Figure 85** and **Figure 86**).

As the assessment interval increases then generally, for the same targetCE weight, the cumulative catches in the first 15 years are greater and the spawning biomass depletion level increase is correspondingly less. As the targetCE weight becomes greater than 0.5 then catches can increase and the depletion level in year 20 can be less than scenarios with smaller targetCE weights. This reflects the greater speed with which the dynamics change at the higher weights on the targetCE (see **Figure 84**).

The variation of the outcomes increases with the assessment interval although this can interact with the block-catch adjustment schedule so that the cumulative-catch in the first 15 years can become more variable in schedule 2.

The proportion of replicate trials of each scenario that breached either the lower or upper TAC limits increased with targetCE weight but also with the block-catch adjustment schedule, where schedule 2 led to more breaches.

9.9.4 Harvest Strategy Selection

The selection of a particular strategy to implement in the Tasmanian abalone fishery is not something that should be done in this report. The management strategy evaluation estimates the outcome of alternatives and the balance between the trade-offs is made clear (for example as seen in **Figure 85**, **Figure 86**, and **Figure 87**). But which particular mix of outcomes is the most desirable by the Industry and managers is not able to be determined. The objective of the MSE was to provide the information to enable an informed selection among different possible harvest strategies to be made rather than to make a single best guess selection.

While it is not the aim of this present work to make a single selection it is possible to describe the implications of the various harvest strategies explored in the MSE. For example, currently (July and August 2016) the preference for the MCDA settings is to use a two-year assessment interval with the second TAC adjustment schedule and a targetCE weight of 0.5 (see **Figure 87** and **Figure 95**). Whether this continues to be the preferred group of settings for the MCDA will depend on whether the predicted outcomes best match the outcomes desired by those who will make the decisions about what specific management objectives will be adopted.

9.10 Supplementary Results

9.10.1 Assessment Interval One-Year

There are sometimes only subtle differences between the application of different TAC adjustment schedules if all other settings are the same. Generally schedule 2 leads to slightly slower responses and sometimes more dramatic changes (**Figure 89**; **Table 22**).

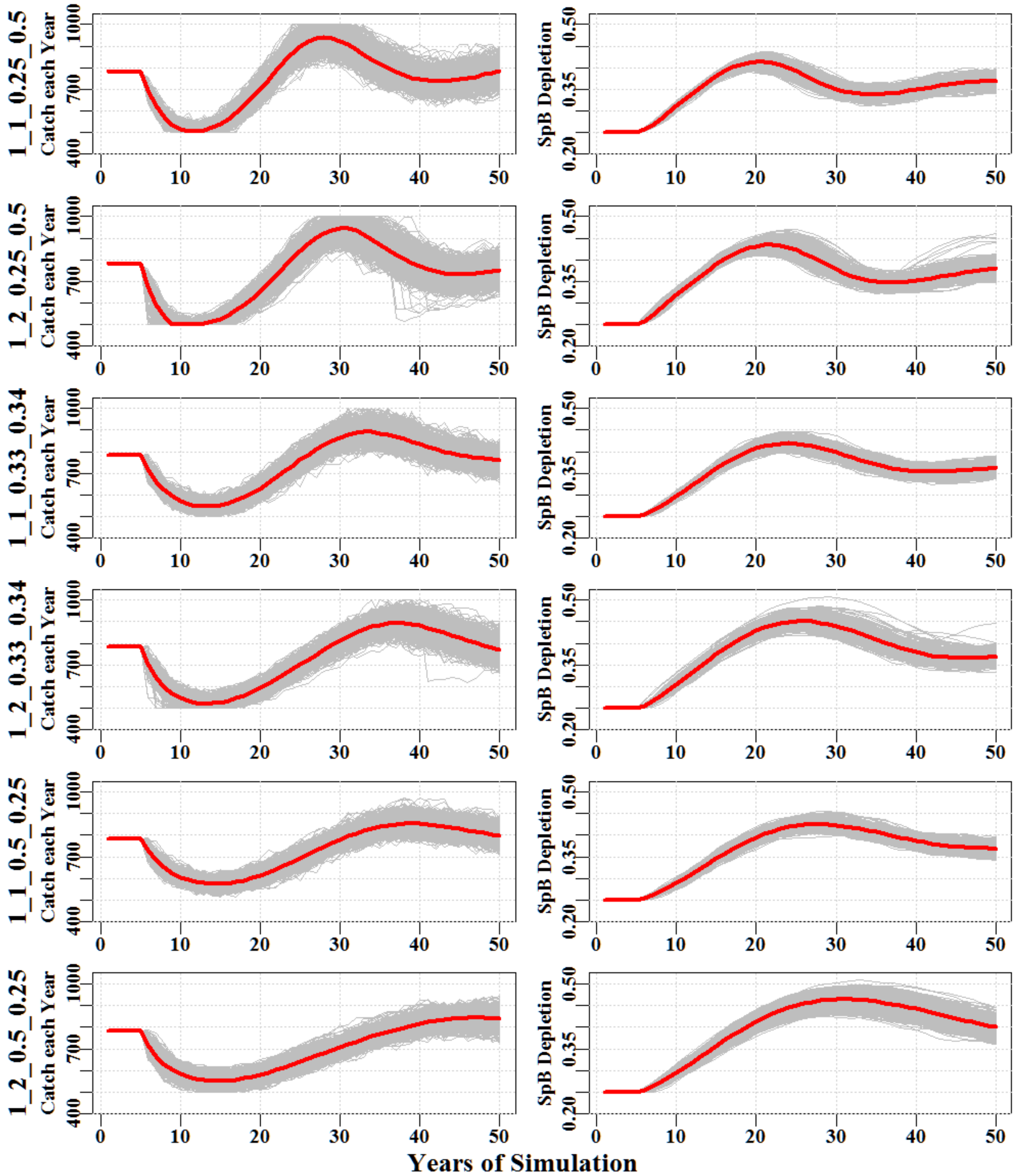

Figure 89. A comparison of size of the options explored with an assessment interval of one-year. The row legends are assessment interval + TAC adjustment schedule + Grad4 weight + targetCE weight. The red lines are the median values in each case and the grey are the 1000 individual runs.

Table 22. Estimates for the median and central 90% quantiles for the cumulative catch from year 6 – 20, and the CPUE and spawning biomass depletion levels in year 20, 15 years after the introduction of the harvest strategy. The scenario legends indicate the assessment interval, the TAC adjustment schedule, and the Grad4 and targetCE weights. See **Figure 89**.

Performance Measure	1_1_0.25_0.5	1_2_0.25_0.5	1_1_0.33_0.34	1_2_0.33_0.34	1_1_0.5_0.25	1_2_0.5_0.25
Catch5%	8470	8046	8655	8253	8939	8509
Catch50%	8677	8368	8891	8495	9165	8832
Catch95%	8914	8601	9119	8760	9383	9152
CPUE5%	125.3	131.7	123.1	130.0	118.2	123.0
CPUE50%	130.5	136.8	127.8	135.6	122.7	129.5
CPUE95%	135.2	142.1	132.5	140.3	127.4	136.0
Depletion5%	0.401	0.418	0.396	0.414	0.383	0.396
Depletion50%	0.415	0.431	0.408	0.429	0.395	0.413
Depletion95%	0.426	0.444	0.420	0.440	0.407	0.430

Table 23. Estimates for the median and central 90% quantiles for the cumulative catch from year 6 – 20, and the CPUE and spawning biomass depletion levels in year 20, 15 years after the introduction of the harvest strategy. The scenario legends indicate the assessment interval, the TAC adjustment schedule, and the Grad4 and targetCE weights. See **Figure 90**.

Performance Measure	2_1_0.25_0.5	2_2_0.25_0.5	2_1_0.33_0.34	2_2_0.33_0.34	2_1_0.5_0.25	2_2_0.5_0.25
Catch5%	8591	8016	8947	8570	9319	8990
Catch50%	9002	8657	9448	9157	9758	9521
Catch95%	9425	9188	9909	9712	10213	10062
CPUE5%	117.3	121.9	107.3	111.3	101.3	104.2
CPUE50%	125.9	132.5	117.0	122.9	110.8	115.7
CPUE95%	134.0	141.0	127.0	134.0	119.9	126.2
Depletion5%	0.381	0.394	0.356	0.367	0.340	0.348
Depletion50%	0.404	0.421	0.381	0.397	0.365	0.378
Depletion95%	0.425	0.449	0.407	0.427	0.389	0.407

9.10.2 Assessment Interval Two-Year

An assessment interval of two-years (**Figure 90**; **Table 23**) invariable slows events down relative to an assessment interval of one-year, with TAC adjustment schedule also adding to the variation expressed. The speed with which the stock achieves the target CPUE also decreases with the weight given to the targetCE.

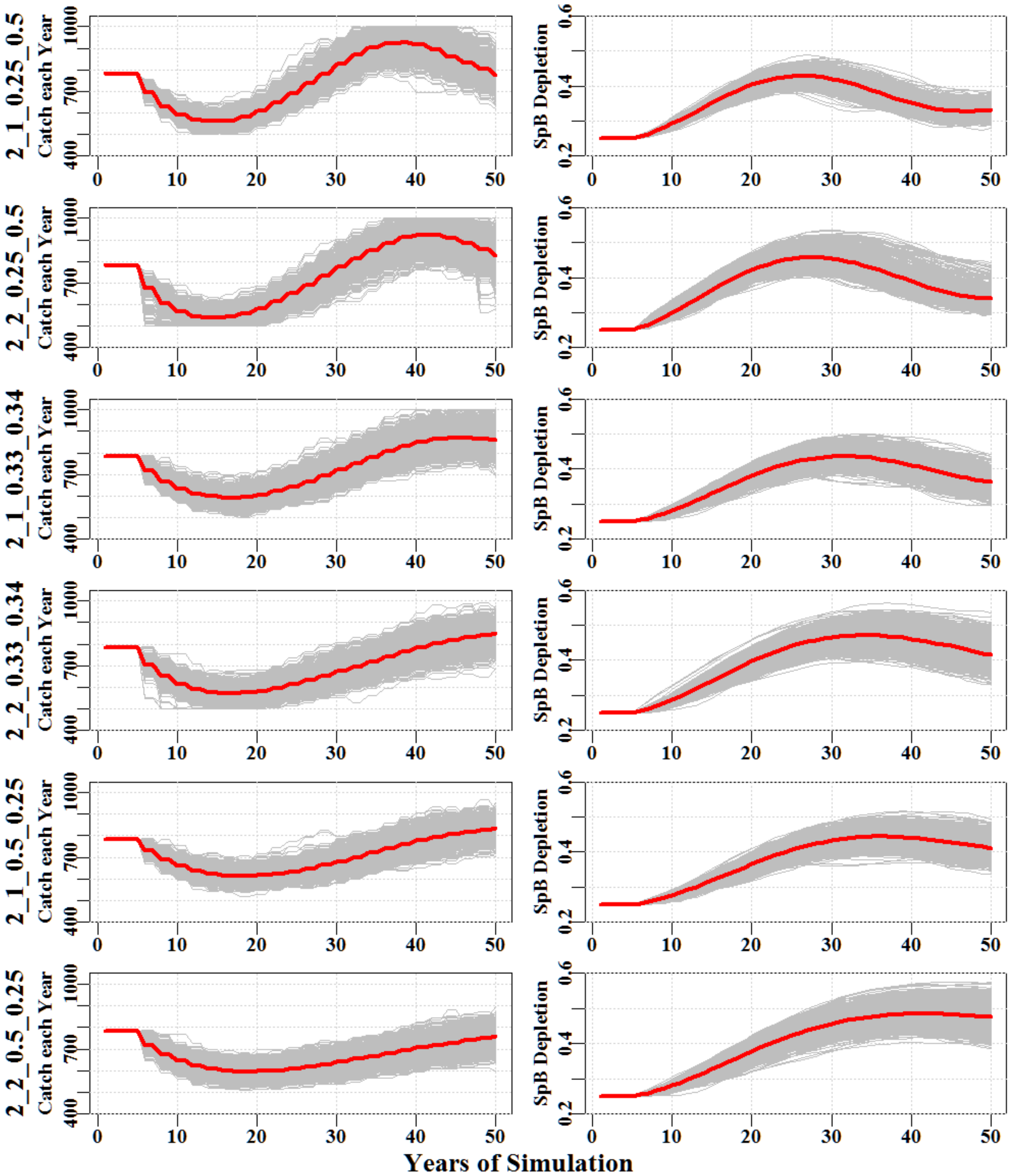

Figure 90. A comparison of size of the options explored with an assessment interval of one-year. The row legends are assessment interval + TAC adjustment schedule + Grad4 weight + targetCE weight. The red lines are the median values in each case and the grey are the 1000 individual runs.

9.10.3 TargetCE Weight = 0.0

The four scenarios where the targetCE weight was set to 0.0 are presented in detail in (**Figure 91** to **Figure 94**). In all cases changes to the assessment interval or TAC adjustment layer mainly altered the variability of the outcomes. But the outcome in all cases was pathological in that catches always declined and the spawning biomass level increased.

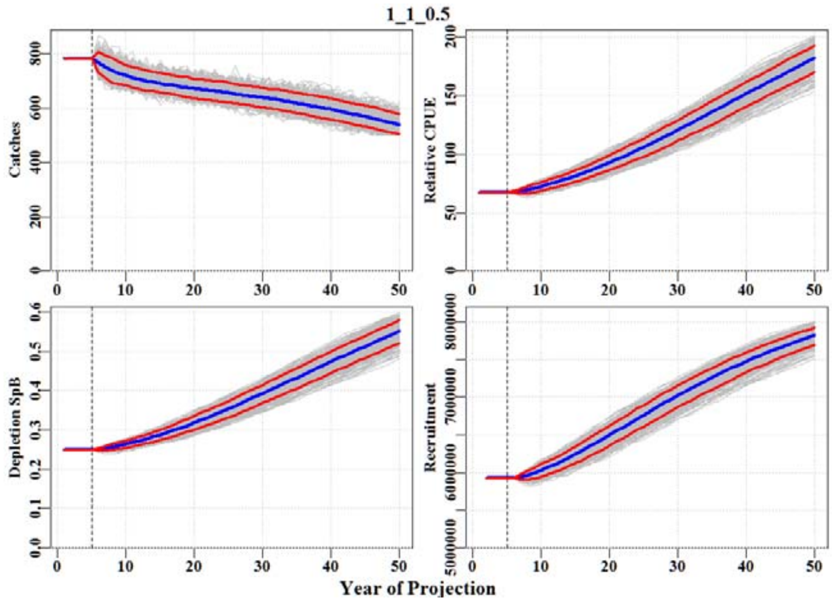

Figure 91. All 1000 replicate trajectories for the scenario with assessment interval of 1 years and TAC adjustment schedule 1 where the targetCE weight = 0.0 and the Grad4 and Rate1 weights are 0.5. The blue lines are the median trajectory and the red lines are the inner 90^{Th} percentiles.

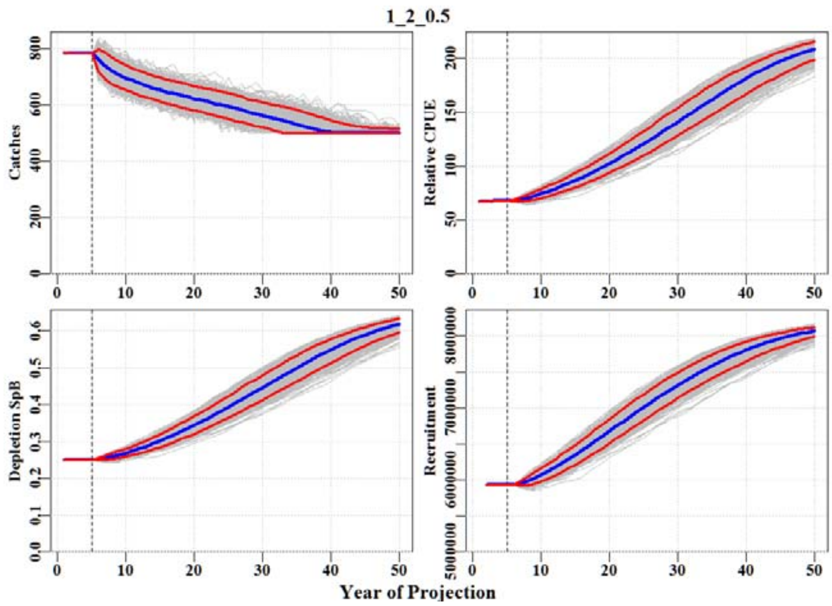

Figure 92. All 1000 replicate trajectories for the scenario with assessment interval of 1 years and TAC adjustment schedule 2 where the targetCE weight = 0.0 and the Grad4 and Rate1 weights are 0.5. The blue lines are the median trajectory and the red lines are the inner 90^{Th} percentiles.

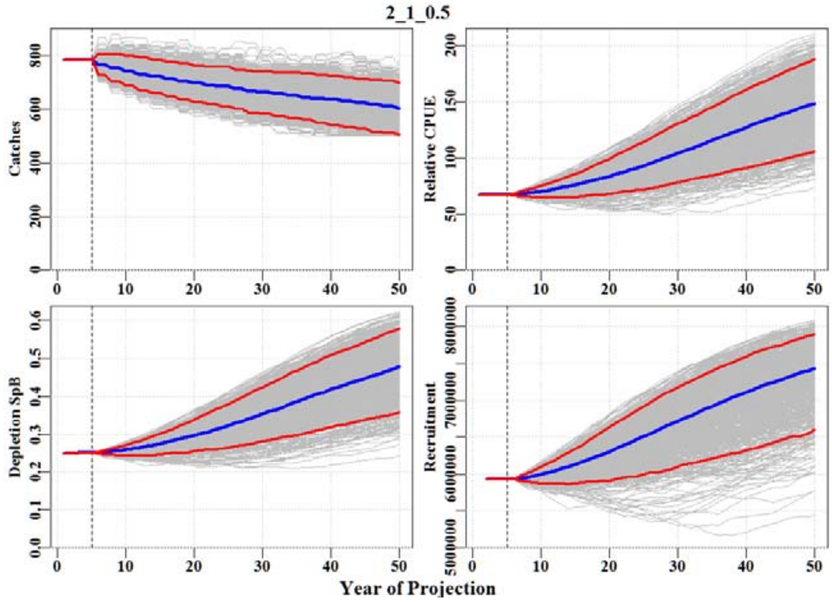

Figure 93. All 1000 replicate trajectories for the scenario with assessment interval of 2 years and TAC adjustment schedule 1 where the targetCE weight = 0.0 and the Grad4 and Rate1 weights are 0.5. The blue lines are the median trajectory and the red lines are the inner 90Th percentiles.

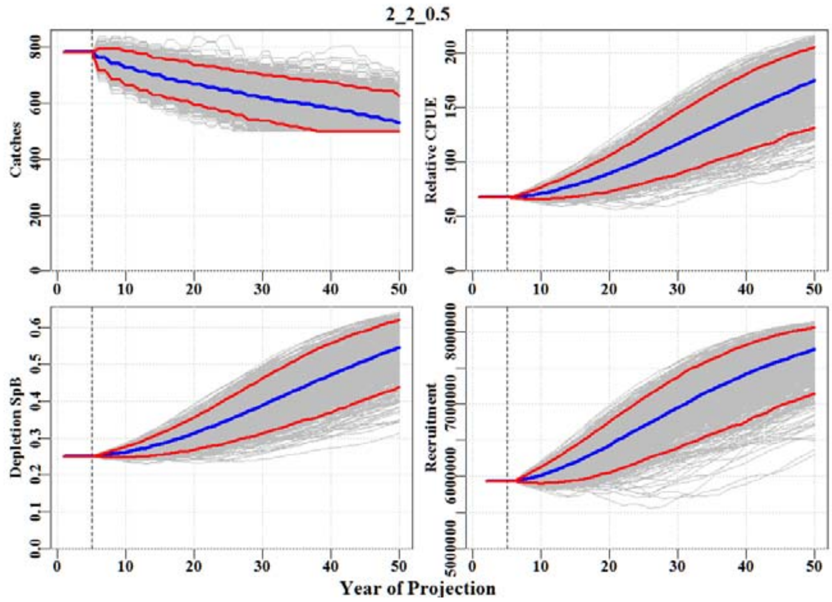

Figure 94. All 1000 replicate trajectories for the scenario with assessment interval of 2 years and TAC adjustment schedule 2 where the targetCE weight = 0.0 and the Grad4 and Rate1 weights are 0.5. The blue lines are the median trajectory and the red lines are the inner 90Th percentiles.

9.10.4 The MCDA Settings in August 2016

Initial exploratory settings for the MCDA applications to the real fishery were to have an assessment interval of two-years, using the TAC adjustment schedule 2, and a weight on the targetCE of 0.5. Altering the weights applied to the Grad4 and Rate1 performance measures had little effect except for when the Grad4 PM was not used i.e. given a weight of zero (**Figure 95**).

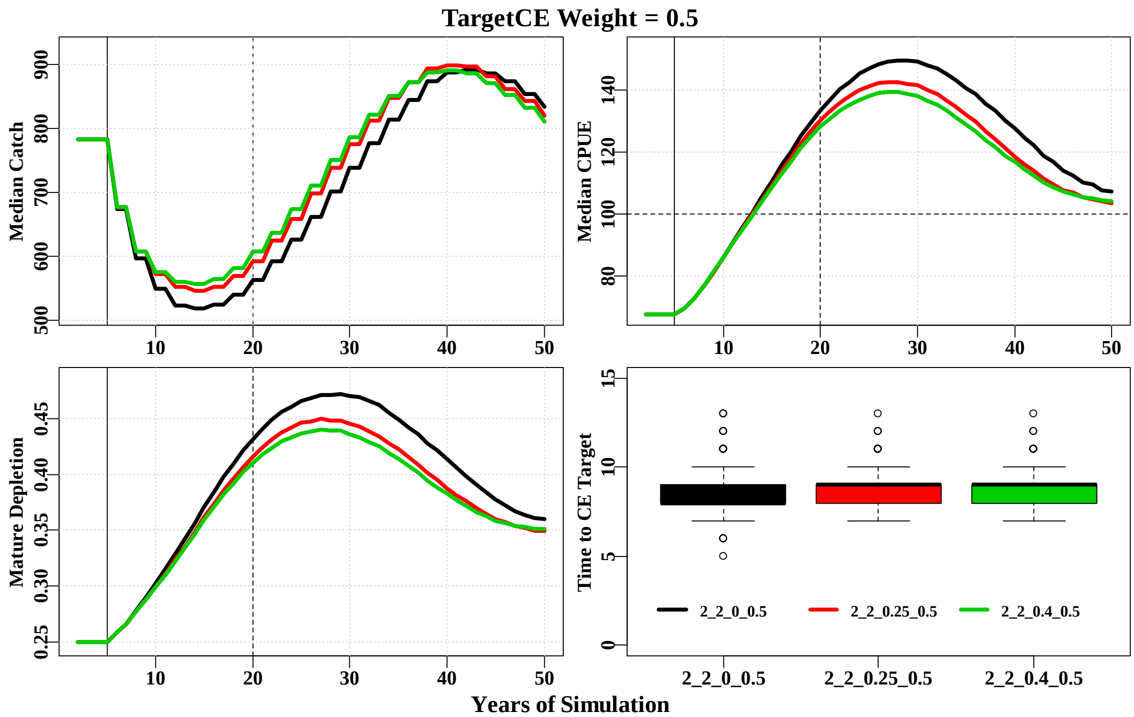

Figure 95. The median trajectories for scenarios with assessment interval of 2 years and TAC adjustment schedule 2 where the targetCE weight = 0.5. The legend labels are the assessment interval, the TAC adjustment schedule the Grad4 and TargetCE weights.

Table 24. Summary statistics for the 56 scenarios where the TargetCE PM is included. The quartiles, mean and standard deviations relate to total catches from years 6 – 20 (C postfix), the CPUE in year 20 (CE postfix), the spawning biomass depletion in year 20 (SB postfix), and the time to attain the CPUE target (MT postfix).

Scenario	5%C	50%C	95%C	MeanC	StDevC	5%CE	50%CE	95%CE	MeanCE	StDevCE	5%SB	50%SB	95%SB	MeanSB	StDevSB	MeanMT	StDevMT
1_1_0.5_0	10557	10856	11132	10852	173	80.9	87.2	93.8	87.2	3.9	0.286	0.303	0.320	0.303	0.011	27.3	2.4
1_1_0.98_0.01	10641	10917	11194	10917	169	79.3	85.9	92.1	85.8	4.0	0.282	0.299	0.316	0.299	0.011	29.6	2.9
1_1_0.6_0.1	10047	10308	10556	10303	153	93.6	99.2	104.7	99.2	3.4	0.320	0.334	0.349	0.334	0.009	20.9	1.5
1_1_0.3_0.1	9867	10123	10394	10127	159	97.4	103.2	108.5	103.1	3.5	0.329	0.344	0.359	0.344	0.009	19.4	1.2
1_1_0.6_0.2	9623	9849	10086	9850	144	103.5	108.7	113.5	108.6	3.1	0.346	0.359	0.371	0.359	0.008	17.3	1.1
1_1_0.5_0.25	9373	9597	9837	9600	140	108.5	113.8	118.5	113.7	3.0	0.359	0.372	0.384	0.372	0.008	15.9	0.9
1_1_0.25_0.25	9174	9405	9630	9403	138	113.0	117.9	122.5	117.8	2.9	0.370	0.383	0.395	0.382	0.007	15.3	0.7
1_1_0.6_0.3	9290	9519	9746	9520	140	109.9	115.1	119.9	115.0	3.0	0.363	0.375	0.388	0.375	0.008	15.2	0.9
1_1_0.25_0.5	8645	8879	9136	8880	148	120.9	126.5	131.7	126.4	3.3	0.390	0.404	0.417	0.404	0.008	12.2	0.5
1_1_0.4_0.5	8768	9006	9284	9010	158	117.8	124.0	129.1	123.8	3.5	0.383	0.398	0.411	0.397	0.009	12.3	0.6
1_1_0.2_0.7	8692	8970	9291	8972	181	115.6	122.9	129.5	122.8	4.2	0.376	0.394	0.410	0.394	0.010	11.1	0.3
1_1_0.1_0.7	8630	8907	9206	8909	175	117.3	124.2	130.5	124.1	4.0	0.380	0.398	0.413	0.397	0.010	11.1	0.3
1_2_0.5_0	9953	10341	10702	10326	270	90.2	98.3	106.8	98.5	5.2	0.311	0.333	0.355	0.333	0.015	21.2	1.9
1_2_0.98_0.01	10076	10473	10813	10455	253	88.0	95.4	103.8	95.6	5.1	0.305	0.325	0.348	0.326	0.014	22.5	2.2
1_2_0.6_0.1	9522	9877	10198	9869	216	101.1	108.1	115.6	108.3	4.4	0.340	0.358	0.378	0.358	0.012	17.9	1.3
1_2_0.3_0.1	8898	9582	9932	9530	336	107.2	114.5	124.3	115.0	5.4	0.355	0.374	0.410	0.377	0.017	16.6	1.2
1_2_0.6_0.2	9142	9449	9757	9444	200	110.4	116.8	123.2	117.0	4.0	0.364	0.381	0.397	0.381	0.011	15.5	1.0
1_2_0.5_0.25	8862	9196	9489	9183	214	115.7	122.0	128.5	122.1	4.1	0.378	0.394	0.410	0.394	0.011	14.5	0.9
1_2_0.25_0.25	8250	8912	9212	8863	285	121.7	127.8	136.3	128.2	4.6	0.393	0.409	0.437	0.411	0.013	13.9	0.8
1_2_0.6_0.3	8819	9120	9420	9109	206	117.0	123.3	129.3	123.3	3.9	0.381	0.397	0.412	0.397	0.010	13.9	0.9
1_2_0.25_0.5	8077	8480	8777	8466	206	128.0	134.4	141.8	134.4	4.0	0.409	0.425	0.442	0.425	0.010	11.7	0.5
1_2_0.4_0.5	8194	8614	8903	8600	207	125.3	131.7	139.1	131.8	4.1	0.402	0.418	0.437	0.418	0.010	11.7	0.6
1_2_0.2_0.7	8184	8528	8865	8523	208	123.8	131.2	139.2	131.5	4.7	0.399	0.416	0.434	0.416	0.011	11.2	0.5
1_2_0.1_0.7	8140	8453	8804	8462	202	124.0	132.6	140.4	132.5	4.8	0.402	0.420	0.436	0.419	0.010	11.2	0.6
2_1_0.5_0	10342	11043	11728	11047	424	65.9	81.8	97.5	81.7	9.5	0.249	0.291	0.333	0.290	0.026	31.6	7.2

2_1_0.98_0.01	10623	11071	11471	11057	256	73.1	82.3	91.8	82.5	5.8	0.265	0.290	0.316	0.291	0.016	32.7	5.8
2_1_0.6_0.1	10044	10598	11122	10599	333	80.0	92.6	104.7	92.3	7.3	0.286	0.318	0.349	0.317	0.020	24.7	4.4
2_1_0.3_0.1	9744	10518	11292	10513	456	76.5	93.5	110.3	93.4	10.0	0.276	0.322	0.366	0.322	0.027	24.2	5.4
2_1_0.6_0.2	9715	10197	10653	10195	283	91.6	101.2	111.3	101.3	6.1	0.314	0.340	0.367	0.340	0.016	20.3	2.4
2_1_0.5_0.25	9479	9978	10473	9975	295	95.2	105.9	116.3	105.9	6.3	0.324	0.352	0.380	0.352	0.016	18.7	2.0
2_1_0.25_0.25	9261	9889	10514	9886	379	94.2	107.4	120.7	107.4	8.1	0.322	0.357	0.392	0.357	0.021	18.5	2.4
2_1_0.6_0.3	9452	9847	10258	9846	241	100.2	108.9	117.1	108.7	5.1	0.337	0.360	0.381	0.359	0.013	17.8	1.6
2_1_0.25_0.5	8705	9148	9599	9143	268	114.0	122.8	131.8	122.9	5.5	0.372	0.396	0.419	0.396	0.014	14.5	1.0
2_1_0.4_0.5	8845	9222	9600	9219	230	113.6	121.5	129.0	121.4	4.8	0.372	0.392	0.412	0.392	0.012	14.6	0.9
2_1_0.2_0.7	8405	8735	9116	8744	216	122.8	130.4	137.3	130.2	4.4	0.394	0.414	0.432	0.414	0.011	12.8	0.7
2_1_0.1_0.7	8334	8688	9101	8697	230	123.1	131.4	138.8	131.1	4.7	0.396	0.417	0.436	0.416	0.012	12.8	0.7
2_2_0.5_0	9937	10712	11439	10703	472	72.3	89.2	105.5	89.1	10.1	0.267	0.311	0.355	0.311	0.028	26.3	6.0
2_2_0.98_0.01	10313	10752	11203	10755	291	78.9	89.2	98.7	89.0	6.3	0.281	0.309	0.334	0.308	0.017	26.1	3.7
2_2_0.6_0.1	9677	10310	10902	10301	374	85.4	98.5	111.7	98.5	8.0	0.299	0.334	0.369	0.334	0.021	21.4	3.1
2_2_0.3_0.1	9235	10169	10916	10115	547	84.6	100.9	118.5	101.2	10.6	0.298	0.342	0.394	0.344	0.030	20.7	3.6
2_2_0.6_0.2	9372	9912	10435	9907	333	95.9	107.2	118.4	107.2	6.9	0.326	0.356	0.386	0.356	0.018	18.4	2.1
2_2_0.5_0.25	9089	9688	10225	9677	361	100.5	111.7	124.0	111.9	7.1	0.338	0.368	0.401	0.369	0.019	17.2	1.9
2_2_0.25_0.25	8585	9525	10216	9477	507	100.4	114.9	130.0	114.9	9.0	0.339	0.377	0.426	0.379	0.026	16.8	2.1
2_2_0.6_0.3	9079	9567	10035	9554	313	104.5	114.4	124.4	114.5	6.0	0.349	0.375	0.401	0.375	0.017	16.4	1.5
2_2_0.25_0.5	7840	8769	9314	8711	414	119.5	130.1	140.7	130.1	6.4	0.387	0.416	0.455	0.417	0.019	13.6	1.0
2_2_0.4_0.5	7966	8874	9331	8822	379	119.2	128.2	138.6	128.4	5.9	0.386	0.410	0.449	0.412	0.018	13.7	0.9
2_2_0.2_0.7	7681	8207	8751	8196	350	129.4	138.0	147.6	138.3	5.5	0.414	0.439	0.460	0.439	0.015	12.2	0.7
2_2_0.1_0.7	7649	8103	8722	8136	340	130.3	139.0	147.6	139.0	5.4	0.415	0.442	0.462	0.441	0.014	12.2	0.7

Continued on next page.

These scenarios all had an initial depletion level of 40%B_0																
	5%C	50%C	95%C	MeanC	StDevC	5%CE	50%CE	95%CE	MeanCE	StDevCE	5%SB	50%SB	95%SB	MeanSB	StDevSB	MeanMT	StDevMT
1_1_0.5_0.25	11859	12141	12426	12142	178	109.9	115.6	121.2	115.5	3.5	0.365	0.379	0.393	0.379	0.009	1.0	0.0
1_2_0.5_0.25	11309	11677	12014	11672	224	117.6	124.4	131.2	124.3	4.2	0.385	0.402	0.419	0.402	0.011	1.0	0.0
2_1_0.5_0.25	11414	12039	12647	12030	377	104.9	117.2	128.9	117.0	7.2	0.353	0.384	0.415	0.384	0.018	1.0	0.0
2_2_0.5_0.25	11041	11696	12284	11686	382	112.1	123.5	135.6	123.6	7.3	0.372	0.401	0.432	0.401	0.018	1.0	0.0
These scenarios all had an initial depletion level of 55%B_0																	
1_1_0.5_0.25	12123	12530	12924	12530	249	128.0	134.8	141.8	134.9	4.3	0.412	0.428	0.446	0.429	0.011	1.0	0.0
1_2_0.5_0.25	11067	11545	12005	11540	287	144.7	153.0	161.5	153.0	5.1	0.454	0.474	0.496	0.475	0.013	1.0	0.0
2_1_0.5_0.25	10810	11413	12101	11427	395	142.6	155.0	166.2	154.7	7.2	0.449	0.481	0.509	0.480	0.018	1.0	0.0
2_2_0.5_0.25	10275	10794	11378	10800	336	156.4	166.8	176.1	166.5	6.2	0.484	0.510	0.533	0.509	0.015	1.0	0.0

10 The Size-Based Operating Model

10.1 Basic Structure

The annual model is size-structured as a vector of 105 size classes, each of 2 mm, with central mean sizes between 2 and 210 mm, with the maximum size class acting as a plus group. The sexes are not kept separate and the cryptic and emergent components of the stock are combined. A Beverton-Holt stock recruitment relationship (Francis, 1992) is used and all modelled recruitment is assumed to be post-larval and to enter the first size class (1 – 3mm). The post-larval size class was selected as 1 – 3 mm following studies of post-larval abalone in Australia (Cropp, 1989; Daume, 2003). The full size range of the post-larval animals is used so that any time lags within the dynamics that develop because of the time it takes animals to grow to legal sizes are explicitly accounted for in the model; this differs from most size structured models (Breen *et al*., 2003), which usually have a first size class at a size perhaps 40 – 50 mm smaller than the legal minimum length. Smaller abalone generally live in cryptic habitat and only emerge permanently after they achieve a particular size, which differs between areas. In areas where there are large boulders and crevices the size at emergence can be relatively large and, conversely, where there is little cryptic habitat this may lead to abalone emerging at relatively small sizes. In the extreme a lack of cryptic habitat may limit the distribution of abalone. At least in Tasmania the size of emergence cannot be assumed to be the same as the size at maturity. Emergence can be described using a logistic ogive and this can take various shapes and locations with respect to abalone length. This becomes important to the dynamics of a fishery when the size of emergence can extend beyond the legal minimum length (as can occur on the west coast of Tasmania). To account for this the selectivity ogive needs to be multiplied by the emergence ogive.

10.2 Model Equations

10.2.1 Population Dynamics

An annual increment of the vector or numbers at length, $\mathbf{N_t}$, entails growing the animals in each size class using the growth transition matrix, **G**, then applying the survivorship from one year to the next, $\mathbf{S_t}$, which involves natural mortality and may include fishing mortality, and finally adding any recruitment, $\mathbf{R_t}$:

$$\mathbf{N_{t+1}} = \mathbf{S_t G N_t} + \mathbf{R_t} \tag{36}$$

where $\mathbf{R_t}$ is a vector of zeros except for the first size class, $R_{1,t}$ = recruitment in the first size class in year *t*, the first length/size class 1 – 3 mm centred on 2 mm. Alternatively it can be depicted in individual size class form:

$$N_{j,t+1} = S_{j,t} G N_{j,t} + R_{j,t} \tag{37}$$

where *j* is the index for each length class in year *t*.

10.2.2 The Growth Transition Matrix

The size distribution of the abalone stock is described using a range of 2 mm size classes from a minimum size = 2 up to the maximum = 210. Each size class, L_i, has a minimum length, L_{Min}, and a maximum length, L_{Max} each 1 mm below and above the center value, The elements of the growth transition matrix, $G_{i,j}$, are defined using a normal probability density function:

$$G_{i,j} = \int_{-\infty}^{L_i+\frac{LW}{2}} \frac{1}{\sqrt{2\pi}\sigma_{L_j}} e^{-\left[\frac{\left(L_i-\bar{L}_{i,j}\right)^2}{2\left(\sigma_{L_j}\right)^2}\right]} dL \qquad L_i = L_{Min}$$
$$G_{i,j} = \int_{L_i-\frac{LW}{2}}^{L_i+\frac{LW}{2}} \frac{1}{\sqrt{2\pi}\sigma_{L_j}} e^{-\left[\frac{\left(L_i-\bar{L}_{i,j}\right)^2}{2\left(\sigma_{L_j}\right)^2}\right]} dL \qquad L_{Min} < L_i \le L_{Max} \quad (38)$$

where i refers to rows (final sizes) and j refers to columns (initial sizes), and $LW = L_{Max} - L_{Min}$. The expected mean size for each initial size class j is defined using an inverse logistic growth curve that has been found to describe Blacklip Abalone growth well (Haddon *et al*. 2008, Helidoniotis *et al*., 2011); growth is assumed to be constant through time:

$$\bar{L}_{i,j} = L_j + \frac{Max\Delta L}{1+e^{Ln(19)\left(L_j-L50\right)/(\delta)}} \quad (39)$$

which is the center value of each size class, L_j, plus the predicted growth increment for each size class, where $Max\Delta L$ is the maximum growth increment, $L50$ is the length at 50% of $Max\Delta L$, and δ is the length at 5% of $Max\Delta L$ minus $L50$. Variation around the mean expected growth increment, σ_{L_j}, in equation (38) is assumed to vary with the expected growth increment for each size class L_j (Haddon *et al*. 2008):

$$\sigma_{L_j} = \frac{Max\sigma_L}{1+e^{Ln(19)\left(L_j-(\delta+L50)\right)/\left(210-(\delta+L50)\right)}} \quad (40)$$

To correctly describe growth, all columns in the growth transition matrix must sum to 1.0 (so that all animals in a size class remain in the population after growth). To make the largest size class, L_{Max}, into a plus group the final row of the matrix is modified for each column j as:

$$G_{LMax,j} = G_{LMax,j} + \left(1 - \sum_{i=L_1}^{L_{Max}} G_{i,j}\right) \quad (41)$$

10.2.3 Survivorship

The survivorship is simply the proportion of animals in each length class to survive from one year to the next. The assumption is made that natural mortality is constant across size classes. While this is not likely to be true when we include the smallest post-larval size classes in the model, a constant schedule of mortality across these smaller size classes is confounded with recruitment levels into the smallest size class so the end result remains stable. If credible information became available about numbers in those smaller size classes then the assumption of constant natural mortality across all size classes might need to change.

The survivorship term is made up of the survivorship from natural mortality, e^{-M}, where M is the instantaneous rate of natural mortality, multiplied by the complement of the annual harvest rate for each size class j, $s_{j,t}E_jH_t$ in year t:

$$S_{j,t} = (1 - s_{j,t}E_jH_t)e^{-M} \tag{42}$$

H_t is the fully selected annual harvest rate (see later) and for each size class, j, this is modified by the respective size related selectivity, $s_{j,t}$, and emergence from crypsis, E_j (**Figure 96**).

10.2.4 Selectivity and Emergence

Selectivity is described by:

$$s_{j,t} = \frac{1}{1 + \mathrm{e}^{-Ln(19)\left(L_j - L_S 50\right)/\delta_s}} \tag{43}$$

where L_S50 is the length at which 50% of available animals are selected, L_j is the mid-length of size class j, and δ_s is the length at which 95% of animals are selected minus L_S50. There is a year subscript, t, because if the legal minimum length changes then the selectivity would be expected to change.

Emergence from cryptic habitat is also described by a logistic ogive:

$$E_j = \frac{1}{1 + \mathrm{e}^{-Ln(19)\left(L_j - L_E 50\right)/\delta_E}} \tag{44}$$

where L_E50 is the length at which 50% of available animals emerge, L_j is the mid-length of size class j, and δ_E is the length at which 95% of animals are emergent minus L_E50.

10.2.5 Weight and Maturity at Size

Other aspects of the biological properties that vary with size are the weight by size class and the maturity. The weight at size, W_j, relationship is determined by the two parameters a and b:

$$W_j = aL_j^b \tag{45}$$

while maturity at size, m_j, is governed by a and b, where $L_m50 = -a/b$:

$$m_j = \frac{e^{a+bj}}{1 + e^{a+bj}} \tag{46}$$

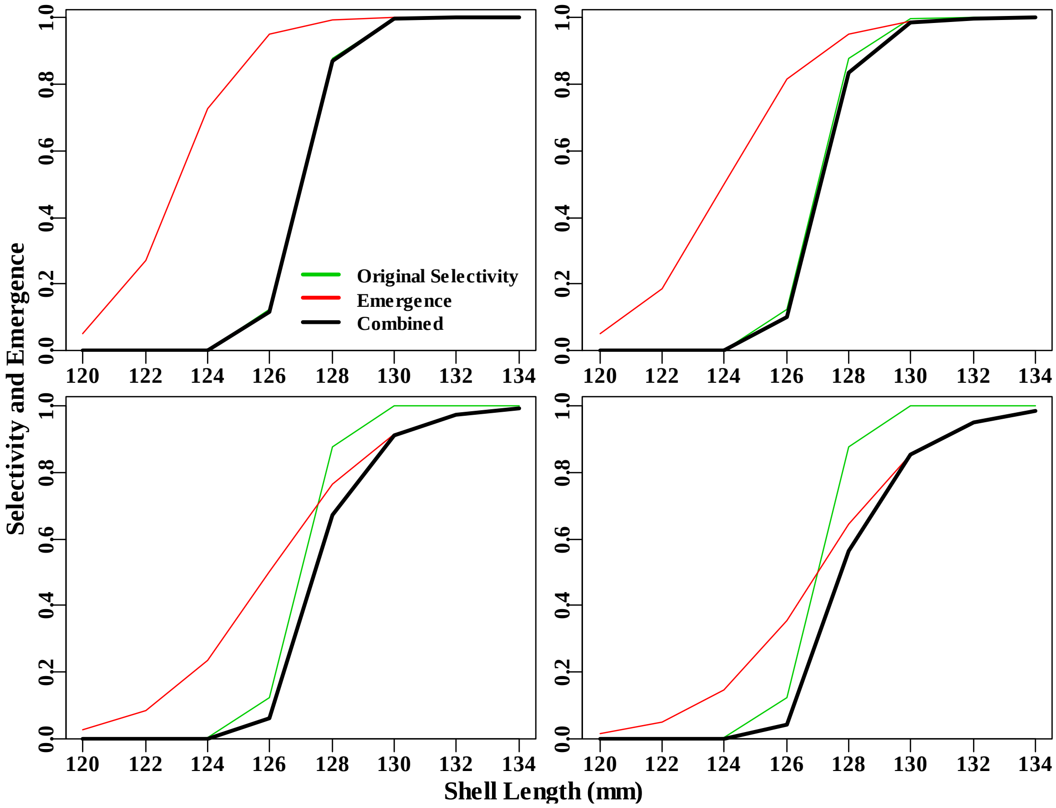

Figure 96. A single selectivity curve with L_s50 = 127 and *a* = -29.92 and *b* = 0.23545 combined with four different emergence curves some affecting the model selectivity and other not.

10.2.6 Annual Harvest Rate

The annual harvest rate is determined from the catches in year *t* divided by the exploitable biomass in the year of harvest:

$$H_t = C_t / B_t^E \tag{47}$$

where the exploitable biomass is estimated at the start of the year (divisible by 1,000,000 to estimate as tonnes):

$$B_t^E = \sum_{L=L_{Min}}^{L_{Max}} s_{t,L} W_L N_{t,L}^E \tag{48}$$

where

$$N_{t,L}^E = G_{i,L} O_L^E N_{t-1,L}^E + E_L N_{t-1,L}^C \tag{49}$$

Catchability can be estimated analytically for each of the two periods *p* as:

$$q_p = \exp\left[\sum_{t=1}^{n_p} Ln\left(I_t / B_t^E\right) / n_p\right] \tag{50}$$

where n_p is the number of years in period *p*.

10.2.7 Model Initiation

The model structure adopted is an extension of the size-based model first proposed by Sullivan *et al*. (1990). has half of natural mortality occurring followed by growth and fishing mortality, followed by the remaining natural mortality. If natural mortality is implemented as half natural mortality, that is $\mathbf{C_S} = e^{-M/2}$ for cryptic and $\mathbf{O_S} = e^{-(M)}$ for emergent, twice in the year, with other dynamics between the natural mortality events then the dynamics can be represented as:

$$\mathbf{N_{t+1} = S_t G N_t + R_t}$$

Recruitment is distributed between the first two size classes (60-62, and 62-64mm) in a 0.9:0.1 ratio, all other size classes being set to zero. Given an array of recruitment residuals and an average recruitment of $\bar{R}$, the recruitment levels in each year R_t are given by:

$$R_t = \bar{R}.e^{N\left(0,\sigma_t^2\right)} \tag{51}$$

The model estimates the $N\left(0,\sigma_t^2\right)$ for each year *t*.

The model is conditioned on catches, that is, the removals are determined from the catches divided by the exploitable biomass:

$$H_t = C_t / B_t^E \tag{52}$$

Where the exploitable biomass is estimated after half of natural mortality, growth, and emergence (divisible by 1,000,000 to estimate as tonnes):

$$B_t^E = \sum_{L=L_{Min}}^{L_{Max}} s_{t,L} W_L N_{t,L}^E \tag{53}$$

where

$$N_{t,L}^E = G_{i,L} O_L^E N_{t-1,L}^E + E_L N_{t-1,L}^C \tag{54}$$

Catchability can be estimated analytically for each of the two periods *p* as:

$$q_p = \exp\left[\sum_{t=1}^{n_p} Ln\left(I_t / B_t^E\right) / n_p\right] \tag{55}$$

where n_p is the number of years in period *p*.

10.2.8 Model Variables

Table 25. Size-structured model variables and the initial values attributed to them conditioned approximately on the south-west coast of Tasmania.

Description	Variable	Value
Growth	MaxΔL	35.918
	L50	125.91
	δ	42.0
	Maxσ_L	5
Size structure	LW	2
	LMax	210
	LMin	2
Legal Minimum Length	LML	127
Maturity	Lm50	125
	δ_m	9.812
Weight at Length	Wta	5.62E-05
	Wtb	3.1792
Natural Mortality	M	0.2
Selectivity	Ls50	140
	δ_s	1.5
Emergence	LE50	120.5
	δ_E	3
Recruitment dynamics	AvRec	13000000
	steepness	0.6
	sigmaR	0.5

10.3 The Operating Model Equations

10.3.1 Model Variables

a,b the weight at length parameters,
α,β are the maturity at length logistic parameters, α/β depicts the length at 50% maturity and 2×Ln(3)/β is the inter-quartile distance,
A the complement of an annual harvest rate (via a selectivity curve, *s*) applied to the emergent animals, (I-**sH**)
$\mathbf{C}_S$ a square zero matrix ($n \times n$) with the survivorships, $e^{-(M/2)}$, by size class down the diagonal elements for cryptic abalone, this involves the survivorship from half the natural mortality (which need not be the same as for emergent abalone,
E a square zero matrix ($n \times n$) with the proportion emergent by size class, Eq (62), arranged along the diagonal elements,
G a square growth transition matrix ($n \times n$), the same for both sexes,
H Annual harvest rate,
I the unit matrix,
I_t the standardized catch rate in year *t*.
L_E50 logistic parameter for the emergence curve, depicts the length at which 50% of cryptic animals become emergent,
L_E95 logistic parameter for the emergence curve, depicts the length at which 95% of cryptic animals become emergent,
$\bar{L}_{i,j}$ the expected mean length of animals starting in size class *j*,
L_m50 logistic parameter for the growth curve, depicts the length at which the growth increment is 50% of the maximum,
L_m95 logistic parameter for the growth curve, depicts the length at which the growth increment is 5% of the maximum,
L_{min} the minimum size class considered,
L_{max} the maximum size class considered,
LML legal minimum length
L_s50 logistic parameter for the selectivity curve, depicts the length at which 50% selection occurs,
L_s95 logistic parameter for the selectivity curve, depicts the length at which 95% selection occurs,
LW the class width in mm,
M natural mortality, which can be different in crypsis and emergent populations,
MaxΔL the maximum growth increment for the inverse logistic curve describing abalone growth, The point at which variation is 5% of the maximum is set at 210mm for the west coast and the 50% point is set at L_m95,
Maxσ_L the maximum standard deviation describing the variation around the mean expected growth increment,
m_L maturity at length *L*,
$\mathbf{N}_t^C$ a vector of numbers-at-size in year *t* for cryptic abalone, with *n* size classes,
$\mathbf{N}^{C*}$ the equilibrium initial population size structure for cryptic animals,
$\mathbf{N}_t^E$ a vector of numbers-at-size in year *t* for emergent abalone, with *n* size classes,
$\mathbf{N}^{E*}$ the equilibrium initial population size structure for emergent animals,

origTAC The TAC at the start of a simulation; allows for repeating the analysis assuming that the control rule used alters the active TAC during each run,

O_S a square zero matrix (n x n) with the survivorships, $e^{-(M/2)}$, by size class down the diagonal elements for emergent abalone, this involves the survivorship from half the natural mortality (which need not be the same as for cryptic abalone,

q the catchability,

R a vector (n) of recruitment numbers (generally zero except for the smallest size classes),

S a square zero matrix (n x n) with the survivorships, $e^{-(M/2)}$, by size class down the diagonal elements for emergent abalone, this involves the survivorship from half the natural mortality,

s_L selectivity of length class l,

σ^j the expected standard deviation for length class j,

σ_R^2 the variance of the recruitment residuals,

TAC total allowable catch (see origTAC)

W_L the weight in grammes of abalone of length L,

WtCE the weight given to the catch effort contribution to the negative log-likelihood,

WtLF the weight given to the proportion length frequency data to the negative log-likelihood,

WtRec the weight given to the penalty on recruitment variation,

10.3.2 Model Initiation

The mortality schedules differ between the cryptic and emergent population components because a constant initial fishing mortality is applied to the emergent population and exactly how the fishing mortality is implemented in the model needs to be reflected in the equilibrium equations. The model structure adopted has half of natural mortality occurring followed by growth and fishing mortality, followed by the remaining natural mortality. If natural mortality is implemented as half natural mortality, that is $\mathbf{C_S} = e^{-M/2}$ for cryptic and $\mathbf{O_S} = e^{-M/2}$ for emergent, twice in the year, with other dynamics between the natural mortality events then the dynamics, first for the emergent numbers at size and then for the cryptic numbers at size can be represented as:

$$\mathbf{N_{t+1}^E} = \mathbf{O_S}\left[\mathbf{GO_S}\left(\mathbf{N_t^E} + \mathbf{EN_t^C}\right)\right] \quad (56)$$

and

$$\mathbf{N_{t+1}^C} = \mathbf{C_S}\left[\mathbf{GC_S}\left(\mathbf{N_t^C} - \mathbf{EN_t^C}\right)\right] + \mathbf{R} \quad (57)$$

at equilibrium

$$\mathbf{N^{C*}} = \left(\mathbf{I} - \left[\mathbf{C_S GC_S}\left(\mathbf{I} - \mathbf{E}\right)\right]\right)^{-1}\mathbf{R} \quad (58)$$

Consequently, for emergent abalone:

$$\mathbf{N^{E*}} = \left(\mathbf{I} - \mathbf{O_S GO_S}\right)^{-1}\mathbf{O_S GO_S EN^{C*}} \quad (59)$$

If there is an initial estimated fishing mortality rate, this can be defined as the complement of an annual harvest rate and is distributed down the diagonal of an otherwise zero square matrix **A**:

$$A_L = (1 - s_{L,t}H_t) \quad (60)$$

where A_L is the survivorship of length class L, $s_{L,t}$ is the selectivity of length class L in year t (which relates to the LML), and H_t is the fully selected harvest rate in year t. With an initial fishing mortality rate there would be no change to the equilibrium for the cryptic component, Eq (58), but the equilibrium numbers for the emergent population would become:

$$\mathbf{N^{E*}} = \left(\left(\mathbf{I} - \mathbf{O_S AGO_S} \right)^{-1} \left(\mathbf{O_S AGO_S EN^{C*}} \right) \right) \tag{61}$$

10.3.3 Biology and Stock Related Statistics

Transfer from crypsis into emergence is described using a standard logistic equation (Haddon, 2011):

$$E_L = \frac{1}{1 + e^{-Ln(19)(L - L_E 50)/(L_E 95 - L_E 50)}} \tag{62}$$

Where E is the proportion of size class L that are emergent, and $L50$ and $L95$ are the usual logistic parameters defining the lengths at which 50% and 95% are emergent.

The growth from size-class to size-class is described by the elements of a growth transition matrix defined by:

$$\begin{array}{ll} G_{i,j} = \displaystyle\int_{-\infty}^{L_i + \frac{LW}{2}} \frac{1}{\sqrt{2\pi\sigma^j}} e^{-\left[\frac{\left(L_i - \bar{L}_{i,j}\right)^2}{2\left(\sigma^j\right)^2}\right]} dL & L_i = L_{Min} \\ G_{i,j} = \displaystyle\int_{L_i - \frac{LW}{2}}^{L_i + \frac{LW}{2}} \frac{1}{\sqrt{2\pi\sigma^j}} e^{-\left[\frac{\left(L_i - \bar{L}_{i,j}\right)^2}{2\left(\sigma^j\right)^2}\right]} dL & L_{Min} < L_i \le L_{Max} \end{array} \tag{63}$$

to ensure that all columns sum to 1.0 and to make L_{Max} a plus group the final row of the matrix is modified for each column j as:

$$G_{LMax,j} = G_{LMax,j} + \left(1 - \sum_{i=L_1}^{L_{Max}} G_{i,j} \right) \tag{64}$$

An alternative approach would be to include a very large number as the upper bound of the last size class. The expected mean size for each size class j is defined using an inverse logistic growth curve that has been found to describe Blacklip Abalone growth well (Haddon *et al*. 2008; Helidoniotis *et al*., 2011):

$$\bar{L}_{i,j} = L_j + \frac{Max\Delta L}{1 + e^{Ln(19)\left(L_j - L_m 50\right)/\left(L_m 95 - L_m 50\right)}} + \varepsilon_{L_j} \tag{65}$$

Variation around the mean expected growth increment is assumed to be normally distributed with a standard deviation that varies with the growth increment (Haddon *et al*. 2008):

$$\sigma_{L_j} = \frac{Max\sigma_L}{1 + e^{Ln(19)\left(L_j - L_m 95\right)/\left(210 - L_m 95\right)}} \tag{66}$$

The weight at size, W_L, relationship

$$W_L = aL^b \tag{67}$$

Maturity at size, m_L,

$$m_L = \frac{e^{(\alpha+\beta L)}}{1+e^{(\alpha+\beta L)}} \tag{68}$$

and selectivity for length *L* in year *t* is defined as:

$$s_{L,t} = \frac{1}{1+\mathrm{e}^{-Ln(19)(L-L_S 50)/(L_S 95-L_S 50)}} \tag{69}$$

Mature or spawning biomass needs to include contributions from both the emergent and cryptic components of the population (thus numbers at size by maturity at size and weight at size:

$$B_t^S = \sum_{L=L_{\min}}^{L_{\max}} \left(N_L^E m_L W_L\right) + \sum_{L=L_{\min}}^{L_{\max}} \left(N_L^C m_L W_L\right) \tag{70}$$

Exploitable biomass is estimated after half of natural mortality, growth, and emergence (divisible by 1,000,000 to estimate as tonnes) and before any fishing mortality occurs in any single year. Only emergent biomass is considered as no fishing mortality is imposed on the cryptic component:

$$B_t^E = \sum_{L=L_{Min}}^{L_{Max}} s_{t,L} W_L N_{t,L}^E \tag{71}$$

where

$$N_{t,L}^E = G_{i,L} O_L^E N_{t-1,L}^E + E_L N_{t-1,L}^C \tag{72}$$

Catchability in a stock assessment model can be estimated analytically as:

$$q = \exp\left[\sum_{t=1}^{n} Ln\left(I_t / B_t^E\right) / n\right] \tag{73}$$

where *n* is the number of years across which the observed catch rates and predicted exploitable biomass are considered. In the simulation model a maximum catch rate, CE_{Max} was used to scale the unfished exploitable biomass to generate a catchability value for each population. The maximum catch rates were randomly selected from a pre-specified distribution, and then the following equation used:

$$q_p = \left(CE_{Max,p} / B_{0,p}^E\right) \tag{74}$$

Where the index is for each population *p* and B_0^E is the unfished exploitable biomass.

10.3.4 Model Dynamics

Once each population is initiated its dynamics can be projected forwards a year at a time depending on how much catch is expected to be taken or how much effort expected to be focussed into each population. The initiation sets up the equilibrium numbers for the initial conditions established for each population. Then given a specific harvest rate for the each population they can be projected forward in yearly steps. This projection is based around what is expected to occur to the numbers of animals in crypsis and then the number of animals emergent. As before, if the fishing mortality rate over a year is defined as the complement of an annual harvest rate and is distributed down the diagonal of an otherwise zero matrix **A**:

$$A_L = (1 - s_{L,t} H_t) \tag{75}$$

where A_L is the survivorship of length class L, $s_{L,t}$ is the selectivity of length class L in year t, and H_t is the fully selected harvest rate in year t. And if natural mortality is implemented as half natural mortality, that is $\mathbf{C_S} = e^{-M/2}$ for cryptic and $\mathbf{O_S} = e^{-(M/2)}$ for emergent, twice in the year, with other dynamics between the natural mortality events then the dynamics can be represented as:

$$\mathbf{N^E_{t+1}} = \mathbf{O_S}\left[\mathbf{G A_t O_S}\left(\mathbf{N^E_t} + \mathbf{E N^C_t}\right)\right] \tag{76}$$

and

$$\mathbf{N^C_{t+1}} = \mathbf{C_S}\left[\mathbf{G C_S}\left(\mathbf{N^C_t} - \mathbf{E N^C_t}\right)\right] + \mathbf{R} \tag{77}$$

10.3.5 Stock Recruitment Relationship

Punt (2003) includes a Beverton & Holt stock recruitment relationship in a size-structured model designed to work with southern rock lobster, and he writes of the two parameters (alpha and beta) being re-parameterized in terms of steepness, *h*. This related to work by Francis (1992) who re-parameterized the Beverton-Holt curve into terms of steepness for age-structured models. This re-parameterization is general across both age-based and size-based models. Recruitment is added to the contents of the first size class (2mm), all other size classes being set to zero.

The size-based equivalent to Francis' (1992) re-parameterization requires the assumption that an unfished population under constant recruitment will achieve a constant size distribution (and presumably a constant age distribution but this remains unknown for abalone). From the constant size distribution it is possible to calculate B_0, the total mature biomass found in the unfished population, which is the equivalent of eq (70) except uses the unfished equilibrium numbers at size eqs (59) and (61). Thus:

$$B_0 = \sum\left(N_L^{E*} m_L W_L\right) + \left(N_L^{C*} m_L W_L\right) \tag{78}$$

which would be the spawning biomass at the start of each year. This equation translates between the equilibrium size distribution produced by the virgin average recruitment level, R_0, into the unfished mature biomass B_0. Francis (1992) used this relation to develop a direct scaling parameter A_0, which was the mass of mature biomass produced at equilibrium from a constant single recruit. By combining this with the virgin recruitment level R_0 a direct estimate of the unfished mature biomass could be produced:

$$B_0 = R_0 A_0 \tag{79}$$

The virgin mature biomass per recruit generated by a constant recruitment level of one (A_0) can be obtained using eqs (76) to (78) with recruitment in eq (77) set to 1.0. With an estimate of A_0 the recruitment levels from plausible levels of B_0 can be obtained from eq (79). Francis' (1992) re-parameterization consisted of re-parameterizing the Beverton-Holt parameters thus:

$$\alpha = \frac{B_0(1-h)}{4hR_0} \qquad \text{and} \qquad \beta = \frac{5h-1}{4hR_0} \tag{80}$$

Punt (2003) used the classic Beverton and Holt equation that used these estimates of α and β, however, the R_0 value can be used directly as in Haltuch et al. (2008):

$$N_{t,0} = \frac{4hR_0 B_t^M}{(1-h)B_0 + (5h-1)B_t^M} e^{\varepsilon_t - \sigma_R^2/2} \tag{81}$$

The $\varepsilon - \sigma_R^2/2$ term is there to allow for bias in the log-normal relationship so that the simulated recruitments relate to the median of the distribution rather than the mode.

In the simulations the stock-recruitment relationship for each population can thus be defined in terms of steepness and by simulating either an unfished virgin recruitment level or an unfished biomass level, with the required values being sampled from predetermined distributions.

10.4 Format of the Data and Control Files

To remain general the MSE framework defines all constants and parameters within a data file with a specified format (**Table 26**). The data input defines some structural global variables, the probability density functions for the various parameters, the filename containing the production curves for each block (used in the initiation of each block), the legal minimum length in each block and year of the simulation, and the fishery data that is used to test the plausibility of each simulation during the conditioning.

The current *AbMSE* R package (see section '10.5.3 The State of Development of the AbMSE R Package') includes a function called *datafileTemplate* which "generates a standard input data file to use as a template. It is possible to define the number of blocks and then, once the data file is created, go in and edit it appropriately to suit exactly your own needs."

The control file is simply a list of control variables such as the harvest control rule being used, the assessment interval, the catch adjustment schedule, and many other details. As with the data file, the R package *AbMSE* contains a function called *ctrlfileTemplate* which generates a standardized input control file which can be used as a template for a real world fishery or a purely hypothetical fishery.

Table 26. The data file containing the characterization of a simulated zone (in this case it relates to blocks 9 – 12 on Tasmania's west coast). The capitalized names are used by the input function to identify the various sections, which can be in any order as long as they are all there. The number after each capitalized names relates to the number of lines of data to be read in within that section.

#BLOCKNAMES	4	nblock			
Blockname	AB09	AB10	AB11	AB12	
numpop	10	11	21	18	
#RANDOMSEED	10				
#SIZECLASS	3				
# Global Constants					
minc	2				
cw	2				
Nclass	105				
#YEARS	3	# defines projections & years of a constant TAC before HCR starts.			
Nyrs	50	# Start with all populations the same			
fixYear	5	# years at constant TAC before HCR starts: used in runSingle			
firstYear	2014	# Number describing the first year eg 2014 - 2014+Nyrs-1			
#PDFS	29				
Parameter	AB09	AB10	AB11	AB12	
1_MaxDL	38.5	37	37.75	36.5	
2_sMaxDL	2.5	2.5	2.5	2.5	
3_L50	125	124	121	120	
4_sL50	5	5	5	5	
5_L50inc	36	42	44	43	
6_sL50inc	1	1	1	1	
7_SigMax	4.581	4.581	4.581	4.581	
8_sSigMax	0.1	0.1	0.1	0.1	
9_LML	140	140	140	140	
10_Wtb	3.161963	3.161963	3.161963	3.161963	
11_sWtb	0.148461	0.1484613	0.148461	0.148461	
12_Wtbtoa	962.8098	962.8098	962.8098	962.8098	
13_sWtbtoa	-14.3526	-14.35264	-14.3526	-14.3526	
14_Me	0.2	0.2	0.2	0.2	
15_sMe	0.003	0.003	0.003	0.003	
16_Mc	0.2	0.2	0.2	0.2	
17_sMc	0.003	0.003	0.003	0.003	
18_AvRec	11.4	11.9	11.2	11.2	
19_sAvRec	1	1	1	1	
20_defsteep	0.6	0.6	0.6	0.6	
21_sdefsteep	0.02	0.02	0.02	0.02	
22_L50C	106.4222	106.42221	106.4222	106.4222	
23_sL50C		0.5	0.5	0.5	0.5
24_L95C		149.3749	149.37486	149.3749	149.3749
25_sL95C	1	1	1	1	
26_MaxCEpar	0.37	0.37	0.38	0.38	
27_MaxCEpar	0.02	0.02	0.02	0.02	
28_selL50p	0	0.25	0	0.25	
29_selL95p	1.5	1.75	1.5	1.75	
#MATURITY	3	at size			
SaMa	-16	-16	-16	-16	
L50Mat	123.384	122.893	112.373	116.345	
sL50Mat	4	4	4	4	

[Data file format continued]

# PRODUCTIVITY	C:/A_CSIRO/Rcode/abalone/SimAb/data/zoneProd_60_4_841_10.csv
filename for the zone production data; used in zoneStart

#SELECTIVITY	50	years		
Year	AB09	AB10	AB11	AB12
Yr1	140	140	140	140
Yr2	140	140	140	140
Yr49	140	140	140	140
Yr50	140	140	140	140
#FISHERY				
#CATCHES	28			
Year	AB09C	AB10C	AB11C	AB12C
1986	133.493	126.864	288.889	193.101
1987	251.988	82.137	339.079	194.819
2012	172.308	145.98	273.049	267.439
2013	158.447	180.498	286.864	251.292
#CPUE	28			
Year	AB09CE	AB10CE	AB11CE	AB12CE
1986	77.51227	89.37418	82.31948	72.29934
1987	76.17527	100.1375	83.47263	70.78706
2012	136.7979	129.83534	107.8681	96.99431
2013	113.0147	121.69961	94.90961	88.66705
#EFFORT	28			
Year	AB09CE	AB10CE	AB11CE	AB12CE
1986	1483	1388	3263	2406
1987	2929	803	3825	2519
2012	1176.2	1134.3	2363.8	2570.4
2013	1287	1501.4	2837.7	2681.6
#STANDARDIZED	28			
Year	AB09SCE	AB10SCE	AB11SCE	AB12SCE
1986	0.549145	0.6066347	0.693266	0.718404
1987	0.565038	0.6924854	0.726154	0.701712
2012	1.016493	0.9283136	0.954819	1.015844
2013	0.891839	0.8622271	0.849696	0.937976

Table 27. The control file containing the details for the simulation runs. Each line title lists the variable name of concern. These variables are read into the list 'control' and then many of these become global variables.

Variable Name	Variable value; some are scalars others are vectors										
batch	TRUE										
replicates	1000										
initDepl	0.25										
assessInterval	1										
recthreshold	1E-07										
hcrLabel	mcda										
mcdaHCR	TRUE										
ConstC	FALSE										
ConstH	FALSE										
pickSched	1										
TACadj	0.75	0.8	0.85	0.9	0.95	1	1.05	1.1	1.15	1.2	1.25
TACadj2	0.25	0.8	0.85	0.9	1	1	1.05	1.1	1.15	1.2	1.2
mcdaWts	0.25	0.5	0.25								
postmcdaWts	0.25	0.5	0.25								
withVariation	TRUE										
cpuePeriod	4										
maxGrad4	0.15										
maxRate1	0.4										
CETarg	100	100	100	100							
deltaCE	45	45	45	45							
implementE	0										
LRPTAC	TRUE										
TACLower	500										
TACUpper	1000										
refyr	20										
withsigR	0.5										
withsigB	0.25										
withsigCE	0.11										

10.4.1 R code for Block Based HCR

New control rules can be added simply by defining new functions in R. Currently their inclusion still requires some customization, but the intent is to make this automatic.

```
#######################   BLOCK BASED HCR
## scores must be combined rbind(gradScore,targScore,rate1Score, etc)
## in the same order as the weights for the different HCR
## scores <- rbind(blkGrad,blkTarg); weight=mcdaWts
##-------------------------------------------------------------------
blockMCDA <- function(scores, weight) {
   if (sum(weight) != 1.0) stop("FATAL ERROR: Invalid weights in
                                 blockMCDA")
   final <- scores    # create a new matrix for the answers
   pickIndex <- numeric(nblock)  # to identify the TACadj vector index
   nHCR <- length(weight)
   lookupindex <- 1:11
   for (HCR in 1:nHCR) final[HCR,] <- scores[HCR,] * weight[HCR]
   finalScore <- colSums(final) + 1   # +1 needed to lookup from 1-11
   for (blk in 1:nblock) pickIndex[blk] <-
                         which.closest(finalScore[blk],lookupindex)
   multiplyTAC <- TACadj[pickIndex]
   return(multiplyTAC)
}  # end of MCDA

targblockHCR <- function(incpueBlock,targetCE,modifyTarg=deltaCE) {
   delCE <- 5.0/modifyTarg
   score <- (delCE * incpueBlock) + 5.0 - (delCE * targetCE)
    score[score > 10.0] <- 10.0
    score[score < 0.0] <- 0.0
   return(score)  # not yet an integer
}  # end of targblockHCR

gradblockHCR <- function(incpueBlock,maxGradient=maxGrad) {
    score <- rep(5,nblock)
    cePeriod <- length(incpueBlock[,1]) # includes implementE
    yrs <- seq(1,cePeriod,1)
    percCE <- apply(incpueBlock,2,(function(x) x/x[1]))
    for (blk in 1:nblock) {
        model <- lm(percCE[,blk]~yrs)
        grad <- model$coeff[2]
        trial <- (5/maxGradient) * grad + 5  # A REAL NUMBER
        if (trial > 10) trial <- 10
        if (trial < 0) trial <- 0
        score[blk] <- trial
    }
    return(score)
} # end of gradblockHCR

rate1blckHCR <- function(incpueBlock,maxGradient=maxGrad) {
    trial <- (incpueBlock[2,]/incpueBlock[1,])-1
    score <- ((5/maxGradient) * trial) + 5
    score[score > 10.0] <- 10.0
    score[score < 0.0] <- 0.0
   return(score)
} # end of rate1HCR

##################  END OF BLOCK BASED HCR
```

10.5Pseudo-code for SimAb Functions

10.5.1 Conditioning the Operating Model

```
Conditioning.r
define directories
call source files
        fishMH.r
        constants.r
        get_functions.r
        zone_functions.r
        plot_functions.r
        RunSpecifications.r
        controlRule.r
set HCR  constC = T
define output filenames using current date time
        makeZone                                        476
                definepops                               71
        FOR pops
                makeabpop                               111
                        STM                              35: fishMH
                        maturity                         93: fishMH
                        WtatLen                          86: fishMH
                        logistic                         107: fishMH
                        Initiation population into 'zone' with no fishing
                do.production                           292
                oneyrgrowth                             209
        END pops
        zoneProperty                                    538
                SummaryMatrix                           558
                getzoneLF                                90: get_functions
        summaryBlock                                   1106
                SummaryMatrix                           558
        fillzoneDef
        getunFished
        print block and zone properties
        blockAv
        save block and zone properties
        blockAv
        Estimate block productivity
        do.blockProd
        save block productivity
        IF plotout
        Plotans
        plotunfishedLF
        plotFisheryData
        plotcompLF
```

10.5.2 Running the MSE Simulations

batchsimab.r
define directories
call source files
- **fishMH.r**
- **constants.r**
- **get_functions.r**
- **zone_functions.r**
- **plot_functions.r**
- **RunSpecifications.r**
- **controlRule.r**

define output filenames using current date time

makeZone					476
	definepops				71
	FOR pops				
		makeabpop			111
			STM		35: fishMH
			maturity		93: fishMH
			WtatLen		86: fishMH
			logistic (selectivity)		107: fishMH
			Initiation population into 'zone' with no fishing		
			do.production		292
				oneyrgrowth	209
	END pops				
zoneProperty					538
	SummaryMatrix				558
	getzoneLF				90: get_functions
summaryBlock					1106
	SummaryMatrix				558
fillzoneDef					1414

read in the productivity file
set the initH and origTAC using zoneProd matrix from productivity file

which.closest				430: fishMH

define matrices
do initial depletion

fishBlockH				1274
	blockCatch			1387
	oneyear			250
		oneyearrec		230
movezoneYear				1067
getzoneDepl				146: get_functions
getblockDepl				178: get_functions

FOR replicates

runSingle				745
	blockStart			697
	new random seed			
		fishBlockH		1278
			blockCatch	1387

oneyear	250
oneyearrec	230
movezoneYear	1071
define matrices	
FOR year	
harvestBlock	403
blockCatch	1387
oneyear	250
oneyearrec	
blockSum	1228
blockwtedCPUE	1241
years of application of HCR	
targblockHCE	100: controlRule
gradblockHCR	110: controlRule
rate1blkHCR	127: controlRule
blockMCDA	84: controlRule
END year loop	
extract results from runSingle including the use of:	
getlistVar	26: get_functions
blockSum	1224
blockCatchCPUE	1252
getLF	110: get_functions
freqMean	201: fishMH
End replicates loop	
writeConstants	
print block properties and summaries	
generate zoneS, zoneSLF, and hcrDetails	
IF batch	
plotSimulation3	1714: plot_functions
plotans	430: plot_functions
plotunfishedLF	292: plot_functions
IF !batch and reps =1	
plotsingleSimulation	775: plot_functions
getzoneDepl	146: get_functions
IF batch	
save all objects used to plot and summarize outputs	

\

10.5.3 The State of Development of the AbMSE R Package

The use of the management strategy evaluation simulation framework for testing alternative harvest strategies designed specifically for particular fisheries is made difficult through the need to use the custom software initially developed in FRDC 2007/020 and developed much further in this present project (FRDC 2013/200). In an attempt to facilitate the application of this software to different fisheries by fisheries scientists in the different jurisdictions in Australia and New Zealand a start has been made to convert the current standalone user-unfriendly R software into what is known as an R package; in this case called AbMSE. However, this package requires further development before it could be uploaded to the standard repository CRAN (https://cran.r-project.org/).

R packages constitute a collection of R functions that have the aim of assisting with particular kinds of analyses. Each of these function have built in documentation that explains the operation of each function and how it fits together with others to achieve the needs of conducting defined analyses. In addition, such packages usually contain what are known as vignettes that provide more detailed introductions and descriptions of how the software is used and the various alternative ways available for its use. Unfortunately, the conversion of the custom software into a user friendly R package is not a minor undertaking and so far the AbMSE package only contains the functions that read in the data and control files and then construct the desired zone before any fishing or depletion has occurred. Thus a typical session might generate a simulated zone with:

```
# Identify the workspace
wkdir <- "C:/A_CSIRO/Rcode/AbMSERun/"
setwd(wkdir)
resdir <- "C:/A_CSIRO/Rcode/AbMSERun/results/"

library(AbMSE)

# identify the data and ctrl files and read them
datafile <- "C:/A_CSIRO/Rcode/AbMSERun/data_west.csv"
ctrlfile <- "C:/A_CSIRO/Rcode/AbMSERun/ctrl_west.csv"
condDat <- readdataFile(datafile)
control <- readctrlFile(ctrlfile)

# make the required variables global
for (i in 1:length(condDat$globals))
  assign(names(condDat$globals)[i],condDat$globals[[i]])
for (i in 1:length(control)) assign(names(control)[i],control[[i]])

out <- makeZone(condDat)  # generate the zone
for (i in 1:length(out)) assign(names(out)[i],out[[i]])

out2 <- zoneProperty(zone)  # summarize its properties ready for printing and saving
ans <- out2$SummaryMatrix
total <- out2$ZoneSummary
unfishedLF <- out2$ZoneLF
msy <- getlistVar(zone,"MSY")

blockProp <- summaryBlock(zone)
zoneDef <- fillzoneDef()
unfished <- zone          # store the original zone in unfished
print(zoneDef)
cat("Time to Make Zone: ",(unclass(Sys.time()) - starttime),"\n\n")
```

11 Conclusions

This work has reviewed the use of Legal Minimum Lengths to enhance sustainability within harvest strategies for abalone stocks. In addition it has used management strategy evaluation to test alternative potential harvest strategies for use with the abalone fisheries around Tasmania (and in principle elsewhere). A number of conclusions from this work were forthcoming.

At a zone-wide scale the legal minimum length (LML) can obviously affect the amount of exploitable biomass available but at the zone scale it is the total allowable catch (TAC) that dominates management concerns. However, at the local reef scale or individual dive scale at which each fishery operates, most divers will have access to sufficient quota to cover the abalone they find so at that scale the TAC is effectively irrelevant. Because divers can potentially remove a high proportion if not all legal sized abalone at a single reef scale and because abalone stocks are made up of very many micro-stocks, sustainability at the local scale is all about the LML and diver behaviour. If the LML is set at a size where there is a risk in some years of the local mature biomass being reduced down to effectively that which exists below the LML, then the risk of local population extinction will be high. This would be especially the case when stocks are relatively depleted and the TAC remains even slightly higher than the current productivity, and critically, the size limit is ineffective at preserving sufficient spawning biomass for local reefs to be self-sustaining. Effective management thus requires that the TAC be set no higher than or below the current productivity and, in addition, that the LML is set at a level that will protect at least a minimum mature biomass should depletion become extreme at local scales. Different ways of determining the value for sustainability of different LML in different places were developed and discussed.

The relative contribution of appropriate TAC settings vs protection guaranteed from the LML and the relevant scales at which each of these output controls act, has not previously been articulated for abalone fisheries, or possibly any fishery. This finding also has broader implications for interpretation of Spatial Management Unit (SMU) scale CPUE calculations in the context of a proxy for biomass at the SMU scale, which increasingly is a metric required of valuable fisheries such as abalone. As articulated in this study, logically, zone-scale harvest rates in an abalone fishery are very different to local harvest rates. Zone-scale harvest rate is the metric typically sought when conducting stock assessments to provide information about a stock's status, however in addition, at least the distribution of local harvest rates is a metric which should be considered to ensure that serial depletion is not occurring. Without fine-scale spatial data, there is no possibility of realising this in an abalone fishery, or any other fishery with a similarly complex spatial structure. Fortunately, in Australia, in addition to Tasmania, such GPS data-logger data are being collected routinely in Victoria and New South Wales and are being introduced in South Australia, which encompasses the main abalone fisheries; similar data are also being collected in New Zealand..

The review and alteration of abalone fishery TACC occurs annually with few exceptions, but this is largely due to tradition and not through a process contrasting the long-term benefits or consequences of annual vs multi-annual assessment intervals. Arguments have been made that in abalone fisheries time was required for the effects of changing a TAC or LML to become apparent and so TAC changes should not occur every year. The current industry preference is to use a two year time-frame should TAC changes be required. The management strategy evaluation simulation framework developed in this project was used to compare outcomes of managing a simulated abalone stock using assessment intervals of 1, 2, 3 and 4 years while keeping other important factors constant. Not surprisingly one effect of a longer assessment interval is to slow events down, which is not always a bad thing. Thus, although stock recovery from depletion is slowed more the longer the assessment intervals, this can also prevent very rapid and dramatic changes in catch levels within the fishery. However, the delays brought about by increasing the assessment interval also have the effect of increasing the variation in all fishery performance metrics. If an assessment interval of more than one year is adopted within the multi-criterion decision analysis (MCDA) then an appraisal of the appropriateness of the TAC set should be conducted each year irrespective of the interval set for changing the TAC, just in case more rapid changes are indicated. In that way the control that might arise from, say, a two-year assessment interval can be obtained without the risk of increasing variation and rapidly declining CPUE through an inability to react quickly. Setting TACs across multiple years also decreases the potential to act rapidly in response to rapid or extreme environmental events such as the March/April 2010 heat related mortality event, which was, to some degree repeated in 2016.

An array of meetings were organized and attended, especially in Tasmania, but also in Victoria, recently in South Australia, but also in New Zealand, where the structure and implementation of formal harvest strategies suited to abalone fisheries have been discussed and reviewed. In each case, the fishing industry in each location has been closely involved. In Tasmania this has been especially the case with industry contributing directly to two formal reviews of abalone harvest strategies and numerous meetings of the FRAG and of sub-groups from the FRAG to discuss and review the work on harvest strategies as it progressed. The advantages relating to public accountability and credibility given to claims of sustainability for the fishery lead industry leaders to encourage the introduction of formal harvest strategies. Even so, gaining wide acceptance of the need for such a management change would be much more difficult without their on-going input and being given opportunities to address some wider industry forums.

The Multi-Criterion Decision Analysis approach was found to be fully capable of combining different fishery performance measures so that a formal and agreed upon harvest control rule can be used to provide defensible management advice concerning total allowable catches. In the empirical Harvest Strategy tested here, as with alternate empirical HS forms, there are many obvious and subtle components involved in established both targets and limits and the structure of the Control Rule, and can include:

1) Exactly which fishery performance measures to use in the MCDA;
2) How the different performance measures affect the eventual outcome and how they may interact;
3) How often a stock is to be assessed and management changes made (the assessment interval);
4) The exact structure of the scoring functions that convert the empirical performance measure values into a particular score;
5) The relative weights to be given to each score when the MCDA combines them; and finally

6) Exactly how the total MCDA score is converted into a change in the catch expected to be taken from the given scale of assessment (e.g. in Tasmania the statistical block).

If any single performance measure dominates the outcomes of the TAC setting process, as the TargetCE performance measure does in the harvest strategies tested here, then the relative weight attributed to that measure needs careful selection. Importantly, the MCDA process has been designed that it is easily open to including other or alternative performance measures, such as those deriving from the spatial data logging as they become viable as working time series allowing them to act as fishery performance measures.

In the different harvest strategy scenarios explored in the management strategy evaluation the TargetCE performance measure was found to be necessary for the harvest strategy to converge on a final stable outcome in terms of CPUE and spawning biomass depletion. Some combinations of weights on the three performance measures led to a failure of those particular harvest strategies to converge on a stable outcome so care is required in their selection. Even when limited to either one or two years, the assessment interval was also found to be highly influential on the harvest strategy outcomes. The longer the assessment interval the more delayed the harvest strategy was in achieving a stable outcome.

There is evidence in Tasmania of an exceptional recruitment event occurring in the early 1990s. This allowed stocks to recover from a badly depleted state quite quickly. It is noteworthy that in the absence of such exceptional recruitment events the simulation modelling suggests that stock recovery, from its current relatively low level, may take possibly decades if further years of relatively low recruitment occur.

Simulations suggest there is a trade-off between the amount of catch taken and the rate of recovery and the final depletion level achieved, with greater recovery achieved the less catch that is taken. However, a particular array of settings defining a single optimal harvest strategy was not selected or put forward, as this should be done by those tasked with setting or recommending policy for the fishery. In numerous meetings with industry and managers there are clearly a wide range of opinions as to how best to move the fishery forwards and towards what final goals. Such important decisions for the Tasmanian abalone fishery still need to be more explicitly articulated before an optimum harvest strategy can be selected. Nevertheless, some emphasis is given here to those strategies that lead to low levels of large and dramatic changes in the fishery. However, the implications of the full range of MCDA settings were explored and are now available to guide final selection.

Finally, the testing of the MCDA was only possible because of the developments of the software management strategy evaluation simulation framework. These developments enabled the testing to operate now at any scale from single small populations up to whole fishery zones. There is now a general structure to the control rules used to generate scores for any given fishery performance measure. A large portion of the code required to generate the simulated stock (be it a zone made up of statistical blocks, or statistical block made up of multiple populations) and conduct the MSE replicates is now encapsulated in an R package, although it still requires some less user-friendly software to put together an operational MSE framework suitable for testing harvest strategies in a different jurisdiction. Even so, the time taken now to implement an MSE to test abalone (or similar invertebrate) harvest strategies elsewhere would only be slightly longer than it would take to condition the model onto a different situation of biological properties.

12 Implications

The management of abalone stocks is difficult for many reasons including their high value and the exceptional levels of spatial structuring found in their stocks. Very many stocks of abalone (*Haliotis* species) around the world have ended by being over-exploited and eventually collapsing (Hobday, 2001). The introduction of formal harvest strategies is an attempt to avoid such a fate for Tasmanian abalone stocks. The current process for setting total allowable catches in Tasmania are relatively informal, have only been recently documented for some recent reviews of the Tasmanian fishery (Buxton et al, 2015; Knuckey, 2015), and, because of the subjective nature of identifying expected catches by statistical block each years' decisions would be difficult to repeat and hence to defend. Currently there is a growing requirement within Australia and around the world for the sustainability credentials of important fisheries to be open to public scrutiny. Within Australia there has been the development of the *Status of key Australian Fish Stocks* process (e.g. Flood et al., 2014), which is leading to a requirement for fisheries management advice and stock status to have an evidential basis expressed in a publically available stock assessment document. This is a valuable change to very many fisheries in terms of increasing the public acceptance of their products but this is especially useful and valuable in fisheries that have important export components, such as all the abalone stocks in South-East Australia. The development of the MCDA process with the testing conducted in this project will enable at least Tasmania to produce repeatable and defensible management advice for its abalone stocks (and the option is always available to the other States). The discussions concerning, and the explicit formal testing of, alternative harvest strategies for abalone stocks has immediate implications for any jurisdiction contemplating or in the process of introducing a formal harvest strategy in its abalone fisheries.

13 Recommendations

The systems developed and results obtained in this project are already being used in the development of a formal harvest strategy within the Tasmanian abalone fisheries, which accounts for half the abalone harvested in Australia, and more than a quarter of the global wild abalone harvest. In addition, the software infrastructure has been used in the western zone of Victoria and discussion have been held in New South Wales, in South Australia, and even in New Zealand, and may have some influence on developments in each jurisdiction.

13.1 Further Development

There is now a Management Strategy Evaluation simulation framework available that can be applied to a wide range of different fisheries at a wide range of different geographical scales. This can be applied to other abalone fisheries but currently it would still be dependent on the first author of this report to run the software or at least spend considerable time demonstrating its use to others.

Predicting this barrier to broader uptake, considerable effort was made by the PI to translate the free form software into what is now a partially documented R package. R packages constitute a collection of R functions that have the aim of assisting with particular kinds of analyses. Each of these function have built in documentation that explains their operation and other documentation explains how the functions can work together to achieve the needs of conducting the defined analyses. The package has been used in the latest simulation runs but currently it can only read in the necessary data and control files and then generate a simulated abalone zone/block, or population. However, it has not yet been developed to enable the full application and comparison of alternative harvest strategies to the simulated zone. To apply the MSE testing to a simulated zone still requires custom software not yet translated into the package, and unfortunately that custom software is certainly not user-friendly. The package development was not part of the original project and is not a minor undertaking. Nevertheless, there has been a good deal of interest expressed by industry and researchers over gaining access to the software to allow them to run their own simulations.

Because of the broad interest in the development of the R package, continued development of this R package, aimed at completing a working version that should be usable by anyone familiar with R and abalone like fisheries, is likely to maximise the extension and adoption of the investment by FRDC in this work.

14 Extension and Adoption

The Buxton Review (Buxton et al 2015) highlighted testing of the MCDA based Harvest Strategy via MSE as an important step prior to formal adoption as the system for determining the Tasmanian Abalone Fishery TACC. The Tasmanian FRAG Spatial Management Evaluation Group, has already accepted key components of this work, and the outcomes of this study will be critical to the eventual acceptance and inclusion by Government in the Tasmanian Abalone Fishery Management Plan of;

1) The MCDA Harvest Strategy as the basis for TACC determination,
2) A revised rationale of establishing appropriate Legal Minimum Lengths.

15 Project Material Developed

During the period of this project numerous presentations were made as was this report. In addition, a partial R package was produced that can be used to produce a simulated abalone zone ready to have its dynamics projected forward. An R binary file that is the usual way these packages are distributed is available with a copy sent to FRDC.

16 Appendix 2: Staff

Malcolm Haddon

Craig Mundy

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