Implementation of dynamic reference points and harvest strategies to account for environmentally driven changes in productivity in Australian fisheries

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ii. Abbreviations

AAO	Antarctic Oscillation Index (Southern Annular Mode)
ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
AFMA	Australian Fisheries Management Authority
AIC	Akaike Information Criterion (a measure of statistical fit)
AMCS	Australian Marine Conservation Society
B	Biomass (of a fish stock)
CIMP	Coupled Model Intercomparison Projects
COMRAC	Commonwealth Research Advisory Committee (FRDC)
CPUE	Catch per unit effort
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CTS	Commonwealth Trawl Sector
DAWE	Department of Agriculture, Water and the Environment (now DCCEEW)
DCCEEW	Department of Climate Change, Energy, the Environment and Water
DFA	Dynamic Factor Analysis
EM	Estimation model (assessment model, in MSE analysis)
eNGO	Environmental non-governmental organization
ENSO	El Niño Southern Oscillation
F	Fishing mortality rate
GHaT	Gillnet, Hook and Trap fishery (Commonwealth)
HCR	Harvest control rule
HIS	Humane Society International
IATTC	Inter-American Tropical Tuna Commission
IPCC	Intergovernmental Panel on Climate Change
IPO	Interdecadal Pacific Oscillation
MSC	Marine Stewardship Council
MSE	Management strategy evaluation
NPF	Northern Prawn Fishery (Commonwealth)
M	Natural mortality rate
MEY	Maximum economic yield
MSHS	Multi-species harvest strategy
MSY	Maximum sustainable yield
OM	Operating model (in MSE analysis)
PDO	Pacific Decadal Oscillation
PEW	PEW Charitable Trusts
PZJA	Protected Zone Joint Authority (Torres Strait)
RAG	Resource Assessment Group (AFMA)
RBC	Recommended Biological Catch
RBP	Redleg Banana Prawns
RS	Regime shift
RSI	Regime shift indices
SAM	Southern Annular Mode
SESSF	Southern and Eastern Scalefish and Shark Fishery (Commonwealth)
SOI	Southern Oscillation Index

SPR	Spawning potential ratio
SS	Stock Synthesis stock assessment software package
SSB	Stock spawning biomass (of a fish stock)
STARS	Sequential *t*-test analysis of regime shifts
TAC	Total Allowable Catch
TPI	Tripole Index for the Interdecadal Pacific Oscillation
ORL	Ornate Rock Lobster (*Panulirus ornatus*)
TSPZ	Torres Strait Protected Zone
TSRA	Torres Strait Regional Authority
UNGA	United Nations General Assembly
VIF	Variance inflation factors, indicating degree of collinearity between variables
WWF	Worldwide Fund for Nature

iii. List of Species

The table below provides a summary of standard common names (according to the FRDC Fish Names Standard https://www.frdc.com.au/knowledge-hub/standards/australian-fish-names-standard) and the scientific names of species in this report, with comments regarding which stocks (where multiple stocks exist) have been evaluated in this report.

Standard name	Scientific Name	Comments
Blue Grenadier	*Macruronus novaezelandiae*	This is assessed as a single stock.
Blue Warehou (eastern and western stocks)	*Seriolella brama*	Blue Warehou has been assessed as separate eastern and western stocks.
Eastern School Whiting	*Sillago flindersi*	This is an eastern Australian stock and differs from the Southern Eastern School Whiting (*Sillago bassensis*) and the Western Eastern School Whiting (*Sillago vittata*). All references to School Whiting in this report refer to Eastern School Whiting.
Gemfish (eastern stock)	*Rexea solandri*	Gemfish are assessed as separate eastern and western stocks. All references to Gemfish in this report refer to the eastern stock.
Jackass Morwong (eastern stock)	*Nemadactylus macropterus*	Jackass Morwong are assessed as separate eastern and western stocks. All references to Jackass Morwong in this report refer to the eastern stock.
Ornate Rock Lobster	*Panulirus ornatus*	This species is referred to in the Torres Strait fishery as the Tropical Rock Lobster and assessed by the Tropical Rock Lobster Resource Assessment Group (TRL RAG). Any references to Tropical Rock Lobster or TRL in this report refer to Ornate Rock Lobster.
Redfish	*Centroberyx affinis*	This is an eastern Australian stock and differs from the Bight Redfish (*Centroberyx gerrardi*).
Redleg Banana Prawn	*Penaeus indicus*	This is assessed as a single stock.
Silver Warehou	*Seriolella punctata*	This is assessed as a single stock.
Tiger Flathead	*Platycephalus richardsoni*	This is assessed as a single stock.

1. Executive Summary

Background

All fish stocks are subject to natural, environmentally driven changes in biological productivity, such as to recruitment or growth rate, that can cause substantial, natural cycles in biomass unrelated to fishing. Recently, persistent declining trends in fish stock productivity have been seen in some Australian stocks, resulting in stocks that are less productive than historically estimated. Several southeast Australian fish stocks have failed to 'recover' to target levels calculated using historical estimates of productivity, despite substantial reductions in catch and effort.

Harvest control rules used to set catch limits for Commonwealth fish stocks assume a ‘static’ B_0 based on historical productivity, or some chosen historical reference level, implicitly assuming that these stocks will recover to historical or ‘average’ biomass levels if left unfished. While the stationarity assumption may be valid when biological parameters vary without trend, this assumption is invalid for stocks exposed to changing environmental conditions that result in directional change in these parameters. For example, a productivity ‘regime shift’ has been assumed for Jackass Morwong east, with the level of unfished spawning biomass (B_0) used in assessments and the reference points used in harvest control rules, being changed to reflect apparent lower productivity.

The need to adapt stock assessment methods and harvest strategies to account for environmentally driven shifts in productivity has been recognised by the Australian Fisheries Management Authority (AFMA) Resource Assessment Groups (RAGs) for several stocks in the Southern and Eastern Scalefish and Shark Fishery (SESSF). Methods are required to detect such changes and incorporate them in assessments and management processes. One such method is ‘dynamic B_0’, which involves estimating the time-series of biomass expected had there never been fishing, under apparent reduced stock productivity.

Several studies have evaluated the use of dynamic B_0 including evaluation of ‘dynamic stock status’ for groundfish stocks off the US West Coast. Stock biomass has been expressed relative to dynamic B_0 by the Western and Central Pacific Fisheries Commission (WCPFC) to support management decision making for about 10 years. It is now common to include some form of time-variation in biological parameters (usually growth) in data-rich stock assessments, and to recognise additional variation in recruitment. Some assessments are starting to report status against ‘dynamic’ reference points that reflect non-fishing effects on the stock. This study evaluates the use of dynamic B_0 and reference points for stocks in the SESSF, as well as for two short-lived, fast growing crustacean stocks off northern Australia.

Purpose

The purpose of this project was (1) to identify candidate fish stocks showing likely environmentally driven productivity change, (2) to conduct comparative assessments for these stocks using equilibrium and dynamic reference points, and (3) to develop and test candidate harvest strategies using dynamic reference points that might appropriately respond to changes in fish stock productivity, including environmentally driven trends in productivity. The outcome of the project is a set of recommendations on future stock assessment approaches, data requirements, harvest control rules and options for management approaches incorporating dynamic productivity and dynamic reference points for Australian fish stocks.

Methods

The project consisted of several sequential components, each built on the results of the preceding component, with new methods developed under each. The project methods included:

- Selection of candidate stocks with a range of biological characteristics for which recent assessments producing estimates of recruitment deviations were available;

- Conducting of retrospective analysis of static and dynamic B_0 for these stocks, comparing what historical RBCs would have been using static and dynamic reference points;
- Evaluation of evidence for non-fishing effects on productivity including: expert-judgement regime shift weight-of-evidence analysis; sequential t-test analysis of regime shifts (STARS) in recruitment deviations; evaluation of the degree to which trends in surplus production can be explained by production models and regime shifts; evaluation of correlations between recruitment deviation trends for the candidate stocks and comparison of trends in fishing and non-fishing effects, as indicated by deviations in dynamic from static B_0;
- Conducting of simulation analyses to explore the performance of static and dynamic B_0-based harvest control rules where various biological parameters (unfished recruitment R_0, asymptotic length L_∞, growth rate K, natural mortality M, and stock-recruitment steepness h) exhibit trends over time;
- Management strategy evaluation (MSE) testing of several candidate harvest control rules using static and dynamic reference points, applying externally driven change in productivity for three of the SESSF stocks (Silver Warehou, Tiger Flathead and Eastern School Whiting) and one northern Australian crustacean stock (Redleg Banana Prawn RBP). For the SESSF stocks, MSE explored scenarios in which non-stationarity was due to time-trends in M and R_0. For the short-lived, fast-growing RBP, MSE was used to explore scenarios in which recruitment was driven by El Niño Southern Oscillation (ENSO) cycles under historical and future climate conditions.

Results

Data requirements for dynamic harvest control rules

The analyses presented in this project largely depended on the results of integrated age-structured stock assessments able to estimate annual recruitment deviations and changes in productivity that can be attributed to those recruitment deviations. Assessments able to estimate dynamic B_0 require consistent and representative data on landings, discards, an index of abundance, along with catch length and age compositions. It is primarily data on annual length- and age-composition that inform estimation of recruitment deviations. All of the evidence for non-fishing effects in this work is derived from the estimates of recruitment deviations.

Evaluation of evidence for non-fishing effects

This project expanded on the expert-judgement approach of Klaer *et al.* (2015), applying a multi-method approach to quantifying evidence for fishing and non-fishing effects, rather than using expert judgement ranking. This included development of methods to calculate and present trends in dynamic B_0 deviations as relative trajectory plots comparing fishing and non-fishing effects over time. These analyses rely on estimates of recruitment deviations derived from Tier 1 assessments to estimate dynamic B_0 deviations over the history of the fishery and require that the estimated stock-recruitment relationship be unbiased given systematic deviations about a stock-recruitment relationship are interpreted by dynamic B_0 as non-fishing effects.

Multiple lines of evidence for fishing and non-fishing effects were evaluated for eight case study stocks: six SESSF stocks (Jackass Morwong east, Redfish, Silver Warehou, Blue Grenadier, Tiger Flathead, Eastern School Whiting) and two short-lived northern crustacean stocks (Ornate Rock Lobster, Redleg Banana Prawn). Analyses showed a wide range of non-fishing effects in terms of magnitude and historical duration for the case study stocks, ranging from strong evidence for non-fishing effects but little overfishing on Jackass Morwong east over 1975–2017, to little evidence for non-fishing effects but substantial overfishing for Redfish.

Tiger Flathead and Eastern School Whiting stocks show little evidence of non-fishing effects or overfishing, with stock status fluctuating close to the management target during 1975–2017. The Blue Grenadier stock shows moderate non-fishing effects in most years, but without trend, with episodic years of stronger, positive non-fishing induced recruitment. This stock is known to show episodic high recruitments between extended periods of lower-than-average recruitment and has remained substantially underfished throughout the analysis period.

The short-lived Redleg Banana Prawn and Ornate Rock Lobster stocks show strong non-fishing effects, but without trend. There has been high inter-annual variability in recruitment driven by environmental factors, including the ENSO cycle and associated changes in e.g. sea temperature, rainfall, ocean currents, and sea surface height. Recruitment variability has resulted, in turn, in high variability in stock biomass and hence fishing intensity, again without trend.

Evidence for strong non-fishing effects on the Jackass Morwong east was reinforced in this project, with a continuous and strong negative trend over the entire analysis period. Over 1975–1995 fishing intensity fluctuated around the target, but over 1996–2014 fishing intensity was moderately above target. Silver Warehou showed a recent negative trend in non-fishing effects over 2008–2017 when fishing intensity was at or below target, with an earlier period of positive non-fishing effects from 1994–1999, followed by a period of overfishing over 1999–2006 over which time there was little evidence of non-fishing effects.

Evaluation of productivity changes in stock assessments

For several stocks in the SESSF, systematic differences between estimated recruitment and that expected from the stock-recruitment relationship have become increasingly evident over the past few decades. These differences may reflect the effects of the environment on recruitment, independent of fishing, leading to a declining trend in recruitment. Over the past decade, Tier 1 assessments for stocks showing persistent low recruitment, such as Jackass Morwong east, Silver Warehou and Redfish, have conducted constant catch projections assume future recruitment will equal recent recruitment, which is below average, as the basis for RBC recommendations. This constitutes a formal response to apparent environmental (non-fishing) effects.

Under persistent below-average recruitment, a stock is no longer likely to fluctuate around historical production levels, and reference points based on static B_0 no longer reflect the levels to which a stock could be expected to rebuild to if fishing were to cease. Estimates of stock status based on dynamic B_0 (the estimate of the level to which a stock would be expected to rebuild under recent productivity parameters) permit an evaluation of the relative effect of fishing compared to the environment, where non-fishing effects appear to have led to changes in productivity. Assessments that have sufficient data to directly estimate time varying parameters (e.g. growth, M, recruitment), can be used to derive dynamic B_0, even when the specific driver of time-variation is unknown.

Performance of static vs. dynamic harvest control rules

Previous studies investigating dynamic B_0 have focused on the performance of HCRs given perfect information about stock size and productivity. The MSE analysis for SESSF stocks incorporated trends in productivity parameters (R_0 or M), observation error and process error in recruitment, resulting in variability around estimated stock size and allowing the trade-offs and associated risk of various HCRs to be quantified.

For both SESSF stocks and RBP, the use of a dynamic B_0 HCR will, on average, result in smaller absolute population size, recommend slightly higher and less variable catch limits than a static B_0 HCR, and there will be a lower probability of zero RBCs. Stock status (or depletion, expressed as a proportion of estimated unfished biomass) depends on which measure of B_0 is used – relative to static B_0 the status will be lower than relative to an estimate of annual unfished biomass (dynamic B_0) for stocks whose productivity is reduced due to environmental effects. However, a stock with environmentally driven, persistent, lower productivity cannot be expected to rebuild to historical levels, even in the absence of fishing.

The SESSF MSE results show that bias occurs in assessments when parameters are time-varying and this is not adequately accounted for in the assessment, with this bias larger when using dynamic B_0-based HCRs. Even though key assessment outputs are biased when using a static B_0 HCR, this HCR is able to keep the static interpretation of stock status above the limit reference point, while keeping the dynamic interpretation at the target reference point. The bias in assessment results for the dynamic B_0 HCRs leads to the static stock status dropping below the limit reference point, and the dynamic stock status not reaching the target reference point. MSE results also indicate that estimates of static B_0 from the assessment (traditionally assumed to be constant) will vary over time in an attempt to accommodate time-varying changes in R_0 and natural mortality, which are not accommodated in the assessment owing to lack of sufficiently informative data.

Small differences in median projected catch seen in MSE results between the static B_0 HCR and the dynamic B_0 HCRs partially relate to RBCs under the static B_0 HCR being the same as those under dynamic B_0 when the stock is above the breakpoint biomass level. RBCs decrease faster to zero when stock status is below the breakpoint of the HCR using static B_0. RBCs are on average somewhat higher using the dynamic B_0 HCR when stock status is below the breakpoint of the HCR but above the LRP because the dynamic LRP is reduced when declines are attributed to the environment, allowing fishing to continue, albeit at lower levels of fishing mortality. The catches from these two approaches converge to a similar value over the course of the projection period as the stock either recovers, or stabilises at a new lower level, although catch limits are slightly higher for the dynamic B_0 HCR.

Management risks and trade-offs

When choosing a management approach and a HCR to be used for stocks that appear to show changing productivity, there needs to be strong evidence that environmental drivers are causing a clear and persistent trend in productivity, and that indications for this are not due to misspecification of assessments or inadequate data. A key challenge is to then detect that productivity is time-varying, which may be difficult for assessments with low levels of data quality and quantity. Consistent declining trends in estimates of unfished biomass from an integrated assessment may provide an indication of time-varying productivity if there is confidence that the assessment is not mis-specified.

Once a stock has been identified and agreed to have been strongly affected by environmental factors, with a directional trend in that effect, appropriate management objectives for that stock need to be established and clearly described, so that a harvest strategy can be designed to meet these objectives under the changed environmental conditions and productivity. The choice of HCR then depends on management objectives and the intent of the harvest strategy under conditions of changing productivity, particularly declining productivity.

The key trade-offs that managers need to consider when selecting a HCR for a stock that appears to be environmentally affected relate to absolute stock size, catch levels, catch variability, and risk of fishery closure (zero RBCs). MSE analyses in this report indicate that use of a static B_0 HCR will result in a larger absolute stock size, with moderately lower RBCs, higher catch variability and higher risk of fishery closure. The opposite trends were found when applying a dynamic B_0 HCR.

When the default proxy targets and limits were incorporated in the Commonwealth Harvest Strategy Policy (2018) there was no consideration of what an appropriate absolute biomass level might be to prevent recruitment impairment of a stock that is declining for environmental reasons. Environmental drivers can conceivably cause a stock to decline to extremely low levels, in which case management targets and limits become largely meaningless and fisheries management may not affect the outcome.

The 'hard limit' dynamic B_0-target and dynamic B_0-slide HCRs tested have attempted to achieve a compromise between the static and fully dynamic HCRs, and a compromise along the trade-off axes, by allowing a decrease in reference points to allow for some catches of a lower productivity stock, while preventing the limit reference point from declining to levels that might compromise the resilience of the stock to rebuild. Determining the range of permissible change in these parameters would need to be determined as part of harvest strategy development and would depend on the species biology, the degree and the persistence to which productivity is expected to be negatively affected by environmental drivers.

Implications for stakeholders

The main implications of this project relate to guidance provided to fisheries resource assessment and management committees on assessment data requirements, evaluating evidence for non-fishing effects, estimation of trends in dynamic B_0; design of HCRs using dynamic reference points; and risks and trade-offs associated with static vs. dynamic harvest control rules. This guidance is intended to assist fisheries managers and stakeholders to determine whether dynamic harvest strategies are appropriate for stocks once management objectives have been established for stocks that are environmentally driven, and design appropriate harvest control rules to achieve those objectives.

Recommendations

1. Data collection programs should focus on sampling the spatial distribution of the fishery, with adequate samples to allow robust estimation of recruitment deviations within integrated assessments, and subsequent estimation of trends in unfished biomass. Where relevant (e.g., for SESSF stocks; longer-lived species), this sampling should focus on collection of age data as these data more directly inform cohort strength through time and thus estimation of recruitment deviations.
2. For stocks with Tier 1 assessments capable of estimating recruitment deviations and trends in dynamic B_0, presentation of assessment results should include trends in dynamic B_0, so that evidence for non-fishing effects can be evaluated, noting that interpretation depends on the assumed unbiasedness of the stock-recruitment relationship.
3. Periodic broader reviews of all evidence for non-fishing effects should be conducted for stocks that remain persistently below target, and near the limit biomass, despite management measures that are expected to reduce fishing mortality to levels that should allow for rebuilding. For stocks with Tier 1 assessments capable of estimating recruitment deviations and trends in dynamic B_0, presentation of assessment results should include trends in dynamic B_0, to evaluate evidence for non-fishing effects.
4. Tier 1 stock assessments should routinely report historical trends in both static and dynamic B_0, and depletion relative to static and dynamic B_0 to identify potential non-fishing effects on stock status.
5. For stocks for which there are inadequate data to conduct a Tier 1 assessment, efforts should continue to develop robust lower information assessment methods that are able to estimate inter-annual changes in productivity (such as persistent declines in recruitment or production) that cannot be fully explained by fishing mortality.
6. Further work is required to fully understand the cause of increased bias in estimates of spawning stock biomass when using dynamic B_0 HCRs.
7. Investigation of directional retrospective patterns in B_0 between assessments should be undertaken as an additional line of evidence suggesting impacts of non-fishing effects.
8. Harvest strategy guidelines and objectives need to be clearly defined. In particular, the intention of the various reference points, particularly the limit reference point, should be clearly defined in the harvest strategy. This definition will need to consider the approach to be taken if a stock has been permanently reduced in productivity and size due to environmental effects.
9. Results indicate that using dynamic B_0 is preferable, and more biologically realistic, to the currently implemented step change in productivity for Jackass Morwong east. Analyses showing evidence of productivity decline for this species suggest that there has been an ongoing decline in productivity, rather than a single step change.

Keywords

Dynamic B_0, B_{Unfished}, dynamic reference points, regime shift, climate change, management strategy evaluation, Commonwealth Southern and Eastern Scalefish and Shark Fishery, Northern Prawn Fishery, Torres Strait Tropical Rock Lobster Fishery, Blue Grenadier, Eastern School Whiting, Jackass Morwong, Ornate Rock Lobster, Redfish, Redleg Banana Prawn, Silver Warehou, Tiger Flathead.

2. Introduction

All fish stocks are subject to natural, environmentally driven changes in biological productivity, such as recruitment or growth rates. These changes may be cyclical, driven by decadal shifts in ocean basin current systems and water temperatures, such as the El Niño Southern Oscillation and the Pacific Southern Oscillation. Resulting recruitment variation can result in substantial, natural cycles in biomass unrelated to fishing, such as the massive changes in biomass of clupeid and engraulid species seen in the eastern boundary upwelling systems off South Africa, Namibia and Peru (see papers in Fréon *et al.* 2009). However, more recently, changes in fish stock productivity have been seen in response to climate change-driven oceanic warming, including in the Torres Strait and off southeast Australia, resulting in stocks that are less productive than historically estimated.

Over the past two decades, several southeast Australia fish stocks have failed to 'recover' to target levels calculated using historical estimates of productivity, despite substantial reductions in catch and effort. Several research projects have concluded that these stocks have undergone an environmentally driven reduction in productivity (Wayte 2013). In recognition of apparent strong non-fishing effects, a productivity 'regime shift' has been assumed for Jackass Morwong east, with allowance in assessments for R_0 (the expected unfished recruitment) and hence reference points used in harvest control rules (HCRs), estimated to have changed to reflect apparent lower productivity. Ecosystem and climate-change modelling have predicted the likelihood of similar changes in productivity for several Australian fish stocks (Fulton 2011).

Even though biological processes are naturally subject to variability, traditional stock assessments have assumed stationarity in parameters, and this impacts the reference points used in the HCRs on which management advice is based. Other than for Jackass Morwong east, HCRs used to set catch limits for Commonwealth fish stocks assume a 'static' B_0 based on historical productivity, or some chosen historical reference level, implicitly assuming that these stocks will recover to historical or 'average' biomass levels if left unfished. Target (usually B_{48} – the 48% of the unbiased spawning biomass, B_0) and limit (B_{20}) reference points calculated from this historical B_0 are used in HCRs to calculate recommended biological catches (RBCs).

While the stationarity assumption may be valid when parameters vary without trend, this assumption is invalid for stocks exposed to changing environmental conditions that result in directional change in biological parameters. Increased time-variation in biological parameters, in particular trends in these parameters and the reference points used in HCRs, are expected with climate change. Methods are required to detect such changes and to incorporate them in assessments and management processes. One such method is to calculate annual unfished biomass under prevailing environmental conditions, commonly termed 'dynamic B_0'. A dynamic B_0 approach to calculating reference points for fisheries management acknowledges that drivers other than fishing pressure influence population size, even where these cannot be explicitly identified.

Several studies have evaluated the use of dynamic B_0, including evaluation of 'dynamic stock status' for groundfish stocks off the US West Coast, when the environment changes the equilibrium biomass in the absence of exploitation (Berger 2019). It is now common to include some form of time-variation in biological parameters other than recruitment in stock assessments and some assessments are starting to report 'dynamic' reference points that reflect the current environmental conditions. The use of dynamic B_0 has been adopted for several tuna stocks managed by the Western and Central Pacific Fisheries Commission.

The need to adapt stock assessment methods and harvest strategies to explicitly and justifiably account for environmentally driven shifts in productivity has been recognised by the Australian Fisheries Management Authority (AFMA) Resource Assessment Groups (RAGs) for several stocks in the Southern and Eastern Scalefish and Shark Fishery (SESSF). At the SESSF South East Resource Assessment Group (SE RAG) stock assessment meeting of November 2018, the RAG included a recommendation in the Strategic Work Plan for a project to evaluate methods and options for dealing with environmentally driven changes in productivity using dynamic reference points. This study reports on work done to evaluate the use of dynamic reference points for SESSF stocks, as well as for two short-lived, fast growing crustacean stocks off northern Australia.

3. Objectives

The objectives of the project were:

1. To review relevant international research and management approaches to account for environmentally driven productivity change in stock assessments, reference points and harvest strategies for selected Australian fish stocks.
2. To identify and describe circumstances and fish stocks for which dynamic reference points should or should not be used in stock assessments and harvest strategies and develop appropriate methodology for conducting assessments using dynamic reference points.
3. To identify selected candidate fish stocks showing likely environmentally driven productivity change, conduct comparative assessments for these stocks using equilibrium and dynamic reference points, and prepare a candidate harvest strategy that includes dynamic reference points for testing in the FRDC Multi-Species Harvest Strategy project.
4. To make recommendations on future implementation of dynamic reference points and harvest strategies for Australian fish stocks.
5. To develop and improve methods for detecting and quantifying changes in productivity (growth and recruitment) in stock assessments, to relate these to environmental mechanisms causing productivity changes, and to evaluate data needs, including environmental indices, required to usefully detect and evaluate productivity change under various circumstances.
6. To consider and evaluate options for effective harvest control rules, incorporating dynamic reference points, that might appropriately respond to changes in fish stock productivity, including environmentally driven trends in productivity.
7. To identify environmental circumstances and fish stock characteristics under which it would be appropriate and advisable to move to using assessments and management approaches incorporating dynamic productivity and reference points, vs. stocks for which dynamic approaches offer no benefit compared to existing equilibrium approaches.
8. To make recommendations on future stock assessment approaches, data requirements, harvest control rules and management approaches incorporating environmental indicators, dynamic productivity and dynamic reference points for Australian fish stocks.

4. Methods overview

A substantial component of this project involved the development of novel or adapted methods to address the questions raised by the report objectives. This work was necessarily exploratory, and it was not clear at the start of the project which methods would turn out to be most appropriate for detecting, evaluating, and responding to changes in productivity for different stocks. Novel approaches needed to be developed, and assessment software modified to address environmentally driven productivity changes.

The project team explored a range of approaches using a variety of assessment software, with later aspects of the work being dependent on results of initial comparative assessments. Details of these methods were therefore not available on project commencement and were developed as the project progressed. Section-specific methods are described in detail under each of the sections of this report, but an overview of the methodological approach under each report section is provided here.

- Relevant international literature on research and management approaches relating to dynamic productivity was reviewed under each of the project components, addressing Objective 1.

Selection of candidate stocks

Candidate stocks were selected from the SESSF and northern crustacean fisheries for which recent integrated assessments with estimates of recruitment deviations were available, and which span a range of biological characteristics. Candidate stocks chosen were Jackass Morwong east, Redfish, Silver Warehou, Blue Grenadier, Tiger Flathead, Eastern School Whiting, Ornate Rock Lobster and Redleg Banana Prawn. Gemfish east and Blue Warehou east and west, for which older assessments were available but without recent estimates of recruitment deviations, were included in the analysis investigating evidence of non-fishing effects.

- This project component addressed Objective 3 regarding selection of candidate fish stocks with a range of biological productivity characteristics.

Retrospective analyses

Retrospective re-analysis of stock assessments for the selected candidate fish stocks was conducted using existing Stock Synthesis (or alternative) software, calculating static B_0 and trends in dynamic B_0 and comparing what historical Recommended Biological Catches (RBCs) would have been under alternative Harvest Control Rules (HCRs) using static and dynamic reference points.

- This workplan component contributed to addressing Objectives 3 regarding identification of candidate fish stocks showing evidence of historical changes in productivity.

Evidence for fishing and non-fishing effects

Evidence for non-fishing effects on productivity was analysed using outputs from the retrospective stock assessments, particularly estimates of annual recruitment deviations and annual surplus production. Analyses for evidence of non-fishing effects included: updating the expert-judgement weight-of-evidence analysis by Klaer *et al.* (2015); sequential t-test analysis of regime shifts (STARS) applied to recruitment deviations, estimated recruitments and surplus production; statistical comparison of the degree to which trends in surplus production can be explained by random perturbations, a production function, a regime shift in production, or a combination of regime shifts and a production function; evaluation of correlations between recruitment deviation trends for the candidate stocks using simple correlation, cluster analysis and dynamic factor analysis; correlation of recruitment deviation dynamic factor indices with environmental indices; comparative analysis of trends in historical overfishing and apparent non-fishing effects, as indicated by deviations in dynamic from static B_0.

- This work component contributed to addressing Objectives 3 and 4, providing evidence for stocks showing non-fishing (environmental) effects on productivity.

Simulation evaluation of alternative dynamic B_0 harvest control rules

Simulation analyses were applied to extend the retrospective re-analysis of stock assessments to exploration of the performance of static and dynamic B_0-based harvest control rules using simulations where various biological parameters (unfished recruitment R_0, asymptotic length L_∞, growth rate K, natural mortality M, and stock-recruitment steepness h) exhibit trends over time. While data available for SESSF stocks are inadequate to allow for the estimation of time-varying trends in these parameters within assessments, this simulation approach allowed for exploration of how catch limits (RBCs) for stocks in the SESSF would differ if management was based on dynamic B_0 under conditions of change in these parameters.

- ➢ This component contributed to addressing Objectives 5, 6 and 7 on methods for quantifying productivity changes in stock assessments and evaluating options for harvest control rules.

MSE of static and dynamic HCRs for SESSF stocks under time varying productivity

Management strategy evaluation (MSE) testing of several candidate harvest control rules was conducted using static and dynamic reference points, applying externally driven change in productivity. MSE was used to evaluate and contrast the performance of a static B_0 HCR and three variants of a dynamic B_0 HCR for three of the SESSF stocks: Silver Warehou, Tiger Flathead and Eastern School Whiting and one northern Australian crustacean stock: Redleg Banana Prawn (RBP). For the SESSF stocks, the MSE explored scenarios in which non-stationarity was due to time-trends in M and R_0, with performance measures based on static and dynamic B_0, as well as total catches and catch variability. Several scenarios were investigated for the three species relating to which parameter was time-varying (none, R_0, M), the trend in time when parameters were time-varying (linear-to-nadir, linear-to-zenith or cyclical) and the HCR used (static B_0, dynamic B_0, variants of dynamic B_0 with a hard limit). For the short-lived, fast-growing RBP, MSE was used to explore scenarios in which recruitment was driven by El Niño Southern Oscillation (ENSO) cycles under historical and future climate conditions. Similarly, performance measures were based on static and dynamic B_0, and included stock status, total catches and catch variability.

- ➢ This component contributed to addressing Objectives 5, 6 and 7 on methods for quantifying productivity changes in stock assessments and evaluating options for harvest control rules.
- ➢ All components contributed to addressing Objectives 4 and 8, providing the information required to support recommendations on future stock assessment approaches incorporating dynamic productivity and reference points.

5. Stakeholder Consultations

Two rounds of consultation were held with key stakeholders to the Commonwealth Southeast Trawl, Northern Prawn and Torres Strait fisheries. The first round of consultation with stakeholders and interested parties was conducted over February–June 2021, providing a background information document and canvassing opinions, comments, questions and concerns regarding the use of dynamic reference points in management of Australian fish stocks. The Second Stakeholder Consultation was conducted in the form of a one-day workshop hosted by AFMA on 22 May 2023 to which all interested parties were invited, either by direct participation or by attending online.

5.1. First stakeholder consultation

The list of stakeholders and interested parties consulted with during the first stakeholder consultation is shown in section 17.4 First Stakeholder Consultation. A wide range of stakeholders with expertise or interest in the Australian trawl and tropical crustacean fisheries was consulted to try to ensure that all key concerns and questions regarding the methodology and outputs of the project were identified.

The major stakeholder in this project is the Australian Fisheries Management Authority (AFMA) who identified the need for work on dynamic reference points in the research plan of the Southern and

Eastern Scalefish and Shark Fishery Resource Assessment Group (SESSFRAG), and who supported the project application through the FRDC Commercial Research Advisory Committee (COMRAC). The example stocks identified for analysis in the project included several stocks in the Commonwealth Trawl Sector (CTS) fishery, and two tropical crustacean stocks in the Torres Strait Ornate Rock Lobster and Northern Prawn Fisheries. Group consultations were therefore held with nine AFMA managers across these three fisheries. To ensure that the compatibility of using dynamic reference points with fisheries policies (particularly the Commonwealth Harvest Strategy Policy and the Environmental Protection and Biodiversity Conservation Act) was properly considered, group consultation was held with the Department of Agriculture, Water and the Environment (DAWE) and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES).

Key industry, indigenous and recreational stakeholders or interested parties were individually consulted. A group of experts with knowledge of the CTS and other Australian fisheries was also consulted, including a previous long-standing Chair of the SESSF RAG (Sandy Morison), and members of the SE RAG with expertise in economics (Sarah Jennings), recreational fisheries and Victorian fisheries research (Ross Winstanley) and commercial fisheries, fisheries research and Chair of the Ornate Rock Lobster and Northern Prawn Fishery RAG (Ian Knuckey). Also consulted were Dr Nick Rayns (previous Executive Manager of AFMA) and Prof. Keith Sainsbury (Associate Professor, Marine System Management at the Institute for Marine and Antarctic Studies, University of Tasmania; past Commissioner on the AFMA Board; with substantial experience in evaluation of management strategies for sustainable use of marine resource; also on the Technical Advisory Board of the Marine Stewardship Council).

Four environmental non-governmental organizations (eNGOs) were identified by AFMA as having previously been involved or interested in the work of AFMA and the RAGs on the fisheries concerned: the Humane Society International (I), the Australian Marine Conservation Society, the Worldwide Fund for Nature (WWF) and the Pew Charitable Trusts (PEW). Representatives of these organizations were individually consulted.

5.2. Background Information Presentation

The first stakeholder consultation questionnaire was accompanied by a background information presentation provided to all stakeholders, and presented to AFMA, ABARES and DAWE at face-to-face and online meetings. With no results available yet from this project for Australian stocks, substantial analysis was conducted for the purposes of this presentation using South Pacific Jack Mackerel as an example stock, to illustrate the use of dynamic refence points and the incorporation of an environmental driver in projections. This stock was chosen for illustrative analysis because it is a large stock with a long history of fishing, with periods of under- and over-fishing, highly variable recruitment, the availability of an environmental index correlated with recruitment, and an integrated stock assessment that estimates trends in dynamic B_0. Results produced for this stock (some of which were included in the presentation) were designed to illustrate all the analyses planned during this project, including projections and management strategy evaluation under variable recruitment, including incorporation of an environmental index in the stock-recruit relationship.

5.3. First stakeholder questionnaire

A questionnaire was used to canvas stakeholder views and was designed to prompt stakeholders to consider a number of aspects when expressing their views, comments, concerns or questions, without constraining their responses through use of predetermined options. The questions asked are shown in the summary of stakeholder responses below. ABARES and the AFMA SESSF, NPF and Torres Strait managerial groups provided collated group responses while other respondents provided responses as individuals. A total of 10 questionnaire responses were received, four of which represented 22 persons across AFMA, DAWE and ABARES, and six of which were received from the identified SESSF experts.

Contacted industry, indigenous, recreational and eNGO respondents chose not to submit questionnaire responses for this first stakeholder consultation, although most did express an interest in the project, and in seeing results. All stakeholders will be provided with copies of the draft project report and will be given an opportunity at that stage to provide their views during the second round of stakeholder consultation conducted towards the end of the project.

Questionnaire responses received from respondents are summarised in Appendix 17.4, under the questions numbered as per the questionnaire. Out of the numerous questions and concerns raised by stakeholders, the project team identified the following key concerns or questions arising from the 1st Stakeholder Consultation for the team to address:

- What proof, or at least persuasive evidence, is there for a substantial negative effect of environmental factors on productivity of selected case study stocks, as opposed to the decline being the result of over-fishing?
- What would be the results of moving to use of dynamic reference points for selected case study stocks, what would the risks and benefits be, and would resulting management approaches be consistent with the Commonwealth Harvest Strategy Policy and EPBC Act?
- What would the consequences be of getting it ‘wrong’, i.e. assuming that there has been an environmentally driven decrease in productivity, and moving to using dynamic reference points, whereas the decline in stock status primarily resulted from over-fishing?

These overview concerns subsume many other stakeholder questions and concerns, and the project team felt that addressing these would largely address many related questions.

5.4. Multispecies Harvest Strategy Workshop

A presentation of results available at the time for the selected case study stocks was given to participants in the MSHS Workshop held at CSIRO Canberra in March 2022. Results presented included: historical trends in dynamic B_0; comparison of recommended biological catches (RBCs) using static and dynamic reference points; historical trends in dynamic B_0 deviations; detection of regime shifts in recruitment deviations, recruitment, and surplus production; alternative production modelling; and correlations in recruitment deviations. These results were used to contrast the relative effects of fishing versus environmental effects for six SESSF case study stocks – Jackass Morwong east, Redfish, Silver Warehou, Blue Grenadier, Tiger Flathead and Eastern School Whiting.

5.5. Second Stakeholder Consultation

A 2nd Stakeholder Consultation was held on 22 May 2023 at the AFMA Head Offices in Canberra, as a workshop with the option of online participation. The list of invitees and participants and the workshop outline are provided in Appendix 17.5: Second Stakeholder Consultation. Key questions and concerns raised by stakeholders in response to a questionnaire circulated to all invitees after the workshop are also summarised Appendix 17.5. Key points arising from questions and comments made at the workshop, or raised in subsequent stakeholder responses, are summarised below, together with initial responses from the project team.

- It was clear from questions at the workshop, and in subsequent written responses, that many stakeholders had difficulty understanding the complex and technical nature of the analyses, particularly the MSE analysis results.

  - Following the workshop, the format for presentation of MSE results was improved to more clearly separate out and clarify results for the different HCRs. A document providing and further explaining these results was sent to all stakeholders and the revised presentation of results is incorporated into this report.

- The main concern expressed by many stakeholders was that clear and irrefutable 'proof' was required that declines in stock abundance have resulted (primarily) from non-fishing effects before consideration should be given to revising management strategies and harvest control rules to acknowledge reduced productivity of those stocks.
  - The report section on evidence for fishing and non-fishing effects presents critical analysis of all available evidence for non-fishing effects, given the available data.
  - However, while evidence for non-fishing effects on some stocks is strong, it is difficult to separate out fishing and non-fishing effects, particularly where fishing impacts have been followed by non-fishing effects, or where they are confounded.
  - Non-fishing effects have always affected stock productivity, but recent climate-change is likely to have imposed directional change in stock productivity, compared to historical fluctuations around an average.
- Insistence on strong evidence for non-fishing effects was expressed by some stakeholders as a need to identify the actual environmental : biological mechanisms to explain reductions in stock productivity, and to be able to clearly attribute changes in biological productivity to those mechanisms.
  - The links between environmental drivers are extremely complex, affecting different life-history stages (from maturation, growth and gonad development to production and survival of eggs, larvae and juveniles), with many environmental factors operating differently at different depths, areas and times of year.
  - Historical efforts to identify such mechanisms have typically only been able to explain short time periods, or anomalous events. It is unlikely that clear, quantitative mechanisms will ever be unambiguously identified for Australian long-lived demersal species caught by trawl.
  - This project has therefore focussed on detecting apparent, but unknown, non-fishing effects on productivity.
- Stakeholders placed increasing emphasis on the need to ensure that all stocks are maintained at levels that will ensure ecosystem function, notwithstanding apparent environmentally driven declines in productivity for some stocks.
  - This is a substantial departure from the current policy intent of limit reference points, which are intended to ensure an adequate biomass to minimise the risk of recruitment impairment. No current limits are based on ecosystem requirements.
  - This seems like a sensible requirement, but it is not clear what biomass of a higher-trophic level species (such as a predatory fish stock) would be required to fulfil which roles in an ecosystem. Ecosystem food webs are notoriously flexible, as shown by dramatic regime shifts between different species assemblages in systems like the Humboldt Current pelagic systems.
  - What is certain is that environmental drivers have always resulted in changes in ecotrophic system components and relationships, and that climate change will cause fundamental and substantial changes in ecosystems and food webs.

- Environmental NGO and Departmental representatives generally expressed a strong reluctance to accept that environmental drivers have been responsible either for depletion, or failure to recover, of fished stocks, preferring to consider fishing mortality to be the primary cause of stock declines and failure to rebuild.

6. Retrospective analysis

Retrospective analysis of assessment results from the most recently available stock assessments for selected test case stocks was conducted using static B_0 and trends in dynamic B_0 to compare what historical Recommended Biological Catches (RBCs) would have been under alternative Harvest Control Rules (HCRs) using static and dynamic reference points.

6.1. Selection of test case stocks

Fish stocks were chosen for analysis in this project based on the following criteria:

- For Commonwealth trawl stocks in the Southern and Eastern Scalefish and Shark Fishery (SESSF), existence of a recent Tier 1 stock assessment conducted using Stock Synthesis, suitable for calculating historical trends in depletion against static and dynamic B_0.
- Exhibiting a range of stock status, from overfished, to between target and limit biomass levels, to consistently above the target biomass.
- Exhibiting a range of trends in estimated recruitment, from long-term and enduring decline, through apparently cyclical or periodic recruitment, to apparently increasing recruitment.
- For tropical crustaceans, stocks for which there appears to be a specific and known environmental driver that affects productivity in a quantifiable way.

The stocks selected for analysis in the project are listed in Table 6-1, showing the year of the most recent assessment and key aspects of the current and historical status of each stock.

Table 6-1. List of stocks chosen for analysis showing key assessment results in terms of final year depletion and years below target or limit (48% B_0 and 20% B_0 for SESSF stocks) according to the most recent assessment available when the project began, showing the main test case stocks chosen for historical dynamic B_0 analysis, and additional stocks added for analysis of evidence for non-fishing effects only.

Species/Stock	Last assessment	Years covered by assessment	Final year depletion	Years <48% B_0	Years <20% B_0
Main test case stocks for historical dynamic B_0 analysis					
Jackass Morwong (eastern stock)	Day and Castillo-Jordán (2018)	1915–2017	14% B_0	28	16
Redfish	Bessell-Browne and Tuck (2020)	1975–2019	3% B_0	39	33
Silver Warehou	Burch *et al.* (2018)	1980–2017	23% B_0	11	0
Blue Grenadier	Castillo-Jordán and Tuck 2018	1960–2017	83% B_0	4	0
Tiger Flathead	Day (2019)	1915–2015	34% B_0	77	24
Eastern School Whiting	Day *et al.* (2020)	1942–2019	33% B_0	28	0
Ornate Rock Lobster	Plaganyi *et al.* (2020)	1973–2019	93% B_0	5	0
Redleg Banana Prawn	Plaganyi *et al.* (2021)	1980–2020	34% B_0	21	1
Additional stocks for evidence analysis					

Gemfish (eastern stock)	Little and Rowling (2008)	1968–2008	15% B_0	26	16
Blue Warehou (eastern and western stocks)	Punt (2009)	1986–2008	-	-	-

6.2. Historical recruitment trends

Over the past two decades, assessments of SESSF stocks have estimated that annual recruitment has declined and remained low over an extended period for the depleted or non-recovering stocks. Whether this has been due to overfishing of the adult stock or due to factors other than fishing that have contributed to poor recruitment, changes in recruitment in these stocks is the key indicator of changes in productivity and is a key focus of the project. The six SESSF test cases and two additional SESSF stocks show a range of historical patterns in estimated recruitment, illustrated in Figure 6-1 to Figure 6-6. These illustrate changes in stock production that have occurred over time.

Jackass Morwong east showed an overall declining trend in estimated recruitment over 1969–2007, with a semi-decadal cycle of higher recruitment peaks in 1979, 1987, 1993 and 2001. Recruitment appears to have been increasing slowly since 2007 (Figure 6-1).

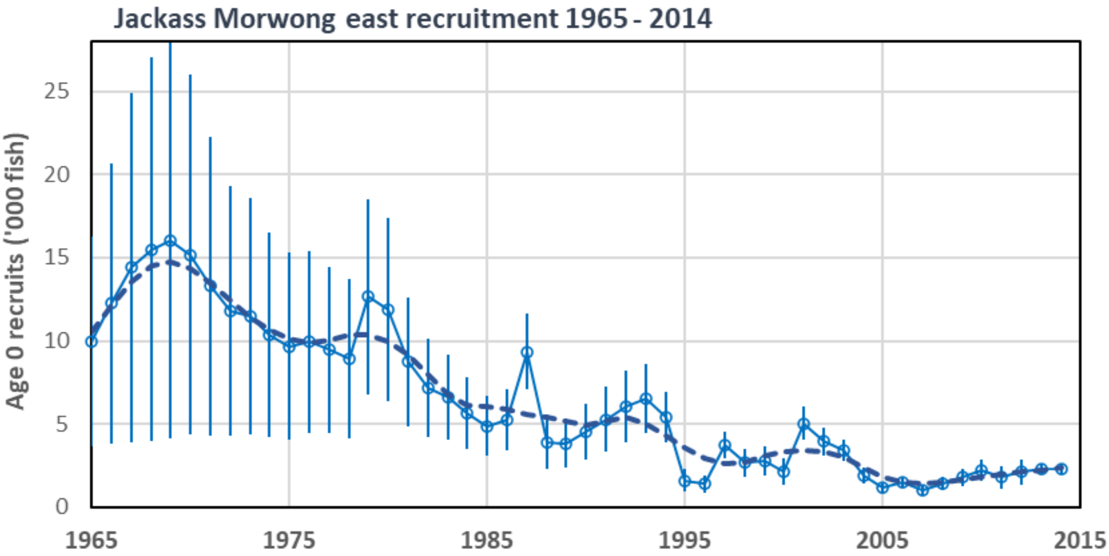


Figure 6-1. Estimated historical recruitment for Jackass Morwong east (1965–2014, excluding years estimated off the stock-recruit curve) with std.devs and a fitted 10-year loess smoother (assessment results from Day and Castillo-Jordán 2018).

After notably high semi-decadal peaks in recruitment in 1977, 1990 and 2000, Redfish has shown low recruitment in 1996–1997 and since 2001 (Figure 6-2).

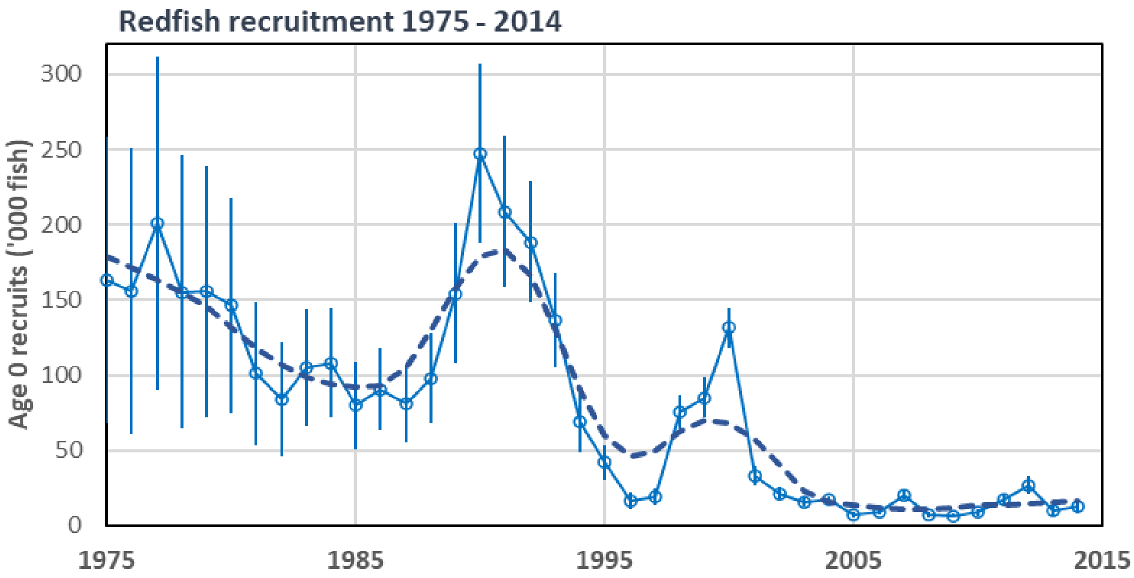


Figure 6-2. Estimated historical recruitment for Redfish (1975–2017, excluding years estimated off the stock-recruit curve), with std.devs and a fitted 10-year loess smoother (assessment results from Bessell-Browne and Tuck 2020).

Silver Warehou has shown highly variable recruitment, with peaks and troughs over 1980–2002, followed by an apparent decline in recruitment to low levels over 2002–2012. Recruitment appears to have increased slowly since 2012 (Figure 6-3).

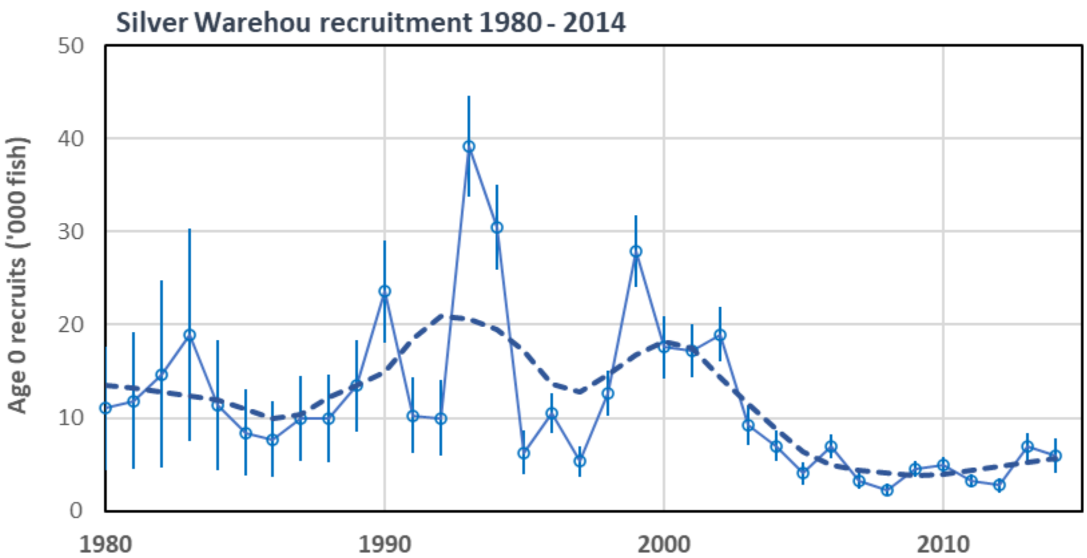


Figure 6-3. Estimated historical recruitment for Silver Warehou (1980–2014, excluding years estimated off the stock-recruit curve), with std.devs and a fitted 10-year loess smoother (assessment results from Burch *et al.* 2018).

Blue Grenadier has shown generally low–moderate recruitment over 1975–2007 with an apparent decadal cycle of higher recruitment in 1984, 1994, 2003 and around 2013. Recruitment in 1994–1995 and over 2010–2014 was notably higher than average (Figure 6-4).

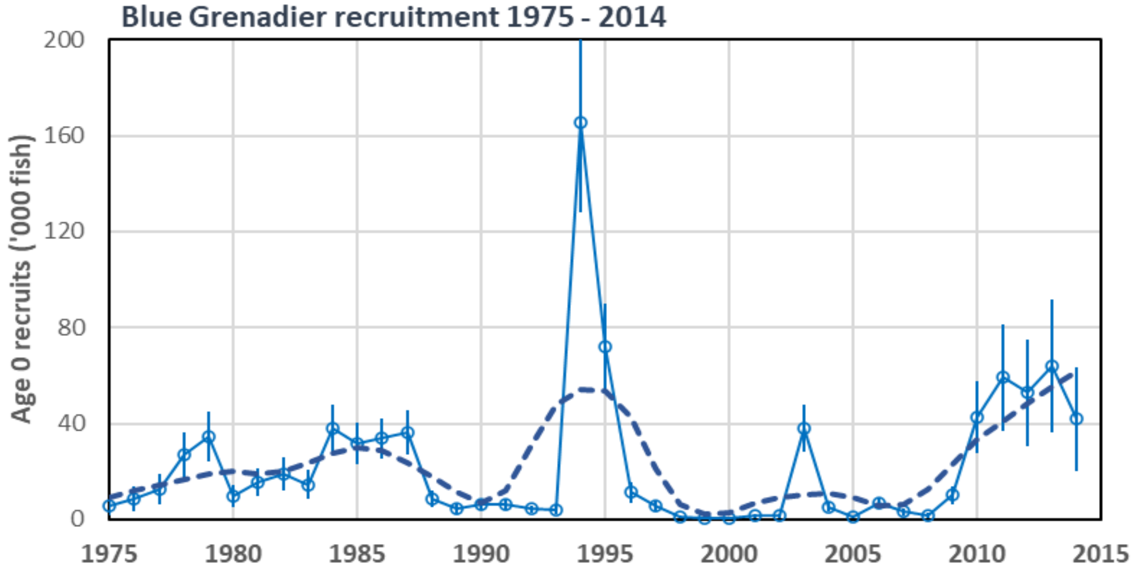


Figure 6-4. Estimated historical recruitment for Blue Grenadier (1975–2014, excluding years estimated off the stock-recruit curve), with std.devs and a fitted 10-year loess smoother (assessment results from Castillo-Jordán and Tuck 2018).

After a period of stable recruitment over 1968–1983, Tiger Flathead has shown highly variable recruitment, with almost interannual high and low peaks and troughs, with an overall slowly increasing trend over 1973–2010 (Figure 6-5).

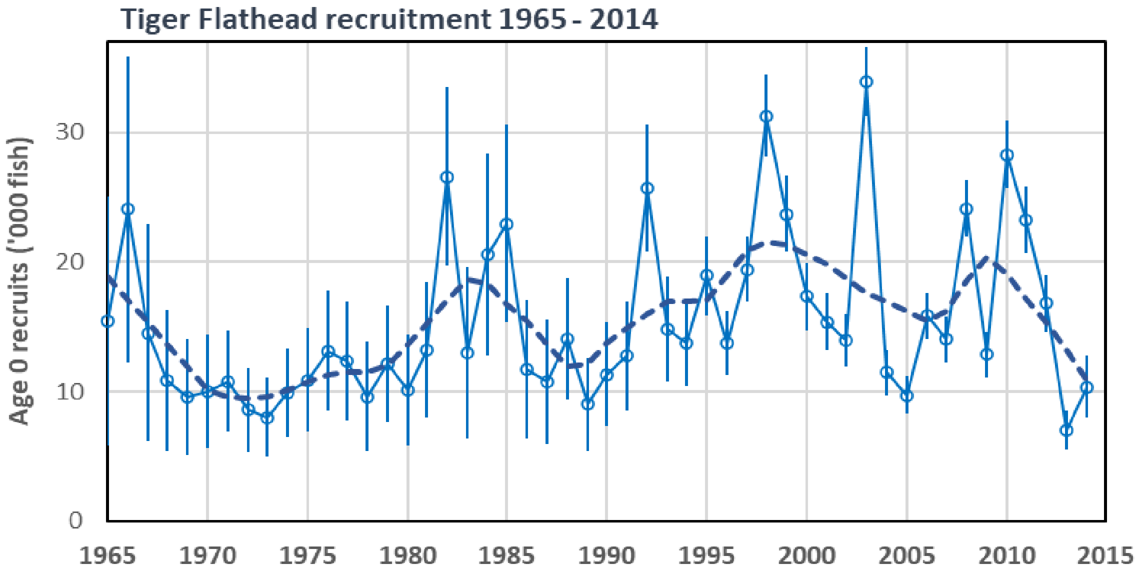


Figure 6-5. Estimated historical recruitment for Tiger Flathead (1965–2014, excluding years estimated off the stock-recruit curve), with std.devs and a fitted 10-year loess smoother (assessment results from Day 2019).

Recruitment of Gemfish east was high during 1968–1983, with decadal peaks in 1972 and 1981. Between 1983 and 1987 there was a steep decline in recruitment which remained at low levels through to 2008, although with continuing minor decadal peaks in in 1990 and 2002 (Figure 6-6).

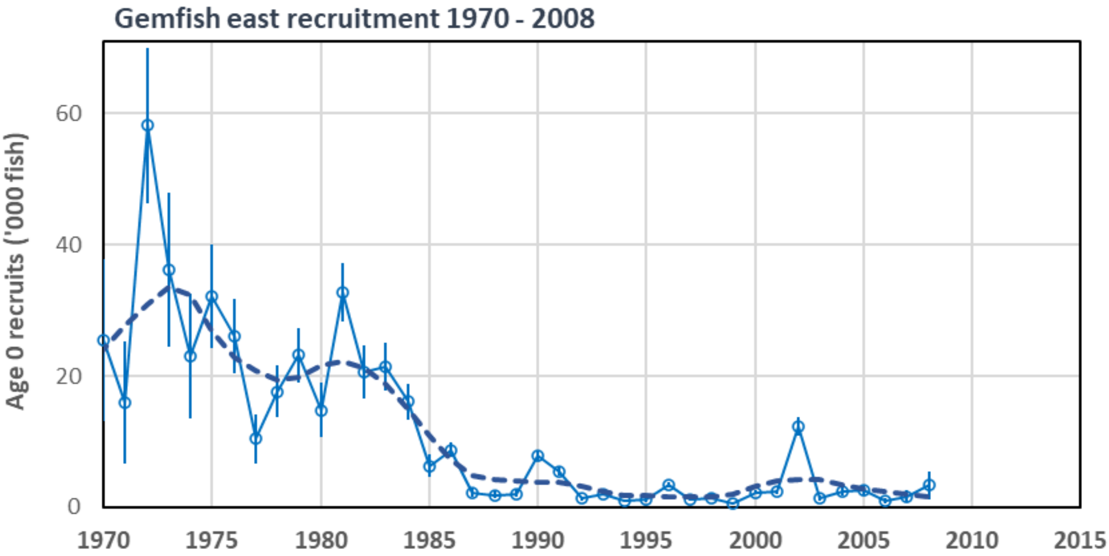


Figure 6-6. Estimated historical recruitment for Gemfish east (1968–2008, excluding years estimated of the stock recruit curve), with std.devs and a fitted 10-year loess smoother (assessment results from Little and Rowling 2008).

6.3. Historical trends in static and dynamic B_0 for SESSF stocks

6.3.1. Estimation of Dynamic B_0 in stock assessments

This section summarises work published in:

Bessell-Browne, P., Punt, A.E., Tuck, G.N., Day, J., Klaer, N., Penney, A., 2022. The effects of implementing a 'dynamic B_0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. Fisheries Research 252, 106306 https://doi.org/10.1016/j.fishres.2022.106306

The calculation of dynamic B_0 trajectories for species in the SESSF is conducted within Stock Synthesis. This involves estimating the biomass that would theoretically have existed in each year had no fishing occurred – referred to as dynamic B_0 (denoted by $B_{F=0}$).

A dynamic B_0 approach to calculate reference points for fisheries management considers drivers other than fishing pressure that influence population size. The theoretical biomass trajectory under the dynamic B_0 approach represents the population size that would have resulted at that time if no fishing of the stock had occurred (MacCall *et al.* 1985, Punt *et al.* 2014a, Punt *et al.* 2014b, King *et al.* 2015, Berger 2019). The population is projected forward without applying fishing pressure, assuming that the deviations in recruitment about the stock-recruitment relation and deviations in growth about expected growth are not influenced by fishing pressure but are due to non-fishing related (i.e. environmental) factors. The annual recruitment deviations from the stock-recruitment curve from the fished and unfished cases are assumed to be the same, explicitly assuming that fishing affects the spawning biomass, but not the recruitment deviations for any particular year. It also assumes that biological parameters, for example natural mortality, growth or fecundity, are not influenced by fishing pressure.

The dynamic B_0 approach differs from the traditional "static" B_0 approach, which uses the average (expected) unfished biomass prior based on biological parameters at the start of fishing (Ricker 1975, Hilborn 2002, Haltuch 2008). Static B_0 assumes that there are no long-term changes in productivity due to fishing pressure or other external drivers. Dynamic B_0 can be calculated alongside static B_0 within the Stock Synthesis modelling framework (Methot and Wetzel 2013). This is implemented by estimating the population size in each year in the model assuming that no fishing had ever taken place. Dynamic B_0, $B_{F=0,y}$, which is the value of B_0 for year y, is estimated as:

$$B_{0,y} = \sum_{a\geq 1} R_{y-a}\, e^{-\sum_{y'=1}^{a} M_{y-y',a-y'}} \sum_{L=1}^{n_L} \phi_{y,a}^{L}\, f_L\, w_L \qquad \text{Eqn 1}$$

where R_{y-a} is the age-0 abundance for females during year y-a had there never been any fishing,
$M_{y,a}$ is the rate of natural mortality for females of age a during year y,
$\phi_{y,a}^{L}$ is the probability during year y that a female of age a is in length-class L,
f_L is the proportion of females in length-class L that are mature,
and w_L is the weight of a female in length-class L.

Ages, a, are summed over the appropriate age range, from age 1 to the maximum age[1]. Eqn 1 assumes that fecundity- and weight-length are time-invariant, but it could be extended to allow for time-varying fecundity- and weight-at-length.

Stock status can then be expressed in terms of spawning biomass relative to dynamic B_0 (calculated as $B_y/B_{0,y}$) and compared to spawning biomass relative to static B_0 (calculated as B_y / B_0^* where B_0^* is static B_0), with target and limit reference points being expressed as proportions of static B_0 or dynamic B_0.

Comparative trends in spawning biomass and dynamic B_0 (unfished spawning biomass) derived from outputs of the most recent assessments are shown in Figure 6-7 to 6-11 for SESSF stocks for which recent (post-2015) assessments are available. These show a wide range of trends in dynamic B_0 compared to static B_0, with greater departure of dynamic B_0 from static B_0 indicating an apparent greater effect on productivity of factors other than fishing.

[1] This is a fairly general formulation. In the majority of applications most of the parameters (e.g., natural mortality and length-at-age) would be time-invariant.

Jackass Morwong east

Jackass Morwong east is the one SESSF stock for which an environmentally driven productivity 'regime shift' has already been implemented in assessments. The process and evidence used to determine that a productivity regime shift appears to have occurred is described in Klaer *et al.* (2015) and the management implications of implementing the regime shift are described in Wayte (2013). This regime shift was considered to have occurred in 1988 and was implemented in stock assessments for Jackass Morwong east from 2010 onwards by allowing a new B_0 which is estimated to be 70% lower than the initial value from 1988 onwards (Day and Castillo-Jordan 2018). Using the most recent assessment incorporating this regime shift, the trend in Jackass Morwong east dynamic B_0 remains above static B_0 until 1987, but declines below static B_0 from 1988 onwards, reflecting the productivity shift that occurred around this time (Figure 6-7).

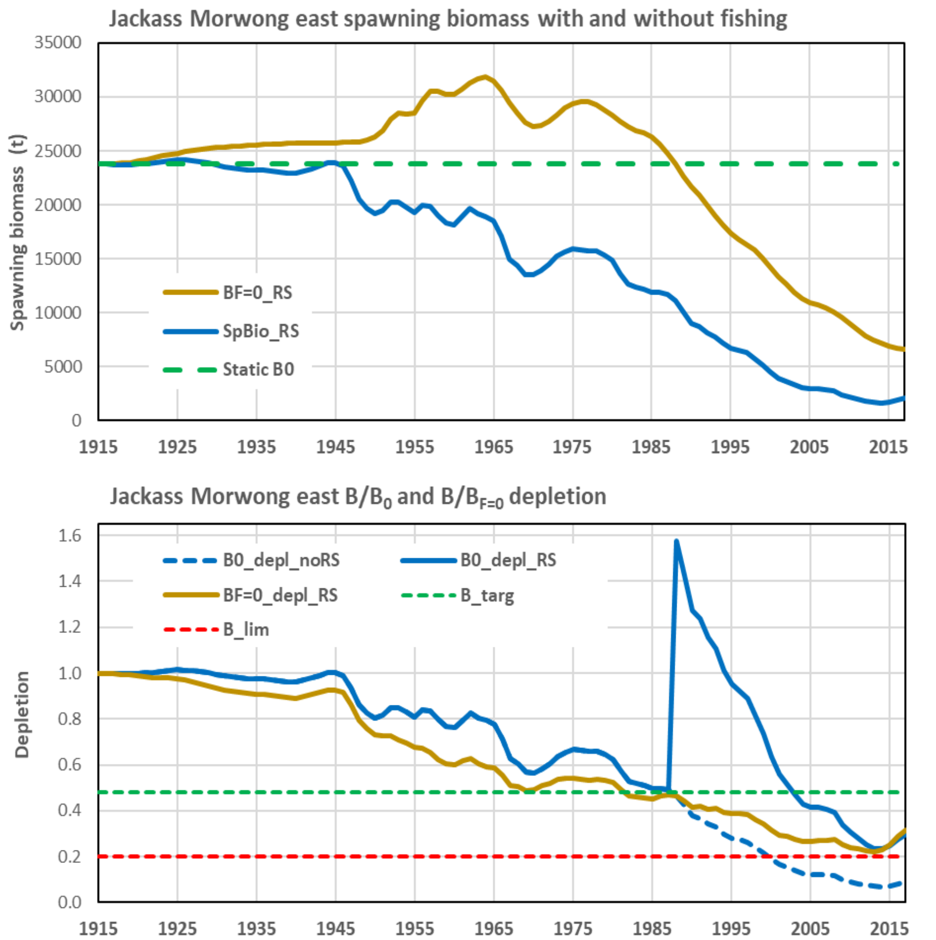


Figure 6-7. Historical stock status for Jackass Morwong east with a regime shift (RS) showing: top - comparative trends in estimated spawning biomass vs. biomass that would have existed in the absence of fishing (dynamic B_0 denoted $B_{F=0}$) and bottom – comparative trends in depletion calculated using static (B/B_0) vs. dynamic ($B/B_{F=0}$) reference levels. Bottom panel shows two alternative trends in depletion, one including the regime shift (RS) considered to have occurred in 1988 (using a lower static B_0 from 1988 onwards), and the other assuming no regime shift (noRS) (using the same B_0 throughout) (assessment results from Day and Castillo-Jordán 2018).

This assessment estimates that dynamic B_0 had been declining for about a decade before 1988 and continued to decline steadily thereafter to only 28% of static B_0 by 2017. The effect of implementing the regime shift is evident from the sharp spike in B/B_0 in 1988, when the B_0 value was decreased.

Without the regime shift, depletion based on a single static B_0 value across the entire period would have continued to decline below the limit in 2000 to reach 8% of static B_0 in 2017 (Figure 6-7 bottom panel dashed blue line). In contrast, $B/B_{F=0}$ (including regime shift) declines steadily from the target level in 1988 to reach virtually the same depletion level as the static B/B_0 depletion in 2017, remaining above the limit.

Redfish

Redfish shows less departure of dynamic B_0 ($B_{F=0}$) from static B_0, remaining above static B_0 for most of the time series and only declining to below static B_0 from 2013 onwards. There are indications of a decrease in production in the decline in $B_{F=0}$ after 2000, but this results in only slight differences in $B/B_{F=0}$ compared to static B/B_0, with the two trends, the times at which the stock is estimated to have declined below the target and limit, and the final depletion values being similar (Figure 6-8).

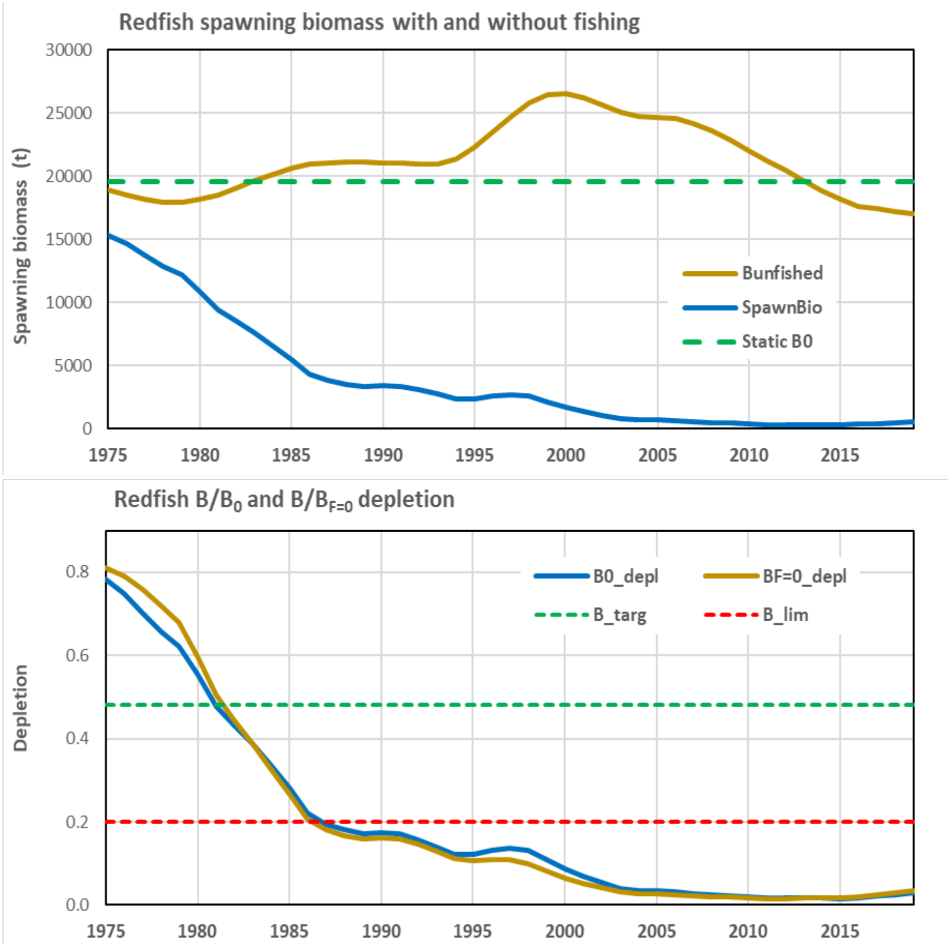


Figure 6-8. Historical stock status for Redfish showing: top - comparative trends in estimated spawning biomass vs. biomass that would have existed in the absence of fishing (dynamic B_0, denoted $B_{F=0}$) and bottom – comparative trends in depletion calculated using static (B/B_0) vs. dynamic ($B/B_{F=0}$) reference levels (assessment results from Bessell-Browne and Tuck 2020).

Silver Warehou

Silver Warehou dynamic B_0 shows marked increases above static B_0 from 1997–2009 in response to recruitment peaks over 1993–1994 and 1999–2002, before declining steadily to below static B_0 from 2011 onwards (Figure 6-9). This trend in dynamic B_0 ($B_{F=0}$) has a marked effect on comparative depletion trends. The dynamic nature of the $B_{F=0}$ reference levels results in $B/B_{F=0}$ following a smoother trend over 1995–2010, without the large increases in depletion shown by static B/B_0. The decline in dynamic B_0 also results in the final $B/B_{F=0}$ being near the target, whereas static B/B_0 is near the limit reference point.

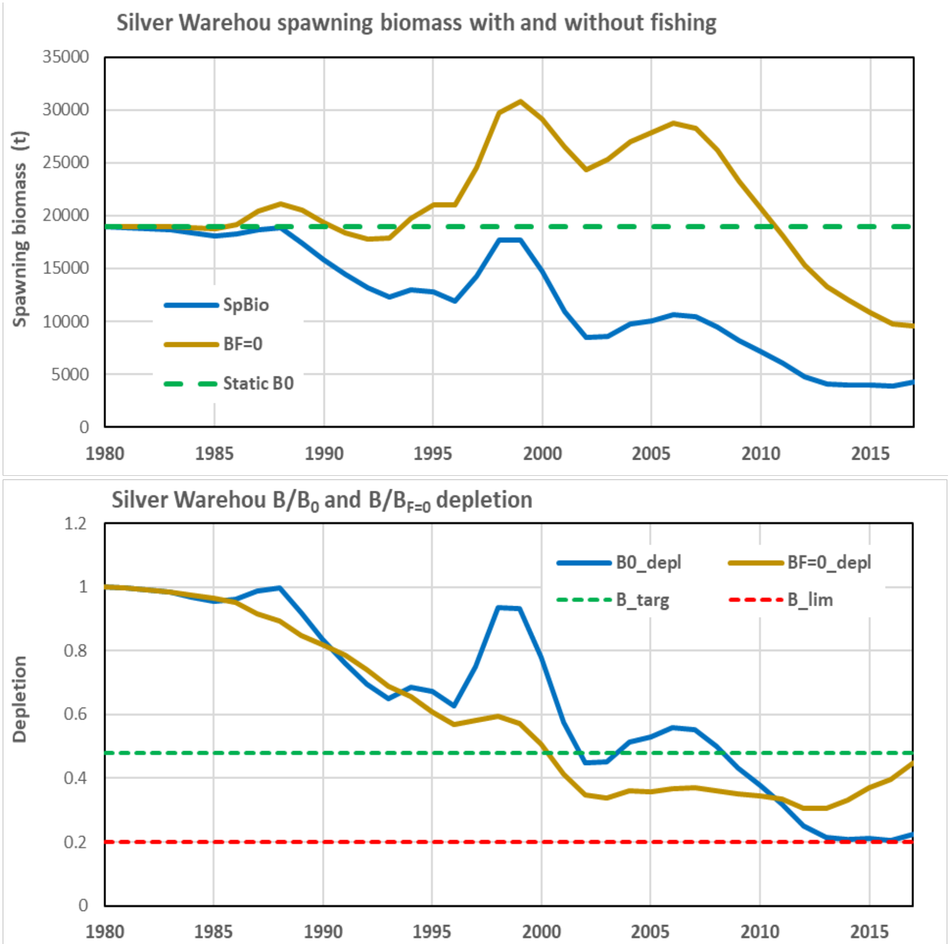


Figure 6-9. Historical stock status for Silver Warehou showing: top - comparative trends in estimated spawning biomass vs. biomass that would have existed in the absence of fishing (dynamic B_0, denoted $B_{F=0}$) and bottom – comparative trends in depletion calculated using static (B/B_0) vs. dynamic ($B/B_{F=0}$) reference levels (assessment results from Burch *et al.* 2018).

Blue Grenadier

As with Silver Warehou, Blue Grenadier shows dynamic B_0 increasing markedly above static B_0 in response to cyclical peaks in recruitment (Figure 6-10). The resulting dynamically shifting reference levels result in the $B/B_{F=0}$ trend following a far smoother trajectory, without the marked peaks and troughs shown by static B/B_0. This would have a significant effect on RBCs calculated using dynamic B_0, which would have far lower inter-annual variability than RBCs calculated using static B_0 reference levels.

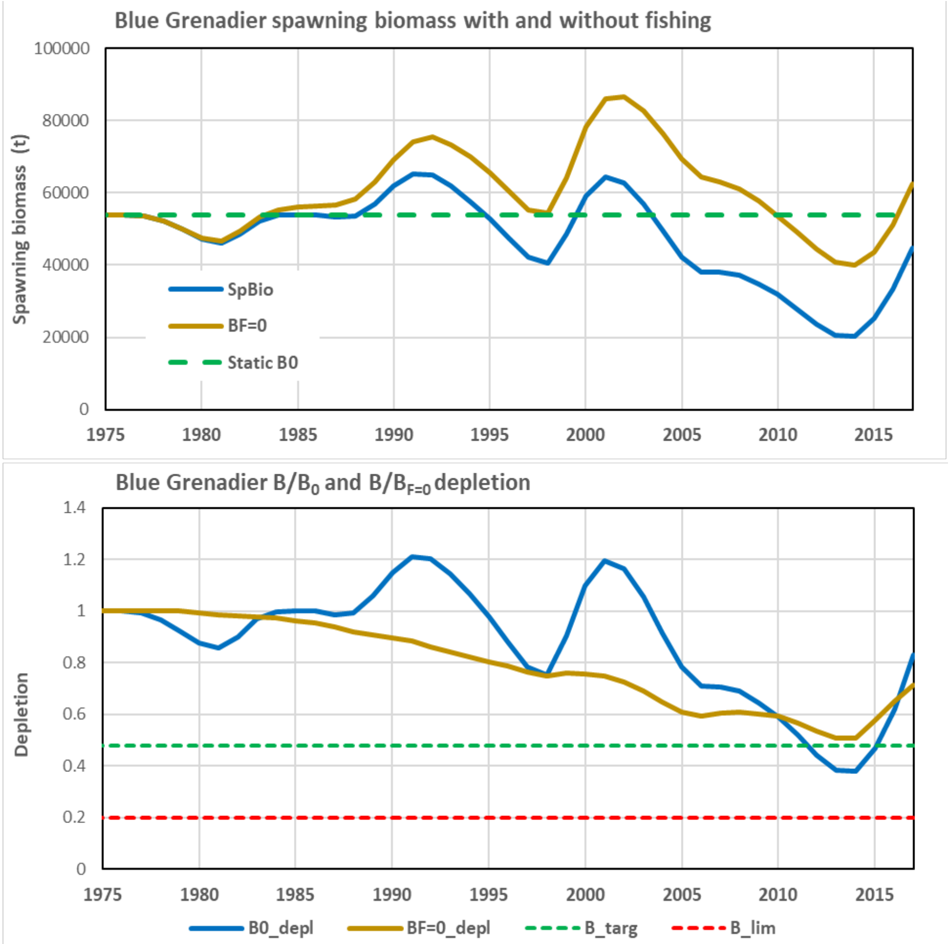


Figure 6-10. Historical stock status for Blue Grenadier showing: top - comparative trends in estimated spawning biomass (SpBio) vs. biomass that would have existed in the absence of fishing (dynamic B_0, denoted $B_{F=0}$) and bottom – comparative trends in depletion calculated using static (B/B_0) vs. dynamic ($B/B_{F=0}$) reference levels (assessment results from Castillo-Jordán and Tuck 2018).

Tiger Flathead

Tiger Flathead shows a substantial decline in dynamic B_0 over 1920–1950, but this increases back to the static B_0 level by 1970 (Figure 6-11). Following another decline to 1984, dynamic B_0 increased to track static B_0 quite closely from 2001 onwards. As a result, while the trend in $B/B_{F=0}$ lies somewhat above that in B/B_0 during times of lower $B_{F=0}$, comparative depletion levels since 2001 have been very similar.

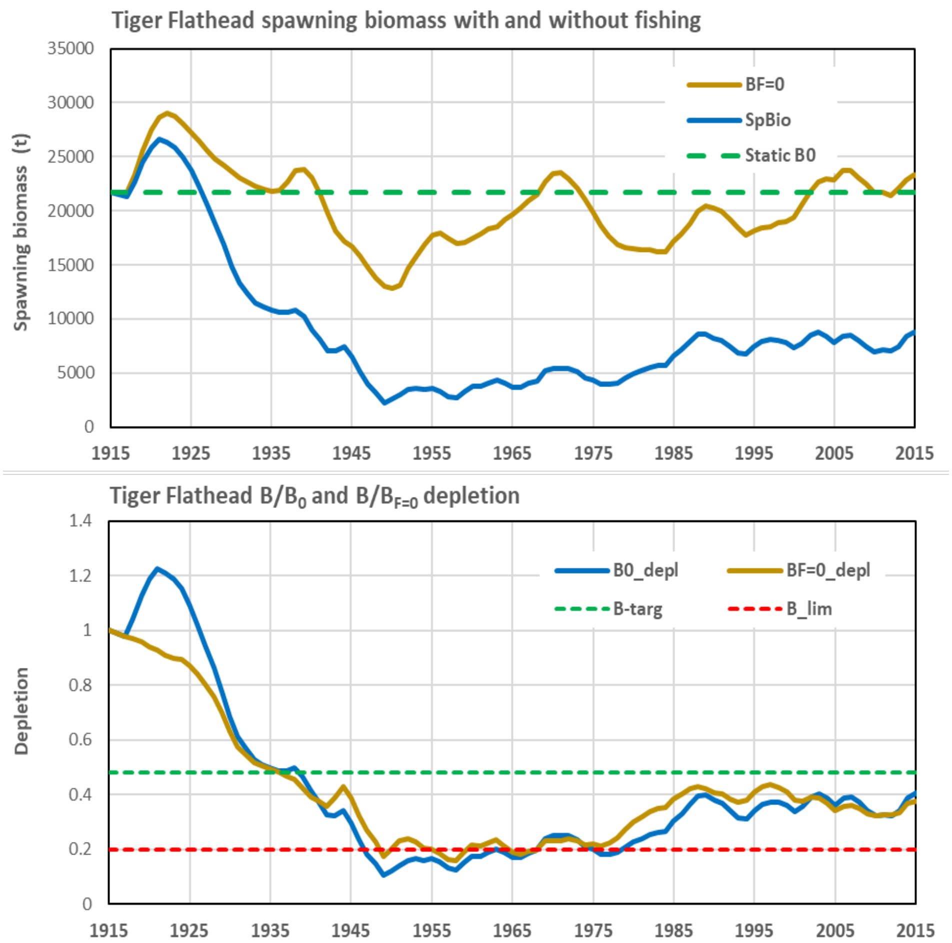


Figure 6-11. Historical stock status for Tiger Flathead showing: top - comparative trends in estimated spawning biomass (SpBio) vs. biomass that would have existed in the absence of fishing (dynamic B_0, denoted $B_{F=0}$) and bottom – comparative trends in depletion calculated using static (B/B_0) vs. dynamic ($B/B_{F=0}$) reference levels (assessment results from Day 2019).

7. Evidence for fishing and non-fishing effects

7.1. Productivity regime shift weight of evidence scoring

The eastern stock of Jackass Morwong is the only SESSF stock fished by the Commonwealth Trawl Sector that has been accepted as having undergone an environmentally induced 'regime shift' around 1988, resulting in enduring reduced expected recruitment and maximum stock size. In identifying and proposing this regime shift, a weight-of-evidence scoring system was developed to summarise and rank evidence for an environmentally induced (non-fishing) shift in productivity for this stock (Klaer *et al.* 2015). To provide a comparable summary of the weight-of-evidence for environmentally induced productivity shifts for the other SESSF case study stock, this weight-of-evidence approach was applied to the other SESSF stocks in this study.

7.1.1. Methods

The weight-of-evidence approach was applied to a range of SESSF species to determine whether there is sufficient justification for consideration of a discrete productivity regime shift for each species. This contrasts with a continuous productivity shift that applies to the dynamic B_0 approach but has application in the identification of species that show evidence of productivity change. In Section 7.2.1 of this report, current base case stock assessment results were subjected to a sequential regime detection algorithm to assess whether regime shifts were evident in the trends of surplus production and the number of age-0 recruits. The analysis here uses the approach of Klaer *et al.* (2015) to examine the regime shift question while considering the certainty of stock assessment inputs, understanding of assessment model structural assumptions, and whether an explanatory hypothesis exists to support or explain the existence of a regime shift more generally.

Species chosen for analysis mirrored those analysed using the sequential regime detection algorithm and were Jackass Morwong east, Redfish, Silver Warehou and Blue Grenadier; and for additional SESSF stocks for which older assessments were available – Blue Warehou east, Blue Warehou west, Tiger Flathead, Eastern School Whiting and Gemfish east.

The most recent available Stock Synthesis (SS) (Methot and Wetzell 2013) assessment results were used to produce plots of spawning biomass or spawning output and recruitment or recruitment deviation series shown in Figure 7-1 to 7-9. Recruitment deviations were not appropriate for examination here for Jackass Morwong east as the stock assessment included the accepted regime shift starting in 1988. Some of these assessments are not recent. Gemfish east has not been assessed using SS since 2010. Results for Blue Warehou (east and west) were from a preliminary 2008 assessment that was not used for management purposes.

Scoring guidelines for each stock are reasonably straightforward (Table 7-1) but judgement on what levels were chosen for individual species is necessarily somewhat subjective. Scores given are in relation to whether the criterion supports evidence for a regime shift in productivity. The following sections examine considerations common to all species as they are subjected to similar data collection, processing, and stock assessment procedures. Those that differ in some respects are also highlighted.

Observed change in a productivity indicator

For purposes here, a productivity indicator is an observation over time of change in some measure of the stock that potentially provides evidence for a change in productivity regardless of the level of fishing pressure. Such indicators may include recruitment estimates from egg, larval or young-of-the-year surveys, biomass indices from fishery catch rates (CPUE) or fishery-independent surveys, or evidence of changing natural mortality from multi-species diet studies or observed fish kills (Klaer *et* *al.* 2015). A long period of change in an indicator such as available biomass despite management intervention, is usually the cause for first consideration of a potential productivity shift.

The weight of evidence framework here was developed for general application to fish stocks regardless of their stock assessment method. Potential productivity indicators may therefore be obtained from existing fishery information even for data-poor species. It is advantageous if the productivity indicators examined for this first criterion are closer to empirical measurements rather than modelled outcomes, as model application and results are examined in more detail using other criteria. SESSF Tier 1 species generally have several observed CPUE indices that are fitted to modelled biomass in the assessments, so biomass trends from those models are normally consistent with CPUE observations and can be used here as proxy abundance "empirical measurements".

This is the most objective of the scoring criteria. It simply requires examination of the apparent trend in a productivity indicator, in this case, spawning output or spawning biomass. Of importance are the length of the apparent change in relation to the lifespan of the species, and the number of stock assessment cycles over which a change has been observed. The question to be answered is whether the current state of stock productivity has changed relative to a past one that appears to be different. This means that for this criterion, only the most recent average state is compared to the historical time where a change appears to have occurred. Any apparent changes in productivity regimes other than the most current one are not considered.

Understanding of assessment model input data

SESSF species are all subject to the same data collection, processing, and stock assessment procedures. However, species differ particularly in the reliability of historical catch records, the effectiveness of fishery CPUE to be a reliable indicator of species abundance, and the availability of a continuous series of age/length composition and discard information. Fishery CPUE is standardised to attempt to account for the influence of spatial/temporal/gear factors on underlying abundance. However, there are no long-term fishery-independent trawl surveys of adult biomass available for the assessment of SESSF species other than eastern Orange Roughy (for which there are acoustic surveys).

For Redfish there is uncertainty associated with historical catch, mostly related to uncertainty and changes in discard practices, but also in historical landings records. Also, there is a question about the reliability of CPUE as an index of abundance, particularly recently.

The level of age/length composition data available differs considerably among the SESSF species for this criterion. A qualitative judgement of this level considered both the proportion of assessment years where composition data are available, and whether sampling was representative of the total catch in any year.

Understanding of assessment model structural assumptions

For SESSF species, potential regime change is primarily indicated by the stock assessment showing recent average recruitment that consistently deviates from the expected pattern as determined by the fitted stock-recruitment relationship. SESSF Tier 1 stock assessments generally only allow for time variation in recruitment. This is primarily determined from the signal in the age- and length-compositions of young fish as they recruit to the fishery and are subject to selection by the fishery throughout their lifetime. There are no earlier age assessment inputs for pre-recruits (such as scientific surveys) for the species examined. Therefore, any ecosystem effects on variation in cohort strength are accounted for in the stock assessments as variation in recruitment to the fishery.

The Blue Grenadier and Eastern School Whiting stock assessments have good supporting evidence for recruitment variability on a short timeframe, but not a regime shift. Recruitment variability for these species is most obviously indicated by input data when compared to other SESSF stock assessments.

Biological causes of productivity change may be due to changes in natural mortality, length-at-age, the length-weight relationship, or maturity-at-age/-length over time. Stock assessments may also assume an inappropriate stock-recruitment relationship (perhaps via inappropriately pre-specified steepness) or assuming fishery selectivity is time-invariant when it has changed through time. Although it is widely recognised that time-variation in natural mortality occurs in nature, estimation of such change is not normally possible in stock assessments given available data and confounding with other stock assessment parameters. Some SESSF stock assessments allow for time changes in fishery selectivity and retention, where sufficient length composition data exist to estimate a step change in selectivity.

Good stock assessments explore alternative structural assumptions as limited by the quality and quantity of input data, often as sensitivity analyses. Assessments that have explored and ruled out alternative structural assumptions that may explain apparent regime shift observations in results score highest on this criterion. For example, apparent regime shifts may disappear from an assessment if a lower stock-recruitment steepness value is assumed. Such explorations should include comparison of goodness-of-fit statistics for those alternative model structures. For an example of an investigation of model structural assumptions versus potential regime shift see IATTC (2019) for Bigeye Tuna.

Wayte (2013) used MSE to show that the consequences of mis-specifying the assessment model for Jackass Morwong east were riskier to the stock if the assessment model assumed that no productivity shift had occurred. Such a risk analysis has not previously been performed for other SESSF species, but was conducted using MSE analysis in this project (see Chapter 9; Appendix 17.2). Retrospective patterns are a potential indication of assessment model misspecification (e.g., see Hurtado-Ferro *et al.* 2015), and removal of such patterns through recognition of productivity change provides supporting evidence. However, Szuwalski *et al.* (2018) found that reference points and management advice were sometimes drastically in error when a process other than the true time-varying process was allowed to vary within assessments, resulting in under-utilizing or over-exploiting the stock. It is therefore important to try and identify the population processes that vary over time when addressing retrospective patterns and providing management advice. This may require increased longitudinal life history studies.

Explanatory hypothesis

A key driver of change in newly recruited fish to those available to the fishery is egg, larval and juvenile survival rates. It has been suggested that a common mechanism is change to the environmental carrying capacity for larvae or juveniles (see Maunder 2022). Understanding of effects of changed environmental conditions on larval abundance for key target species in the SESSF is currently preliminary. Periodic scientific surveys of oceanographic conditions, eddies and upwellings, plankton abundance, and fish larvae are available for the past 25 years. General evidence in support of recent substantial oceanographic change in the southeast Australian region affecting SESSF stocks is provided by Fulton *et al.* (2024). They evaluated the effects of recent oceanographic change on reduced larval survival for Jackass Morwong east, Redfish, Tiger Flathead, Eastern School Whiting and Gemfish. There was less information to support hypotheses for Silver Warehou, Blue Warehou and Blue Grenadier.

Of the stocks examined here, only Jackass Morwong east has been subject to analyses that have led to a more detailed hypothesis on changes in oceanographic conditions affecting larval survival that matches with observations of potential productivity regime change in available adults. Wayte (2013) notes that the species is atypical among temperate finfish species in that they have an extended offshore pelagic post-larval stage, and that it is likely that environmental factors to which they are exposed have a substantial influence on post-larval survival. Observations of the southward shift of the ocean current system were correlated with the apparent shift in stock productivity.

Table 7-1. Regime shift weight of evidence scoring guidelines (Klaer *et al.* 2015).

Score	Observed change in a productivity indicator	Understanding of assessment model input data	Understanding of assessment model structural assumptions	Explanatory hypothesis
0	Short period less than one generation.	Model input uncertainties are unknown.	Key population parameters affected have not been identified.	The mechanism is unknown.
1	More than one generation.	Several model inputs are uncertain and have not been characterised.	Modelled changes in one or more key population parameters have fitted with observed biomass changes.	A plausible mechanism for productivity shift has been developed from general knowledge of biophysical processes.
2	Multiple generations and across several assessment/ management cycles.	Uncertain model inputs have been characterised and plausible ranges for that uncertainty have been investigated.	Modelled changes in key production parameters have been somewhat validated by investigation of alternative model structures and/or improved model behaviour such as the removal of retrospective patterns.	Output from a limited biophysical or multispecies model is consistent with observed patterns of change in productivity.
3	Multiple generations and across many regular assessment/management cycles in the same timeframe.	The character of model inputs is well understood and uncertainty has largely been eliminated or well estimated statistically.	Validated modelled changes are consistent with output from a biophysical or multispecies model.	Output from a comprehensive biophysical multispecies model is consistent with observed patterns of change in productivity.

It is only the first indicator in the above scoring table (Observed change in a productivity indicator) that is a direct measure of possible productivity change. However, the other three indicators all relate to confidence in the first indicator: whether there are signs of misspecification in the assessment used to generate the results (primarily recruitment deviations) used to score the first indicator; and whether the likely mechanism for the productivity change is understood. These three confidence scores therefore add to the first productivity change score, depending on the confidence in the first indicator.

Table 7-2. Summary of regime shift weight of evidence scores by stock.

Stock	Observed change in a productivity indicator	Understanding of assessment model input data	Understanding of assessment model structural assumptions	Explanatory hypothesis	Evidence score
Jackass Morwong east	Medium-lived species with 30 years of low spawning biomass. Several assessment cycles. (**3**)	Stock biology well characterized. Catch and its composition is well known. Some of the uncertainty in CPUE accounted for. Percentage of overall catch covered by size/age sampling is relatively low. (**2**)	Modelled annual recruitment residuals below average for past 30 years. Fit to the data is improved by a regime shift; lower steepness cannot account for decline. Risk assessment conducted. (**2**)	Some knowledge of larval distribution and recent changes in ocean circulation conditions lead to a plausible mechanism. Regime change observations consistent with ecosystem models. (**2**)	**9**
Redfish	Long-lived species with 20 years of low spawning biomass. Few Tier 1 assessments. (**2**)	Stock biology well characterized. Catch and its composition is uncertain historically. Uncertainty in availability across habitats may affect CPUE. Percentage of overall catch covered by size/age sampling for exploitation history is relatively low. (**1**)	Modelled annual recruitment residuals are consistent with the fitted time-invariant stock-recruitment relationship and overfishing. (**0**)	Some knowledge of larval distribution and recent changes in ocean circulation conditions lead to a plausible mechanism. (**1**)	**4**
Silver Warehou	Medium-lived species with 10 years of low spawning biomass. (**1**)	Stock biology moderately characterized. Catch and its composition is uncertain historically. Seme of the uncertainty in CPUE accounted for. Percentage of overall catch covered by size/age sampling is medium. (**1**)	Modelled annual recruitment residuals below average for past 13 years. Retrospective pattern alleviated via assumption of current low recruitment regime. (**2**)	Larval biology poorly understood. Mechanism for poor recruitment not understood. (**0**)	**4**
Blue Grenadier	Medium-lived species with 3 years of high spawning output. (**0**)	Stock biology well characterized. Catch and its composition is well known. Some of the uncertainty in CPUE accounted for. Percentage of catch covered by size/age sampling is high. (**2**)	Modelled annual recruitment residuals generally above average for past 8 years. Known high recruitment variability well accounted for in the assessment and indicated by the data. (**0**)	Larval biology poorly understood. Mechanism for recruitment variability not understood. (**0**)	**2**

Stock	Observed change in a productivity indicator	Understanding of assessment model input data	Understanding of assessment model structural assumptions	Explanatory hypothesis	Evidence score
Blue Warehou east	10 years of spawning biomass from a 23-year history. Status of early higher points uncertain. (**2**)	Stock biology moderately characterized. Catch and its composition is uncertain historically. Little of the uncertainty in CPUE accounted for. Percentage of overall catch covered by size/age sampling is relatively low. (**1**)	Modelled annual recruitment residuals generally below average for last 11 years of the assessment period. (**1**)	Larval biology poorly understood. Mechanism for poor recruitment not understood. (**0**)	**4**
Blue Warehou west	No apparent recent period of above/below average spawning biomass. (**0**)	Stock biology moderately characterized. Catch and its composition is uncertain historically. Little of the uncertainty in CPUE accounted for. Percentage of overall catch covered by size/age sampling is relatively low. (**1**)	No apparent recent period of above/below average recruitment residuals. (**0**)	Larval biology poorly understood. Mechanism for poor recruitment not understood. (**0**)	**1**
Tiger Flathead	No apparent recent period of above/below average spawning biomass. (**0**)	Stock biology well characterized. Catch and its composition is well known. Some of the uncertainty in CPUE accounted for. Percentage of catch covered by size/age sampling is high. (**2**)	No apparent recent period of above/below average recruitment residuals. (**0**)	Some knowledge of larval distribution and recent changes in ocean circulation conditions lead to a plausible mechanism. (**1**)	**3**
Eastern School Whiting	No apparent recent period of above/below average spawning biomass. (**0**)	Stock biology well characterized. Catch and its composition is well known. Uncertainty in CPUE accounted for. Percentage of catch covered by size/age sampling is high. (**2**)	No apparent recent period of above/below average recruitment residuals. (**0**)	Some knowledge of larval distribution and recent changes in ocean circulation conditions lead to a plausible mechanism. (**1**)	**3**

Stock	Observed change in a productivity indicator	Understanding of assessment model input data	Understanding of assessment model structural assumptions	Explanatory hypothesis	Evidence score
Gemfish east	Medium-lived species with 18 years of low spawning biomass. Many assessments historically. (**3**)	Stock biology well characterized. Catch and its composition is well known for years sampled. Percentage of catch covered by size/age sampling is medium. (**2**)	Modelled annual recruitment residuals generally below average for past 24 years. (**1**)	Some knowledge of larval distribution and recent changes in ocean circulation conditions lead to a plausible mechanism. (**1**)	**7**

7.1.2. Regime shift evidence results

Values for weight-of-evidence (Table 7-2) show that consideration of productivity regime change is most supported for Jackass Morwong east and Gemfish east, based on the guideline that values are over or equal to 7 recommended by Klaer *et al.* (2015). In that study, both species were examined but only Jackass Morwong east was recommended. However, in this updated analysis both species have scores increased by 1 for improved knowledge via explanatory hypothesis, and by 1 for Jackass Morwong east for an extended period of apparent low spawning biomass. This analysis provides new results for the remaining previously unexamined species. All fall short of the required score of 7 to indicate a regime shift in productivity. Silver Warehou, however, receives a high score based on results from the stock assessment model and would benefit from improved information for the other criteria.

Spawning biomass/spawning output and recruitment deviation series

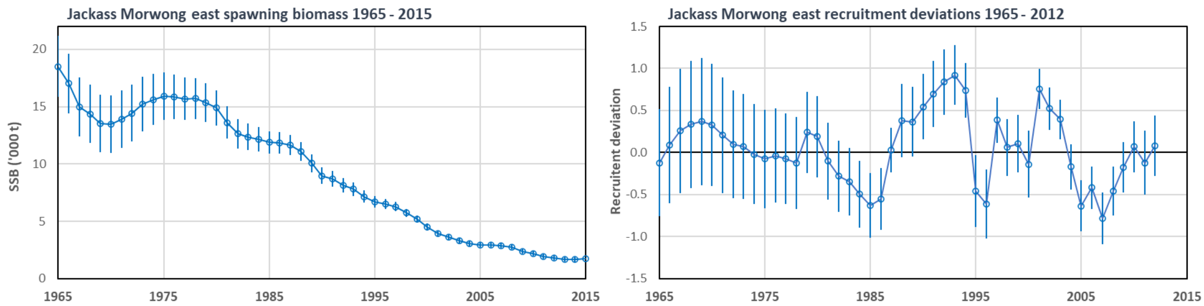


Figure 7-1. Estimates of spawning stock biomass and recruitment deviations from the 2021 assessment of Jackass Morwong east with, std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

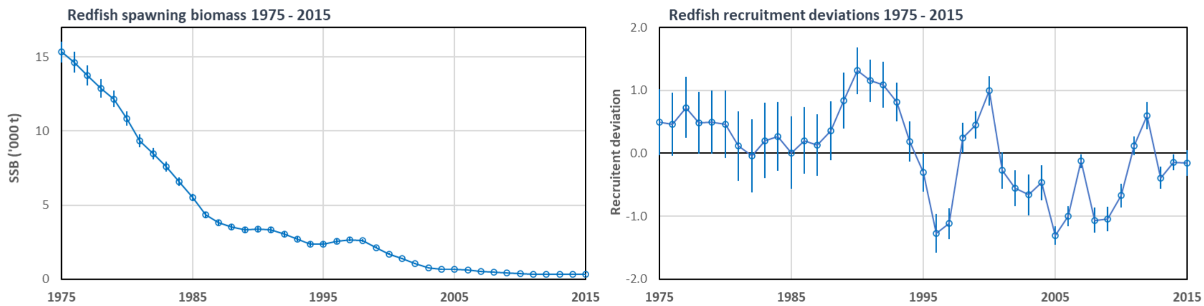


Figure 7-2. Estimates of spawning stock biomass and recruitment deviations from the 2020 assessment of Redfish, with std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

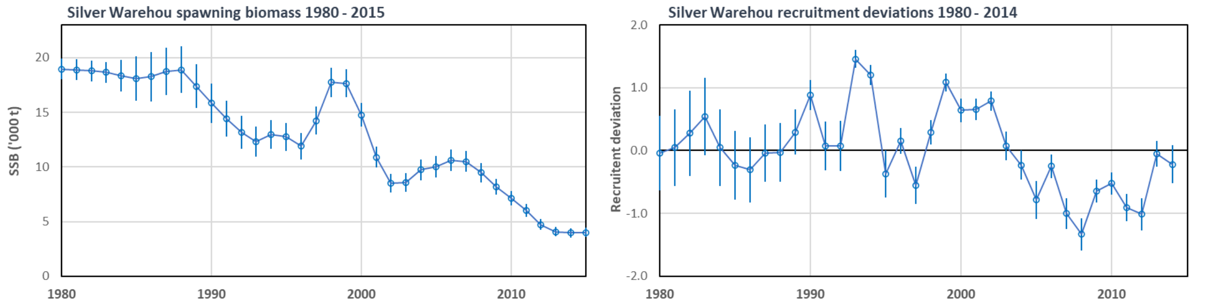


Figure 7-3. Estimates of spawning stock biomass and log recruitment deviations from the 2021 assessment of Silver Warehou, with std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

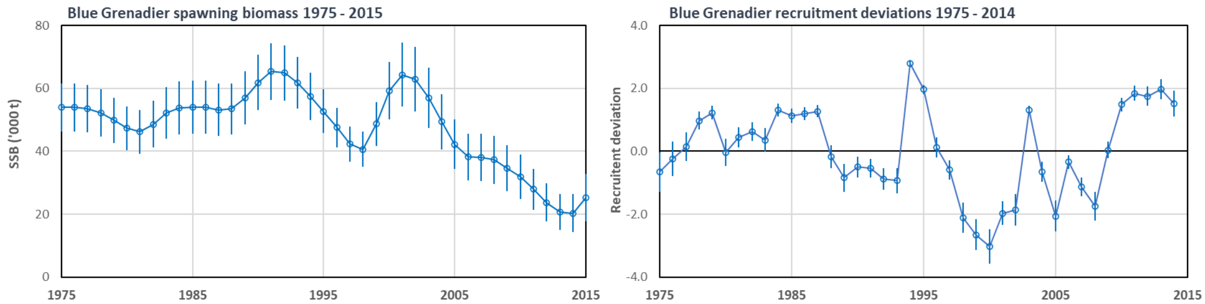


Figure 7-4. Estimates of spawning stock biomass and log recruitment deviations from the 2021 assessment of Blue Grenadier, with std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

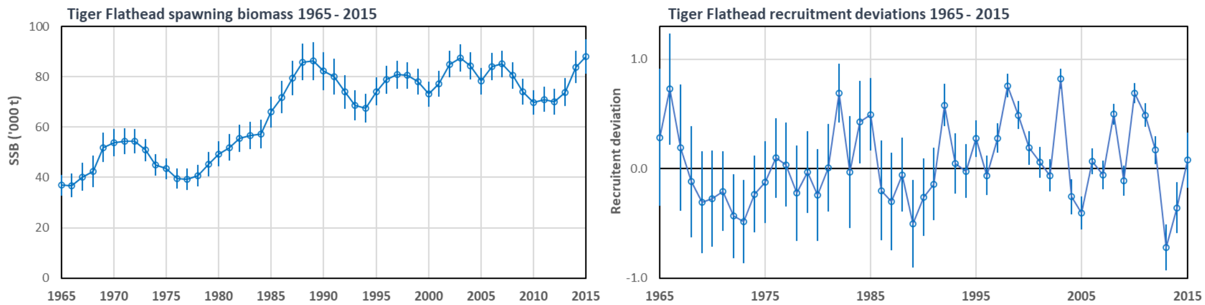


Figure 7-5. Estimates of spawning stock biomass and log recruitment deviations from the 2019 assessment of Tiger Flathead, with std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

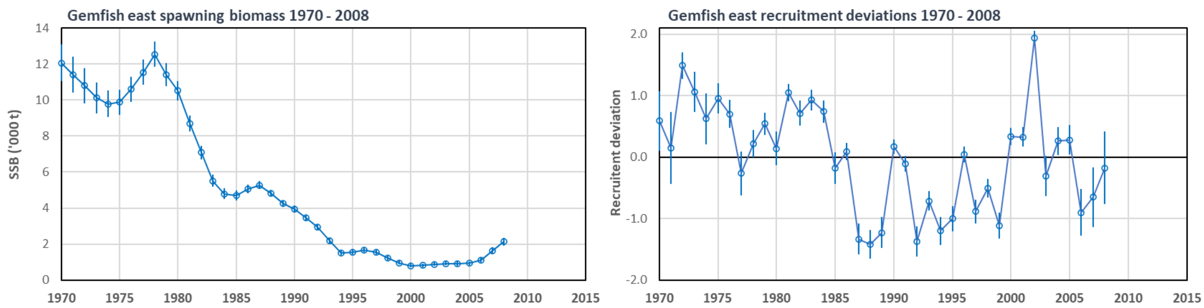


Figure 7-6. Estimates of spawning stock biomass and log recruitment deviations from the 2008 assessment of Gemfish east, with std.devs (excluding recruitment deviations estimated off the stock-recruit curve).

7.2. Recruitment and productivity regimes analysis

The weight-of-evidence approach in the section above relies on expert judgement, guided by an agreed scoring framework, to rank the likelihood that stock assessment results indicate the occurrence of a sustained regime shift in productivity. These indicators include a measure of production and recruitment (numbers of age 0 recruits). Such measures may alternately be subject to time-series analysis to try and statistically determine whether there have been persistent changes that indicate the occurrence of one or more regime shifts.

7.2.1. Recruitment regime shift detection

Estimated recruitment for the SESSF stocks investigated show a wide range of historical trends. As a first step towards determining whether these trends contain information on periods of differing productivity, a sequential *t*-test analysis of regime shifts (STARS) analysis (Rodionov 2004, Rodionov and Overland 2005) was applied to detect potential regime shifts in annual recruitment deviation and in recruitment. Significant shifts in recruitment deviations would indicate a departure of estimated recruitments from the stock-recruit curve fitted in the assessment, although this needs to be interpreted with caution as assumptions regarding steepness can lead to deviations from the curve, for example unexpectedly low recruitment values.

Shifts in recruitment itself may indicate different regimes of stock production, possibly caused by, or contributed to by, factors other than fishing. Sellinger *et al.* (2024) found that that 57% of 432 stocks in the RAM Legacy database did not have a significant correlation between spawning biomass and recruitment over the observed biomasses, with environmental conditions playing a larger role in recruitment variation than spawning biomass. The detection of regime shifts in recruitment time series was highly dependent on the detection method used, but 46% of the analysed stocks without a significant correlation between spawning biomass and recruitment were estimated to have experienced at least one regime shift driven by environmental conditions.

The Regime Shift Indices (RSI) produced by the algorithm are the cumulative sum of the normalized annual anomalies between two detected regime periods (see Rodionov 2004 for methods):

$$RSI_{i,j} = \sum_{i=j}^{j+m} \frac{x_i^*}{l\sigma_l}, m = 0, 1, \dots, l-1$$

where: $RSI_{i,j}$ – cumulative Regime Shift Index over regime period *i* to *j*
l – cutoff length (years) of the regimes to be determined for variable x
j – possible start point for new regime R2
x_i^* – anomaly, difference between x_i and $\overline{x}'_R$, the mean value for the new regime

σ_l – average variance for running l year intervals
m – counter for years added to RSI estimation after start year j

The presence of outliers can result in the average not being representative of the mean value of the regimes, and this may markedly affect the results of the regime shift detection. The weight for the data value should be chosen such that it is small if that value is considered as an outlier. The detection algorithm uses the Huber's weight function, where data value weight w_i is calculated as:

$$w_i = \min(1, x_i/|x_i^*|)$$

where x_i^* is the deviation from the expected mean value of the new regime, normalized by the standard deviation averaged for all consecutive sections of the cut-off length in the series. If anomalies are less than or equal to the value of the parameter then their weights are equal to one. Otherwise, the weights are inversely proportional to the distance from the expected mean value of the new regime (https://www.beringclimate.noaa.gov/regimes/help.html). Resulting outliers are indicated as open circles in the regime shifts analysis figures below. To facilitate comparison between results for different stocks, the same settings were used for all analyses: Shifts detected in the mean values; Significance level 0.1; Cutoff length 10 years; Huber's weight parameter 1.

Rodionov (2004) developed the regime shift detection algorithm to detect environmentally driven regime shifts, and it has been used for this purpose by Rodionov and Overland (2005). However, it must be noted that the algorithm simply detects what are estimated to be significant changes (using *t*-tests) in the mean values of the parameter being analysed between two consecutive time periods. These differences may be caused by factors other than environmental drivers, such as mis-specification of the assessment model used to produce the results subjected to STARS analysis, and should not necessarily be interpreted as evidence for an environmentally driven shift in productivity. Several other factors may conceivably prevent an overfished stock from rebuilding, including trophic interactions such as predation on juveniles, or genetic drift and divergence (Ovenden *et al.* 2020).

Nonetheless, the occurrence of shifts in indicators of stock production may provide a useful starting point to look for further evidence, or for environmental drivers, that may be correlated with changes in productivity at the times indicated, particularly if coincident shifts are observed across several stocks (such as shown by Rodionov and Overland 2005 for the Bering Sea ecosystem).

7.2.2. Regime shifts in surplus production

Regime shift detection was extended to surplus production, using the approach adopted by Vert-Pre *et al.* (2013). Annual estimated surplus production was calculated from estimated total biomass values in the latest assessment for each stock using the formula:

$$S_y = B_{y+1} - B_y + C_y \quad \text{(Vert-Pre \textit{et al.} 2013)}$$

where S_y is surplus production in year y, B is estimated total biomass in years y and $y + 1$ and C_y is total catch including discards in year y.

In applying this approach to estimated surplus production, it must be noted that outputs from stock assessments are subject to process error, and differences in production may result from such error. Ideally, independent estimates of biomass should be used. However, the primary indicator used to detect regime shifts in this STARS analysis was recruitment deviation, with the implicit assumption that the assessments models used to estimate these recruitment deviations are not substantially mis-specified. STARS analysis of recruitment estimates and of surplus production estimated from assessment results was simply applied to confirm whether shifts in recruitment deviation in the assessments translated into shifts in actual recruitment, and so in surplus production.

7.2.3. Regime shift results for selected SESSF stocks

Jackass Morwong east

Since 2010, stock assessments for Jackass Morwong east have included a regime shift, assumed to have occurred in 1988. It would be inappropriate to use recruitment deviations derived from an assessment that incorporates a regime shift, to look for a regime shift. The 2018 stock assessment for Jackass Morwong east (Day and Castillo-Jordán 2018) was therefore re-run using the same input data and model specifications but removing the assumption of a regime shift and the ability to estimate a change in B_0 in 1988. The revised recruitment estimates and deviations were used in the STARS analysis for this stock.

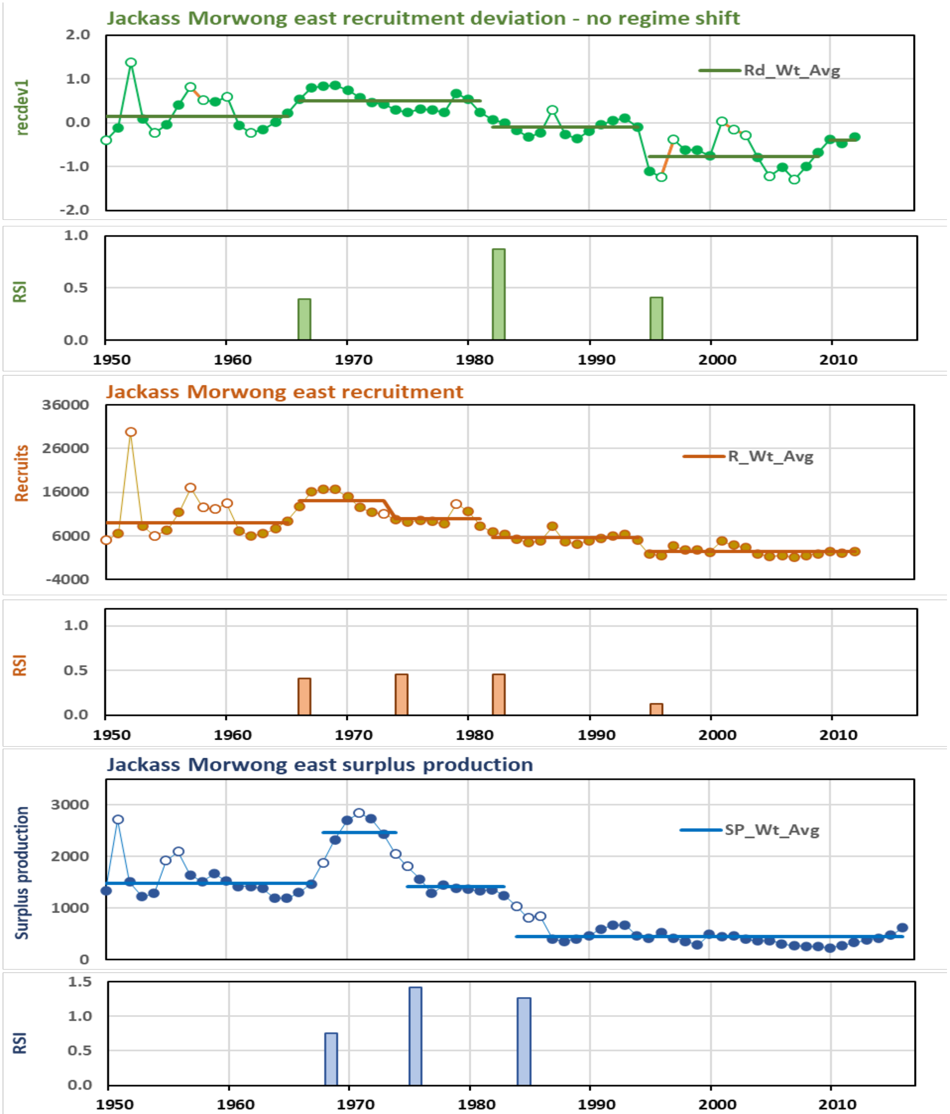


Figure 7-7. STARS analysis of apparent productivity shifts in Jackass Morwong east (revised assessment without a regime shift) as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1950–2016 (assessment results revised from Day and Castillo-Jordán 2018 by removal of the regime shift). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

The STARS analysis for Jackass Morwong east detects apparent downwards shifts in recruitment deviation and recruitment in 1982 and 1995 (Figure 7-7). The analysis of recruitment estimates also detects a preceding downwards shift in recruitment in 1974.The downward shift in 1982 seems to correlate with the start of the 1981–1986 transition period between the higher and lower productivity regimes. Downwards recruitment shifts in 1974 and 1982 translate into substantial downwards shifts in surplus production, after which surplus production has remained at a low level.

Redfish

The analysis for Redfish detects a downward shift in recruitment deviation in 1995 with a downward shift in recruitment in the preceding year, although substantial peaks in deviations and recruitment are classified as outliers either side of this shift (Figure 7-8).

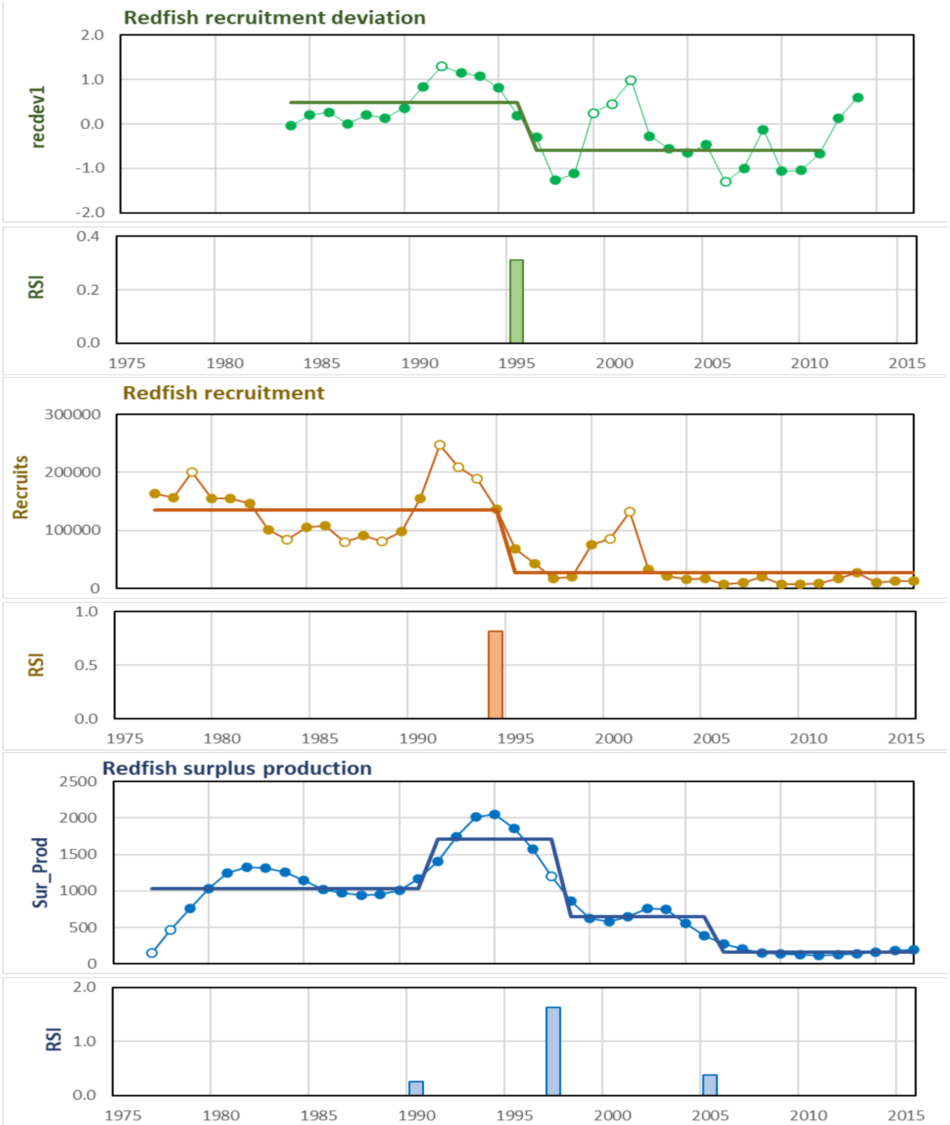


Figure 7-8. STARS analysis of apparent productivity shifts in Redfish as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1975–2015 (assessment results from Bessell-Browne and Tuck 2020). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

An upward trend in recruitment deviations from 2009 onwards is not reflected in recruitment or surplus production given the lower biomass and hence expected recruitment in those years. A large spike in recruitment in 1992–1994 is considered to consist of outliers, rather than a regime shift, and exceeds a second estimated peak in recruitment in 2001–2002, also classified as outliers. Substantially reduced biomass of this stock will result in reduced recruitment, but not necessarily in reduced recruitment deviations. The downward shift in recruitment in 1994–1995 is followed by a downward shift in surplus production in 1997, followed by a second downward shift in surplus production in 2005 that is not reflected in recruitment, although there is a low outlier in recruitment deviations in that year. The apparent upward trend in recruitment deviations from 2009 onwards is not reflected in recruitment or surplus production.

Silver Warehou

The analysis for Silver Warehou shows a single downward shift in recruitment deviation (Figure 7-9).

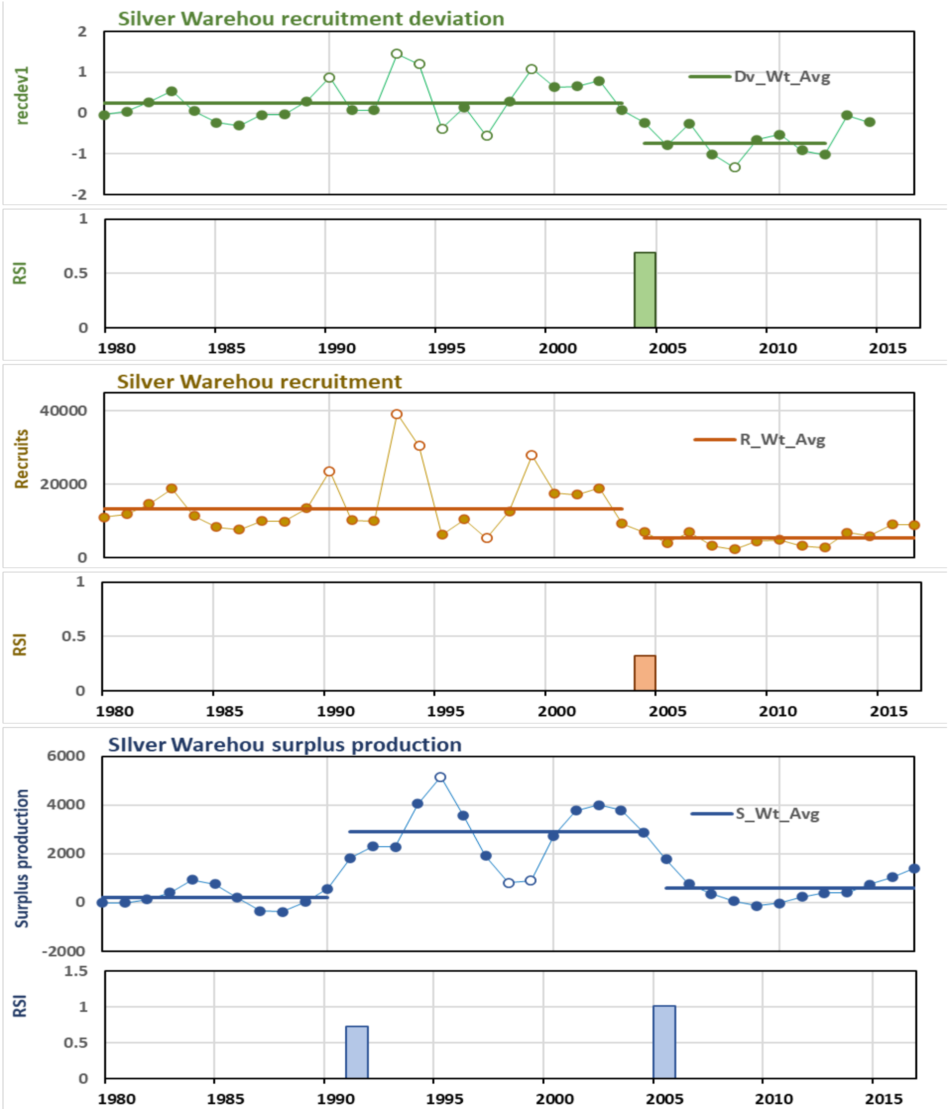


Figure 7-9. STARS analysis of apparent productivity shifts in Silver Warehou as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1980–2017 (assessment results from Burch *et al.* 2018). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

There is only a moderate difference in the average recruitment values over the periods prior to and after 2004, but this translates into a downward shift in surplus production in 2005. Surplus production shows an upward shift in 1991 that is not detected in recruitment deviations or recruitment, separating surplus production into three periods of low – high – low production.

Blue Warehou east

The analysis for Blue Warehou east shows a substantial downward shift in recruitment deviation in 1994, following a single high recruitment in 1993 classified as an outlier (Figure 7-10). The downward shift in recruitment does not translate into a decrease in surplus production, with no regime shifts detected in surplus production.

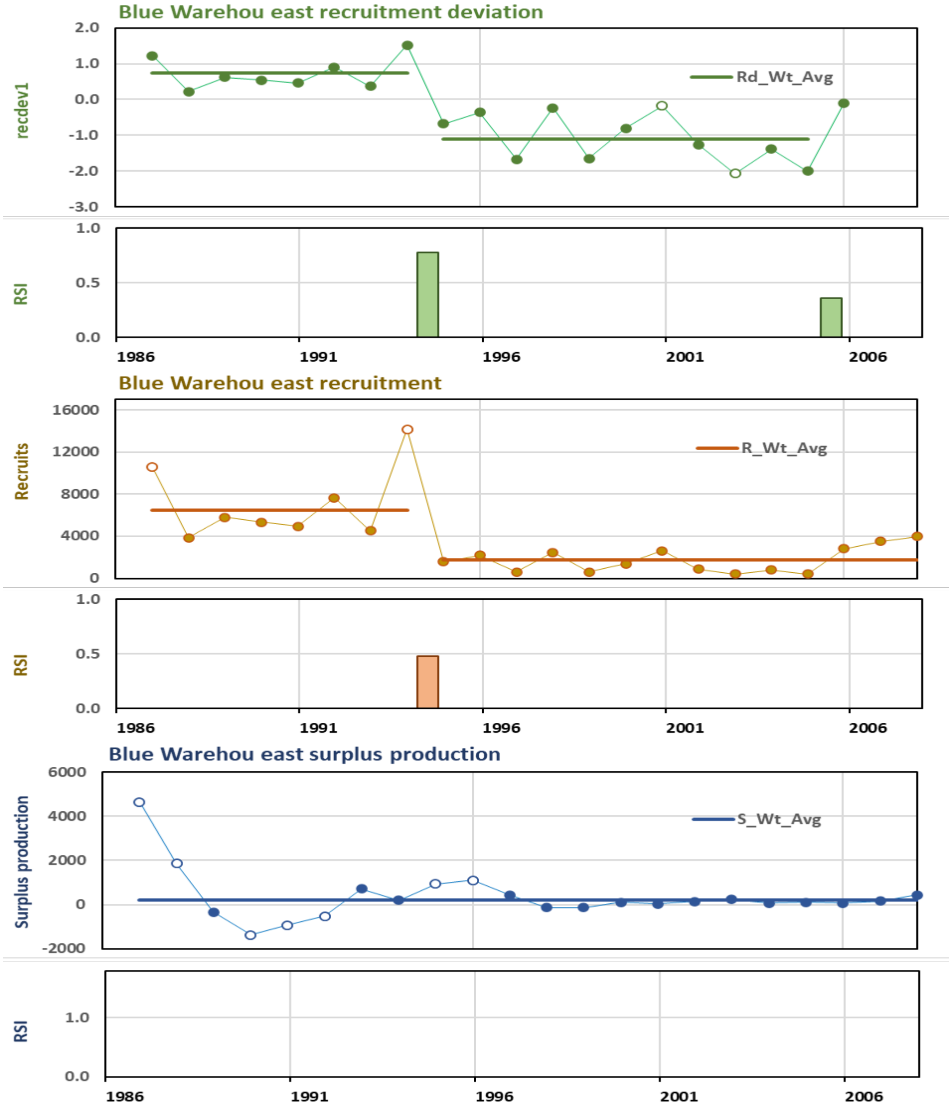


Figure 7-10. STARS analysis of apparent productivity shifts in Blue Warehou east as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1986–2008 (assessment results from Punt 2009). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Blue Warehou west

The analysis for Blue Warehou west shows a minor downward shift in recruitment deviation in 2004 that has no corresponding shift in recruitment, although an apparent decline from a high recruitment in 2001 is excluded due to the 2002 peak being classified as an outlier (Figure 7-11). In contrast, the analysis finds an upward shift in surplus production to a higher level from 1994 onwards, with subsequent fluctuations being classified as outliers.

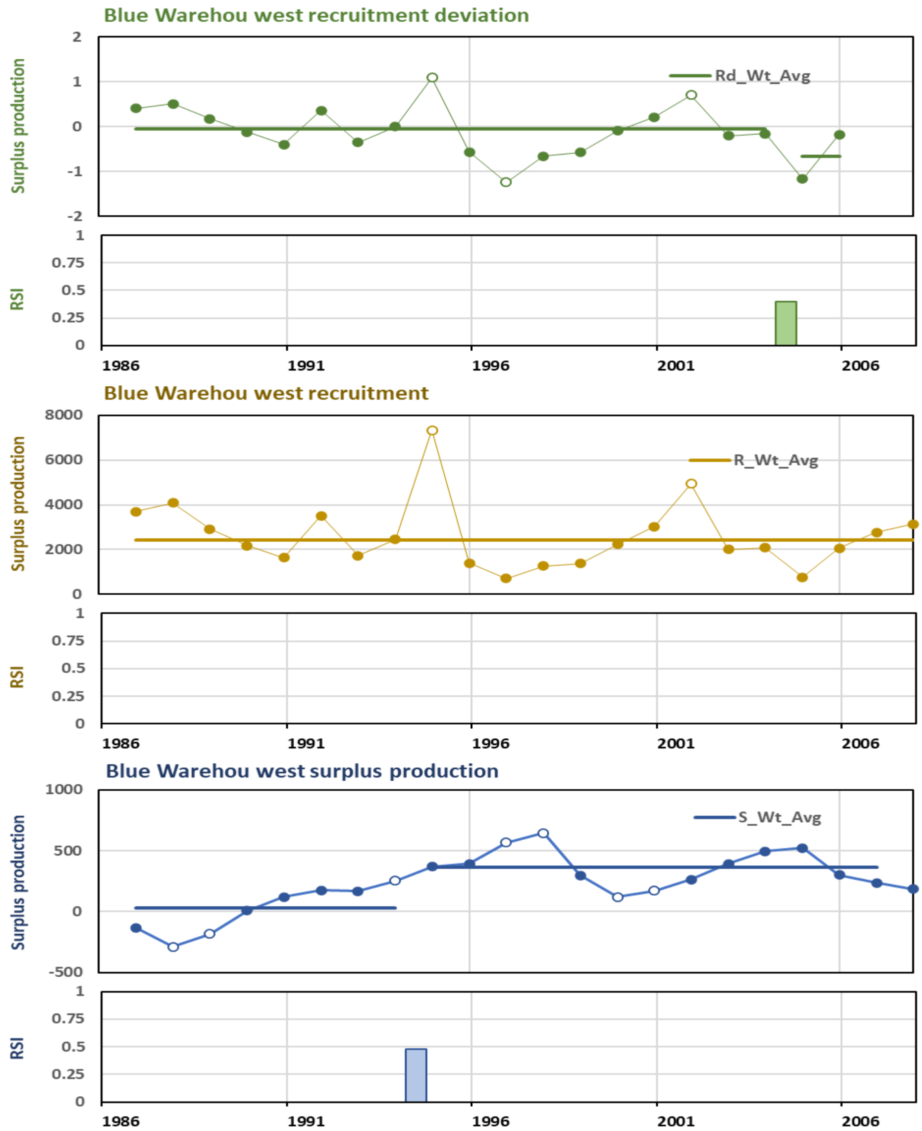


Figure 7-11. STARS analysis of apparent productivity shifts Blue Warehou west as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1986–2008 (assessment results from Punt 2009). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Gemfish east

The analysis for Gemfish east shows a downward shift in recruitment deviation in 1985 and an upward shift back to the historical high level in 2000 (Figure 7-12). The 1995 downward shift is preceded by a downward shift in recruitment in 1984 and, although there is a single higher recruitment in 2002, classified as an outlier, there is no upward shift in recruitment corresponding to the 2000 upward shift on deviations. The downward shifts in recruitment deviations and recruitment are followed by a downward shift in surplus production in 1986, with production remaining at low levels after that.

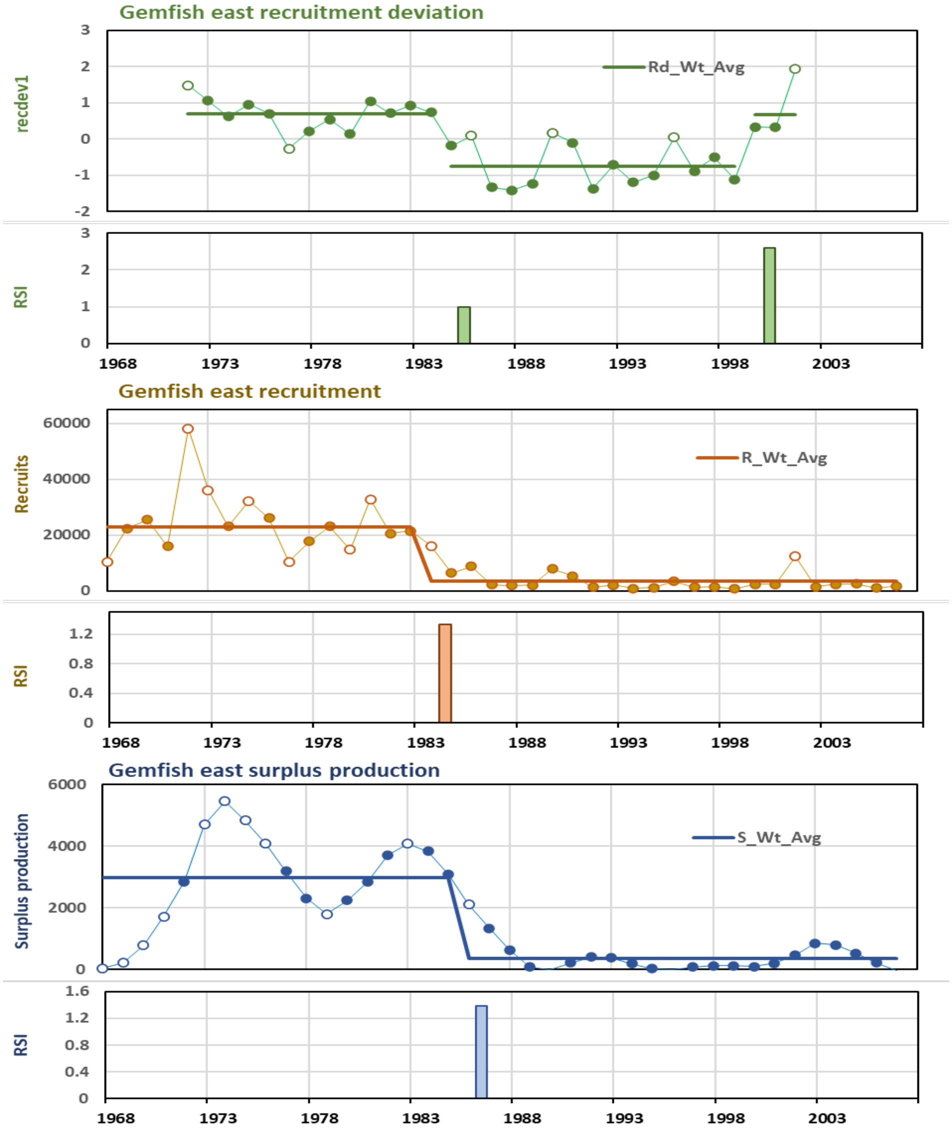


Figure 7-12. STARS analysis of apparent productivity shifts in Gemfish east as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1968–2007 (assessment results from Little and Rowling 2008). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Blue Grenadier

The analysis for Blue Grenadier shows a downward shift in recruitment deviation in 1998 that has no corresponding shift in recruitment (Figure 7-13). A large upwards shift in recruitment deviation is detected in 2009 which corresponds with an apparent upward shift in recruitment in 2010. The largest spike in recruitment in 1994–1995 is considered to consist of outliers, rather than a regime shift, but substantially exceeds the increased recruitment over the increased level from 2010 onwards. The upward shift in recruitment deviations and recruitment in 2009–2010 is reflected in an upward shift in surplus production in 2011, with surplus production subsequently continuing at a historically high level.

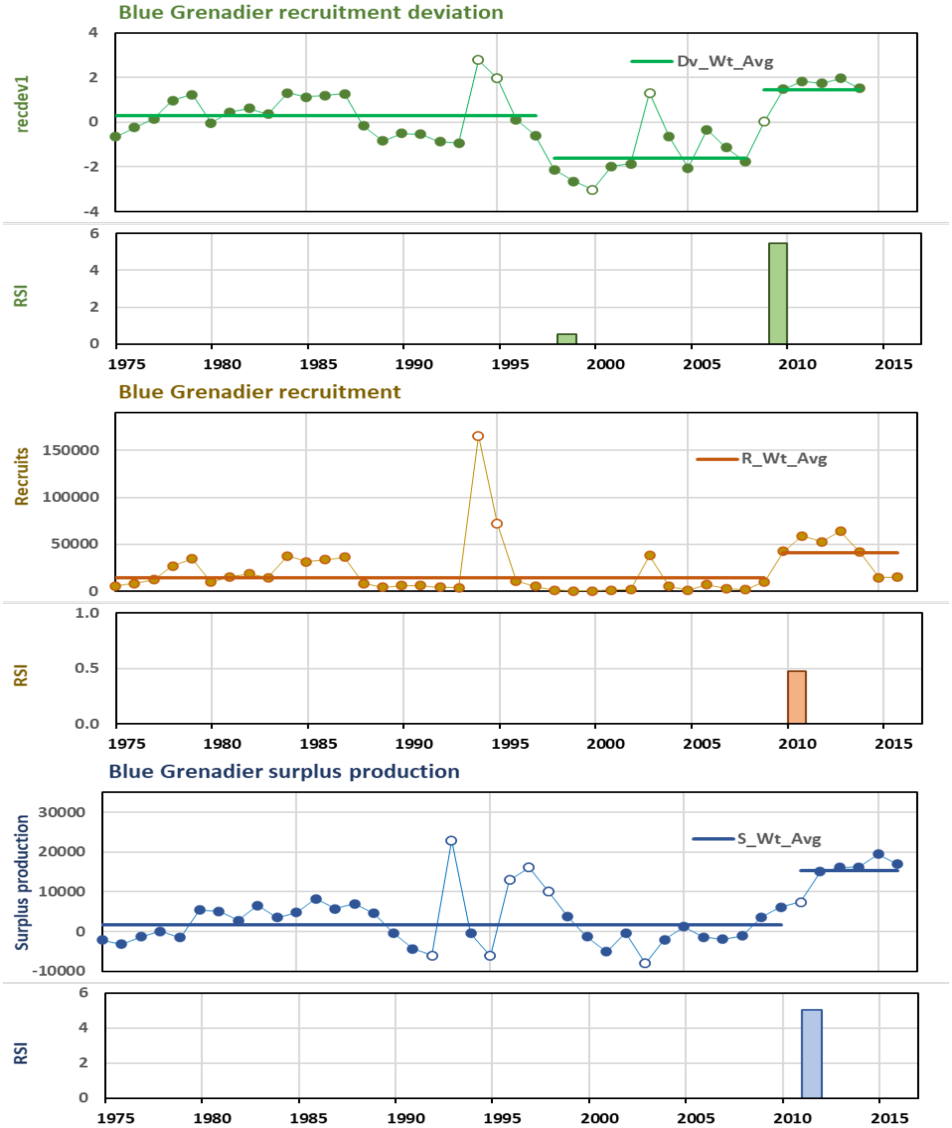


Figure 7-13. STARS analysis of apparent productivity shifts in Blue Grenadier as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1975–2017 (assessment results from Castillo-Jordán and Tuck 2018). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Tiger Flathead

The analysis for Tiger Flathead shows a minor downward shift in recruitment deviation in 1968 followed by an upward shift in 1992 to above the previous high level (Figure 7-14). However, numerous high and low recruitments across these periods are classified as outliers. Recruitment deviation and recruitment trends are more accurately described as spiky, with little evidence of regimes, although with an increase in frequency of high recruitments after 1980. A slight upward shift in recruitment in 1997 follows the upward shift in recruitment deviations in 1992, with the algorithm selecting different years to identify a regime with increased recruitment after 1990. High recruitment deviations and recruitments from 1982–1985 are classified as outliers but an upward shift in surplus production is detected in 1983, followed by another slight upward shift in 1999. The analysis generally indicates an increase in recruitment and production since about 1980.

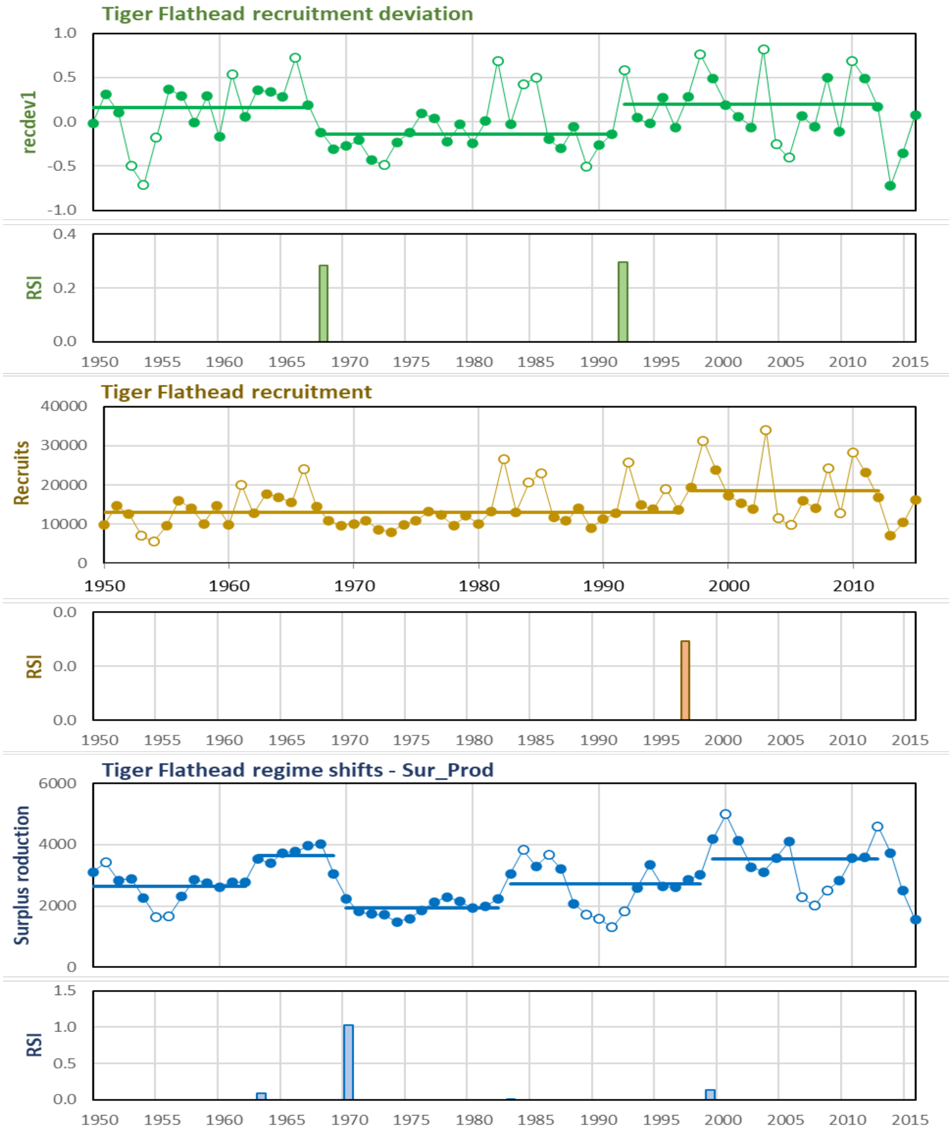


Figure 7-14. STARS analysis of apparent productivity shifts in Tiger Flathead as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1980–2017 (assessment results from Day 2019). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Eastern School Whiting

The analysis for Eastern School Whiting shows a downward shift in recruitment deviation in 2006 followed by an upward shift to the earlier level in 2016 (Figure 7-15). These shifts are reflected in similar shifts in recruitment in the same years. There is an apparent downward shift in surplus production in 2006 to a level of consistently lower production, until an upward shift again in 2013. These appear to be alternating productivity regimes, but no consistent decline.

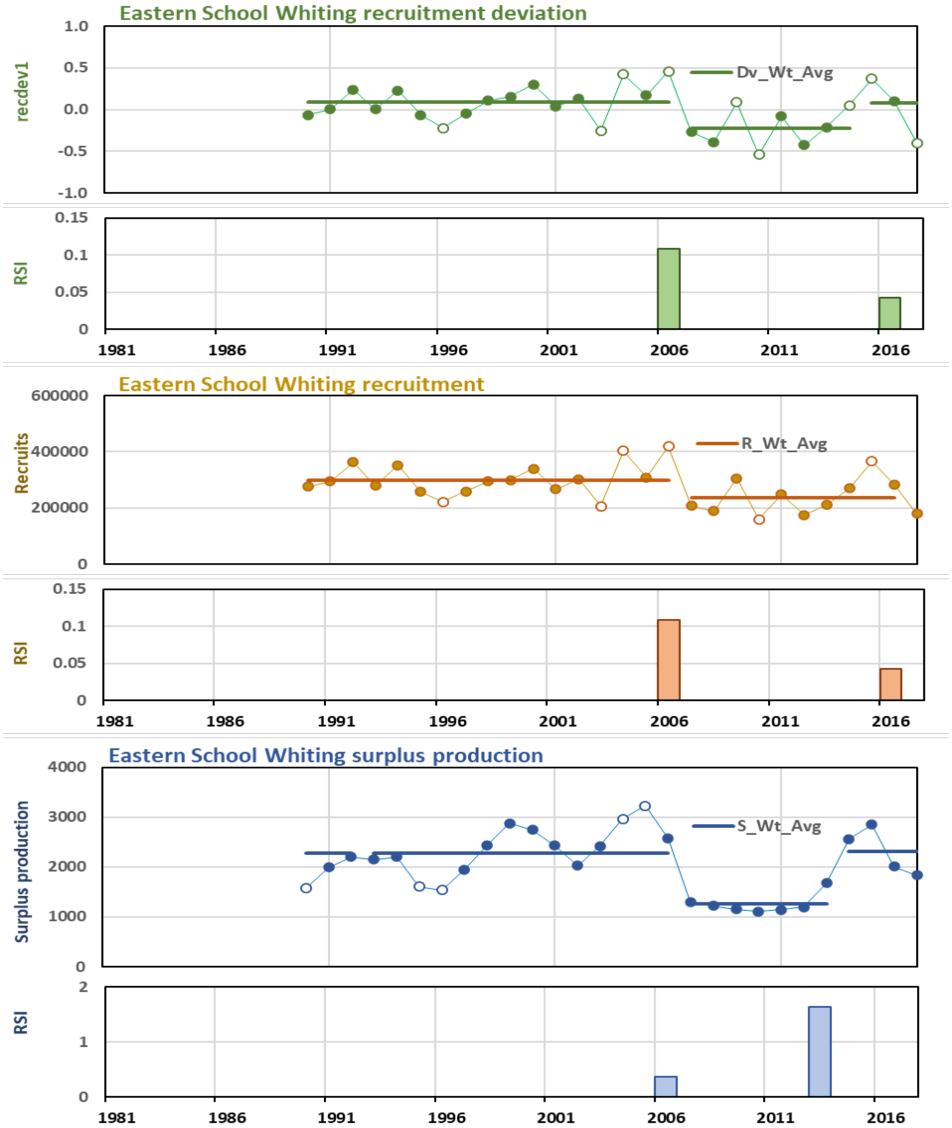


Figure 7-15. STARS analysis of apparent productivity shifts in Eastern School Whiting as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1980–2017 (assessment results from Day *et al.* 2020). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

7.2.4. Regime shift results for Northern crustacean stocks

Ornate Rock Lobster

Ornate Rock Lobster shows apparent downward shifts in recruitment deviation in 1998 and 2016, with corresponding downward shifts in recruitment in 1997 and 2015 (Figure 7-16). Between these, recruitment shows an upward shift in 2008, although deviations and recruitment can more correctly be described as highly variable, with numerous high and low values being classified as outliers. An upward shift in surplus production in 2018 cannot be considered a regime shift given it occurs at the end of the time series.

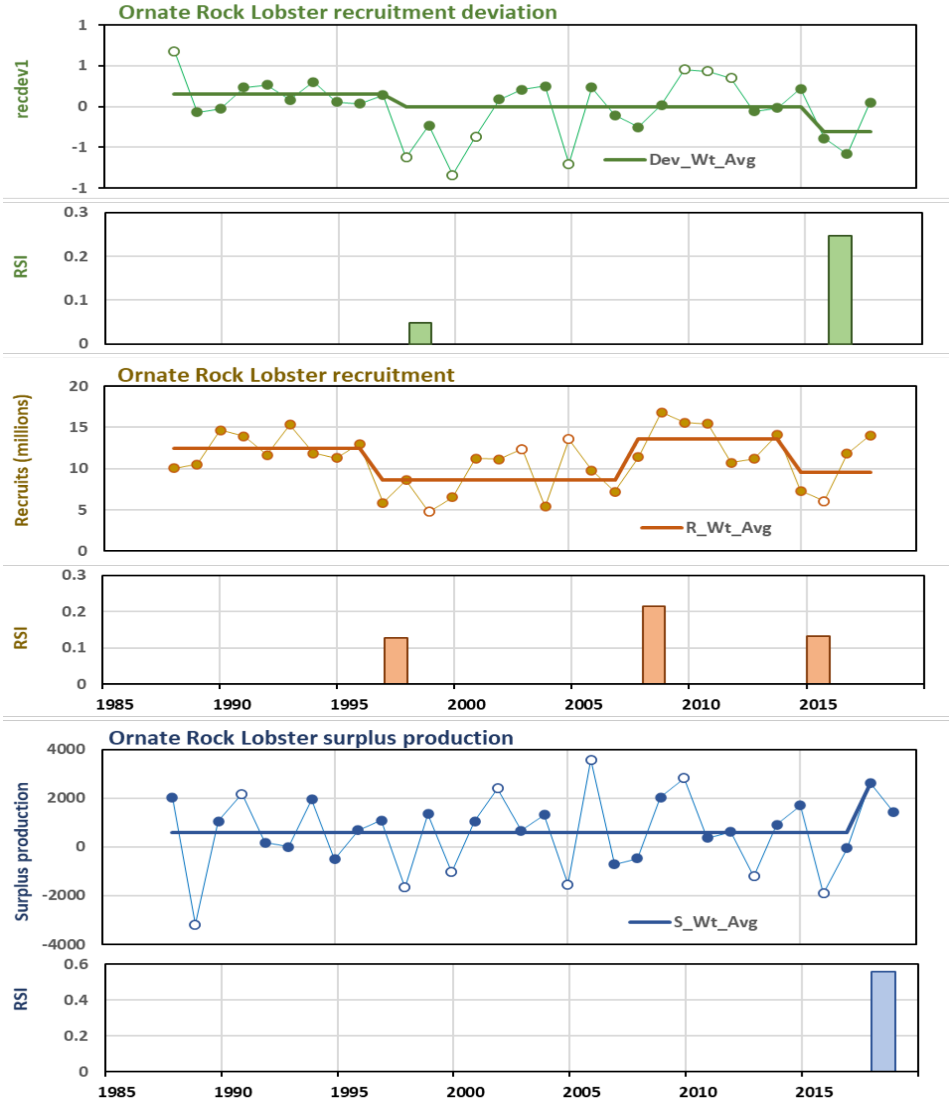


Figure 7-16. STARS analysis of apparent productivity shifts in Ornate Rock Lobster as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1975–2017 (assessment results from Plagányi *et al.* 2020). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Redleg Banana Prawn

The detection algorithm detects a slight downward shift in recruitment deviation and recruitment in 2015, although classifying the substantial decrease in recruitment deviation in that year as an outlier (Figure 7-17). Both recruitment deviation and recruitment return to at or above average levels by 2018. These detected shifts translate into a slight downward shift in surplus production in 2019, but this single low production value is unlikely to indicate a regime shift.

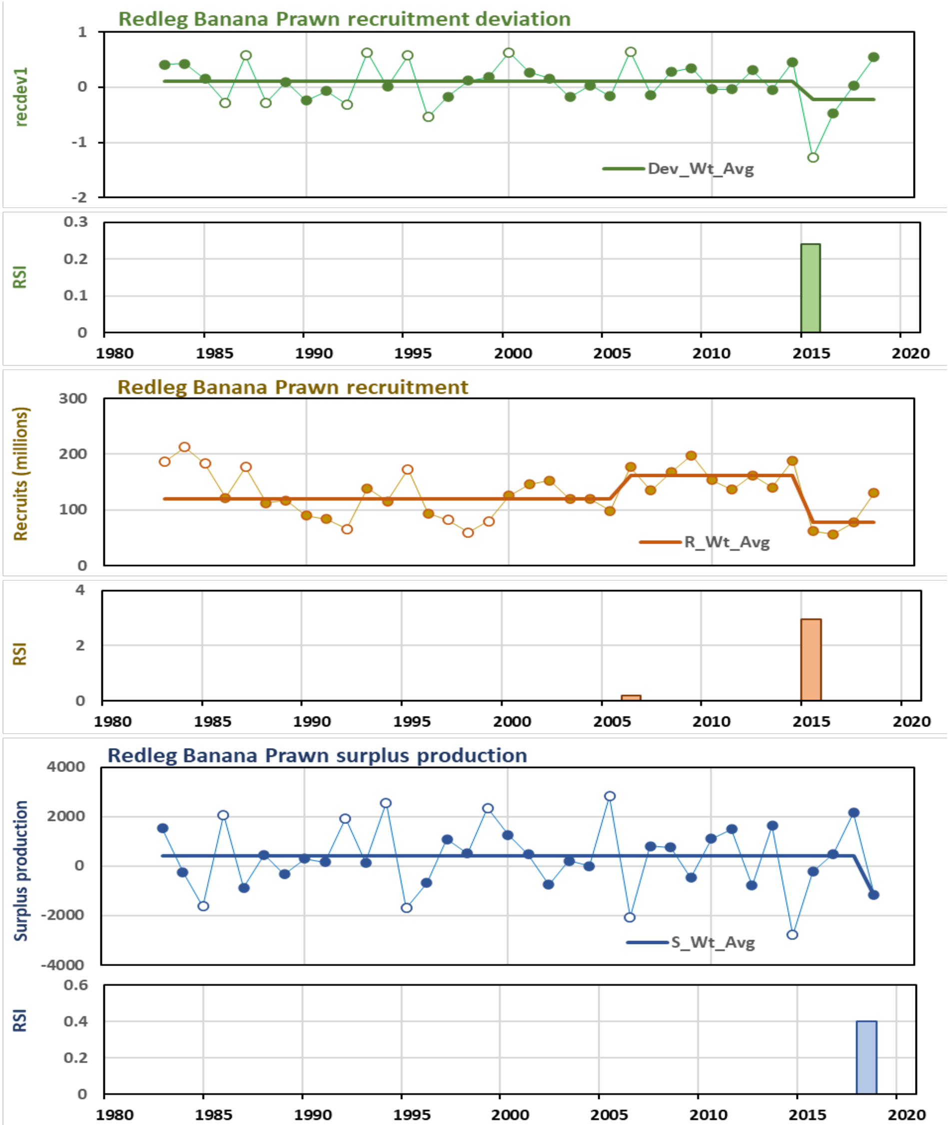


Figure 7-17. STARS analysis of apparent productivity shifts in Redleg Banana Prawn as indicated by recruitment deviations (top panels), recruitment (middle panels) and surplus production (bottom panels) over the period 1980–2019 (assessment results from Plagányi *et al.* 2021). Filled circles indicate the estimated recruitment deviation and recruitment values, with open circles indicating those considered by the algorithm to be outliers. Columns indicate the detected regime shifts.

Regime shift detection provides no persuasive evidence for regime shifts in either Redleg Banana Prawn or Ornate Rock Lobster. Rather, these stocks show high interannual variability indicating that, if there are non-fishing effects, then these occur over a period of only one to a few years and fluctuate between positive and negative effects for these short-lived species.

7.3. Regimes alternative production model analysis

Trends in estimated surplus production can be fitted using alternative production models, to evaluate the degree to which observed patterns of surplus production can best be explained by simple averages ('random effects'), a single production model (changes in parental biomass due to fishing), regime shifts (mainly non-fishing effects), or a production model with added regime shifts (combination of fishing and non-fishing effects). The equations used were those given in Vert-Pre *et al.* (2013):

Surplus production: $$S_y = B_{y+1} - B_y + C_y$$

where S_y – surplus production over year y
B_y – estimated biomass in year y
C_y – catch removed between times y and y+1

Fox production model: $$\hat{S}_y = -em\left(\frac{B_y}{B_\infty}\right) ln\left(\frac{B_y}{B_\infty}\right)$$

Where $\hat{S}_y$ – predicted surplus production for a given biomass in year y
m – maximum sustainable yield (fitted by the Fox model)
B_y – estimated biomass in year y
B_∞ – equilibrium unfished biomass (fitted by the Fox model)

Four models were fitted to annual surplus production values for each stock: a single average across all years, a single Fox production model across all years, separate averages across each regime period, and separate Fox production models across each regime period (using methods in Vert-Pre *et al.* (2013). Some stocks showed multiple regime shifts in surplus production and inclusion of multiple regime shifts would improve the explanatory power of regimes and regimes-Fox models. However, only the one main regime shift for each stock was applied here, to make results more comparable across stocks.

Model selection

Diagnostics used to determine the degree of fit of each model to the estimates of surplus production are described in detail in Vert-Pre *et al.* (2013). The comparison of the four models used the AICc, which identified the most parsimonious model, and was calculated as follows:

$$AIC_c = -2log(L) + 2k + \frac{2k(k+1)}{N-k-1}$$

where L is the likelihood of the data given the parameters, k is the number of parameters, and N is the number of data points. The preferred model is the one with the lowest AICc.

The Fox model has three parameters (m, B∞, and σ). The number of parameters in the regimes model varies, with one parameter for the average surplus production during each period, one parameter for each breakpoint, and an additional parameter representing the value of σ. The mixed model has one parameter for each breakpoint, one parameter for each m, and two additional parameters (B∞ and σ). The null model has two parameters: the average surplus production and σ. To calculate the AICc weights, the difference between the best model and each model i (Δi) was first calculated:

$$\Delta_i = AIC_{C_i} - min(AIC_C)$$

The weights for each model (w_i) were then calculated from the Δi:

$$w_i = \frac{e^{-0.5\Delta_i}}{\sum_{j=1}^{4} e^{-0.5\Delta_i}}$$

7.3.1. SESSF stocks

Jackass Morwong east

Regimes shifts analysis indicates that there has been a downward regime shift in recruitment deviation, recruitment and surplus production for Jackass Morwong east over 1982–1984. Assuming a single regime shift in surplus production in 1984, changes in historical surplus production for Jackass Morwong east are best explained by the regime shift alone (Figure 7-18 c), or slightly less so by separate production models for each regime period (Figure 7-18 d), with comparatively poor fit by a single production function across the history of the fishery.

In looking at the fits of the various models to the annual estimates of surplus production obtained using assessment results, it is important to recognise that the purpose of this analysis is not to specify a production model that obtains best fit to the surplus production results. The purpose is to pre-specify four alternative models using simple averages, averages across different regimes, a single Fox model across all years, and two Fox models across different regimes. The fits of all models may be poor, but the purpose of the analysis is to evaluate whether inclusion of a regime shift, and division of the models into two models across two separate regimes, results in any improvement in fits to the surplus production estimates.

Redfish

Redfish shows a single downwards regime shift in recruitment deviation and recruitment in 1994–1995 which translates into a downward shift in surplus production in 1997. Surplus production appears to show a slight downward shift in 2005. Assuming a single regime shift in 1997, historical changes in Redfish surplus production are best explained by a single production function across all years (Figure 22b) or separate production functions across the two regimes (Figure 7-19 d). Separate averages across the two regimes provide less explanatory power, indicating that the decline in this stock appears to have resulted mainly from fishing, possibly with overlain non-fishing effects.

Silver Warehou

Recruitment deviations and recruitment indicate a single regime shift for Silver Warehou in 2004, which translates into a decrease in surplus production in 2005. Surplus production shows an additional apparent increase from historically low levels in 1991. Assuming a single regime shift in 2005, historical changes in surplus production for Silver Warehou are best explained by separate Fox models across each of the two regimes (Figure 7-20d), but not by regime shifts alone, as shown by the substantial fluctuations in production during the first regime. No other model offers any explanatory power, indicating that historical changes in Silver Warehou stock production and status resulted from a combination of fishing and non-fishing effects.

Blue Warehou east

Recruitment deviations and recruitment indicate a single regime shift for Blue Warehou east in 1994, but with no corresponding shift in surplus production. Assuming a single regime shift in 1994, the historical trend in surplus production is best explained by a single average (Figure 7-21 a) or single Fox model (Figure 7-21 b), confirming no evidence for a regime shift.

Blue Warehou west

Surplus production indicates a single downward regime shift for Blue Warehou west in 1994, but with no corresponding shifts in recruitment. Assuming a single regime shift in 1994, the historical trend in surplus production is best explained by a Fox-Regimes model (Figure 7-22 d), or a Regimes model Figure 7-22 c), indicating that there was a regime shift in surplus production. However, the production trend over the first regime is better described as a steady increase up to the second higher regime, rather than a lower production level.

Gemfish east

Gemfish east shows a single downward regime shift in recruitment deviation, recruitment and surplus production over 1984–1986. Assuming a single regime shift in 1986, historical changes in surplus production are best explained by separate averages across the two regimes (Figure 7-23 b), and slightly less so by separate production models across the two regimes (Figure 7-23 d). A single production model across all years offers reasonable explanatory power, suggesting that fishing contributed to the decline of this stock in the mid-1980s.

Blue Grenadier

Blue Grenadier shows episodic recruitment peaks, well above long-term average recruitment. The more isolated of these recruitment peaks are considered outliers by the regime shift detection algorithm, rather than regime shifts. However, numerous years of recent high recruitment are considered to indicate an upwards regime shift in recruitment deviations, recruitment and surplus production over 2009–2011. Assuming a single regime shift in 2011, historical changes in Blue Grenadier surplus production are best explained by the regime shift alone (Figure 7-24 c), and slightly less so by separate production models across the two regimes (Figure 7-24 d). A single production model across all years offers no explanatory power, indicating that surplus production changes, driven by episodic recruitment spikes, are predominantly caused by non-fishing effects.

Tiger Flathead

Recruitment deviation, recruitment and surplus production for Tiger Flathead all show high inter-annual variability, with the regime shift detection algorithm classifying many high and low values as outliers, particularly from 1984 onwards. This high level of variability makes it unlikely that real regime shifts could be detected, particularly using a cutoff length of 10 years.

Tiger Flathead shows increased recruitment deviation in 1992 and recruitment in 1997, but these only translate into a weak increase in surplus production in 1999. An apparent strong decrease in recruitment deviation in 1968 does not show up in recruitment but translates into a strong decrease in surplus production in 1970. Several record high recruitments over the past decade, translating into increased surplus production, explain the apparent increase in production from 1999 onwards. Assuming a single regime shift in 1999, recent changes in Tiger Flathead surplus production are best explained by separate Fox production models across the two regimes (Figure 7-25 d). Separate averages across the two regimes offer reasonable explanatory power, indicating that changes in production have results both from fishing and non-fishing effects. However, production in this stock shows more variability than enduring regimes, with differences between regimes being moderate.

Eastern School Whiting

Eastern School Whiting shows a downward shift in recruitment deviations, recruitment and surplus production in 2006, followed by an increase back to previous higher levels in 2016, indicating alternating higher and lower productivity regimes. Assuming a single downward regime shift in 2006, changes in Eastern School Whiting surplus production are best explained by separate Fox production models across the two regimes (Figure 7-26 d), with a single Fox model offering reasonable explanatory power due to inclusion of the higher recent production in the second regime (Figure 7-26 b). Inclusion of the second upward regime shift would result in a regime-shift or Fox-regimes model being preferred, to model the alternating higher and lower production regimes.

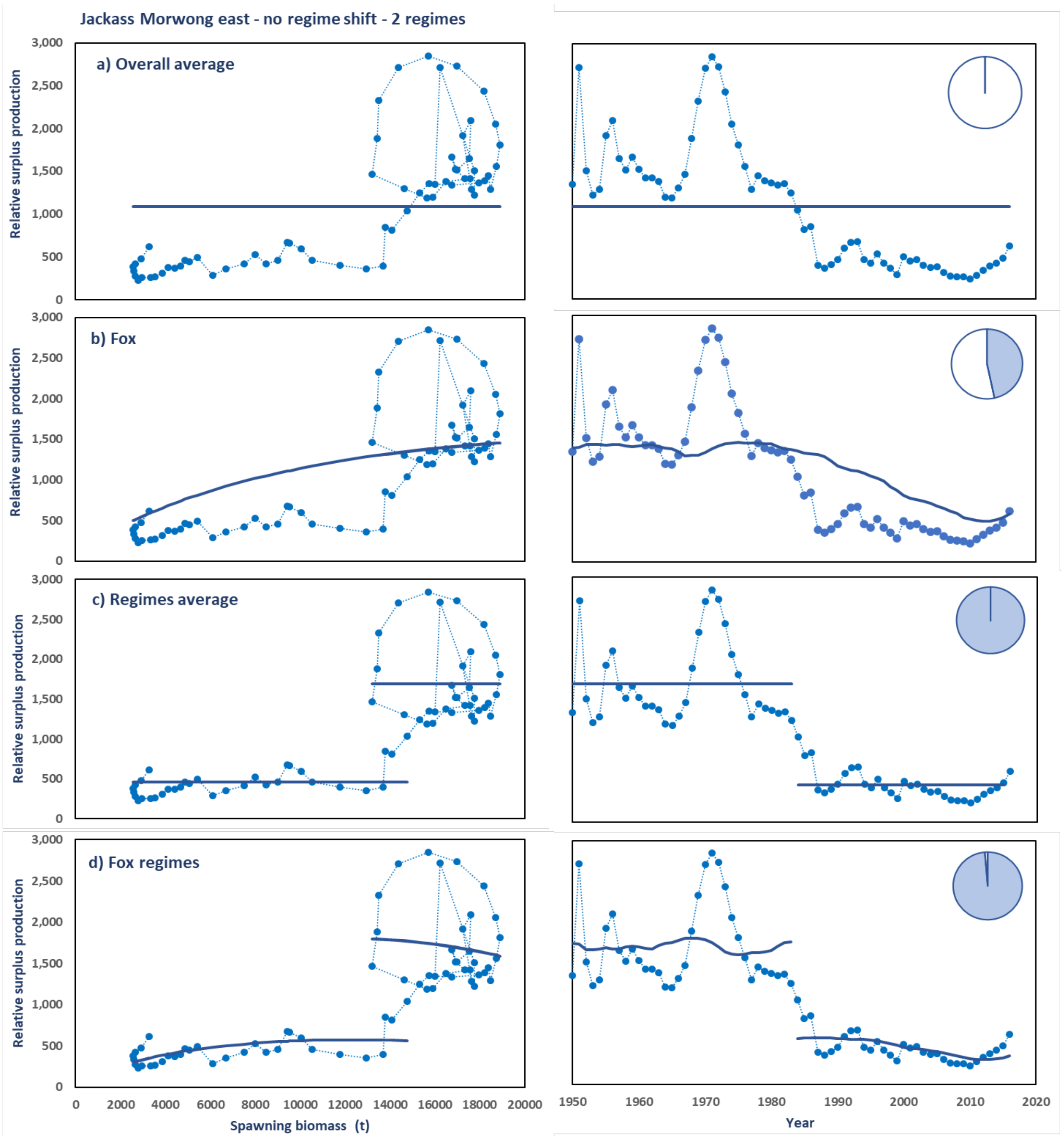


Figure 7-18. Alternative model fits to annual surplus production trends for Jackass Morwong east assuming a single regime shift in 1984, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

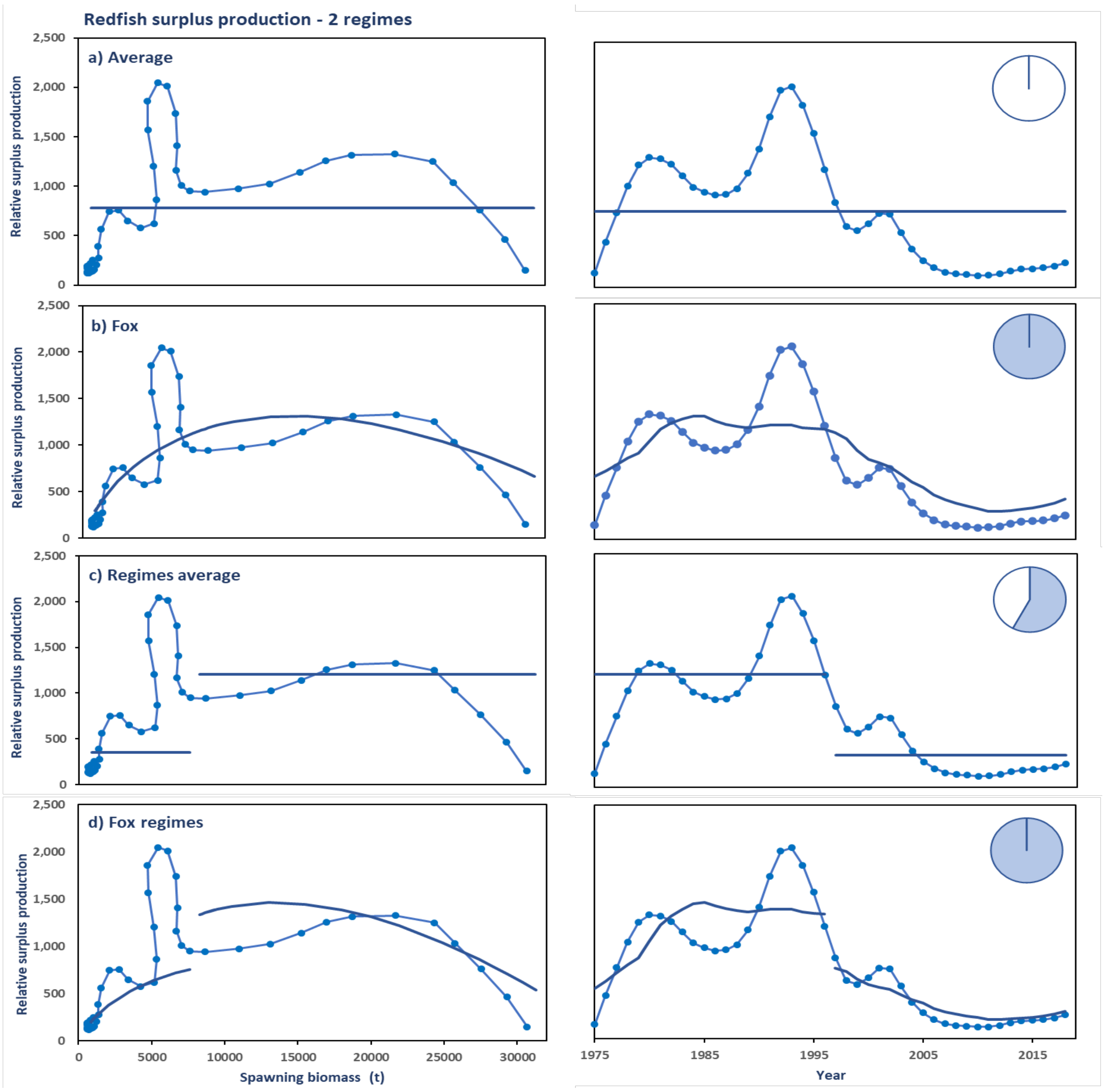


Figure 7-19. Alternative model fits to annual surplus production trends for Redfish assuming a single regime shift in 1997, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

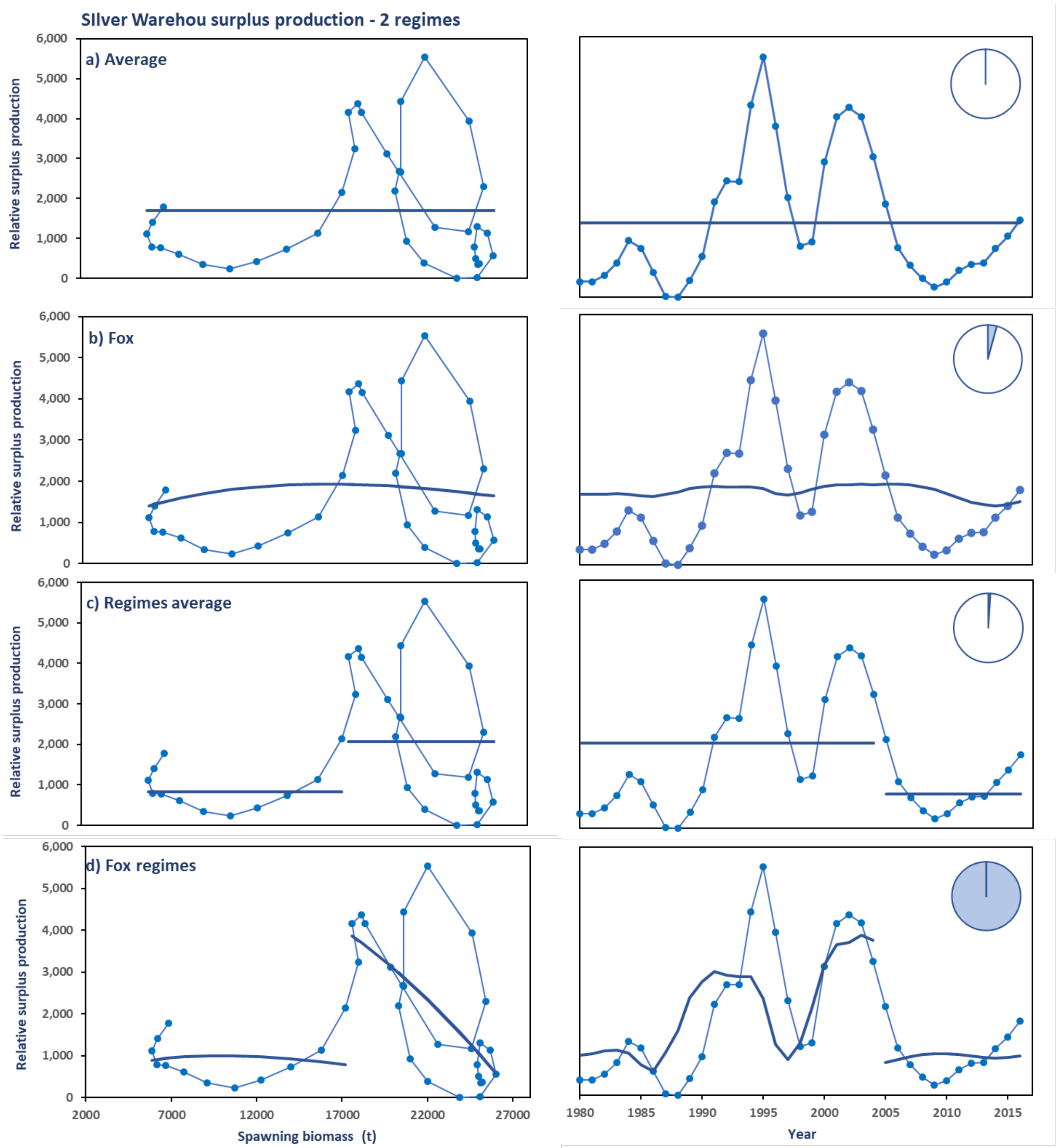


Figure 7-20. Alternative model fits to annual surplus production trends for Silver Warehou assuming a single regime shift in 2005, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

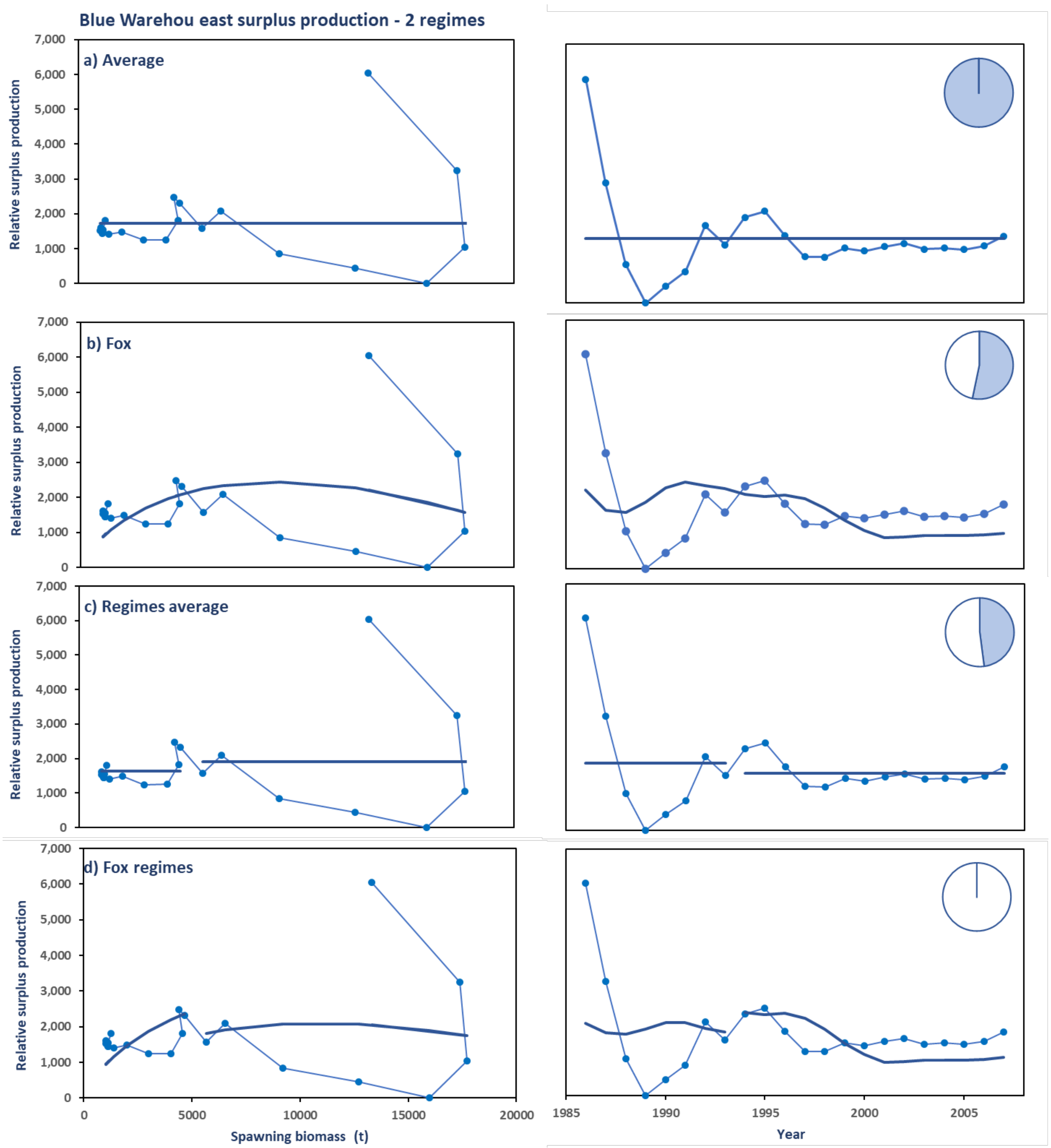


Figure 7-21. Alternative model fits to annual surplus production trends for Blue Warehou east assuming a single regime shift in 1994, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

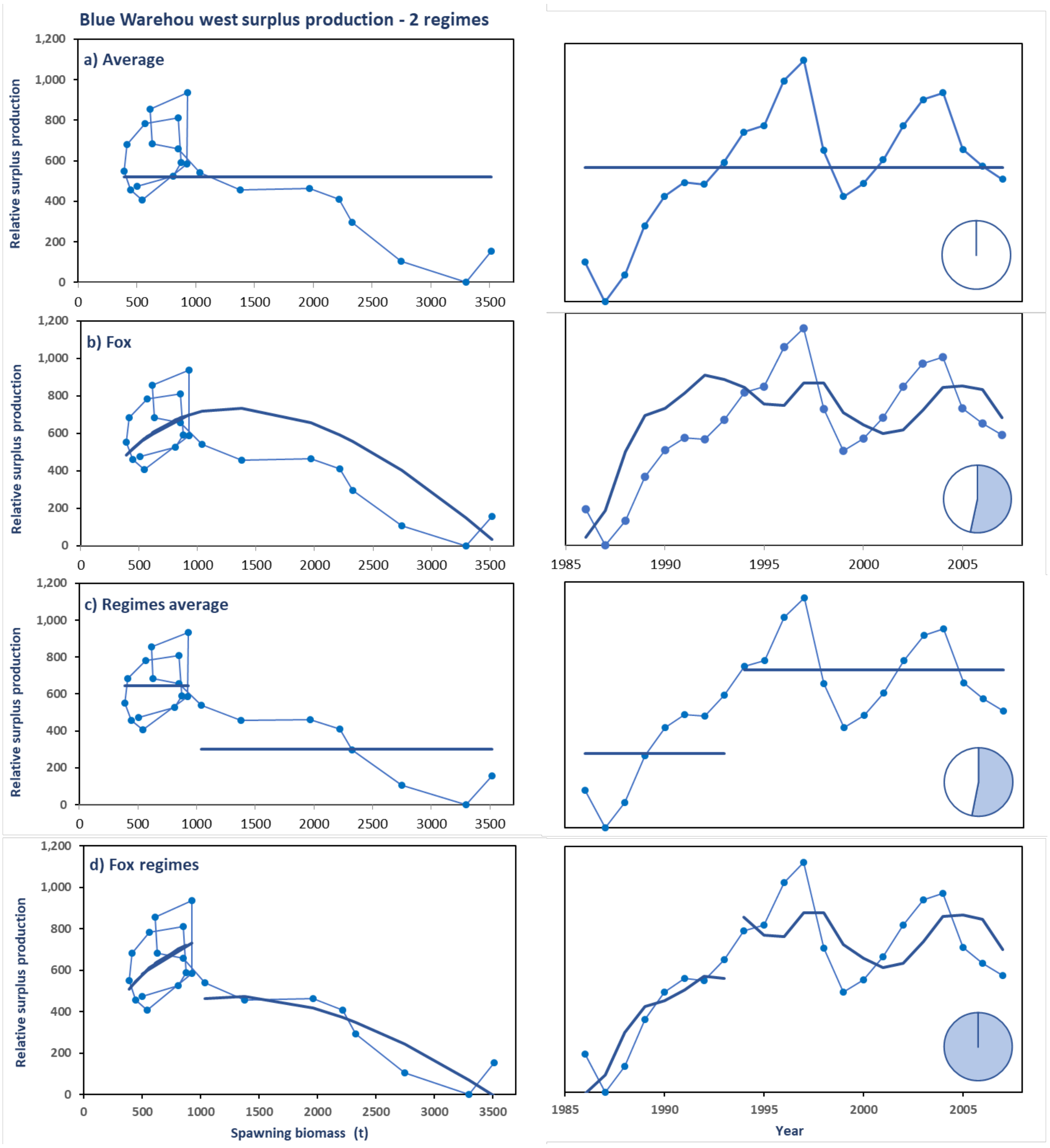


Figure 7-22. Alternative model fits to annual surplus production trends for Blue Warehou west assuming a single regime shift in 1994, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

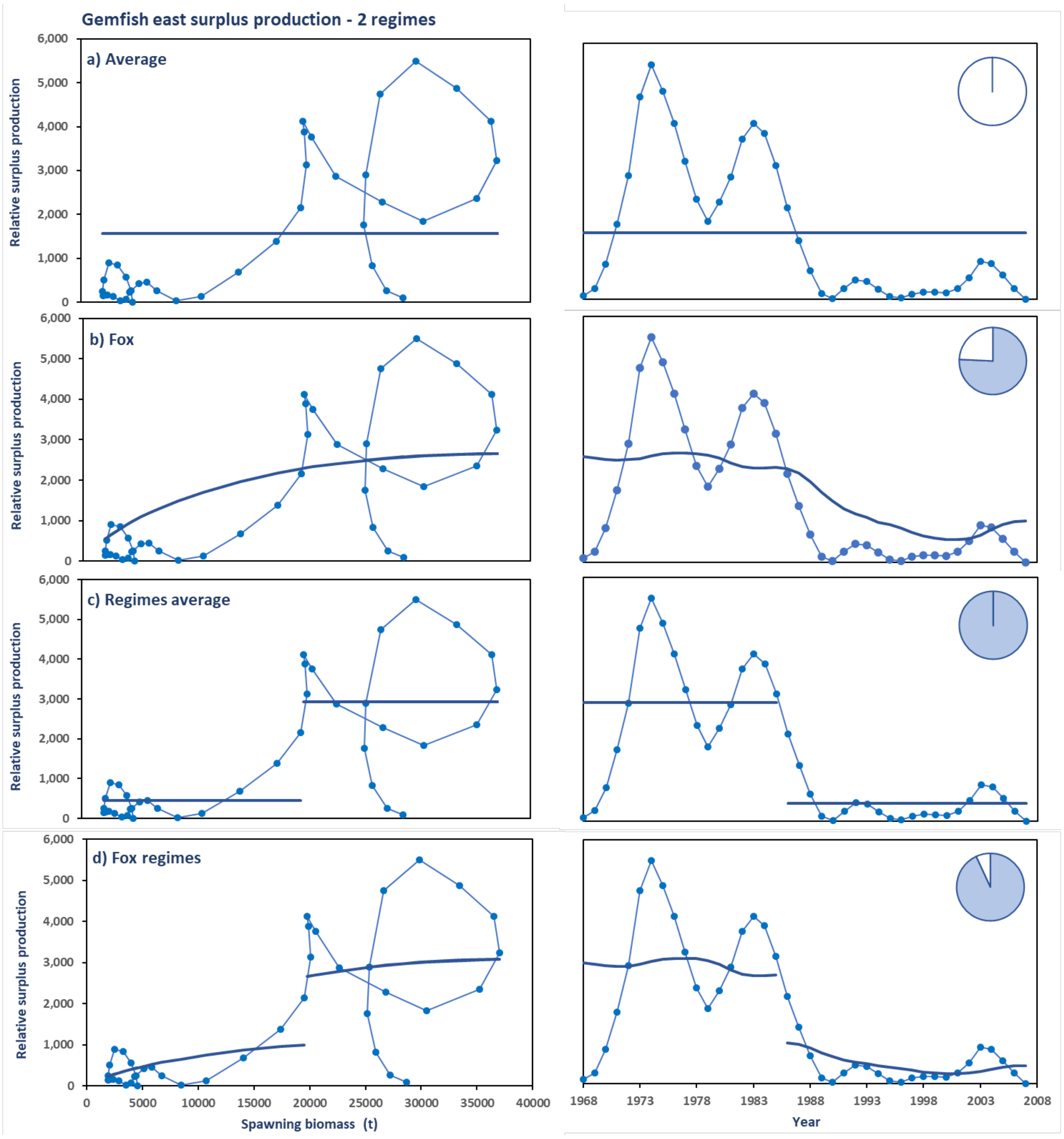


Figure 7-23. Alternative model fits to annual surplus production trends for Gemfish east assuming a single regime shift in 1986, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

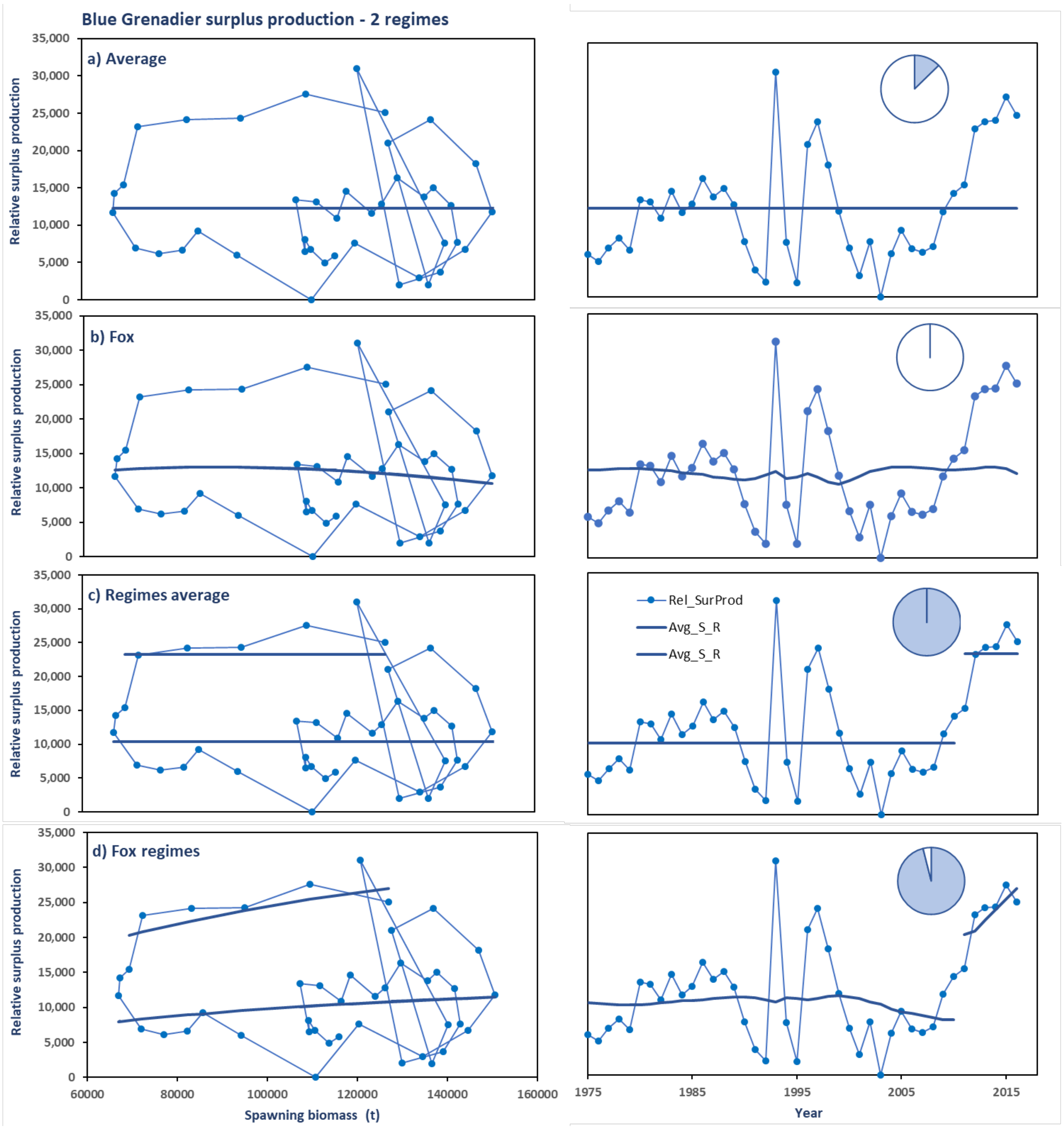


Figure 7-24. Alternative model fits to annual surplus production trends for Blue Grenadier assuming a single regime shift in 2011, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

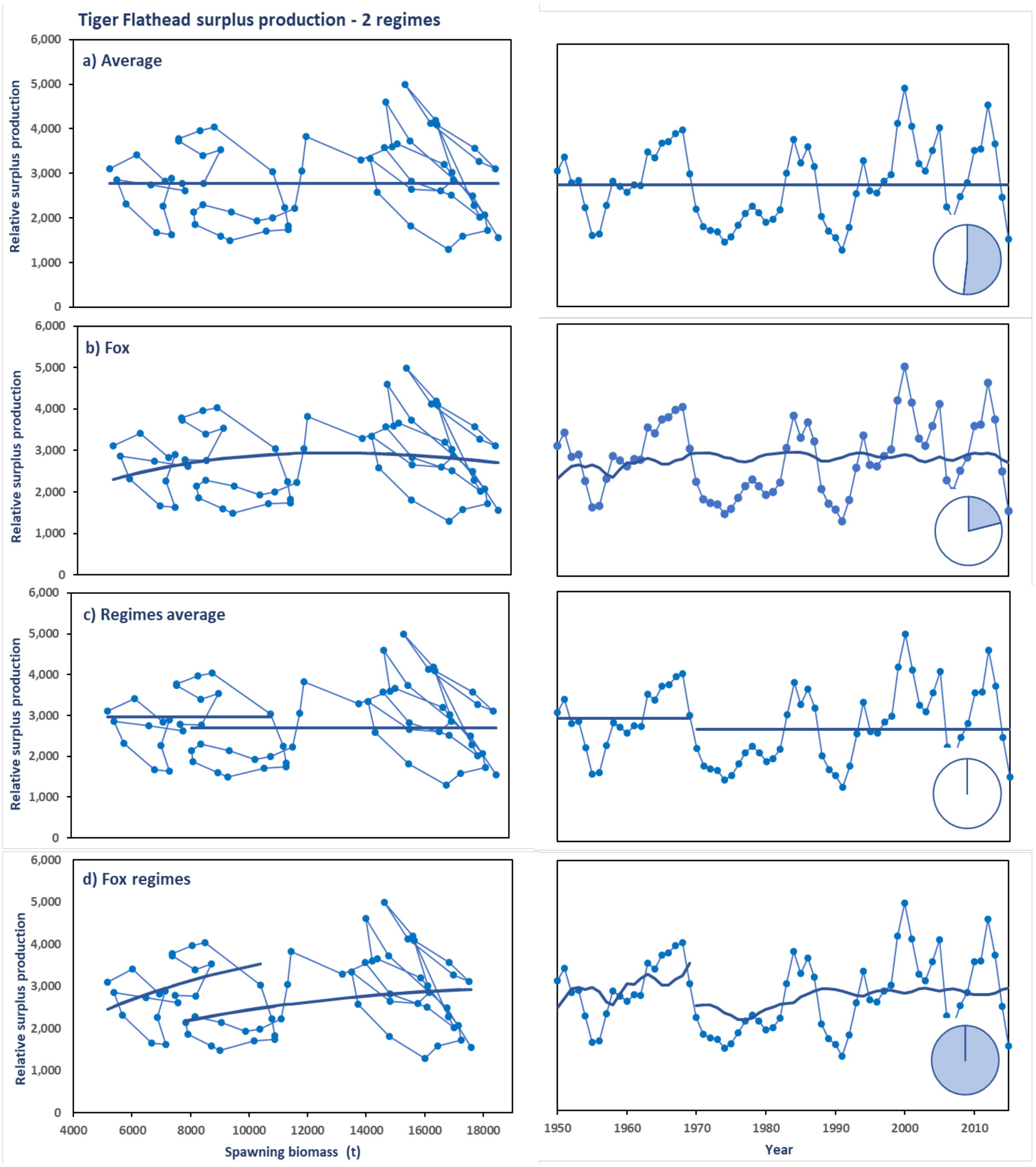


Figure 7-25. Alternative model fits to annual surplus production trends for Tiger Flathead assuming a single regime shift in 1999, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

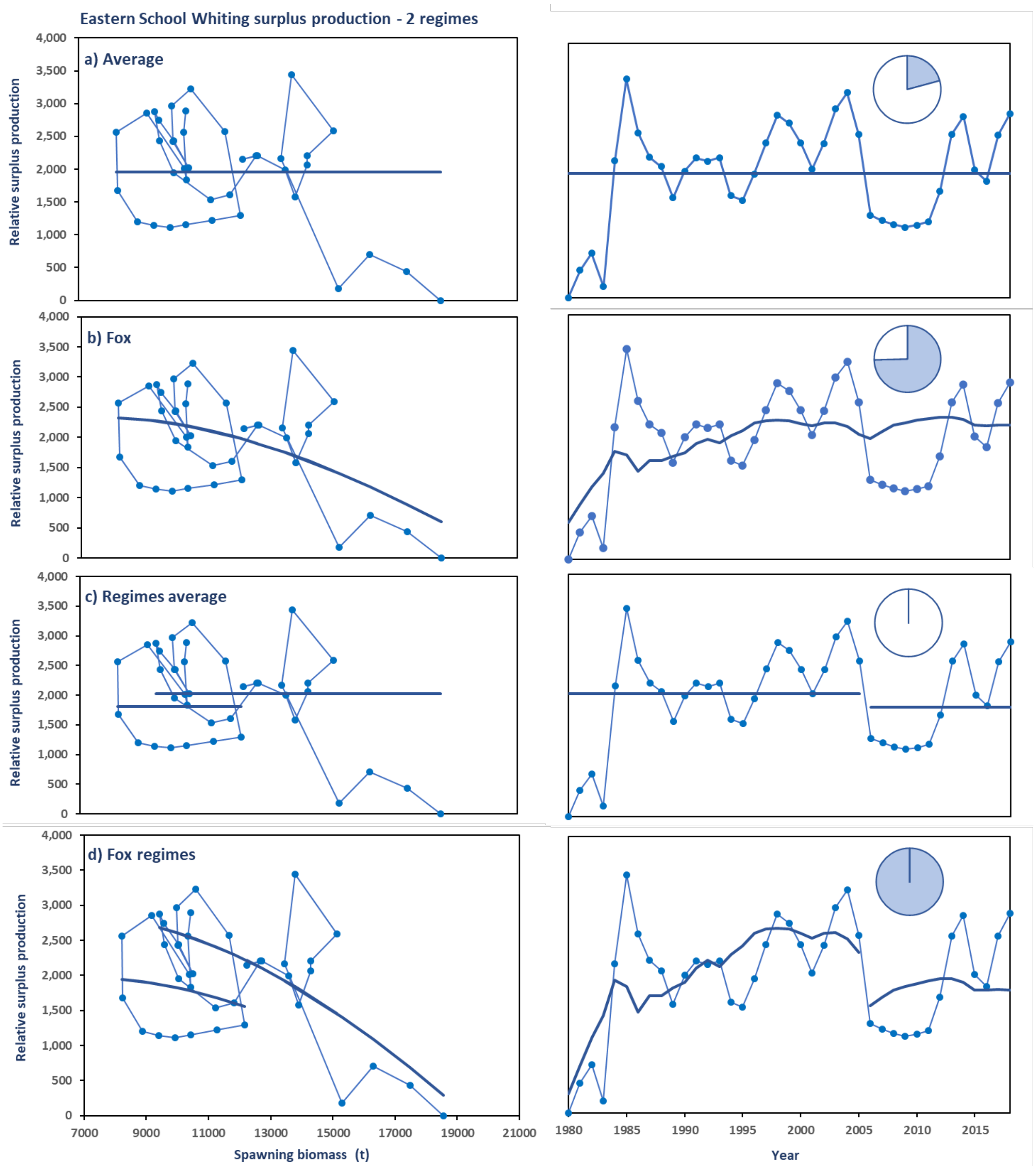


Figure 7-26. Alternative model fits to annual surplus production trends for Eastern School Whiting assuming a single regime shift in 2006, showing: a) single average across all years; b) single Fox production model across all years; c) separate averages across the two regime periods; and d) separate Fox production models across the two regime periods. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

7.3.2. Northern crustacean stocks

Ornate Rock Lobster

Ornate Rock Lobster surplus production shows high interannual variability, but no evidence of actual regime shifts. Changes in historical production for this stock are therefore best explained by a single production model across all years, with no regime shifts (Figure 7-27). There are probably non-fishing effects underlying the high interannual variability.

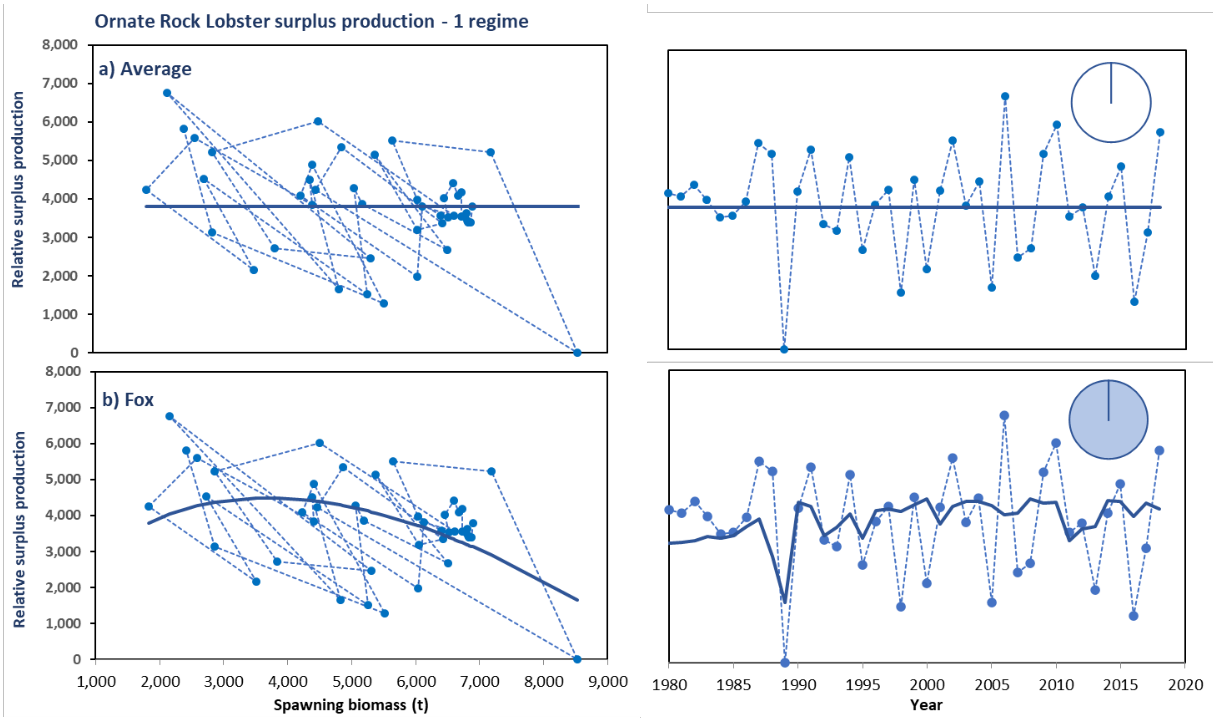


Figure 7-27. Alternative model fits to annual surplus production trends for Ornate Rock Lobster with no regime shifts, showing: a) single average across all years; b) single Fox production model across all years. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

Redleg Banana Prawn

Redleg Banana Prawn surplus production shows high inter-annual variability, but no evidence of real regime shifts. Changes in historical production for this stock are therefore best explained by a single production model across all years, with no regime shifts (Figure 7-28). There are known non-fishing effects underlying the high interannual variability, but without resulting in a trend or persistent shift.

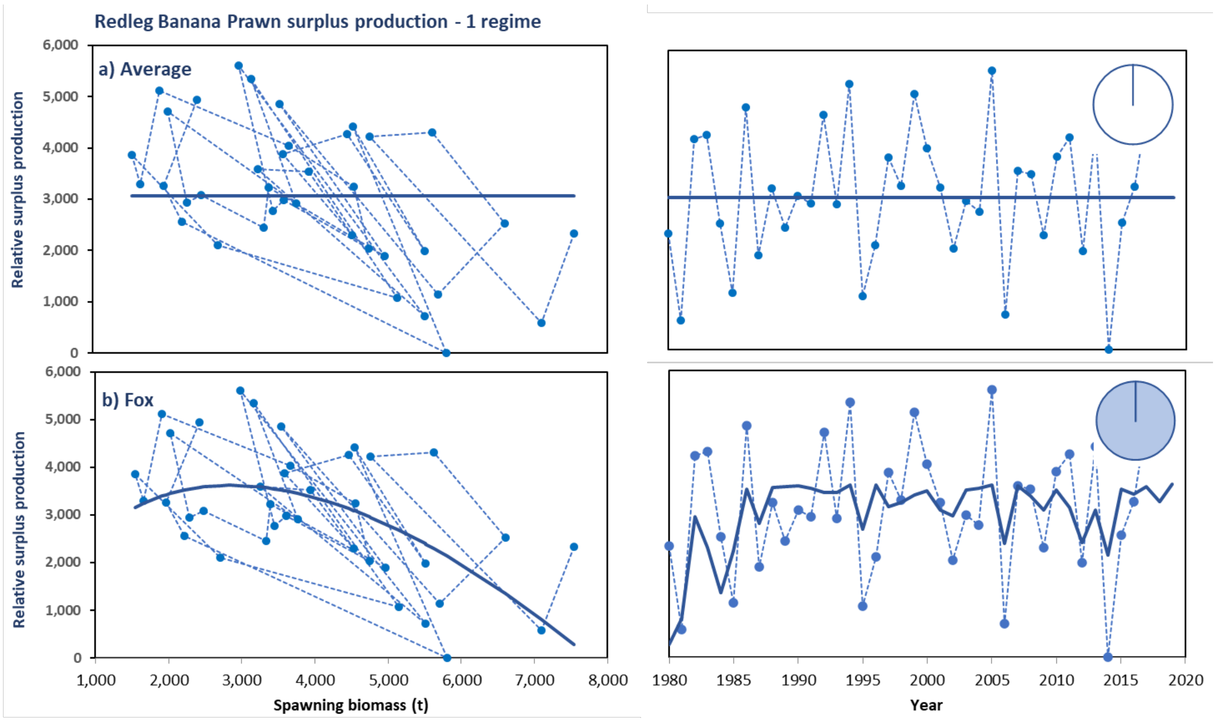


Figure 7-28. Alternative model fits to annual surplus production trends for Redleg Banana Prawn with no regime shifts, showing: a) single average across all years; b) single Fox production model across all years. Left column shows relative surplus production against spawning biomass, right column against year. Pie charts show the relative proportion of deviation explained from 0% (highest AIC) to 100% (lowest AIC).

7.3.3. Overview of best-fit production models

Model selection (AIC) criteria for the four alternative models fitted to historical trends in surplus production for nine SESSF and two northern crustacean stocks (Figure 7-18 to Figure 7-28) were used to calculate relative weights for each model using the methods in Vert-Pre *et al.* (2013). Relative model weights are compared in Figure 7-29, showing the degree to which historical production trends for the various stocks are best explained by fishing effects on adult biomass (as indicated by the fit to a production model), regime shifts, or a combination of the two.

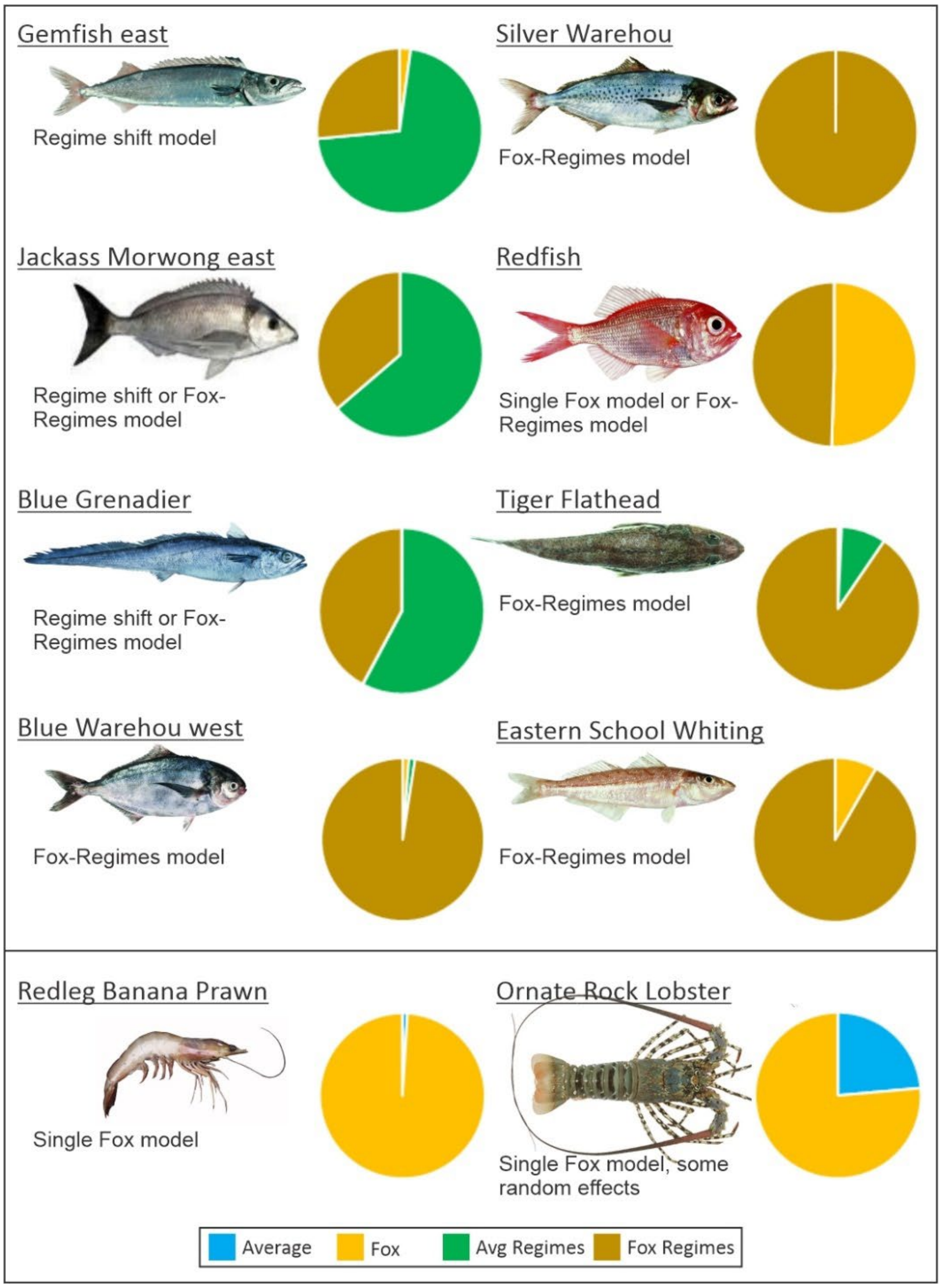


Figure 7-29. Relative model-fit weights of the four alternative models fitted to historical surplus production for four SESSF and two northern crustacean stocks, showing the degree to which production models, regime shifts, or a combination of the two, best explain observed historical production trends.

7.4. Evaluation of recruitment deviation correlations for SESSF stocks

7.4.1. Recruitment deviation estimates

Recruitment deviations estimated by the most recent Stock Synthesis assessments available at the time, conducted for Jackass Morwong east, Silver Warehou, Redfish, Tiger Flathead and Eastern School Whiting were used as input for the analysis of recruitment deviation correlations. These included the pre-2021 assessments used in the retrospective analysis of trends in dynamic B_0 for Redfish, Tiger Flathead and Eastern School Whiting, and the 2021 assessments for Jackass Morwong east, Silver Warehou and Blue Grenadier. The year ranges for estimated recruitment deviations from these assessments for each stock are shown in Table 7-3.

Table 7-3. Details of the stock assessments used in analysis of recruitment deviation correlations between six SESSF stocks, showing the year ranges for which recruitment deviations were considered to have been reliably estimated for each stock.

Species	Primary author	Year	Number of genders	RecDev Year Range
Jackass Morwong east	Day	2021	1	1945–2015
Silver Warehou	Bessell-Browne	2021	1	1980–2017
Redfish	Bessell-Browne	2020	2	1968–2015
Blue Grenadier	Tuck	2021	2	1974–2015
Tiger Flathead	Day	2019	2	1915–2015
Eastern School Whiting	Day	2017	1	1981–2016

Some of the correlation methods applied require that there be no missing values in the series to be compared, so analyses were restricted to the period 1981–2015 over which recruitment deviations were estimated for all six case study stocks.

7.4.2. Correlation between recruitment deviation trends

Annual recruitment deviation values from these assessments were analysed for correlations in recruitment deviation between stocks over the period 1981–2015. Following initial analysis of likely stock groupings based on correlations and cluster analysis (see below) trends in normalized (mean=0, std.dev=1) recruitment deviations are shown for Jackass Morwong east, Silver Warehou and Redfish in Figure 7-30, and for Blue Grenadier, Tiger Flathead and Eastern School Whiting in Figure 7-31. Similarities and differences between these trends are visually clearer when plotted using a seven-year Loess smoother (Figure 7-32).

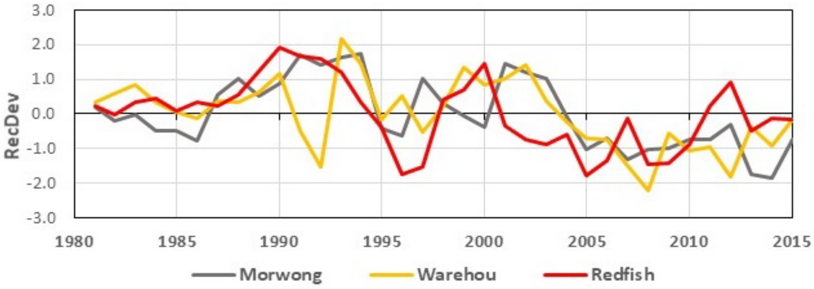


Figure 7-30. Comparison of annual recruitment deviations over the period 1981–2015 for Jackass Morwong east, Silver Warehou and Redfish from the most recent stock assessments. (Each series has been normalized to mean=0 and std.dev=1.)

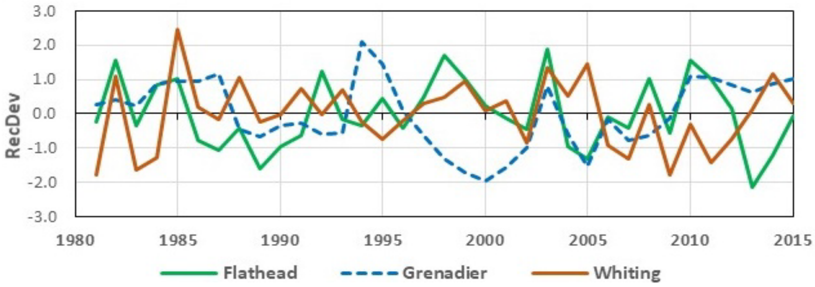


Figure 7-31. Comparison of annual recruitment deviations over the period 1981–2015 for Blue Grenadier, Tiger Flathead and Eastern School Whiting from the most recent stock assessments. (Each series has been normalized to mean=0 and std.dev=1.)

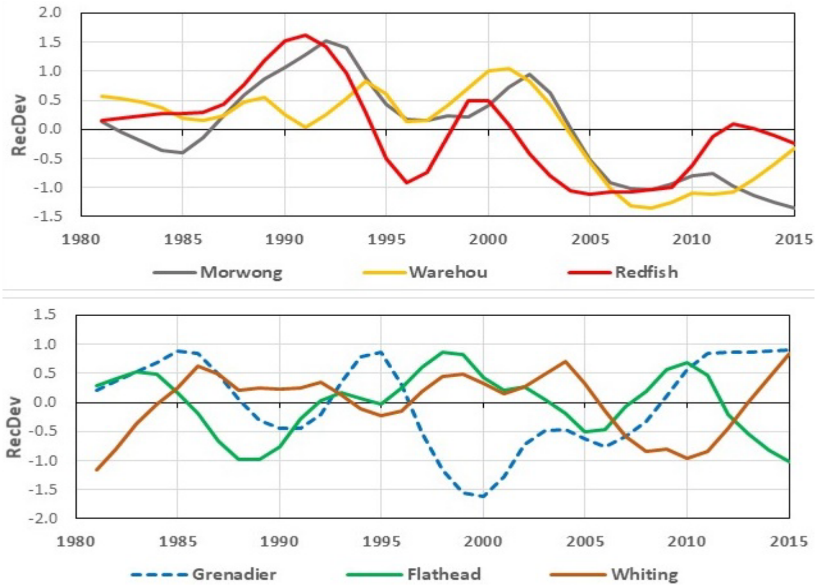


Figure 7-32. Comparison between smoothed trends in recruitment deviation (seven-year Loess smoother) for the recruitment deviations trends shown in Figure 7-30 and Figure 7-31.

Visually, there appear to be correlations between recruitment deviation peaks and troughs for Jackass Morwong east, Silver Warehou (other than 1992) and Redfish in terms of periods of above expected and below expected recruitment, and in periods of increase and decrease (Figure 7-30). Noting that these three stocks have all shown 'one-way trip' declines since at least the mid-1980s, over-estimation of steepness (resulting in recent below average recruitment and negative recruitment deviations for all stocks) may have contributed to this correlation. Interpreting these trends is further complicated by the fact that the Silver Warehou assessment covers separate eastern (SESSF zones 10–30) and western (SESSF zones 40–50) area, with more than half of the catch currently coming from the western area.

Correlation is less apparent between trends for Tiger Flathead and Eastern School Whiting (Figure 7-31). There do appear to be some coincident periods of increase, stable (although variable) and decrease in recruitment deviations, but with opposing trends at other times. Recruitment deviations for Blue Grenadier do not appear to be positively correlated with those for any of the other stocks (Figure 7-31.

Spearman rank correlations between recruitment deviation trends for each pair of stocks are summarised in Table 7-4. Highest positive correlations (0.583, 0.461, 0.321) were found between Jackass Morwong east, Redfish and Silver Warehou. These correlations are significant at the 99% level for Jackass Morwong east : Silver Warehou and Jackass Morwong east : Redfish, and at the 90% level for Silver Warehou : Redfish[2]. Blue Grenadier shows weak negative correlations (-0.217 to -0.158) with Jackass Morwong east, Silver Warehou and Eastern School Whiting.

Table 7-4. Spearman correlations between annual recruitment deviation series for six SESSF case study stocks over the period 1981–2015 (above the diagonal), with *p* values (below the diagonal). Bolded *p* values show > 90% probabilities of positive correlation.

Stock	Jackass Morwong	Silver Warehou	Redfish	Blue Grenadier	Tiger Flathead	Eastern School Whiting
Jackass Morwong		0.583	0.451	-0.200	0.116	0.134
Silver Warehou	**0.000**		0.321	-0.158	-0.111	0.103
Redfish	**0.007**	**0.061**		-0.059	-0.008	0.011
Blue Grenadier	0.248	0.362	0.735		0.055	-0.217
Tiger Flathead	0.506	0.525	0.963	0.752		0.078
Eastern School Whiting	0.442	0.553	0.952	0.210	0.658	

7.4.3. Cluster analysis of recruitment deviations

Correlations between recruitment deviations for the six SESSF case study stocks were explored using cluster analysis using the package 'TSClus' in R (Montero and Vilar 2014). Four alternative measures of dissimilarity available in TSClus were applied, focussing on factor-based (model-free) and complexity-based approaches. The clustering methods used are listed in Table 7-5, with a brief description of the measure of dissimilarity used by each method (see Montero and Vilar 2014 for detailed explanation of the mathematical measures used in each of these methods).

Model-based clustering approaches were not used as these assume specific underlying models to fit the data series before measuring dissimilarity between them. It is not known whether there are underlying models driving trends in recruitment deviations, or what form such models might take.

[2] The statistical significance of these correlations should be interpreted with care because the recruitment deviations are (a) not independent, and (b) have unequal variances.

Results of the cluster analyses conducted using the methods listed in Table 7-5 are shown in Figure 7-33.

Table 7-5. List of alternative measures of dissimilarity used in cluster analysis of recruitment deviation trends for six SESSF stocks over the period 1981–2015, with description of the measures of dissimilarity used by each method.

Method	Measure of Dissimilarity
Model free approaches	
Based on raw data	
EUCL	Euclidean distance
Covering both proximity of values and behaviour	
CORT	First order temporal correlation coefficient
Based on correlations	
COR	Correlation-based distances
Complexity-based approaches	
NCD	Normalized compression distance

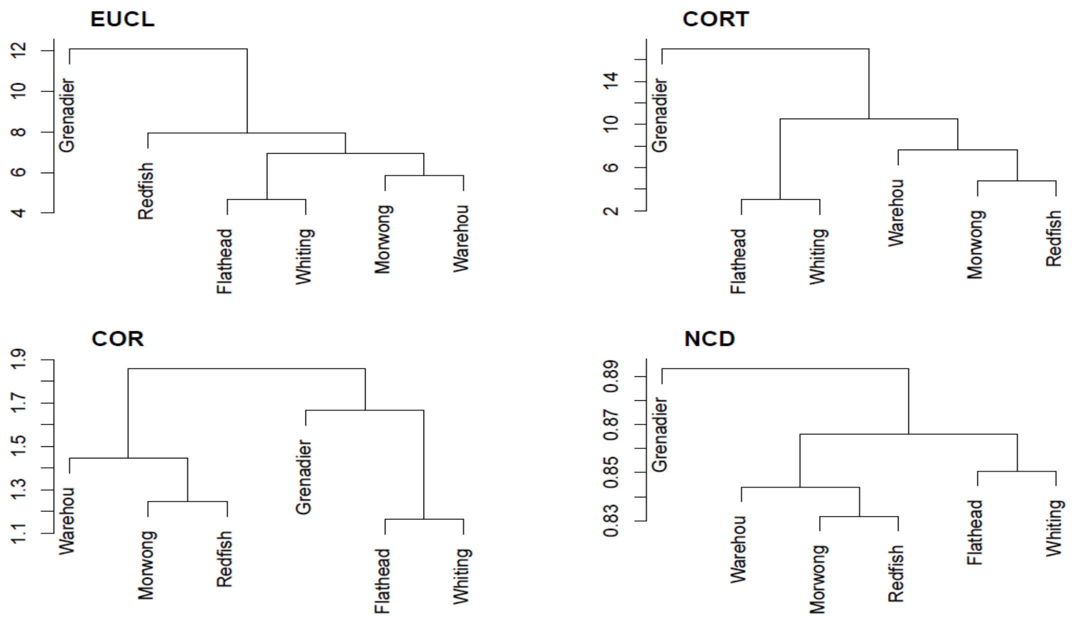


Figure 7-33. Cluster analysis comparing alternative groupings of recruitment deviation time series six SESSF case study stocks over 1980–2014, using four different measures of dissimilarity (see Montero and Vilar 2014 for details of methods).

Use of different measures of dissimilarity results in some differences in the clusters found using each method, but certain consistent clustering patterns emerge:

- Blue Grenadier clusters out on its own in three of the analyses (EUCL, CORT, NCD), or loosely associated with Tiger Flathead and Eastern School Whiting (COR), indicating an apparent lack of correlation of Blue Grenadier recruitment deviations with those for other stocks.
- The clustering of Jackass Morwong east, Silver Warehou and Redfish expected from correlations is found in three analyses (CORT, COR, NCD), with Jackass Morwong east and Silver Warehou clustering together using the EUCL method.
- Tiger Flathead and Eastern School Whiting cluster together in all of the analyses.

These results broadly support the Spearman correlations in Table 7-4, indicating three groups with correlated trends in recruitment deviations: 1) Jackass Morwong east, Silver Warehou and Redfish; 2) Tiger Flathead and Eastern School Whiting; and 3) Blue Grenadier alone.

7.4.4. Dynamic factor analysis

Dynamic Factor Analysis (DFA) methods (Zuur *et al.* 2003; Zuur and Pierce 2004) were used to detect unknown but influential underlying trends in recruitment deviations for the six stocks. The approach taken was essentially that of Castillo-Jordán *et al.* (2015) who investigated correlations between recruitment deviations for 30 southern hemisphere teleost species. All six SESSF stocks were included in the analysis, allowing the model fitting procedures to attempt to fit trends to all stocks, potentially confirming or contradicting the correlation and cluster analysis results. Analyses were conducted by fitting multivariate autoregressive state-space models using the MARSS package (Holmes *et al.* 2012) in R.

A suite of models was first fitted to the estimated normalised recruitment deviations for the six stocks, exploring four options for the variance-covariance matrix structure (Table 7-6) and from one to five underlying trends. Using the Akaike Information Criterion corrected for small samples to aid in model selection, the model with unequal variances, zero covariance and two underlying trends provided the most parsimonious model (Table 7-6, model 7, lowest AICc 568.5). This model was used as the 'best' model in further analyses. Given that the correlation and cluster analysis results indicated that the stocks clustered into three groups, a model assuming three underlying trends (model 8) was also explored, despite this having a somewhat poorer fit and larger AICc than the best model, to allow for the detection of three underlying trends potentially separately related to the three stock groups.

Table 7-6. Model specifications and fits (log Likelihood and AICc) for the suite of 20 alternative DFA models tested for fitting recruitment deviations for six SESSF stocks. The best fit (model 7, AICc 568.5) with diagonal and unequal variance-covariance matrix and two underlying trends is bolded. (See documentation for the MARSS package for explanation of the matrix forms).

Model	R variance matrix form	Trends	Log-Likelihood	K	AICc	Δ AICc
1	diagonal and equal	1	-277.52	7	569.6	1.06
2	diagonal and equal	2	-271.76	12	569.1	0.57
3	diagonal and equal	3	-272.67	16	580.2	11.63
4	diagonal and equal	4	-272.67	19	587.3	18.81
5	diagonal and equal	5	-272.67	21	592.3	23.73
6	diagonal and unequal	1	-271.83	12	569.2	0.72
7	**diagonal and unequal**	**2**	**-265.67**	**17**	**568.5**	**0.00**
8	diagonal and unequal	3	-264.14	21	575.2	6.66
9	diagonal and unequal	4	-264.21	24	582.9	14.38
10	diagonal and unequal	5	-264.25	26	588.2	19.65
11	equalvarcov	1	-277.52	8	571.7	3.22
12	equalvarcov	2	-271.74	13	571.3	2.81
13	equalvarcov	3	-272.49	17	582.2	13.64
14	equalvarcov	4	-272.49	20	589.4	20.90
15	equalvarcov	5	-272.49	22	594.4	25.87
16	unconstrained	1	-264.31	27	590.9	22.41
17	unconstrained	2	-250.47	32	576.9	8.34
18	unconstrained	3	-251.17	36	589.7	21.22
19	unconstrained	4	-250.55	39	597.4	28.91
20	unconstrained	5	-252.75	41	608.0	39.47

Fitting two underlying trends to six stocks

The two underlying trends estimated for the six stocks using model 7 are shown in Figure 7-34. The factor loadings, showing the relative contribution of each DFA trend by stock are shown in Figure 5.6. The factor loadings indicate the influence that each recruitment deviation time series has on each trend. Trend 1 mainly reflects trends in recruitment deviation for Jackass Morwong east, Silver Warehou and Redfish, with some contribution by Eastern School Whiting. Trend 1 is slightly negatively related to Blue Grenadier and not related to Tiger Flathead at all. Trend 2 mainly reflects the recruitment deviation trend for Blue Grenadier, although with some contribution by Redfish. Trend 2 is slightly negatively related to Tiger Flathead.

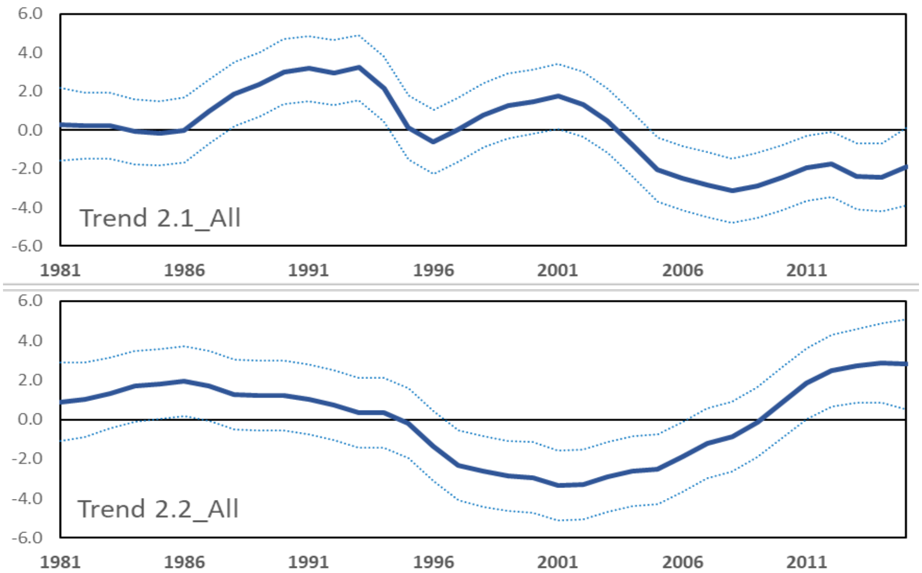


Figure 7-34. Underlying trends (with 95% CIs) detected by a DFA model fit to recruitment deviation series for six SESSF stocks over the period 1981–2015, with the model specified to fit two trends to an 'diagonal and unequal' variance-covariance matrix.

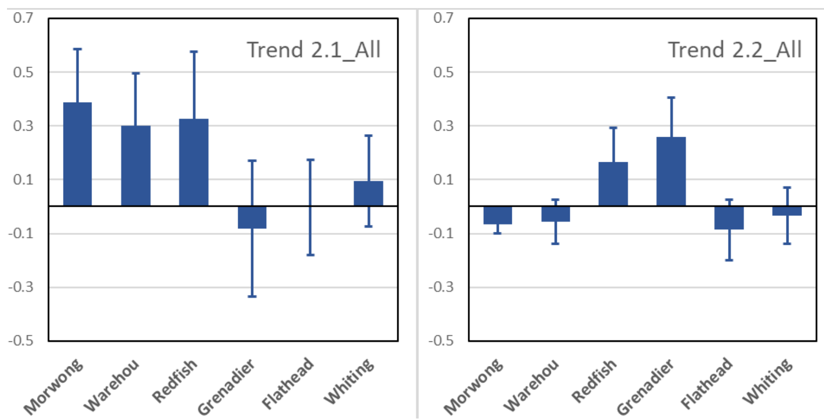


Figure 7-35. Factor loadings (with 95% Cis) for each stock resulting from fitting two underlying trends to recruitment deviations for six SESSF stocks over the period 1981–2015.

The DFA model fits resulting from the combined fitting of these two underlying trends to the recruitment deviations for each stock are shown in Figure 7-36. Allowing for two underlying trends results in a reasonably good fit for Jackass Morwong east, moderately good fits for Silver Warehou and Redfish and some degree of fit to Blue Grenadier, with some outliers. The model is unable to replicate the trend in recruitment deviations for Tiger Flathead and Eastern School Whiting, with wide 95% CIs spanning the full range of the recruitment deviations for these stocks. This is not unexpected given the low loadings in Figure 7-35.

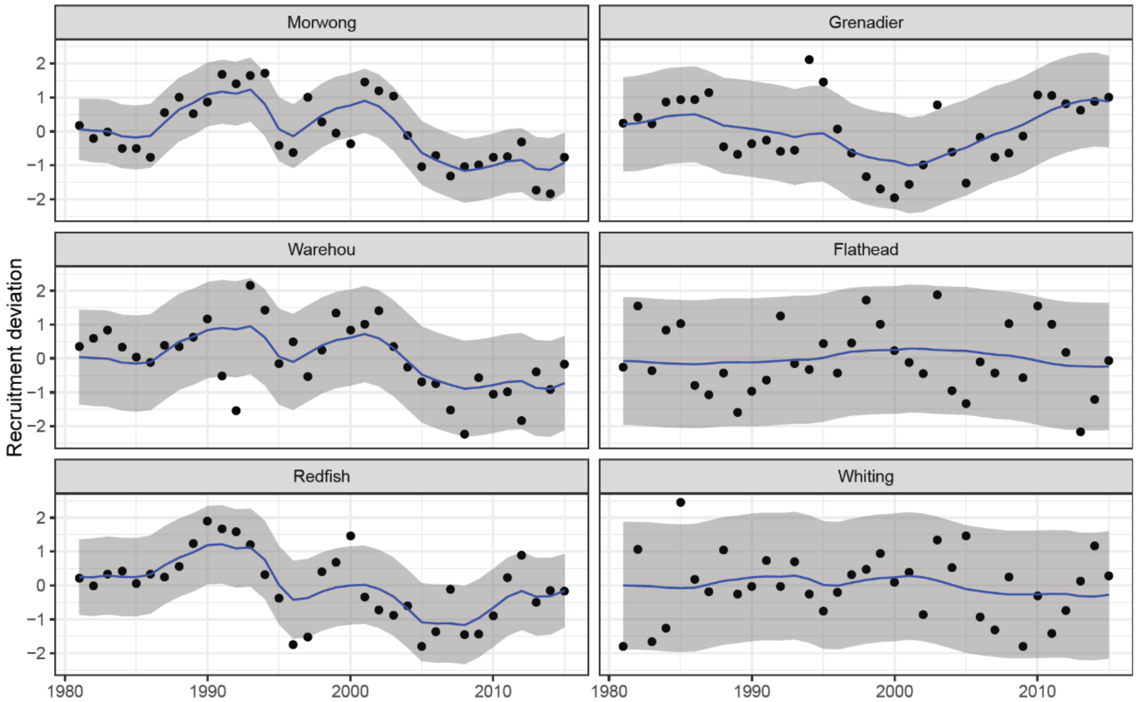


Figure 7-36. DFA model fits (blue lines with shaded 95% CIs) to the recruitment deviations for six SESSF stocks (points) over the period 1981–2015, based on fitting two underlying trends.

In looking at the 'fits' of the underlying DFA trends to the recruitment deviation estimates for each stock, it is important to realise that poor fits are expected and are as informative as good fits. Given multiples stocks, some of which may have correlated trends in recruitment deviations and some of which will not, extremely poor fits are expected for the stocks that are not correlated to others. That is what is seen here, with the underlying trends providing a reasonable fit to the recruitment deviations for Jackass Morwong, increasingly poorer fits to Silver Warehou and Redfish, and no fit at all to Tiger Flathead and Eastern School Whiting.

Fitting one underlying trend to six stocks

The second best model indicated by AICc in Table 7-6 was obtained using a 'diagonal and equal' model with two underlying trends (Δ AICc 0.57). The results were very similar to the 'diagonal and unequal' two trends model, and so are not shown here. The 'diagonal and equal' two trends model showed a similar first trend with slightly lower factor loadings for Jackass Morwong east, Silver Warehou and Redfish, and an identical second trend (and factor loadings). The third best model was obtained using a 'diagonal and unequal' model to fit a single trend to all six stocks (Δ AICc 0.72). The resulting single trend from this model is shown in Figure 7-37 and the factor loadings, showing the relative contribution of each recruitment deviation time series to this trend, are shown in Figure 7-38.

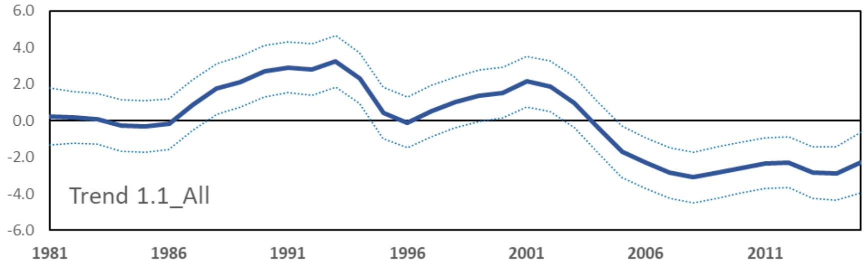


Figure 7-37. Underlying trend detected by a DFA model fit to recruitment deviations for six SESSF stocks over the period 1981–2015, with the model specified to fit one trends to a 'diagonal and unequal' variance-covariance matrix.

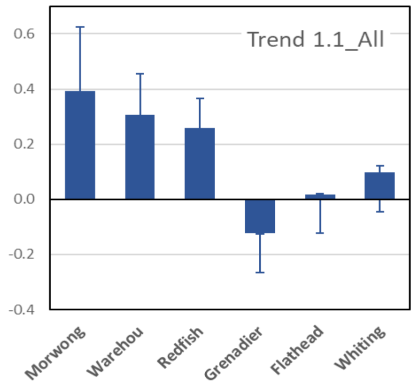


Figure 7-38. Factor loadings for each stock resulting from fitting of one underlying trend to recruitment deviations for six SESSF stocks over the period 1981–2015.

The fits of a single underlying trend to the six stocks results in a very similar predictions as for the first trend in the two-trend model (Figure 7-39).

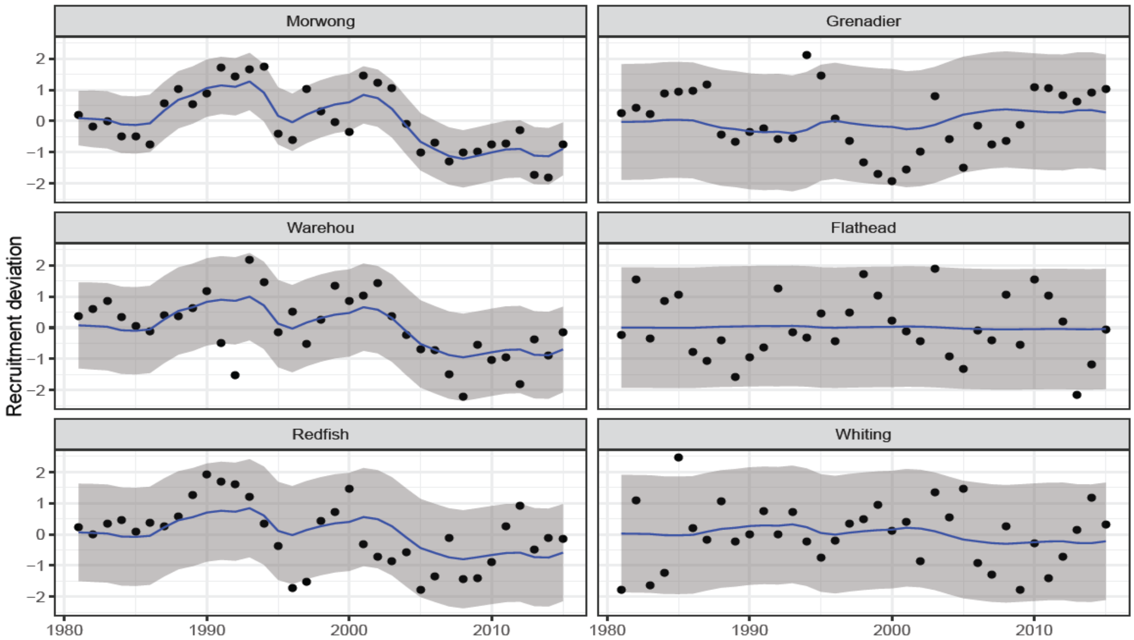


Figure 7-39. DFA model fits (blue lines with shaded 95% Cis) to recruitment deviations for six SESSF stocks over the period 1981–2015, fitting one underlying trend to the recruitment deviation series for each stock.

Allowing for only one trend provides similar fits as the two-trend model for Jackass Morwong east, Silver Warehou and Redfish, with a good fit for Jackass Morwong east, a moderately good fit for Silver Warehou and slightly poorer fit for Redfish. The poorer fit for Redfish results from the fact that the second trend in the two-trend model was partially related to Redfish. Not allowing for a second trend (which in the two-trend model was primarily related to Blue Grenadier) results in the model not fitting the recruitment deviations for Blue Grenadier, in addition to again not fitting the recruitment deviations Tiger Flathead or Eastern School Whiting, with wide 95% CIs spanning the full range of the recruitment deviations for these three stocks.

Fitting one underlying trend to five stocks

Attempted fitting of three trends to the six stocks resulted in the addition of a third trend entirely driven by Blue Grenadier, closely mirroring the Blue Grenadier recruitment deviations and over-fitting of the Blue Grenadier recruitment deviations (results not shown here). The influence of including Blue Grenadier, as evidenced by the fitting of a separate trend entirely driven by Blue Grenadier in a three-trend analysis, and the fact that Blue Grenadier clusters out separately in the cluster analysis methods used, indicates that Blue Grenadier does not share a common underlying recruitment deviation trend with the other stocks and could be excluded from the DFA analysis. The DFA trend analyses were therefore repeated excluding Blue Grenadier, to determine underlying trends using only five stocks.

An exploratory suite of models was again fitted to the normalised recruitment deviations for the five stocks, excluding Blue Grenadier, exploring four options for the variance-covariance matrix structure and from one to four underlying trends. The model with a 'diagonal and unequal' variance-covariance matrix and one underlying trend provided the best model (Table 7-7, model 5, lowest AICc 468.6). A single-trend analysis was therefore run for the five stocks using this model.

Table 7-7. Model specifications and fits (log Likelihood and AICc) for the four DFA models with diagonal and unequal variance-covariance matrix tested for fitting recruitment deviations for five SESSF stocks, excluding Blue Grenadier. The best fit (model 4, AICc 468.6) with one underlying trend is bolded.

Model	R matrix form	Trends	Log-Likelihood	K	AICc	Δ AICc
5	**diagonal and unequal**	**1**	**-223.647**	**10**	**468.6**	**0.00**
6	diagonal and unequal	2	-221.001	14	472.6	3.99
7	diagonal and unequal	3	-221.093	17	480.1	11.45
8	diagonal and unequal	4	-221.090	19	485.1	16.45

The resulting single trend (Trend 1.1_NoGren) fitted to the recruitment deviations for the five stocks (i.e., excluding Blue Grenadier), is shown in Figure 7-40 and the factor loadings for this trend are shown in Figure 7-41.

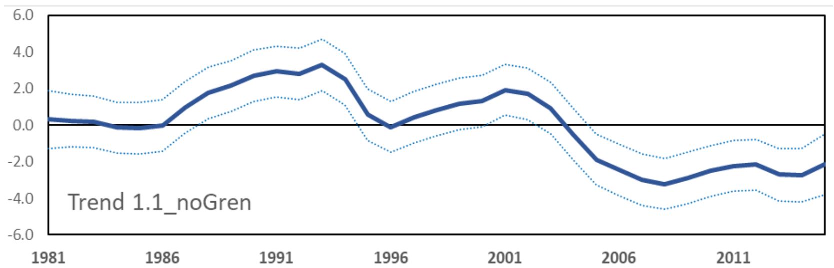


Figure 7-40. Underlying trend detected by a DFA model fit to recruitment deviation series for five SESSF stocks, excluding Blue Grenadier, over the period 1981–2015, with the model specified to fit one trend to an 'unequal and diagonal' variance-covariance matrix.

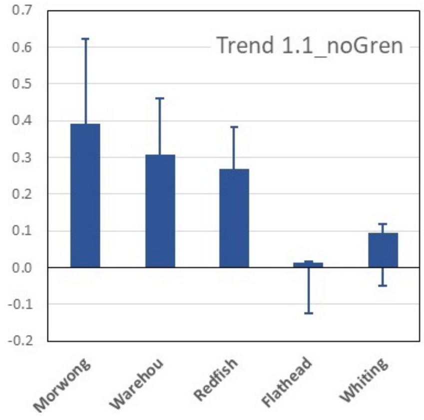


Figure 7-41. Factor loadings for each stock resulting from fitting of one underlying trend to the recruitment deviations for five SESSF stocks, excluding Blue Grenadier, over the period 1981–2015.

The single trend fitted to the recruitment deviations for the five stocks is quite similar to the first trend in the two-trend model (Figure 7-34) and virtually identical to the single trend fitted to six stocks (Figure 7-37). As indicated by factor loadings (Figure 7-41), this trend is primarily related to recruitment deviation series for Jackass Morwong east, Silver Warehou and Redfish. The DFA model fits resulting from the combined fitting of these three underlying trends to the recruitment deviations for the five stocks are shown in Figure 7-42.

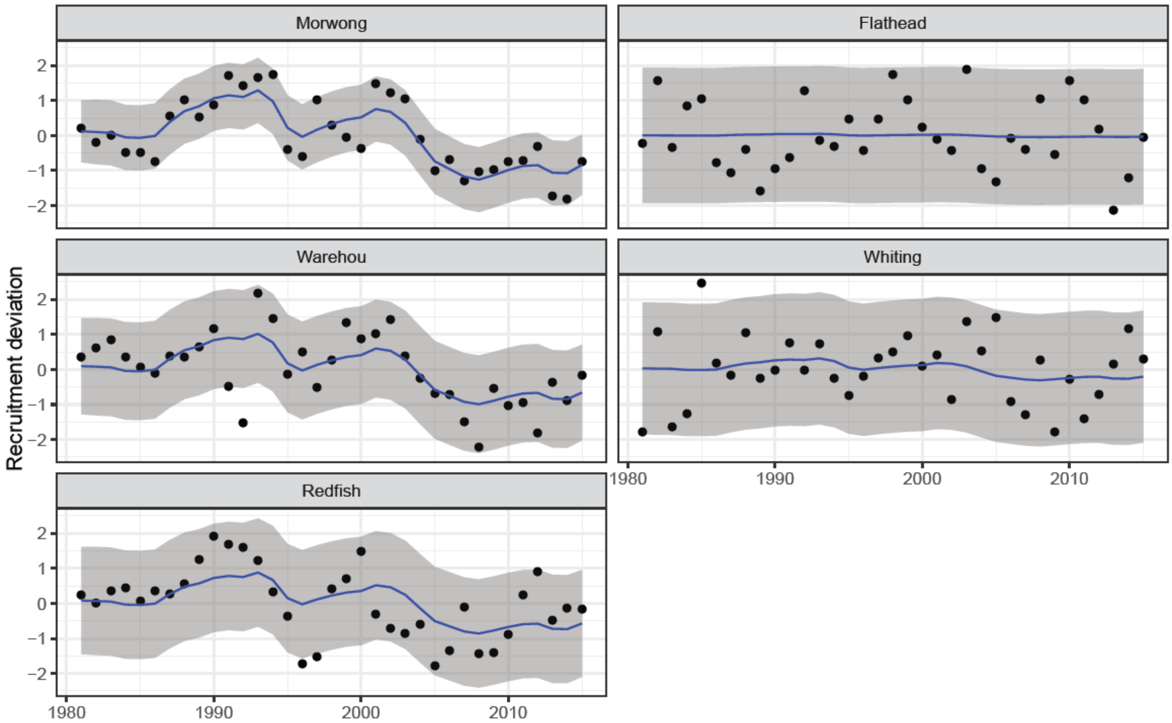


Figure 7-42. DFA model fits to recruitment deviation series for five SESSF stocks, excluding Blue Grenadier, over the period 1981–2015, fitting one underlying trend to the recruitment deviation series for each stock.

Allowing for only one trend across five stocks (excluding Blue Grenadier) (Figure 7-42) results in almost identical fits to recruitment deviations for Jackass Morwong east, Silver Warehou and Redfish as given by the single trend model fitted to six stocks (Figure 7-39). The analysis is again unable to mic the recruitment deviations for Tiger Flathead or Eastern School Whiting, with wide 95% CIs spanning the full range of the data.

Attempted fitting of two trends to five stocks (excluding Blue Grenadier) resulted in a second trend entirely driven by Redfish (essentially mirroring the Redfish recruitment deviations), with resulting over-fitting of the Redfish recruitment deviations (results not shown here). Using the same methodology, Castillo -Jordán *et al.* (2015) identified three dominant recruitment patterns across 30 stocks from Australia, New Zealand, Chile, South Africa, and the Falkland Islands using data from 1980 to 2010. Stocks of hakes and lings from Australia, New Zealand, Chile, and South Africa exhibited a detectable degree of synchrony among species.

7.4.5. Correlation of recruitment deviation trends with environmental indices

Southern Pacific region environmental indices

The identification of a consistent DFA trend underlying the recruitment deviations for Jackass Morwong east, Silver Warehou and Redfish raises the question of whether any correlation can be found between the DFA trends and environmental indices for the southern Pacific region. Castillo-Jordán *et al.* (2015) explored the correlation between trends in recruitment deviations with three ocean basin-scale environmental indices relevant to the southern Pacific Ocean region: the Interdecadal Pacific Oscillation (IPO), Southern Oscillation Index (SOI) and the Southern Annular Mode (SAM). They found that the IPO and SOI showed the strongest correlation with New Zealand Hoki (same species as Blue Grenadier, *Macruronus novaezelandiae*) and Australian Jackass Morwong (*Nemadactylus macropterus*) (r = 0.50 and r = –0.50). Plagányi *et al.* (2021b) also identified the SOI as being correlated with recruitment of Redleg Banana Prawn, with poor prawn catch years being related to the January level of the Southern Oscillation Index (as a proxy for sea level) and the combined January to February rainfall.

Monthly values for these and related indices were obtained from: Pacific Decadal Oscillation (~IPO) https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/pdo.long.data; the Tripole Index for the Interdecadal Pacific Oscillation (TPI) https://psl.noaa.gov/data/timeseries/IPOTPI/tpi.timeseries.ersstv5.data; the Southern Oscillation Index Standardised (SOI) https://www.ncdc.noaa.gov/teleconnections/enso/soi; Antarctic Oscillation Index (~Southern Annular Mode, AA–, ~SAM) - https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/aao/monthly.aao.index.b79.current.ascii.table. Tables of monthly index values were obtained and averaged across months to generate average annual indices over 1975–2015, shown in Figure 7-43.

These indices for the South Pacific region are inevitably correlated, being generated using the same variables from similar oceanic areas (sea surface height, sea surface temperatures, wind direction and strength). It is visually apparent that the TPI and SOI are closely inversely correlated (Figure 7-43). Spearman rank correlations between these four indices are summarised in Table 7-8. The Tripole Index for the Interdecadal Pacific Oscillation (TPI) is closely inversely correlated with the SOI (ρ = -0.94), the two indices essentially being the inverse of each other. The TPI is highly correlated with the PDO (ρ = 0.68). As a result, the SOI is inversely correlated with the PDO (ρ = -0.61).

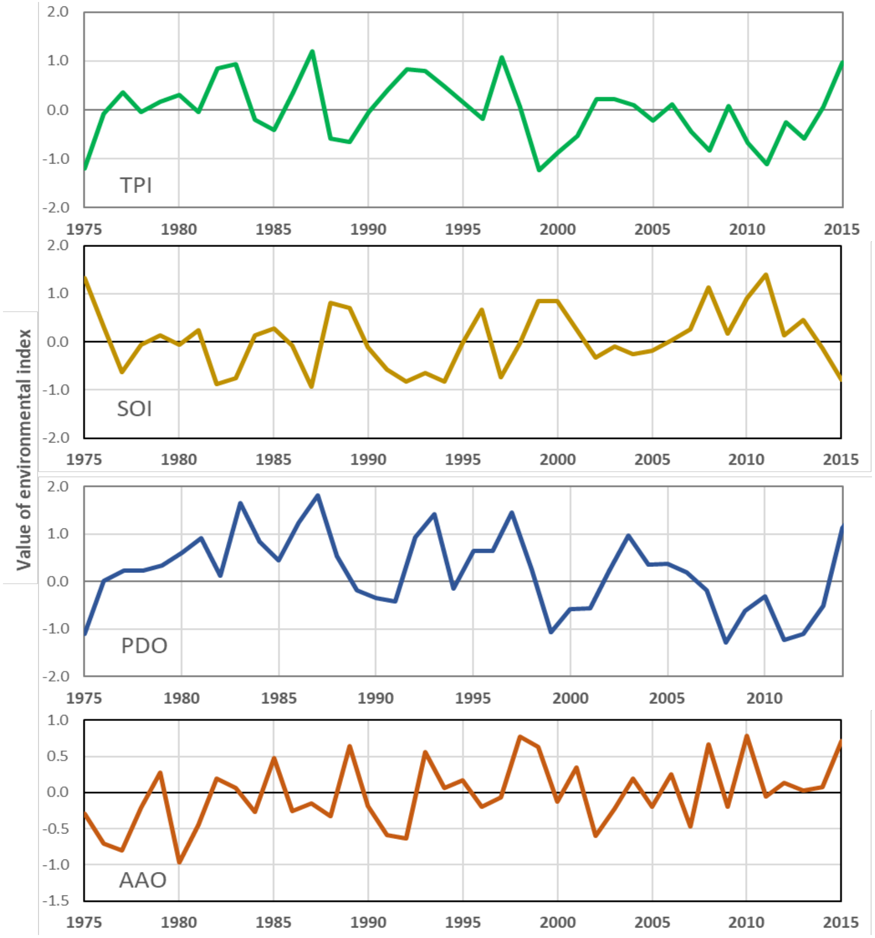


Figure 7-43. Average annual values over 1975–2015 for the Tripole Index (Interdecadal Pacific Oscillation) (TPI), the Southern Oscillation Index (SOI), the Pacific Decadal Oscillation (PDO) and the Antarctic Oscillation (Southern Annular Mode) (AAO).

Variance inflation factors (VIFs) for these indices confirm a high degree of collinearity between the inversely correlated TPI and SOI, and the other indices (Table 7-9), indicating that they should not be used together as predictors of recruitment deviations for SESSF stocks. Avoiding using environmental indices that are significantly correlated with one another means that only one of the correlated SOI, TPI and PDO indices can be used, with the AAO being the only index not correlated with the other three. This is not unexpected, given that the first three relate to the southern Pacific Ocean whereas the AAO relates to the Southern Ocean.

Table 7-8. Spearman rank correlations (above the diagonal) between southern Pacific region environmental indices over 1970–2015, with probability values (below the diagonal). Bolded *p*-values indicate a 99% probability that the two indices do not differ significantly from one another. Indices are the Tripole Index for the Interdecadal Pacific Oscillation (TPI), Southern Oscillation Index (SOI), Pacific Decadal Oscillation (PDO), and the Antarctic Oscillation (~Southern Annular Mode) (AAO).

Index	TPI	SOI	PDO	AAO
TPI		-0.94	0.68	-0.06
SOI	**0.00**		-0.61	0.04
PDO	**0.00**	**0.00**		0.03
AAO	0.30	0.31	0.31	

Table 7-9. Variance inflation factors (VFIs) indicating the degree of collinearity between alternative southern Pacific environmental indices as potential predictors for recruitment deviations. VIF factors > 10 are considered to indicate high collinearity of those variables with others, indicating that they should not be used as independent predictors together with the other variables.

Index	VIF
AAO	1.04
PDO	2.58
SOI	10.39
TPI	13.88

Choice of DFA trend to use with environmental correlations

The primary trends found in all of the DFA analyses are highly correlated (r^2 = 0.96–1.00, Figure 7-34, Figure 7-37 and Figure 7-40), with all analyses essentially finding the same primary trend driven by recruitment deviations for Jackass Morwong east, Silver Warehou and (to a lesser extent depending on whether 2nd and 3rd trends are estimated) Redfish. Addition of a second trend (primarily related to Blue Grenadier) or removal of Blue Grenadier from analysis, resulted in only slight differences to the primary trend. Given that recruitment deviations for Blue Grenadier do not appear to be correlated with those for any of the other stocks, the single trend, no Blue Grenadier DFA analysis primary trend T1.1_noG (Figure 7-40) was used to investigate possible correlations between the DFA trend underlying recruitment deviations for Jackass Morwong east, Silver Warehou and Redfish, and the various southern Pacific Ocean environmental indices.

DFA trend correlations with environmental indices

The most likely mechanisms for environmental effects on abundance of age zero recruits are effects on egg production, as a result of impacts on adult nutrition and fecundity, or effects on larval and juvenile survival rates due to changes in the environmental carrying capacity for larvae or juveniles (Maunder 2022). It would be expected that there would be a lag of at least one year between the effects of an environmental index on spawning and larval production, and subsequent recruitment of age zero fish to the population. Spearman correlations between the DFA trend T1.1_noG and the southern Pacific environmental indices with a lag of one year are shown in Table 7-10.

Table 7-10. Spearman rank correlations between the primary (no Blue Grenadier) DFA trend T1.1_noG and four ocean-basin environmental indices for the southern Pacific region over the period 1981–2015, with a lag of one year between the environmental indices and the DFA trend.

Index	TPI Lag_1	SOI Lag_1	PDO Lag_1	AAO Lag_1
T1.1_NoG	0.238	-0.269	0.226	-0.149

Correlations between DFA trend T1.1_noG and environmental indices Lag_1 are weak and non-significant at $p < 0.05$, with the highest correlation being -0.269 with the SOI. A comparison of DFA trend T1.1_noG against the SOI Lag_1 (Figure 7-44 a) shows that this weak negative correlation results from periods of substantial difference between the DFA trend T1.1_noG and the SOI, e.g. over 1990–1995 and from 2004 onwards. However, there are also periods of positive correlation between trend T1.1_noG and the SOI Lag_1, e.g. 1981–1990 and 1996–2004.

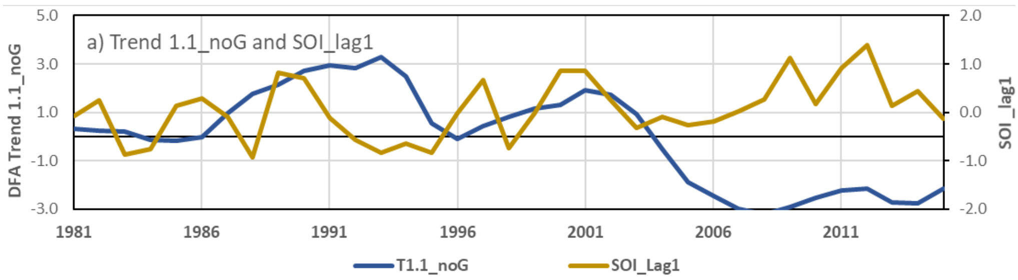


Figure 7-44. Comparison between DFA (no Blue Grenadier) analysis primary trend T1.1_noG and the average annual Southern Oscillation Index (SOI) with a lag of one year.

Inspection of Figure 7-44b indicates that there are extended periods when the slopes (rate and direction of change) of the two trends appear to be similar. This was explored by calculating the interannual slopes ($\delta[T1.1]$ and $\delta[SOI]$) of the T1.1_noG and the loess smoothed SOI Lag_1 trends:

$$\delta[T1.1_y] = T1.1_y - T1.1_{y-1}$$

$$\delta[SOI_y] = SOI_y - SOI_{y-1}$$

The trends in inter-annual slopes are plotted in Figure 7-45 (each normalised to a mean of 0 and standard deviation of 1) and show extended periods of apparent correlation between the inter-annual slopes of trend T1.1_noG and the SOI Lag_1. However, there is clearly an additional lag (>1) in this correlation.

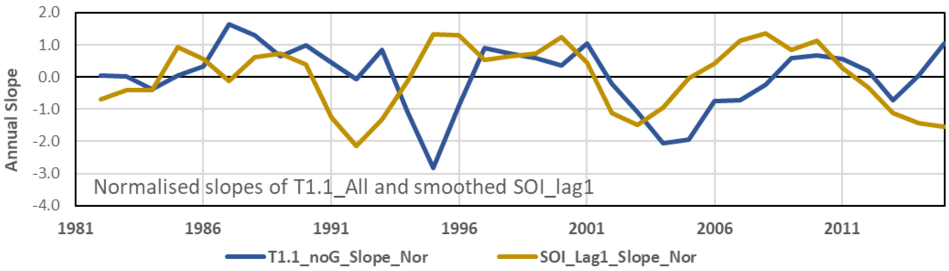


Figure 7-45. Comparison between inter-annual slopes of DFA (no Blue Grenadier) analysis primary trend T1.1_noG and the loess smoothed (period 7 years) SOI Lag_1 (each normalised to a mean of 0 and standard deviation of 1).

Highest correlation between these two trends in slopes is obtained with a lag of three years (ρ= 0.625), with the resulting comparative trends in slopes shown in Figure 7-46.

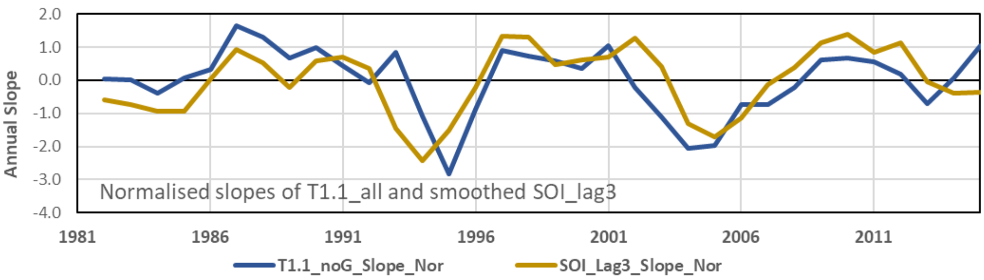


Figure 7-46. Comparison between inter-annual slopes of DFA (no Blue Grenadier) analysis primary trend T1.1_noG and the loess smoothed (period 7 years) SOI Lag_3 (each normalised to a mean of 0 and standard deviation of 1).

Possible mechanisms for environmental correlation with a three-year lag

The apparent correlation between the DFA trend T1.1_noG and SOI Lag_3 is striking, but may be spurious, given the data manipulation required to generate the plots. It does raise the question of how a three-year lag could occur between an environmental index and age 0 recruitment, and why the correlation is evident between rates of change rather than actual values.

The three species with correlated recruitment deviation trends each have an age of maturity around five years, with first maturity around three years. A negative SOI is associated with hotter ambient air temperatures and low rainfall, with less silica injected into local waters. At the time the fish were planktonic or early settlers, inshore or estuarine associated individuals would have poor physical conditions and those with oceanic larvae initially would be experiencing primary production in the lowest 10% of historical time series (Dr Beth Fulton pers comm). The correlation between slopes of these indices, rather than the indices themselves, would suggest that the effect of an environmental change results not just from the change, but from the rate of change (the interannual slope of the SOI), with more rapid environmental changes having a greater effect.

It would be challenging to incorporate this complex relationship into stock assessments and would not be justified without further exploration of how such a relationship could occur. It is likely that we will never be able to reliably identify the specific mechanisms by which environmental factors influence stock productivity and are certainly unlikely to ever obtain adequate data to incorporate into stock assessments. The deviation of dynamic B_0 from static B_0 would include such effects, with dynamic reference points potentially being able to compensate for such environmental effects despite the mechanism being unknown.

7.4.6. Conclusions

- Trends in recruitment deviation for Jackass Morwong east, Silver Warehou and Redfish over 1981–2015 are correlated, and can be reasonably well fitted by the primary underlying trend fitted using dynamic factor analysis.
- If two DFA trends are estimated, then the second trend is primarily driven by Blue Grenadier. If three trends are fitted to six stocks, then the second trend is strongly driven by Redfish and the third trend overfits Blue Grenadier. If two trends are estimated based on recruitment deviations for five stocks, excluding Blue Grenadier, then the second trend overfits Redfish.
- There is a weaker but detectable correlation between recruitment deviations for Tiger Flathead and Eastern School Whiting although, when analysed together with the other four stocks, DFA analysis is unable to mimic the recruitment deviations for these two stocks. Blue Grenadier shows little correlation in recruitment deviation trends with the other five stocks.
- There are decadal peaks and troughs in the first DFA trend driven by Jackass Morwong east, Silver Warehou and Redfish. There are decadal cyclical trends in the Southern Oscillation Index, but the correlation with the DFA at a lag of one year is weak.
- There is an apparent, but possibly spurious (given the number of correlations examined) correlation between the slopes of the DFA primary trend and the Southern Oscillation Index, with correlation being highest with a lag of three years. This three-year lag in environmental impact might indicate that environmental effects are impacting adult fish nutrition and fecundity over an extended period.

7.5. Historical trends in fishing intensity

The predominant concern raised by stakeholders and fisheries managers during stakeholder consultations has been that declines in recruitment and production for SESSF stocks may have been mainly the result of overfishing, and that it would be incorrect to attribute these declines to environmental factors. Adoption of dynamic targets and limits where environmental factors were not the predominant cause of declines in production may result in ongoing over-fishing and further depletion of the stock.

In addition to evaluating the available evidence for environmental effects on productivity and stock size, this project has therefore also evaluated the relative levels of over-catch and overfishing for the SESSF and northern crustacean case study stocks, as estimated by retrospective re-running of the most recent Tier 1 assessments for these stocks and retrospective application of harvest control rules to estimate illustrative RBCs, had the dynamic B_0 HCRs been applied at the time.

7.5.1. Evaluation of historical over-catch

This section summarises aspects of the work published in:

Bessell-Browne, P., Punt, A.E., Tuck, G.N., Day, J., Klaer, N., Penney, A., 2022. The effects of implementing a 'dynamic B_0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. Fisheries Research 252, 106306
https://doi.org/10.1016/j.fishres.2022.106306

Results of retrospective assessments for the SESSF case study stocks conducted under this project have been published in a scientific paper (Bessell-Browne *et al.* 2022, Appendix 16.1). These results include calculation of historical illustrative RBCs that would have been recommended each year, given the retrospective estimated annual depletion and estimates of F_{Target}, if all other aspects of the assessment had remained as estimated in each year and the current SESSF harvest control rule had been applied historically. It should be noted that the current SESSF harvest control rule has only been applied since 2006.

A similar analysis was applied to results from retrospective re-running of recent assessments for Torres Strait Ornate Rock Lobster (ORL) and northern Redleg Banana Prawn (RBP), applying theoretical control rules that reduced F from F_{Targ} at B_{Targ} to zero at B_{Lim}. These HCRs are not currently used for ORL or RBP management and were not used for either stock prior to about 2005 but were applied retrospectively here to calculate illustrative historical RBCs for comparison with catches. HCR specifications used to calculate retrospective, illustrative RBCs for the two crustacean stocks were: ORL: $F_{\text{Targ}} = 0.163$, $B_{\text{Targ}}/B_0 = 0.480$, $B_{\text{Lim}}/B_0 = 0.320$; RBP: $F_{\text{Targ}} = 0.140$, $B_{\text{MEY}}/B_0 = 0.55\text{B}_0$, $B_{\text{Lim}}/B_0 = 0.230$. Comparison of historical trends in catch and retrospective RBCs from these assessments for the six SESSF stocks and two northern crustacean stocks are shown in Figure 7-47.

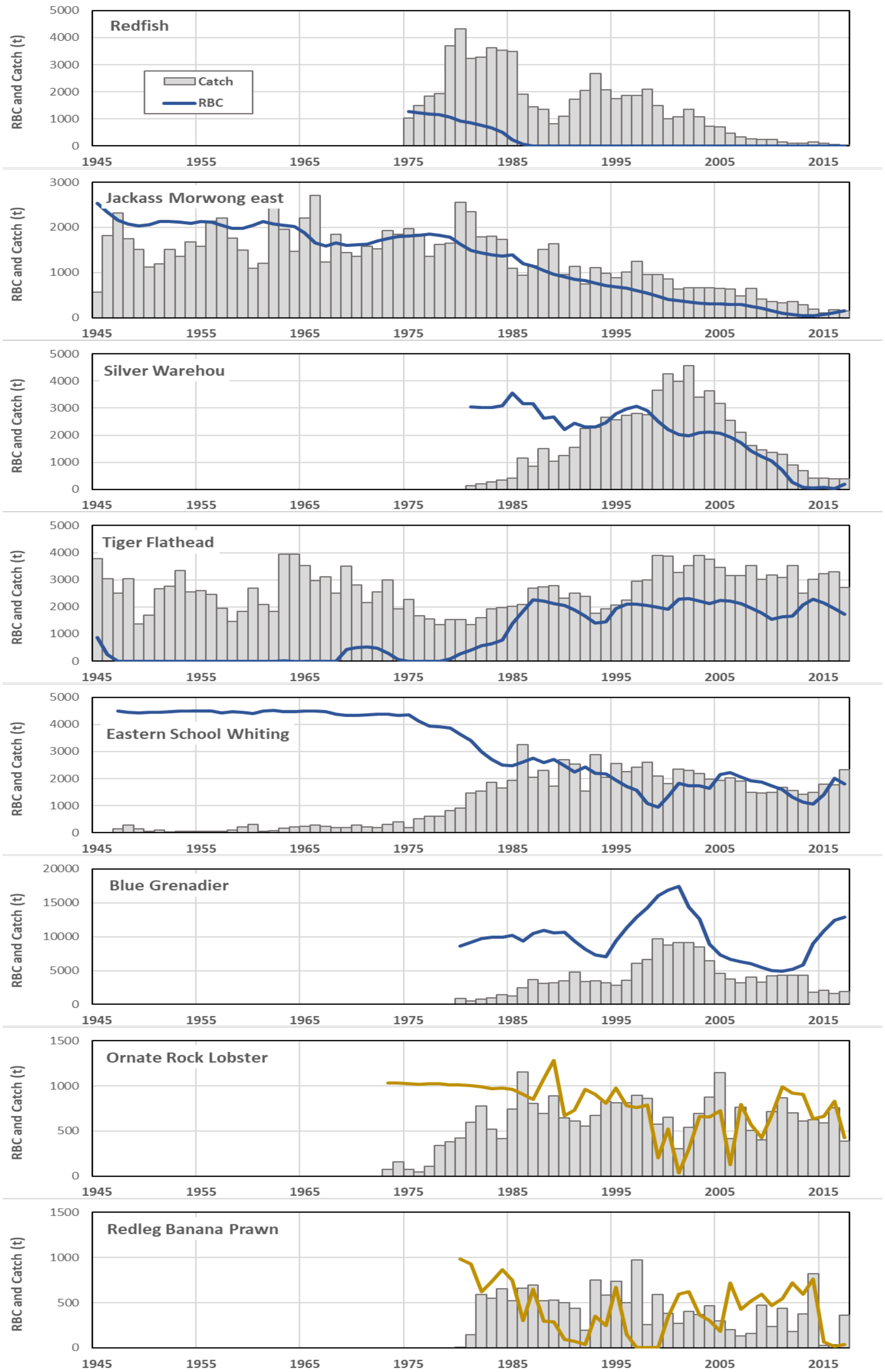


Figure 7-47. Comparison of historical catches of six SESSF and two northern crustacean stocks, and retrospective recommended biological catches (RBCs) that would have been recommended had the current SESSF 20:35:48 harvest control rule been applied to the estimate historical depletion of SESSF stocks against static B_0, and similar harvest control rules been applied to the crustacean stocks.

Number of years of over-catch

To provide aggregated indices for historical over-catch, differences between historical catches and retrospective (illustrative) RBCs are summarised in several ways. Number of years of over-catch is simply the count of the number of years in a chosen period with Catch > RBC. The number of years for which retrospective (and not implemented) RBCs were exceeded over 1975–2017 is shown for the six SESSF stocks and two northern crustacean stocks in Figure 7-48. This shows that reported catches exceeded retrospective RBCs in more than 10 years for all stocks other than Blue Grenadier. However, these results are misleading as annual over-catches of all of but three of these stocks were small, with under-catches in other years, resulting in an overall under-catch (summed over the entire time series) for all stocks other than Redfish, Tiger Flathead and Jackass Morwong east.

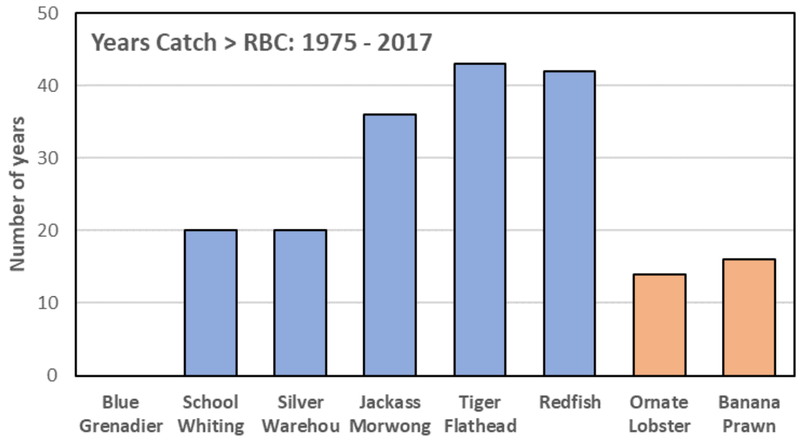


Figure 7-48. Number of years in which Catch > RBC for six SESSF stocks and two northern crustacean stocks over 1975–2017. Note that the number of years with assessment estimates differs among stocks, with some series starting after 1975 (see Figure 7-47).

Average annual Over-catch

The number of years in which Catch > RBC (Figure 7-48) is not a particularly useful measure of over-catch. It is more meaningful to quantify the overall or average magnitude of over-catch over the chosen period. The annual average over-catch needs to be used if the periods of years covered by retrospective assessments differs for different stocks, as it does for the stocks in Figure 7-47. Average annual over-catch can be calculated as:

$$\frac{\sum_{y=1}^{n}(C_y - RBC_y)}{n}$$

where n is the number of years in the series
$y = 1$ is the start year in the historical series
$y = n$ is the end year in the series
C is the catch during year y
RBC is the retrospective RBC during year y

This provides a measure of the average annual tonnage of over-catch (or under-catch) over a chosen period of years, intuitively easy for stakeholders to understand, with positive values indicating over-catch and negative values indicating under-catch. Estimated average annual over-catches for the six SESSF and two northern crustacean case study stocks are shown in Figure 7-49.

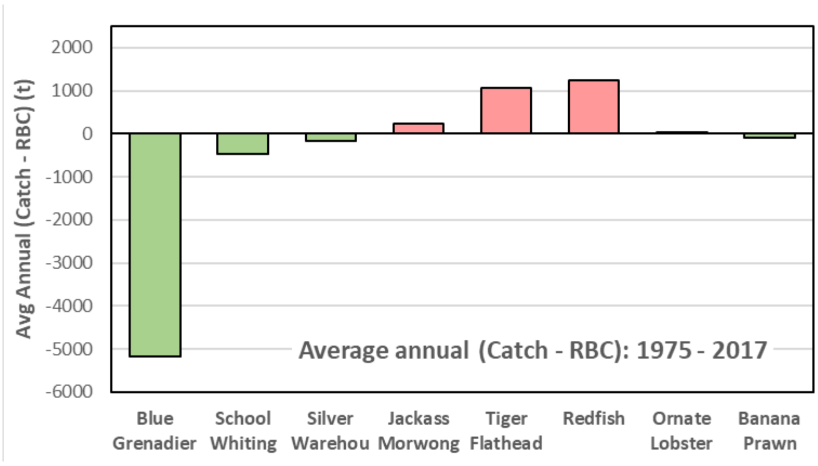


Figure 7-49. Average annual over-catch (Catch – RBC) (t) for six SESSF stocks and two northern crustacean stocks over the period 1975–2017.

Using this measure, the only stocks with an average annual over-catch were Redfish, Tiger Flathead and Jackass Morwong east. The retrospective average annual over-catch of Redfish over 1975–2017 was 1,255 t/year, largely over 1979–1985, and from 1985–2005 when RBCs would have been zero had the SESSF HCR been applied at the time. In contrast, Blue Grenadier was under-caught over 1975–2017 by an average 5,184 t/year, primarily due to lack of capacity in the fishing fleet to exploit sudden and large increases in biomass. The other stocks which for which there were more than 10 years of over-catch had average annual catches near of slightly below the average RBCs.

Average over-catch ratio

Average annual over-catch expressed as the difference between Catch and RBC in tons will provide larger estimates of over-catch for larger stocks with inherently larger RBCs and catches, making comparison between large and small stocks using this measure misleading. This issue can be removed by expressing over-catch as the ratio of Catch/RBC. For the over-catch ratio measure it is necessary to first sum catches and RBCs over the chosen period of years before calculating the Catch/RBC ratio, because RBCs have been set to zero for several years for stocks such as Redfish, which would result in undefined values for the Catch/RBC ratio in those years. The ratio was therefore calculated using sums over the entire chosen time period:

$$\frac{\sum_{y=1}^{n} C_y}{\sum_{y=1}^{n} RBC_y}$$

where *n* is the number of years in the series
y = 1 is the start year in the historical series
y = *n* is the end year in the series
C is the catch during year *y*
RBC is the retrospective RBC during year *y*

This results in ratio values > 1 for over-catch, and < 1 for under-catch. This measure can be expressed in log-space, which results in positive values for ratios > 1 (over-catch) and negative values for ratios < 1 (under-catch), making the distinction visually clearer.

$$ln\left(\frac{\sum_{y=1}^{n} C_y}{\sum_{y=1}^{n} RBC_y}\right)$$

This measure avoids the problem of over-catch tonnages being larger for large stocks, making comparison of over-catch ratios between stocks more meaningful. Using this measure, the over-catch ratio for Redfish over 1975–2017 is 6.44 (log ratio 1.86) where the ratio for Blue Grenadier is 0.40 (log ratio -0.91). Comparisons of the linear and log overfishing ratios for the six SESSF stocks over 1975–2017 are shown in Figure 7-50. This comparison emphasises the over-catch of Redfish over 1975–2017, with annual catches over the period estimated to be over six times the retrospective RBCs that would have been recommended had the SESSF HCR been applied at the time. In comparison, historical average over-catches of Tiger Flathead and Jackass Morwong east were moderate, catches of ORL were very close to RBCs and the other stocks were under-caught.

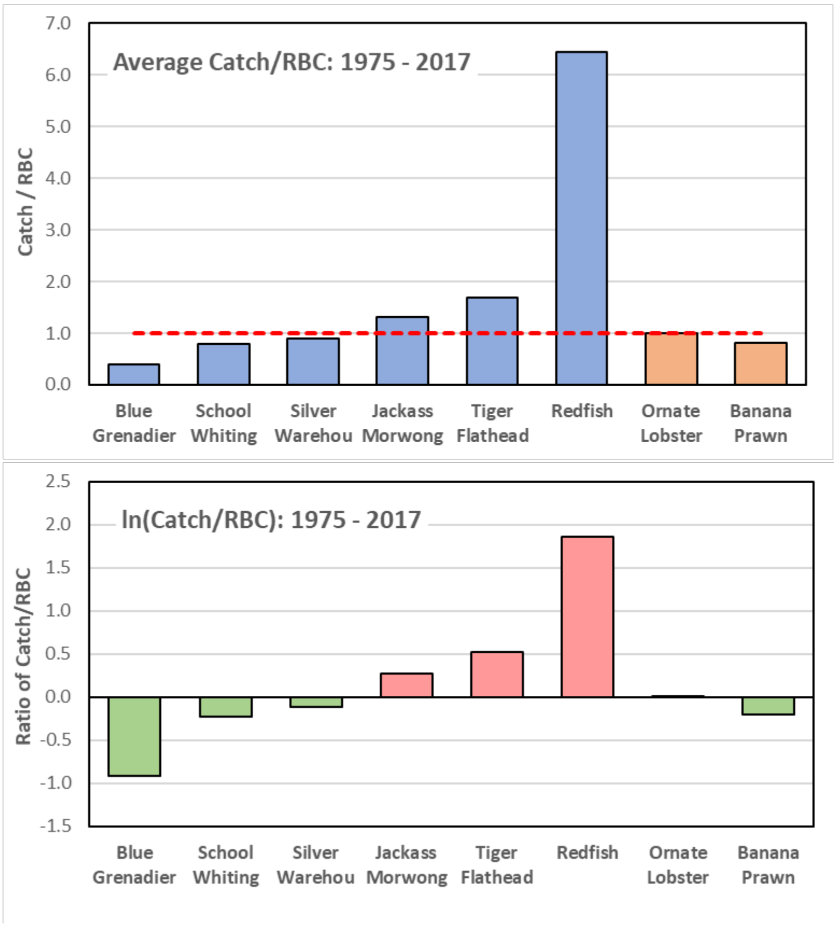


Figure 7-50. Comparison of over-catch ratios (Catch/RBC) for six SESSF stocks over the period 1975–2017 expressed in linear (top panel) and log (bottom panel) space. The optimal fishing level (Catch = RBC) is 1 in the top plot and 0 in the bottom plot, distinguishing between overcaught and undercaught stocks.

7.5.2. Evaluation of historical overfishing

The above measures of over-catch are intuitively easy to understand. However, the effects of fishing derived from stock assessments are more usually expressed using some measure of fishing intensity compared to a fishing intensity level calculated to maintain the stock near a specified biomass target. This is related to the fact that HCRs are typically expressed in terms of fishing mortality rates, with fishing intensity being expressed in terms of annual fishing mortality rate compared to a target fishing mortality rate, such as F/F_{MSY}, in 'Kobe' plots developed to show stock status trajectories in terms of B vs. F for international tuna fisheries. Cordue (2012) provides a fishing intensity metric based on spawning potential ratios (SPR) to provide for comparability in estimated fishing intensity across years for fisheries with changing relative effort across multiple fleets with differing selectivities and relative fleet *F*'s.

To provide a measure of overfishing, estimated annual 1-SPR fishing intensity values are expressed as ratios of 1-SPR_{Target}, which can then be plotted against depletion (B/B_0) to provide historical stock status trajectory plots (see 'Kobe' plots in recent stock assessments for Jackass Morwong east (Day *et al.* 2021) and Silver Warehou (Bessell-Browne and Day 2021)). Using this ratio implies that values of (1-SPR) > (1-SPR_{Target}) indicate overfishing, being fishing intensity levels above those required to rebuild the stock to, and maintain the stock near, the target biomass level. This definition of overfishing is consistent with UN General Assembly requirement that "*The fishing mortality rate which generates maximum sustainable yield should be regarded as a minimum standard for limit reference points*" (UNGA 1995, Annex II), with technical justification provided by Caddy and Mahon (1995).

Average overfishing ratio

Historical trends in inter-annual (1-SPR)/(1-SPR_{Target}) were generated from results of the retrospective re-assessments for the six SESSF stocks. To provide average values for comparison with the average over-catch measures per stock, these fishing intensity trends were averaged by year over 1975-2017 to provide average overfishing ratios, calculated as:

$$\left(\sum_{y=1}^{n} {(1-SPR_y)}\Big/{(1-SPR_{Targ})}\right)\Big/n$$

where *n* is the number of years in the series
y = 1 is the start year in the historical series
y = n is the end year in the series
SPR_y is the spawning potential ratio during year y
SPR_{Targ} is the spawning potential ratio required to maintain the stock at the target *B* level

Stock assessments for ORL and RBP are conducted using bespoke models that do not generate estimates of 1-SPR. For these two crustacean stocks, comparable fishing intensity measures were calculated using F/F_{Targ} instead, calculated as:

$$\left(\sum_{y=1}^{n} {(F_y)}\Big/{(F_{Targ})}\right)\Big/n$$

where *n* is the number of years in the series
y = 1 is the start year in the historical series
y = n is the end year in the series
F_y is the fishing mortality rate during year y
F_{Targ} is the fishing mortality rate required to maintain the stock at the target *B* level

The resulting average annual overfishing ratios per stock over 1975–2017 are shown in Figure 7-51.

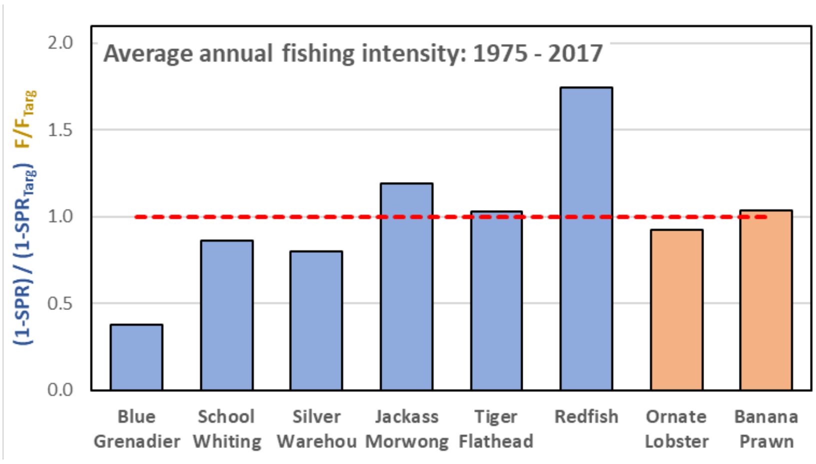


Figure 7-51. Comparison of average annual overfishing ratios *(1-SPR)/(1-SPR$_{Targ}$)* for six SESSF stocks and *F/F$_{Targ}$* for two northern crustacean stocks over 1975–2017. The red dashed line indicates the target fishing intensity level.

Relative overfishing ratios differ slightly the over-catch ratios for some stocks, with overfishing being comparatively lower (in relation to the target) than over-catch for Tiger Flathead, Silver Warehou and Ornate Rock Lobster (compare Figure 7-50 and Figure 7-51).

7.5.3. How did such historical overfishing occur?

Initial results of retrospective re-assessments and comparisons of historical catches and retrospective RBCs were presented to stakeholders at a meeting of the Australian Fisheries Management Authority (AFMA) Southern and Eastern Scalefish and Shark Fishery Resource Assessment Group (SESSF RAG) on 26 August 2021. The question that was immediately raised in response was: How did such levels of over-catch occur for stocks such as Redfish, despite management arrangements for at least part of that time?

The main explanation is that the current SESSF harvest strategy, including the 20:35:48 harvest control rule used to calculate retrospective RBCs used in historical over-catch calculation, was only developed after the 2005 Ministerial Direction to AFMA (Commonwealth of Australia 2005). AFMA itself was only established in February 1992 following promulgation of the Australian Commonwealth *Fisheries Administration Act 1991* and *Fisheries Management Act 1991*, so substantial historical over-catches of e.g. Tiger Flathead and Redfish predate the Commonwealth management arrangements implemented from 2006 onwards.

The Ministerial Direction required AFMA to "*cease overfishing and recover overfished stocks to levels that will ensure long term sustainability*", and it was well understood at the time that SESSF stocks had been over-fished prior to 2005. The Ministerial Direction also included guidance on how cessation of overfishing and recovery of stocks was to be achieved. This guidance contributed to development of the first Harvest Strategy Policy for the SESSF in 2006, and to the Commonwealth Harvest Strategy Policy in 2007. Smith *et al.* (2008) note that the SESSF Harvest Strategy led to substantial reductions in TACs for SESSF stocks, but only from 2006 onwards, with the current SESSF harvest control rule not being used to set TACs prior to 2006.

Most of the retrospectively estimated historical over-catch, calculated by applying the current SESSF harvest control rule back in time, was therefore made before the post-2005 precautionary management arrangements and the 20:35:48 HCR were in place. The relative proportions of over-catch (in years where catches exceeded RBCs, years of under-catch excluded) over 1975–2005 and

2006–2017 are shown in Figure 7-52 for the six SESSF stocks. There were no years of over-catch for Blue Grenadier. 70% of the over-catch of Silver Warehou and 80% of the over-catch of Jackass Morwong east and Eastern School Whiting was made prior to 2006. 96% of the over-catch of Redfish was made prior to 2006. Only for Tiger Flathead have over-catches since 2005 made up a substantial proportion (42%) of the total over-catch over 1975–2017. These results confirm what was known at the time of the Ministerial Direction – SESSF stocks were subject to considerable overfishing prior to 2005.

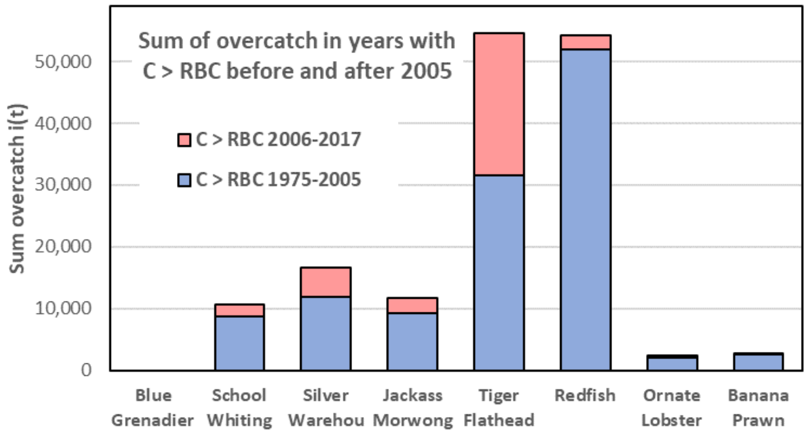


Figure 7-52. Sum of over-catch tonnage (C – RBC) in years where over-catch occurred (C > RBC) for six SESSF stocks over the periods 1975–2005 and 2006–2017.

7.6. Historical trends in dynamic B_0 deviation

Differences in the deviation of estimated dynamic B_0 from static B_0 for the example stocks provides a measure of the degree to which factors other than fishing appear to have caused changes in productivity and production. Where there is an increasing or decreasing trend in this deviation, this would indicate an increase or decrease in production that does not appear to be caused by fishing mortality. A decline in dynamic B_0 to levels well below estimated static B_0 would indicate that factors other than fishing have resulted in a decline in stock productivity and production to below levels seen historically.

The deviation φ_y of dynamic B_0 ($B_{F=0}$) from static B_0 in any particular year *y* can be calculated as:

$$\varphi_y = ln(B_{F=0}/B_0)$$

The annual dynamic B_0 deviations calculated as above are summarised in Figure 7-53 for the six SESSF stocks and two northern crustacean stocks for which dynamic B_0 has been calculated from recent assessments.

Whether the $B_{F=0}$ deviations are positive or negative depends on the value for B_0 for each stock. For the same trend in $B_{F=0}/B_0$ deviation, high values for B_0 will result in most $B_{F=0}$ deviations being negative (such as for Redleg Banana Prawn), while lower B_0 values will result in $B_{F=0}$ deviations being distributed above and below B_0 (such as for Ornate Rock Lobster or Silver Warehou).

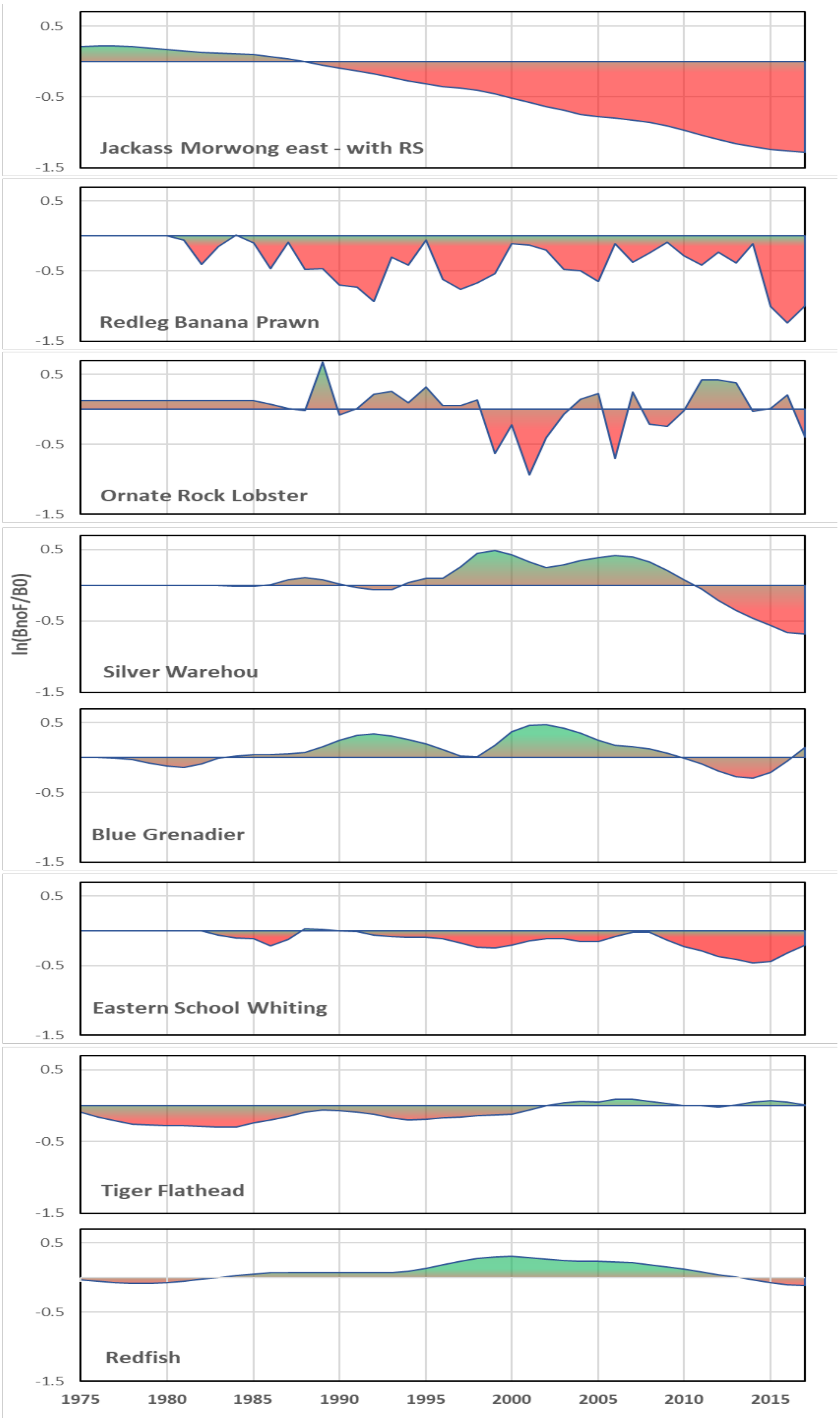


Figure 7-53. Comparison of historical trends in annual dynamic B_0 deviation ($\ln(B_{F=0}/B_0)$) for six SESSF stocks and two northern crustacean stocks over the period 1975–2017, ranked in descending order of summed absolute dynamic $B_{F=0}$ deviation from static B_0.

To obtain a measure of the cumulative, absolute deviation of $B_{F=0}$ from B_0, the effect of the relative position of B_0 can be removed by converting the annual deviations to absolute values, indicating magnitude of deviation from the expected B_0 due to non-fishing effects, either up or down. These can be summed over any chosen period of years to show overall deviation $\boldsymbol{\varphi_{y1,y2}}$ of $B_{F=0}$ above or below static B_0 over years ($y1 - y2$):

$$\boldsymbol{\varphi_{y1,y2}} = \sum_{y=y1}^{y2} \left| \boldsymbol{ln}\left({B^{y}_{F=0}}/{B_0} \right) \right|$$

where $y1$ is the first and $y2$ is the last year in the series of years being summed.

Where different periods of years are to be compared for different stocks, or where some stocks have missing values in a chosen period, the average absolute deviation over different periods for different stocks can be used, as follows:

$$\overline{\boldsymbol{\varphi}}_{y1,y2} = \frac{\sum_{y=y1}^{y2} \left| \boldsymbol{ln}\left({B^{y}_{F=0}}/{B_0} \right) \right|}{\boldsymbol{y2 - y1 + 1}}$$

Over the period 1975–2017, $B_{F=0}$ series for the various stocks start in different years. To compare overall dynamic B_0 deviation between stocks, the average $\overline{\boldsymbol{\varphi}}_{y1,y2}$ was therefore used in Figure 7-54 (over the relevant periods for each stocks) to compare the average (Figure 7-54 top panel) and average absolute (Figure 7-54 bottom panel) $B_{F=0}$ deviations over the period 1975–2017 for each stock, ranked in decreasing order of average absolute dynamic B_0 deviation.

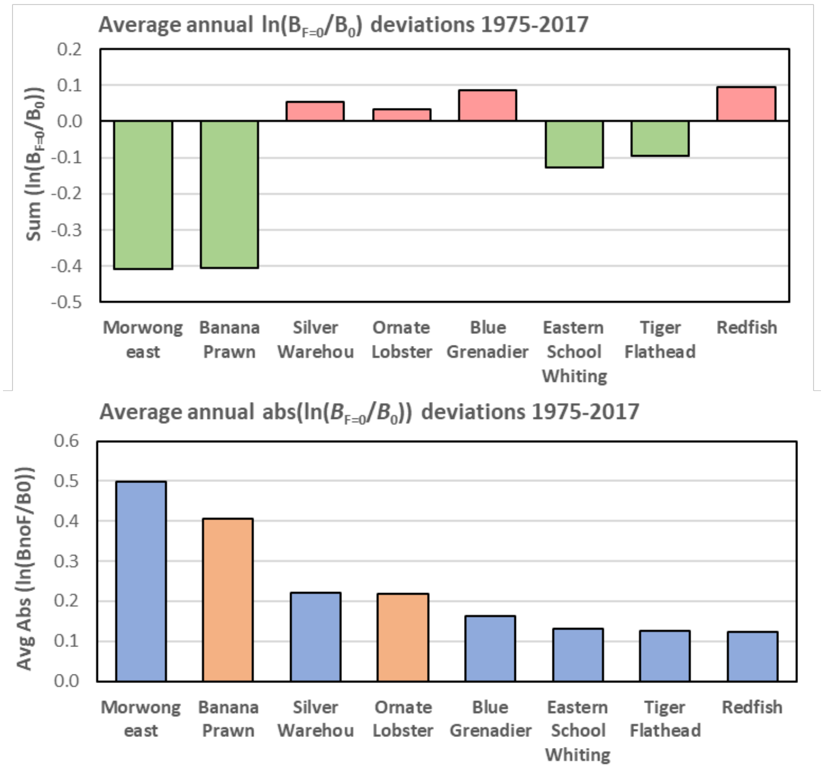


Figure 7-54. Comparison of average annual $ln(B_{F=0}/B_0)$ deviations (top panel) and average absolute annual $ln(B_{F=0}/B_0)$ deviations (bottom panel) over 1975–2017 for five SESSF and two northern crustacean stocks, ranked in descending order of absolute dynamic B_0 deviation, or apparent non-fishing effect.

The magnitude of the average overall deviations in Figure 7-54 provides a comparison of the apparent cumulative non-fishing effects on each stock over 1975–2017, expressed as average deviations (top panel) and absolute average deviations (bottom panel). The two panels provide an interesting contrast between averaging the positive and negative deviations, versus converting these to absolute deviations before averaging them. For example, the overall average dynamic B_0 deviations for TRL is small, as a result of dynamic B_0 fluctuating repeatedly above and below static B_0. In contrast, the overall deviations for Jackass Morwong East and Redleg Banana Prawn are large and negative, as dynamic B_0 is predominantly below static B_0 (see Figure 7-53). These results depend on the position of B_0, as the relative positive vs. negative deviations will shift as B_0 moves up or down.

Looking at absolute average deviations, Jackass Morwong East shows the highest overall level of non-fishing effects, with a high level also for Tropical Rock Lobster. Silver Warehou, Banana Prawn and Blue Grenadier show moderate non-fishing effects while Eastern School Whiting, Tiger Flathead and Redfish show the lowest apparent non-fishing effects.

7.7. Relative fishing vs. non-fishing effects trajectories

The above measures of fishing effects (over-catch and overfishing) and non-fishing effects (as indicated by dynamic B_0 deviation) are summarised in Table 7-11 for the six SESSF stocks and two northern crustacean stocks over 1975–2017.

Table 7-11. Summary of measures of historical over-catch (total and average over-catch, linear and log over-catch ratios), overfishing (1-SPR ratios) and non-fishing effects (dynamic B_0 deviation) for six SESSF stocks and two northern crustacean stocks over 1975–2017.

Index	Blue Grenadier	Eastern School Whiting	Silver Warehou	Jackass Morwong east	Tiger Flathead	Redfish	Ornate Lobster	Banana Prawn
				Over-catch				
Years C>RBC	0	20	20	36	43	42	14	16
Total (C-RBC)	-222,893	-19,942	-7,616	10,242	45,952	53,952	70	-3,590
Average (C-RBC)	-5,184	-464	-177	238	1,069	1,255	2	-94
Avg (C/RBC)	0.403	0.796	0.898	1.310	1.682	6.438	1.004	0.817
ln(Avg(C/RBC))	-0.91	-0.23	-0.11	0.27	0.52	1.86	0.00	-0.20
				Overfishing				
Years (Fishing intensity > Target)	0	15	15	36	23	41	17	16
Avg (Fishing Intensity/Target) ((1-SPR)/(1-SPR_{Targ}) or F/F_{Targ})	0.375	0.863	0.798	1.188	1.029	1.747	0.923	1.034
				Non-fishing effects				
Avg ($\ln(B_{F=0}/B_0)$)	0.088	-0.128	0.055	-0.408	-0.096	0.095	0.034	-0.406
Avg Abs($\ln(B_{F=0}/B_0)$)	0.163	0.131	0.220	0.498	0.125	0.123	0.217	0.407

Having developed measures of fishing and non-fishing effects and used these to derive historical trends and averages over time, these can be combined to generate two-dimensional relative effects trajectory plots. Similar in design and intent to stock status ('Kobe') trajectory plots, Relative Effects TRAjectory plots ('Retra' plots) provide an at-a-glance comparison of the relative historical effects of fishing and non-fishing factors on a stock (as determined from an agreed Tier 1 stock assessment) by plotting an index of fishing intensity against the dynamic B_0 deviation index of non-fishing effects, and allowing one to Retrace the steps that the stock has taken under fishing and non-fishing effects.

Figure 7-55 shows a simplified, averages-only version of such a plot, plotting the average (1-*SPR*)/(1-*SPR*$_{Targ}$) ratios from Figure 7-51 and Table 7-11 against dynamic B_0 deviations from Figure 7-54 (top panel) and Table 7-11 for six SESSF stocks and two northern crustacean stocks over 1975–2017. Standard deviations have been added to these averages to provide information on the ranges in the relative effects for each stock.

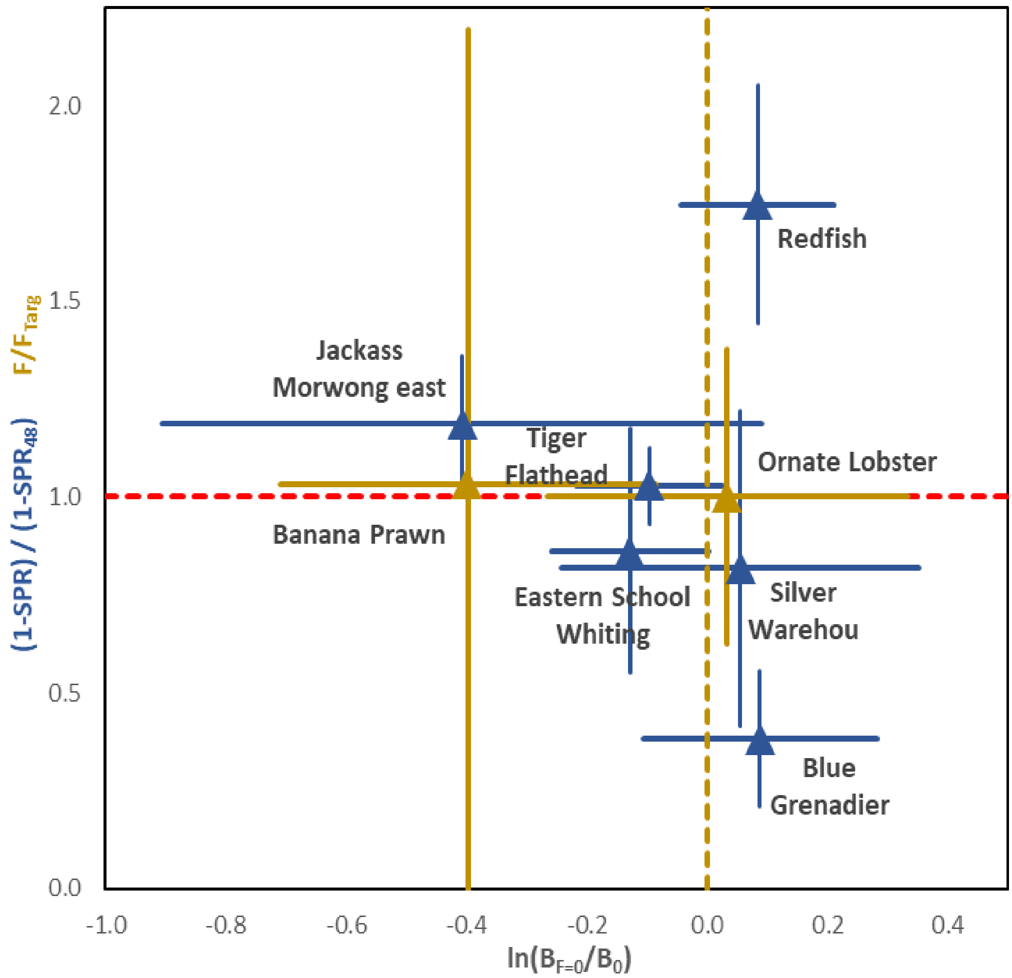


Figure 7-55. Relative effects averages plot showing averages (blue and orange triangles) and standard deviations (horizontal and vertical lines) of fishing intensity ((1-SPR)/(1-SPR$_{Targ}$) or F/F$_{Targ}$) against dynamic *B*$_0$ deviation (ln(*B*$_{F=0}$/*B*$_0$)) for six SESSF stocks and two northern crustacean stocks over 1975–2017. The vertical orange line indicates the position of static *B*$_0$ and the horizontal red dashed line indicates the target fishing intensity ratio above which overfishing can be considered to be occurring.

The true value of such plots lies, however, in plotting the historical trajectories of fishing and non-fishing indices, as is done in Kobe plots. Figure 7-56 shows Retra plots for each of the six SESSF stocks over 1975–2017, comparing trends in fishing and non-fishing effects over time. Figure 7-57 similarly shows Retra plots for the two northern crustacean stocks over 1975–2017, comparing trends in fishing and non-fishing effects over time.

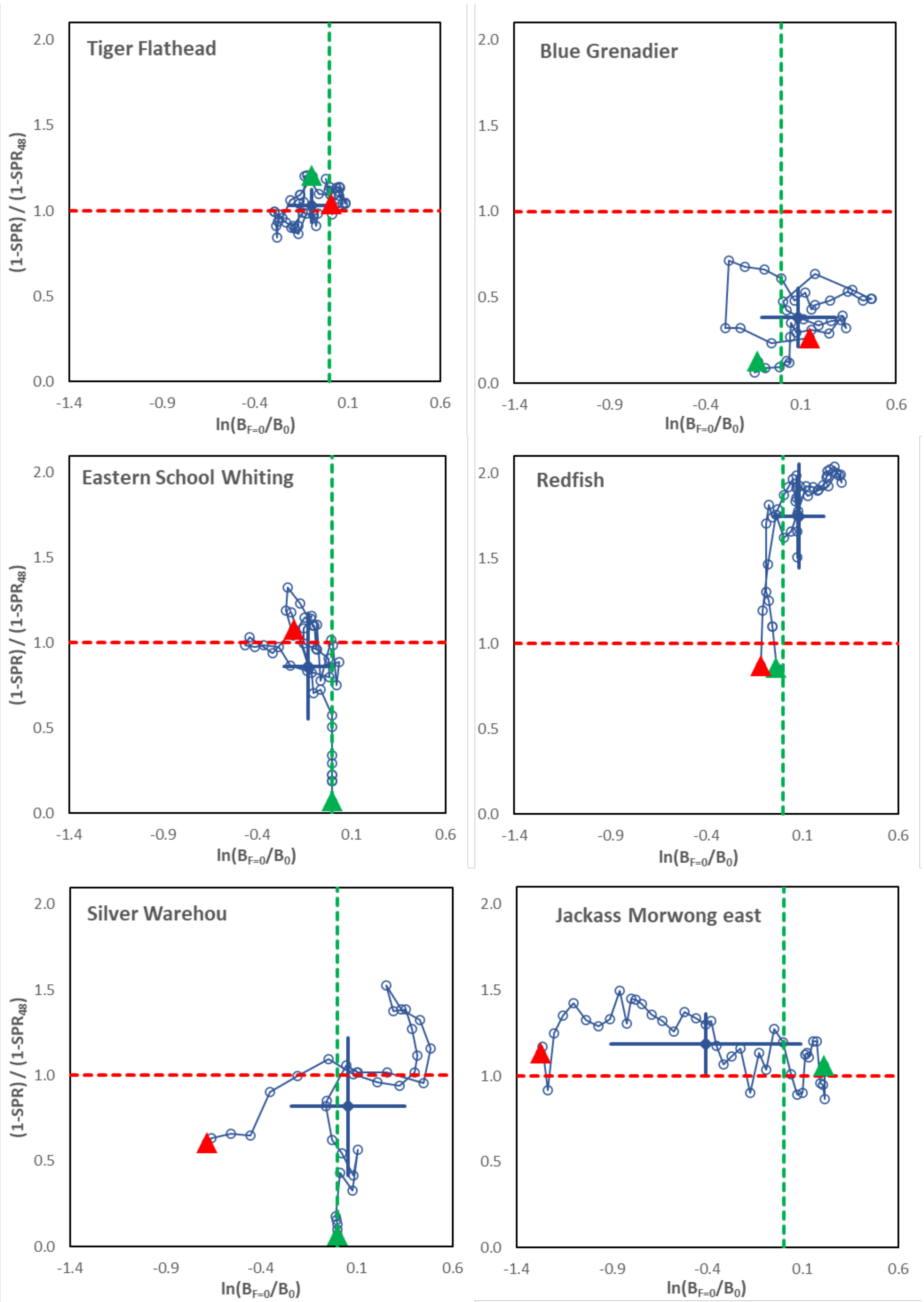


Figure 7-56. Relative effects trajectory ('Retra') plots showing historical trends in non-fishing effects ($\ln(B_{F=0}/B_0)$) vs. fishing intensity ($(1\text{-}SPR)/(1\text{-}SPR_{Targ})$) for six SESSF stocks over 1975–2017. The start of each trajectory is indicated by the green triangles and the end by the red triangles. Averages and standard deviations of fishing and non-fishing effects over the period are shown by the thick blue horizontal and vertical lines.

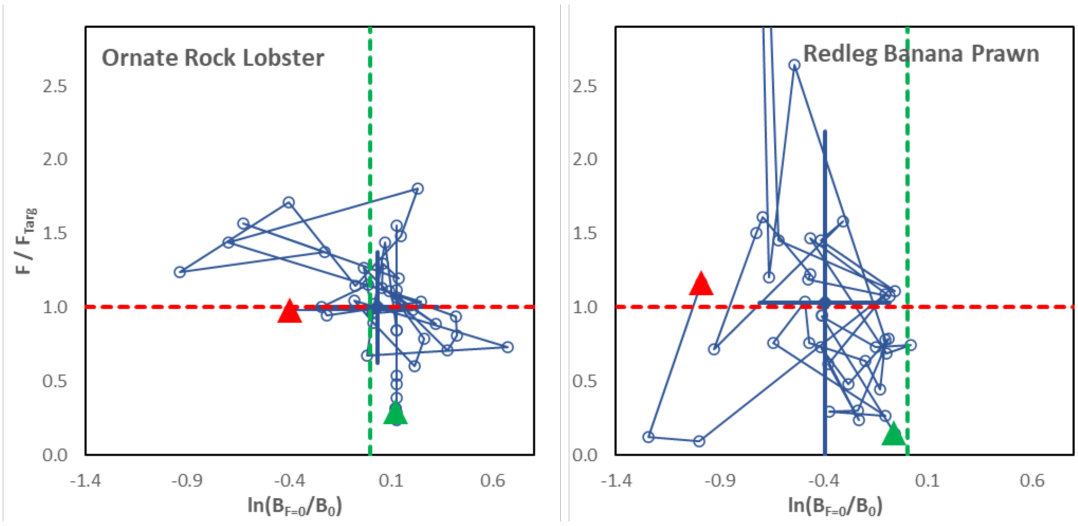


Figure 7-57. Relative effects trajectory ('Retra') plots showing historical trends in non-fishing effects ($\ln(B_{F=0}/B_0)$) vs. fishing intensity (F/F_{Targ}) for two northern crustacean stocks over 1975–2017. The start of each trajectory is indicated by the green triangles and the end by the red triangles. Averages and standard deviations of fishing and non-fishing effects over the period are shown by the thick blue horizontal and vertical lines.

These plots provide useful overviews of the comparative fishing vs. non-fishing effects over the history of the fishery. For example, having remained near or slightly above the fishing intensity target for the first half of the period, Jackass Morwong east has been subject to a continuous and rapid increase in negative non-fishing effects to high levels for more than two decades, with associated overfishing. Silver Warehou only shows a brief period of overfishing from 1999–2007 but has been subject to increasing non-fishing effects for the past decade. Redfish was subject to moderate positive non-fishing effects between 1995 and 2010 but has endured heavy overfishing for most of the period. Fishing intensity on Tiger Flathead has remained close to the target throughout the period, with moderate non-fishing effects between 1976 and 2000. Blue Grenadier has shown cyclical periods of non-fishing effects, mostly positive, and has been markedly under-fished throughout the period.

7.8. Summary of evidence for Fishing and Non-fishing Effects

All evidence calculated in the sections above is summarised in Table 7-12, in which quantitative evidence scores or estimates are summarised for each stock for all the evidence types analysed in this chapter. Evidence scores in the table are colour coded to indicate the extent to which the fishing or non-fishing effects have affected each stock (red – negative effect, green – positive effect). The surplus production model that best explains the observed regime shifts in surplus production has been bolded for each stock (noting no regime shifts were detected for crustacean stocks), and the single main surplus production regime shift included in the production modelling analysis is bolded for each stock. The weight of evidence score for Gemfish east has not been included in this table as the most recent assessment was older than assessments for other stocks and did not provide recruitment deviations or dynamic B_0 estimates, and so Gemfish East was excluded from other evidence analyses.

Key evidence indicators from Table 7-12 are plotted in Figure 7-58 for effects of fishing (over-catch ratios and overfishing ratios) and in Figure 7-59 for non-fishing effects (regime shift weight of evidence scores and dynamic B_0 deviations), to provide a quick visual comparison of the relative fishing and non-fishing effects on each stock.

Table 7-12. Summary of evidence for fishing and non-fishing effects for case study stocks, derived from results presented in this chapter, ranked in descending order of dynamic B_0 deviation.

Indicator	Jackass Morwong east	Redleg Banana Prawn	Silver Warehou	Ornate Rock Lobster	Blue Grenadier	Eastern School Whiting	Tiger Flathead	Redfish
Productivity regime shift weight of evidence								
Productivity regime shift weight of evidence score	9	–	4	–	2	3	3	4
Recruitment and Productivity Regime shifts								
Regime shifts: recruitment deviations	1966 ↑ 0.39 1982 ↓ 0.87 1995 ↓ 0.41	2015 ↓ 0.24	2004 ↓ 0.69	1998 ↓ 0.05 2016 ↓ 0.25	1998 ↓ 0.53 2009 ↑ 5.47	2006 ↓ 0.11 2016 ↑ 0.04	1968 ↓ 0.28 1992 ↑ 0.30	1995 ↓ 0.31
Regime shifts: recruitment	1966 ↑ 0.41 1974 ↓ 0.45 1982 ↓ 0.46 1995 ↓ 0.13	2015 ↓ 2.95	2004 ↓ 0.32	1997 ↓ 0.13 2008 ↑ 0.21 2015 ↓ 0.13	2010 ↑ 0.48	2006 ↓ 0.11 2016 ↓ 0.04	1997 ↑ 0.03	1994 ↓ 0.82
Regime shifts: surplus production	1968 ↑ 0.75 1975 ↓ 1.42 **1984 ↓ 1.26**	2018 ↓ 0.40	1991 ↑ 0.72 **2005 ↓ 1.01**	1982 ↑ 0.56	**2011 ↑ 5.04**	**2006 ↓ 0.37** 2013 ↑ 1.63	1963 ↑ 0.09 **1970 ↓ 1.03** 1999 ↑ 0.13	1990 ↑ 0.25 **1997 ↓ 1.63** 2005 ↓ 0.39
Surplus production trend explained by: production model vs. regime shifts	Average: 0 Fox: 0 **RegShft: 0.637** Fox-Reg: 0.363	Average: 0.003 **Fox: 0.332** (no RegShfts)	Average: 0 Fox: 0 RegShft: 0 **Fox-Reg: 0.999**	Average: 0.236 **Fox: 0.764** (no RegShfts)	Average: 0.001 Fox: 0 **RegShft: 0.578** Fox-Reg: 0.421	Average: 0.001 Fox: 0.083 RegShft: 0 **Fox-Reg: 0.917**	Average: 0.005 Fox: 0.002 RegShft: 0.088 **Fox-Reg: 0.904**	Average: 0 **Fox: 0.505** RegShft: 0 Fox-Reg: 0.495
Fishing effects								
Overcatch: 1975-2017 years of (Catch > rRBC)	36	16	20	14	0	20	43	42
Overcatch: 1975-2017 Average–annual (Catch - RBC)	238	-94	-177	2	-5184	-464	1069	1255
Overcatch ratio: 1975-2017 (Catch/RBC)	1.310	0.817	0.898	1.004	0.403	0.796	1.682	6.438

Overfishing: 1975-2017 years of fishing above (1-SPR_{TARG})	36	16	15	17	0	15	23	41
Overfishing: 1975-2017 average annual (1-SPR)/(1-SPR_{TARG})	1.188	1.034	0.798	0.923	0.375	0.863	1.029	1.747
Dynamic B_0 deviation								
$B_{F=0}$ deviation: 1975-2017 avg annual abs(ln($B_{F=0}/B_0$))	0.498	0.407	0.220	0.217	0.163	0.131	0.125	0.123
Primary DFA trend fit								
Rec.dev average residuals from DFA primary trend	0.48	–	0.52	–	0.77	0.77	0.81	0.64

<u>Note</u>: Quantitative evidence scores or estimates are summarised for each stock for all the evidence types analysed in this chapter. Evidence scores have been colour coded to indicate the extent to which the fishing or non-fishing effects have affected each stock (red –negative effect, green – positive effect). The surplus production model that best explains the observed regime shifts in surplus production has been bolded for each stock (noting no regime shifts detected for crustacean stocks), and the one main surplus production regime shift included in the production modelling analysis is bolded for each stock. (Note: the weight of evidence score for Gemfish East has not been included in this table, as the most recent assessment was older than assessments for other stocks and did not provide recruitment deviations or dynamic B_0 estimates, and so Gemfish East was excluded from other evidence analyses.)

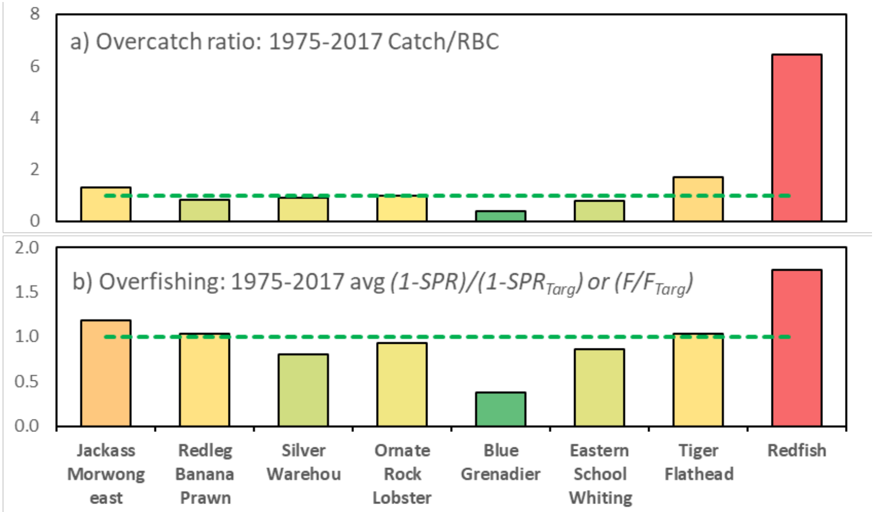


Figure 7-58. Comparison of key fishing effects for each stock from evidence summary in Table 7-12: a) Estimated over-catch ratio (Catch/RBC) over 1975–2017; and b) Overfishing ratio (average $(1-SPR)/(1-SPR_{Targ})$ for fish stocks or (F/F_{Targ}) for crustacean stocks) over 1975–2017.

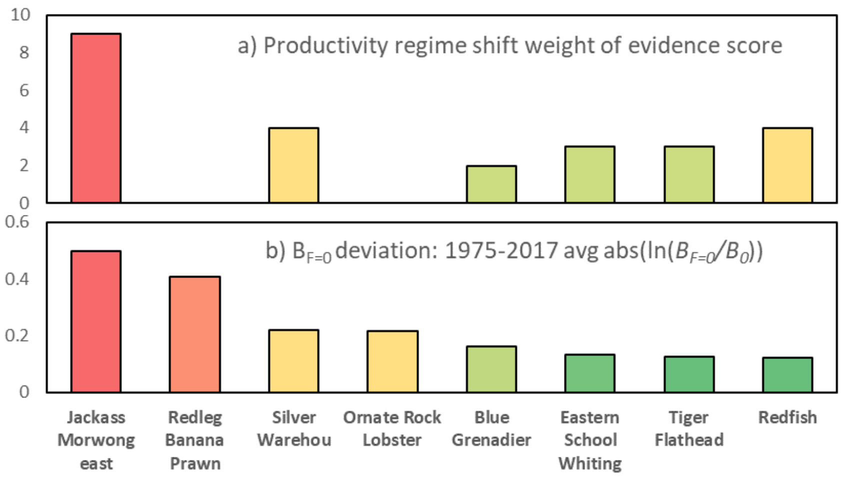


Figure 7-59. Comparison of key fishing effects for each stock, from evidence summarised in Table 7-12: a) productivity regime shift weight of evidence score (noting that there was no evidence score calculated for crustacean stocks); and b) average absolute ($B_{F=0}/B_0$) deviation over 1975–2017.

When the stocks are ranked in descending order of dynamic B_0 deviation (Figure 7-59 b) there is an evident inverse relationship between the relative magnitude of fishing and non-fishing effects. These results are calculated from the outputs of the same stock assessments, which provide evidence of both fishing and non-fishing effects, depending on the degree to which fishing and stock biology can explain assessment estimates of changes in stock abundance.

These assessment-derived measures of fishing and non-fishing effects could not be calculated for the other stocks considered under the weight of evidence analysis – Gemfish east, Blue Warehou east and Blue Warehou west – because the most recent assessments for these stocks were old, and did not produce estimates of dynamic B_0 or *1-SPR*. However, regime shifts STARS analysis was possible as recruitment deviations were available. Table 7-13 summarises the regime shift weight of evidence scores and the detected STARS analysis regime shifts for these stocks.

Table 7-13. Summary of evidence for fishing and non-fishing effects for secondary study stocks, derived from results presented in this chapter, ranked in descending order of regime shift weight of evidence score.

Indicator	Gemfish east	Blue Warehou east	Blue Warehou west
Productivity regime shift weight of evidence			
Productivity regime shift weight of evidence score	7	4	1
Regime shifts			
Regime shifts: recruitment deviations	1985 ↓ 0.98 2000 ↑ 2.58	1995 ↓ 0.77 2005 ↑ 0.36	2004 ↓ 0.39
Regime shifts: recruitment	1984 ↓ 1.36	1995 ↓ 0.48	
Regime shifts: surplus production	**1986 ↓ 1.38**		1995 ↑ 0.48
Surplus production trend explained by: production model vs. regime shifts	Average: 0 Fox: 0.022 **RegShft: 0.713** Fox-Reg: 0.265	**Average: 0.824** Fox: 0.094 RegShft: 0.074 Fox-Reg: 0.008	Average: 0.000 Fox: 0.012 RegShft: 0.012 **Fox-Reg: 0.976**

The regime shifts detected in STARS analysis results (see Table 7-12 and Table 7-13) are summarised in Figure 7-60, which shows years in which negative or positive regime shifts were detected in either recruitment deviations, recruitment or surplus production for any of the stocks, overlaid with the annual average smoothed Southern Oscillation Index with 1 lag of one year.

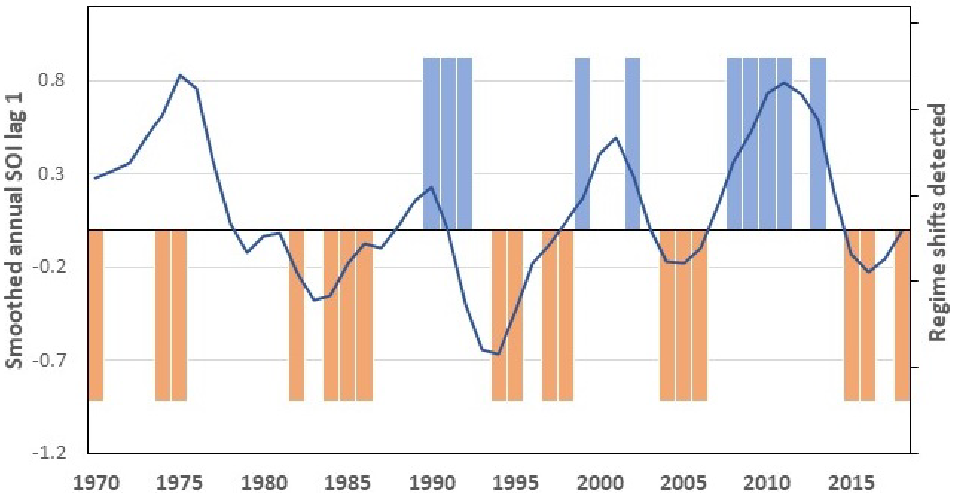


Figure 7-60. Overlay of the average annual Southern Oscillation Index (blue line, smoothed, lag 1) with whether positive (blue bars) or negative (orange bars) regime shifts were detected for any of the stocks in each year.

From 1980 onwards, there seem to be some correlations between peaks and troughs in the smoothed SOI and years in which positive or negative regime shifts were detected for at least one stock. As is so often the case with attempts to correlate broad-scale environmental indices with changes in fish stocks, this apparent correlation does not hold over 1970–1980, when a peak in the SOI corresponds with negative regime shifts in three years.

The regime shifts in Figure 7-60 seldom occur with a single stock in any period, with typically two, three or four stocks showing a regime shift in one of the measures analysed (recruitment deviation, recruitment, or surplus production) over the periods when shifts were detected.

Table 7-14. Summary of stocks for which negative or positive shifts were detected using STARS analysis of trends in recruitment deviations (Rd), recruitment (R) and surplus production (S) over groups of years coinciding with peaks and troughs in the smoothed Southern Oscillation Index (as illustrated in Figure 7-60).

Negative– shifts	
1970 - 1975	Jackass Morwong east (R,S), Tiger Flathead (S)
1982 - 1986	Jackass Morwong east (Rd,R,S), Gemfish east (Rd,R,S)
1994 - 1998	Jackass Morwong east (Rd,R), Blue Grenadier (Rd), Redfish (Rd,R,S), Blue Warehou east (Rd,R), Ornate Rock Lobster (Rd,R)
2004 - 2006	Silver Warehou (Rd,R,S), Eastern School Whiting (Rd,R,S), Redfish (S), Blue Warehou west (Rd)
2015 - 2018	Eastern School Whiting (R), Redleg Banana Prawn (Rd,R,S), Ornate Rock Lobster (Rd,R)
Positive Shifts	
1990 - 1992	Silver Warehou (S), Tiger Flathead (Rd), Redfish (S)
1999 - 2002	Tiger Flathead (S), Gemfish east (Rd)
2008 - 2013	Blue Grenadier (Rd,R,S), Eastern School Whiting (S), Ornate Rock Lobster (R)

Masking of fishing or non-fishing effects

It is possible that strong fishing effects mask non-fishing effects for stocks strongly affected by fishing, and it is conceivable that stocks subject to strong non-fishing effects (e.g. Jackass Morwong east) may also have been negatively affected by fishing, but this effect is masked. Similarly, stocks strongly affected by fishing (e.g. Redfish) may also have been affected by non-fishing effects, but this effect is masked. This could extend to a key concern raised by stakeholders, that fishing could have exerted the initial negative effect on a stock, followed by stronger (but masked) non-fishing effects on the depleted and less resilient stock.

8. Simulation evaluation of alternative dynamic B_0 harvest control rules

This chapter summarises work published in:

Bessell-Browne, P., Punt, A.E., Tuck, G.N., Day, J., Klaer, N., Penney, A., 2022. The effects of implementing a 'dynamic B_0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. Fisheries Research 252, 106306 https://doi.org/10.1016/j.fishres.2022.106306

(See published paper attached in Appendix 17.1)

8.1. Introduction

Best practice for fisheries management is to use harvest control rules that have been evaluated relative to the agreed management objectives to make recommendations for management actions. Harvest control rules typically include biological reference points that are related to the unfished conditions ('B_0'). The inputs to harvest control rules are often based on the results of stock assessments that involve fitting a population dynamics model to monitoring data for the fishery. Many model-based stock assessments assume stationarity, i.e., that the values of model parameters are constant over time (Fulton 2011). However, the parameters that determine the population dynamics of marine fishes and invertebrates (distribution, recruitment, growth, natural mortality, etc.) vary over time naturally, and time-variation in biological and fishery (e.g., selectivity and catchability) parameters and the reasons for such variation have been a focus for study by fishery scientists for over a century (e.g., Hjort 1914, Clark *et al.* 1999, Quinn and Deriso 1999; Stawitz *et al.* 2015). This variation has variously been attributed to fishery or environmental factors or to a synergy of the two (e.g., Enberg *et al.* 2012). Exacerbated time-variation in biological parameters, in particular trends in these parameters and hence the reference points included in stock assessments and harvest control rules, are expected with changing climate (e.g., Brander 2007, Hollowed *et al.* 2013, Szuwalski & Hollowed 2016; Barrow *et al.* 2018), necessitating new approaches for including such variation in stock assessments and management advice.

MacCall *et al.* (1985) introduced the concept of 'dynamic B_0', which is the reference level of unfished biomass, B_0, under prevailing environmental conditions. A dynamic B_0 approach to calculating reference points for fisheries management acknowledges that drivers other than fishing pressure influence population size, even where these cannot be explicitly identified. The theoretical biomass trajectory under the dynamic B_0 approach represents the population size that would have resulted if no fishing of the stock had occurred throughout its history, but other parameters had remained as estimated in the assessment (MacCall *et al.* 1985, Punt *et al.* 2014, King *et al.* 2015, Berger 2019, O'Leary *et al.* 2020). In reality, it is likely that the biomass trajectory (hence 'dynamic stock status') would have changed had the stock been managed using dynamic reference points, altering the catch history. The dynamic B_0 approach differs from the traditional 'static' B_0 approach, which uses the average (expected) unfished biomass based on the values of biological parameters at the start of fishing as a fixed reference point for calculating stock status estimates (Ricker 1975, Hilborn 2002). In addition, static B_0 assumes that there are no long-term changes in productivity due to fishing pressure or environmental change.

It is expected that dynamic B_0-based harvest control rules (HCRs) would outperform those based on static B_0 when productivity is time-varying, and the results of the retrospective Chapter 6 and associated paper in Appendix 17.1 indicate that values for the RBCs for species in the SESSF would have differed historically for some stocks had stock status been calculated based on dynamic B_0. However, it is unclear how much management performance (such as values for expected yield and stock status) would have changed depending on whether a static or dynamic B_0 approach to providing management advice was adopted.

An evaluation of HCRs is undertaken here to evaluate effects on management performance. For simplicity, the analyses simulate the assessment process (i.e., the consequences of error when conducting assessments) by adding random error to the estimate of current biomass used in the HCR, and no implementation error is taken into account.

8.2. Methods

The details of the methods can be found in Bessell-Browne *et al.* (2022; Appendix 17.1). The analyses involve defining an operating model based on a single-sex, age-structured population dynamics model and parameterizing it based on growth, natural mortality and selectivity for three SESSF species: Tiger Flathead, Blue Grenadier, and Eastern School Whiting (M=0.27yr^{-1}, 0.17yr^{-1}, and 0.6yr^{-1} respectively, Table 8-1). These species were selected to capture a range for both longevity and variation in recruitment about the stock-recruitment relationship. The operating model can be parameterized to allow various parameters (unfished biomass B_0, unfished recruitment R_0, asymptotic size L_∞, growth rate κ, natural mortality M, and stock-recruitment steepness h) to vary over time with pre-specified trends as well as in an auto-correlated manner. The annual removals are based on an HCR (first implemented in 2006, Smith *et al.* 2008) that may or may not use dynamic B_0. Implementation error, the possibility of the Total Allowable Catches (TACs) differing from the RBCs, and carryover provisions (AFMA 2021), are ignored for simplicity. Bycatch TACs, set for fisheries that may otherwise be closed are included in some scenarios.

Table 8-1. Values for the parameters of the simulation model. The last six rows list the ratio of the slope at the origin of the stock-recruitment relationship given changes to the biological parameters (values for a 50% increase then decrease) to that for the parameter values in the upper part of the table. See Supplementary Fig. S2 for length-at-age, selectivity-at-age, fecundity-at-age, and weight-at-age by species before account is taken of time-varying growth.

Parameter	Tiger flathead	Blue grenadier	School whiting
Plus-group age	30	30	10
Length (Age 0) (cm)	9.1	9.8	7.3
L_∞ (cm)	56.0	100.4	23.1
κ (yr^{-1})	0.173	0.226	0.329
Growth CV	0.108	0.124	0.094
M (yr^{-1})	0.27	0.17	0.60
α_W	0.00000588	0.00001502	0.0000132
β_W	3.31	2.73	2.93
m_1 (cm)	30.0	63.7	16.0
m_2 (cm^{-1})	0.25	0.26	2.00
s_1 (cm)	31.8	81.2	16.6
s_2 (cm^{-1})	0.30	0.20	1.18
Steepness (h)	0.72	0.75	0.75
σ_R	0.70	1.00	0.70
Slope at the origin			
Change in B_0	(1,1)	(1,1)	(1,1)
Change in R_0	(1.357,0.623)	(1.361,0.617)	(1.340,0.629)
Change in ℓ_∞	(0.578,2.848)	(0.376,1.932)	(0.525,3.689)
Change in κ	(0.656,2.200)	(0.521,1.540)	(0.610,2.497)
Change in M	(0.474,3.597)	(0.192,2.292)	(0.412,4.920)
Change in h	(388.5,0.253)	(333.0,0.359)	(6.467,0.262)

Five scenarios incorporating time-varying parameters are considered in addition to time-invariant and stochastic variation. The scenarios consider knife-edged changes in the values of the parameters as well as linear changes over time, and also explore the impact of the periods for the change of 20- and 50-years within a 200-year projection period in which catch limits are set annually using one of the harvest control rules (Table 8-2).

Table 8-2. The scenarios used in the simulation analysis, indicating the biological parameters that were varied in each scenario (denoted Y if included). Note that σ_R is set to the values in Table 8-1 unless stated otherwise and separate analyses are conducted for each biological parameter. The simulations vary each biological parameter in turn, except for the last, which varies B_0 and M simultaneously.

Table 8-2. The scenarios used in the simulation analysis, indicating the biological parameters that were varied in each scenario (denoted Y if included). Note that σ_R is set to the values in Table 8-1 unless stated otherwise and separate analyses are conducted for each biological parameter. The simulations vary each biological parameter in turn, except for the last, which varies B_0 and M simultaneously.

Scenario	Biological parameter						
	B_0+	R_0+	ℓ_∞	κ	M	h	Other
Reference							
Knife-edged; period=20 years	Y	Y	Y	Y	Y	Y	
Zig-zag; period= 20 years	Y	Y	Y	Y	Y	Y	
Linear decline in 50 years	Y	Y	Y	Y	Y	Y	
Knife-edged; period=50 years	Y	Y	Y	Y	Y	Y	
Zig-zag; period= 50 years	Y	Y	Y	Y	Y	Y	
Autocorrelation in recruitment							ρ_R=0.707
Variability in growth increment							ρ_R=0.2, ρ_G=0.707
Variability in L_∞							ρ_L=0.2, ρ_L=0.707
Variability in M							ρ_M=0.2, ρ_M=0.707
Initial depletion = 0.1B_0							
Time-variation in B_0 and M simultaneously	Y				Y		

+ The scenarios in which B_0 is time-varying involve time-variance in both the B_0 and R_0 parameters of the stock-recruitment relationship while the scenarios in which R_0 is time-varying involve setting B_0 to the value for year 0 of the projection period (see Eqn 8b).

A range of HCRs were investigated (Figure 8-1). These included, Static B_0, Dynamic B_0, Dynamic B_0-target (this HCR is identical to the dynamic B_0 HCR except that B_{LIM} is set to 20% of the B_0 in year 0 and B_{BRK} is the maximum of 0.35 $B_{0,y}$ and B_{LIM}) and Dynamic B_0-slide (this HCR is identical to dynamic B_0-target except that the limit reference point is scaled linearly between 10% and 20% of B_0^* depending on the ratio of 0.35 $B_{0,y}$ and 20% of B_0 in year 0).

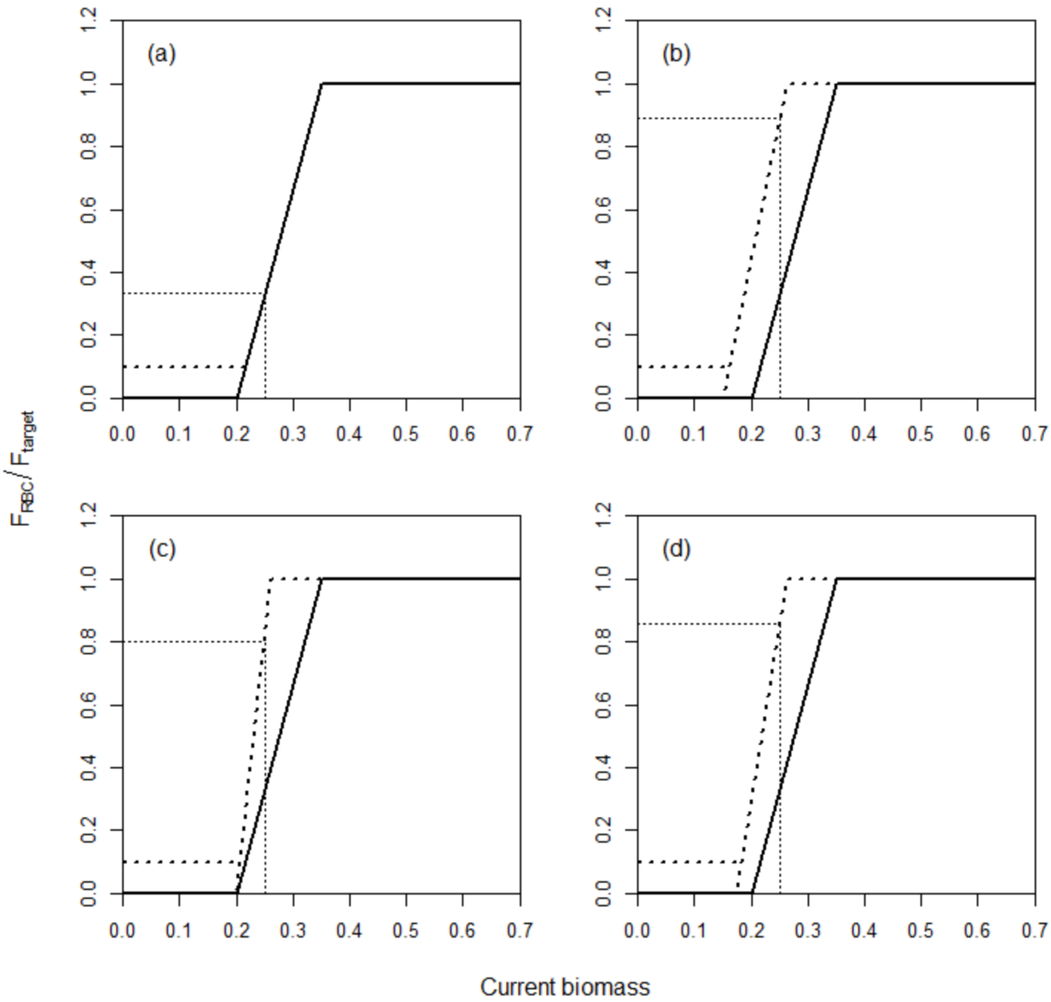


Figure 8-1. Illustrations of the two versions (no minimum target fishing mortality, and a minimum target fishing mortality of 0.1F_{48}) of the four harvest control rules (a: static B_0; b: dynamic B_0; c: dynamic B_0-target; d: dynamic B_0-slide) and their application when current biomass is 0.25 and dynamic B_0 is 75% of static B_0 (dashed lines; upper line 'with floor', lower line 'no floor'). The solid line in each panel is the HCR based on static B_0 with no minimum target fishing mortality, and the dotted line is the value F_{RBC}/F_{target} when biomass is 25% of static B_0.

The first 30 years of the modelled period are a burn-in, during which there is stochastic variation in recruitment about the stock-recruitment relationship, in M, L_∞, and in the growth increment (the latter three sources of variation are part of the model specification), but the expected values for none of the parameters are time-varying. Fishing mortality for years 0-29 is constant and set for each of the 500 simulation replicates so that spawning biomass relative to spawning biomass at the start of year 0 equals a pre-specified value (0.5 for most analyses, close to the nominal target depletion for species in SESSF of 0.48).

The extent of change in the parameters is selected so that MSY is either increased or decreased by up to a maximum of 50%. The base scenarios explored include a reference scenario in which none of the biological parameters are time-varying and cases in which each biological parameter in turn is allowed to be time-varying. The base simulations ignore temporal auto-correlation in recruitment, random variation in L_∞ and M, and random variation in growth increment, which are explored in sensitivity analyses. The sensitivity of the results to allowing M and B_0 to vary simultaneously is also explored to consider a case in which MSY halves due to an increase in larval mortality as well as age 0+ mortality, as might be expected given the impacts of climate change.

8.3. Results

Spawning biomass varies without trend when none of the biological parameters vary over time ('Reference' in Figure 8-2). The remaining cases lead to variation in unfished biomass over time, except when steepness is time varying (Figure 8-2). There is little impact of time-variation in unfished biomass when steepness is changing over time because the stock is not driven to levels at which stock-recruitment effects come into play.

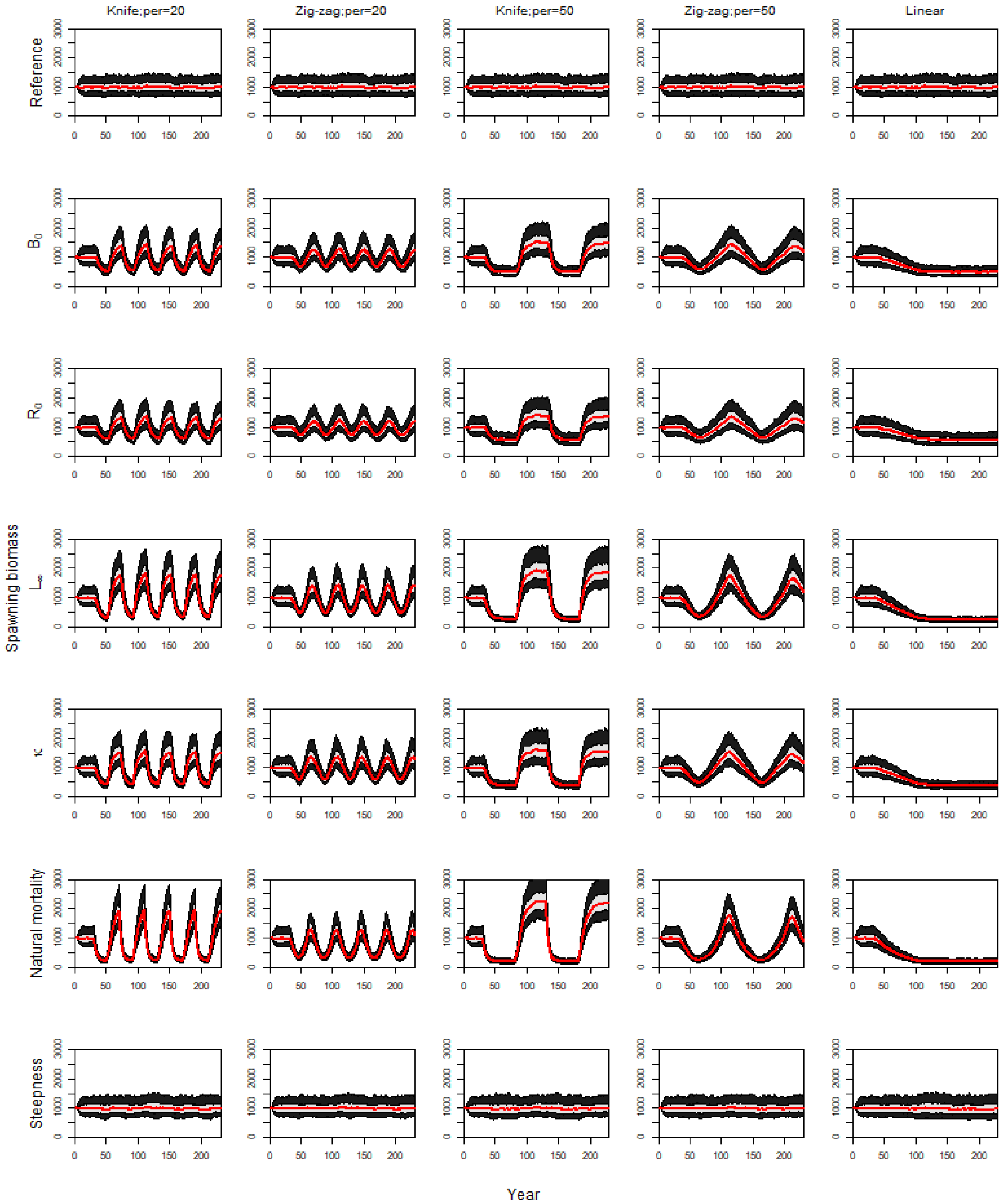


Figure 8-2. Time-trajectories of unfished spawning biomass (red median; light shading 50% intervals; dark shading 90% intervals) for the reference analysis and six ways that environmental variation can impact biological parameters (rows) for Tiger Flathead. The columns indicate how the time-variation impacts the parameters.

Unfished biomass does not differ much depending on whether a biological parameter changes in a knife-edged manner or in a zig-zag pattern (Figure 8-2). There is little difference between allowing R_0 or B_0 to vary over time (Figure 8-2). In contrast, allowing L_∞, κ, and M to vary over time leads to a wide range in stock statuses (Figure 8-2). This occurs because the parameters are assumed to change linearly over time and the extent to which a parameter must change to achieve a 50% increase or decrease in MSY is not symmetric (see Appendix 17.1, Supplementary Table S1), so the average value (over the 200-year projection period) for a time-varying parameter will not equal the base value.

There is relatively little difference in trade-off between lowest depletion and average catch, and AAV and average catch between the HCRs with and without the floor on target fishing mortality, except (as expected) that risk and average catch are somewhat larger and AAV somewhat lower with the floor than if there is no floor (Figure 8-3). The HCRs based on dynamic B_0 (c, d, e, g, h, and i) lead to much lower inter-annual variation in catch limits than the HCRs based on static B_0 (b and f), because the catch limits are not reduced as much when stock size is low. This effect is clear for all scenarios, including the reference scenario (Figure 8-3), with the effect being largest when a biological parameter declines linearly to a nadir (Figure 8-3, right column). There is a trend (not evident when steepness is time-varying) for lower catches to be associated with larger levels of inter-annual variation in catches.

The trade-offs among average catch, lowest depletion, and AAV differ quantitatively among the three species (see Appendix 17.1*,* Fig. 9; Supplementary Fig. S6). However, the qualitative impact of the various HCRs given time variation in the biological parameters is robust to species life history.

Allowing for temporal auto-correlation in the deviations about the stock-recruitment relationship leads to greater risk than for the reference scenario (a distribution for the lowest depletion that is shifted to lower values and greater probabilities of dropping below 10% of static B_0) and higher AAVs (see Appendix 17.1*,* Supplementary Fig. S6b). In addition, the inter-simulation variation in the values of the performance metrics is greater when recruitment is auto-correlated.

Allowing for time-variation in growth increment (see Appendix 17.1*,* Supplementary Fig. S6c) leads to similar consequences as allowing for auto-correlation in recruitment. Time variation in L_∞ and natural mortality (see Appendix 17.1*,* Supplementary Figs S6d and S6e) also leads to greater risk, greater inter-annual variation in catch and greater inter-simulation variation, but the effect of variation in L_∞ is more marked, particularly in terms of greater risk than the other factors.

Allowing B_0 and M to vary simultaneously (with a combined change in MSY of ±50%) has little impact on the trade-off between catch and AAV, but leads to greater risk (as quantified by a shift in the lowest depletion distribution to lower values) (see Appendix 17.1, Supplementary Fig. S6f). The trade-off between average catch and AAV is robust to an initial stock status of 0.1 but, as expected, the lowest depletion distribution is shifted to lower values (it cannot be greater than 0.1 given this is the initial value) (see Appendix 17.1, Supplementary Fig. S6g).

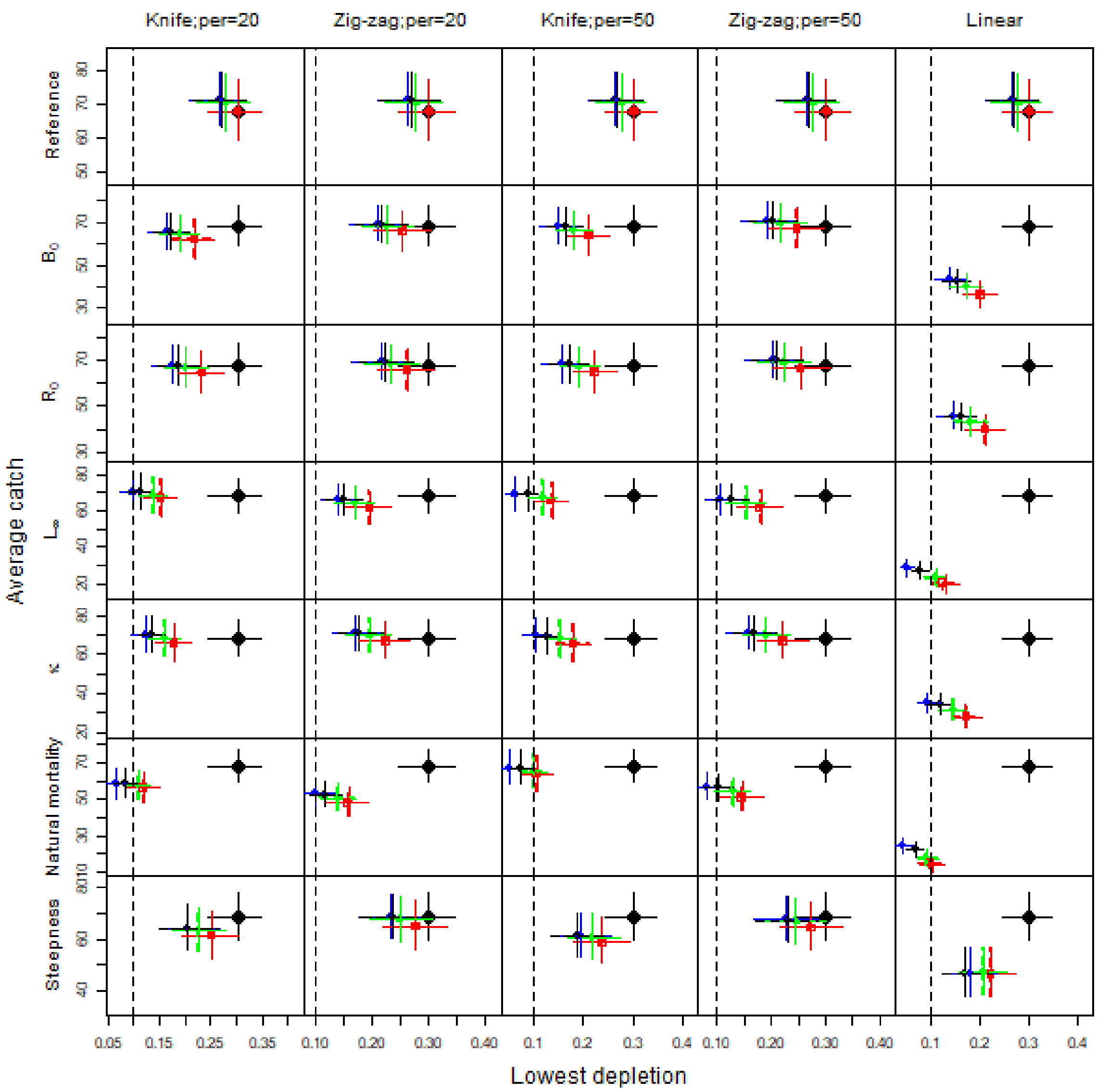


Figure 8-3. Trade-off plot (average catch vs lowest depletion) for the base scenarios for Tiger Flathead (red: static- B_0; blue: dynamic B_0; green: dynamic B_0-target; black: dynamic B_0-slide). Results are shown the two versions of each HCR option ('floor' vs 'no floor'; solid and dashed lines), but these are largely indistinguishable. The lowest depletion for a simulation is the lowest spawning stock biomass expressed relative to static B_0. The large black circle is the result for the static B_0 HCR for the reference case (no time-varying parameters). The results are summarized by the median and 90% intervals. The vertical dotted line at 0.1 denotes 10% of static B_0.

8.4. Discussion

The simulations under the alternative HCRs lead to the conclusion that catches could be higher overall under a dynamic B_0 approach, although at the cost of lower stock sizes on occasion. One reason for the improved catch, unrelated to the use of dynamic B_0, is that the target reference point for fishing mortality in the SESSF, F_{48}, was selected to maximize economic yield (Smith *et al.* 2008). Fishing harder than F_{48} will consequently lead to higher yield but not necessarily higher profits. Explicit consideration of the costs of fishing are beyond the scope of the present study, in particular because the unfished biomass of each stock in the simulations was not based on the actual assessments for the stocks concerned and because only one fleet was modelled for each stock (most actual stock assessments for SESSF species include multiple fleets).

A clear advantage of the dynamic B_0 approach is the lower inter-annual variation in catch limits. This is not surprising because dynamic B_0 will tend to keep harvest rates higher in the face of declining stocks if the decline is attributed to changed environmental conditions, and hence avoid the reduction in target fishing mortality associated with the slope of the SESSF harvest control rule.

Previous simulation evaluations of dynamic vs static B_0-based HCRs (e.g., Berger 2019, A'mar *et al.*, 2009) only allowed for time-variation in B_0. This study explored the implications of time-variation being applied to the parameters of the growth model (L_∞ and κ), natural mortality, and the steepness of the stock-recruitment relationship. Except when steepness is time-varying, the qualitative effects of time-variation in biological parameters on performance is robust to the process involved. The results for time-varying steepness are different as the HCRs explored in this report all aim to move stocks to levels at which recruitment is not strongly dependent on spawning biomass. The quantitative values for the performance metrics depend on which biological parameter is time-varying, with time-variation in L_∞, κ, and M potentially leading to higher risk. However, this conclusion needs to be tempered with the fact that the amount by which a biological parameter needs to be adjusted to achieve an increase or decrease in MSY of 50% differs among parameters (see Appendix 17.1, Supplementary Table S1).

The two variants of the dynamic B_0 HCR (dynamic B_0-target and dynamic B_0-slide) led to performance metrics that were intermediate between those for static-B_0 and dynamic-B_0. They have the advantage of imposing a limit reference point that reflects historical conditions instead of allowing (in principle) stock status to be based on a limit reference point that could not be reduced to near zero.

9. MSE of static and dynamic HCRs for SESSF stocks under time varying productivity

This chapter summarises work published in:

Bessell-Browne, P., Punt, A.E., Tuck, G.N., Burch, P., Penney, A., 2024. Management strategy evaluation of static and dynamic harvest control rules under long-term changes in stock productivity: A case study from the SESSF. Fisheries Research 273, 106972 https://doi.org/10.1016/j.fishres.2024.106972

(See published paper attached in Appendix 17.2)

9.1. Introduction

To compare the performance of harvest control rules (HCRs) based on static B_0 and dynamic B_0 under conditions of changed productivity, this chapter (and the associated paper in Appendix 17.2) undertakes a full management strategy evaluation (MSE) for three species in the Southern and Eastern Scalefish and Shark Fishery (SESSF). MSE is a simulation tool that allows various alternative biological and management scenarios to evaluate the comparative strengths and weaknesses of various assessment methods and management strategies (Bunnefeld *et al.* 2011, Punt *et al.* 2016).

As discussed in previous chapters, changing environmental conditions are anticipated to exacerbate time-dependent fluctuations in the parameters governing the population dynamics of marine organisms. Trends in biological parameters, including distribution, recruitment, growth, and natural mortality will vary and this necessitates the development of new methods to incorporate this variability into stock assessments and management processes. While biological processes will always be subject to time variation, many stock assessments assume stationarity in parameters and this impacts the biological reference points that are used in the harvest control rules (HCRs) on which management advice is based (Fulton,, 2011). While the stationarity assumption may be valid when parameters vary without trend, it is becoming increasingly untenable for many stocks as they are exposed to changing environmental conditions that result in directional change in biological parameters. This is particularly apparent in HCRs that are based on biomass relative to unfished conditions (B_0), with this generally referred to as 'stock status' or 'depletion'. HCRs that can incorporate time-varying parameters are required, especially when biological parameters exhibit a trend.

In many jurisdictions, assessments are limited to estimating time-varying parameters by estimating the deviations in recruitment about an underlying stock-recruitment relation (referred to as "recruitment deviations"). Therefore, less data intensive techniques than direct incorporating of environmental variables linked to biological processes are required to detect time variation and incorporate it within assessments and management processes. Dynamic B_0 is one such method. Typically, assessments use the estimate of static B_0 from the first year of the assessment and take this to be the 'unfished' level, whereas dynamic B_0 incorporates variation through time due to factors other than fishing. Dynamic B_0 calculates a theoretical biomass trajectory that represents the population size that would have resulted had the stock never been fished, assuming all other parameters (including recruitment deviations) remain as estimated in the assessment (MacCall *et al.* 1985, Punt *et al.* 2014, King *et al.* 2015, Berger 2019, O'Leary *et al.* 2020, Bessell-Browne *et al.* 2022).

The key difference between reference points calculated using static and dynamic B_0 is that when using static B_0, the assumption is that there has been no change in reference points through time, whereas when using dynamic B_0, reference points vary with recently estimated recruitment deviations. Therefore, basing stock status and management advice on static B_0 assumes that there have been no long-term changes in productivity due to fishing pressure or environmental change, or that fishing-induced changes are potentially reversable.

Bessell-Browne *et al.* (2022; Appendix 17.2; Chapter 8) conducted a retrospective analysis of stock status based on static and dynamic B_0 for several of the stocks in the SESSF off south-east Australia. Bessell-Browne *et al.* (2022) also explored how Recommended Biological Catches (RBCs) would have changed had management advice been based on dynamic B_0. Berger (2019) explored the effects of basing HCRs on dynamic B_0, but only for the case of time-variation in a single biological parameter, while Bessell-Browne *et al.* (2022) explored the consequences of applying dynamic B_0-based HCRs when several parameters, including unfished recruitment, are time-varying. This chapter expands on the work of Berger (2019) and Bessell-Browne *et al.* (2022) by undertaking MSE, which investigates the full management feedback cycle to compare the performance of HCRs based on static B_0 and dynamic B_0 for three species in the SESSF with different life history characteristics under conditions of changed productivity.

9.2. Methods

The full details of the methods applied can be found in Bessell-Browne *et al.* (2024; Appendix 17.2). Simulations were undertaken for three SESSF species: Silver Warehou (*Seriolella punctata*), Tiger Flathead (*Neoplatycephalus richardsoni*) and Eastern School Whiting (*Sillago flindersi*). These species represent a range of life history characteristics.

The first step in an MSE requires that a set of scenarios is chosen for evaluation; that is, a set of parameterisations of the operating model (OM) that represents the real world. A management strategy is then chosen from among a set of identified options. In fisheries, the OM consists of a population dynamics model, a data-generation module, and a component to allow future projections of the population model given input from assessment models and HCRs. The general design of a MSE is presented in Figure 9-1. The values for the parameters of the MSE's operating OM were based on their most recent assessments (Bessell-Browne and Day 2021, Bessell-Browne 2022, Day *et al.* 2020). The OM for this study is an age-structured population dynamics model with a Beverton-Holt stock-recruitment relationship that has bias-corrected deviations (Wayte 2009).

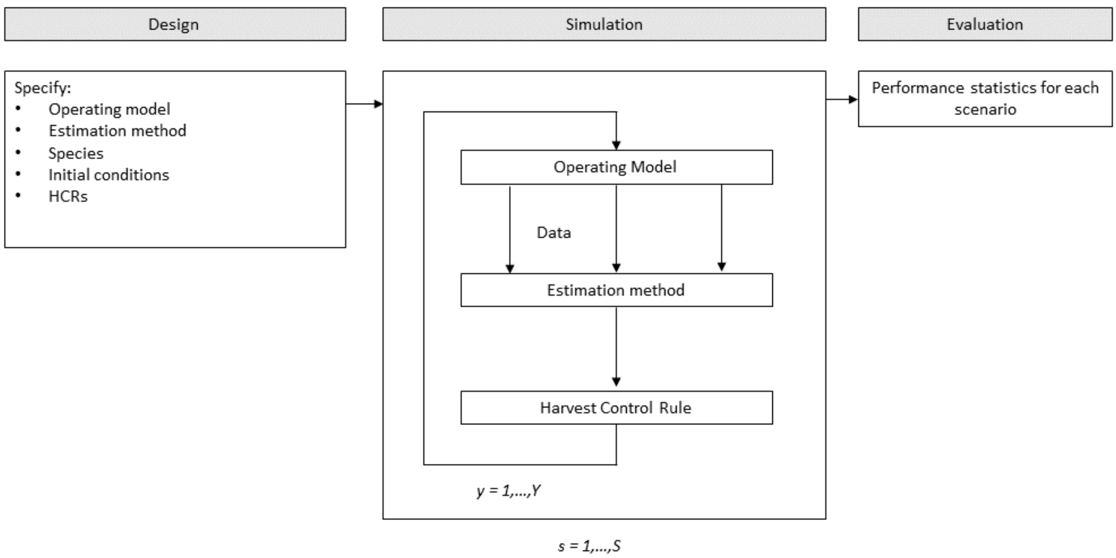


Figure 9-1. The general framework of the MSE. A management strategy and parameterisation of the operating model (OM) are chosen (a design), simulated over Y years and S simulations, and performance measures recorded. The management strategies can be evaluated using the performance measures once all scenarios are complete.

The assessment of stock status using the data from the OM is based on an estimation method (EM) using Stock Synthesis (version SS3.30.15.03, Methot and Wetzel 2013). Monitoring data used by the EM and derived from the OM include annual catch, length- and age-compositions, discard rates and catch rates (related to available biomass). Each of these input datasets have associated observation error. For every projected year, the EM applies a specified HCR to estimate the Recommended Biological Catch (RBC) to set the total allowable catch for the following year before the process is repeated.

The values for two parameters of the OM (R_0 and M) were allowed to be time-varying to mimic two of the possible effects of environmental drivers on population dynamics. Comparisons were made with a scenario in which these values were time-invariant. The value of R_0 was decreased by 50% and changes in M were calculated to result in the same magnitude of change in *SSB* as the R_0 scenarios. The values of these parameters remained time invariant in the EM, with R_0 estimated and allowed to vary, while M was pre-specified and remained constant. Three trends in the time-varying parameters were considered: a “linear-to-nadir” trend for R_0, a “linear-to-zenith” trend for M and a cyclical trend for R_0 and M. The linear-to-nadir scenario had a 10-year ramp from the base level of R_0 to half of the original value, while the linear-to-zenith scenario had a 10-year ramp from the base level of M to 25% larger than the original value (Figure 9-2). Each parameter then remained at this level for the remaining 40 years of the projection period. The cyclical trend followed a half circle, with a gradual 25-year decline in R_0 to half of the original level, while M increased to match the magnitude of decrease in R_0, followed by a 25-year increase, finishing back at the original level at the end of the projection period (Figure 9-2).

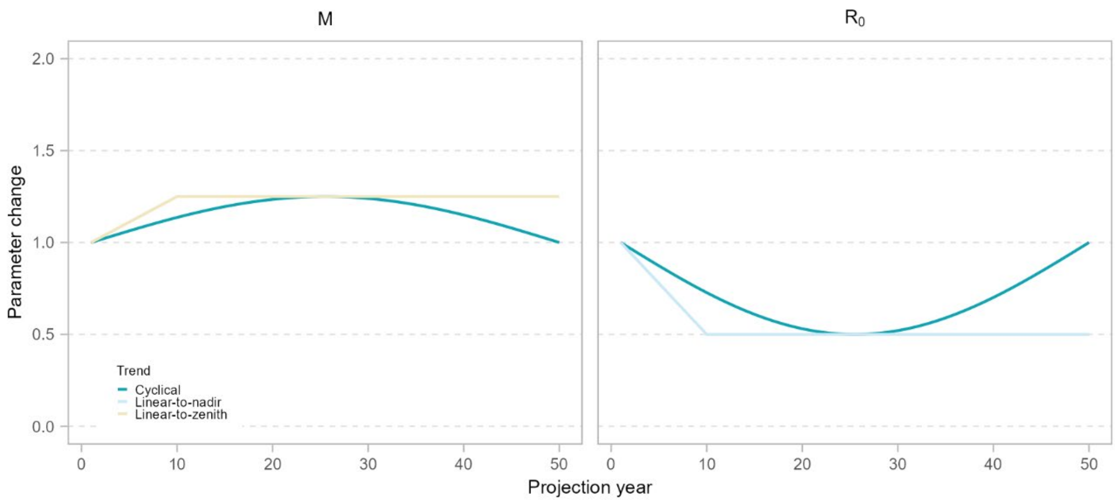


Figure 9-2. Illustration of the temporal patterns in parameters implemented over the 50-year projection period for *M* and R_0. The dark blue line shows the cyclical trend, the light blue line the linear-to-nadir trend, and the yellow line the linear-to-zenith trend.

To determine the annual value of dynamic B_0, the “unfished” spawning stock biomass time-series is calculated by projecting the population forward from its initial state without applying fishing mortality, assuming that the relevant deviations, such as deviations in recruitment about the stock-recruitment relationship and deviations in growth about expected growth, are not influenced by fishing pressure and are only influenced by non-fishing related factors (such as environmental drivers). Stock status can then be expressed in terms of spawning biomass relative to dynamic B_0 (calculated as $B_y/B_{F=0}$ and denoted as $B_{F=0}$) and compared to spawning biomass relative to static B_0 (calculated as $B_y/B_{t=0}$ where

$B_{t=0}$ is static B_0), with target and limit reference points of the HCRs being expressed as proportions of static $B_{t=0}$ or dynamic $B_{F=0}$.

The SESSF uses a tier-based harvest strategy, where Tier 1 assessments are the most robust and data rich, involving an integrated assessment (Dichmont *et al.*, 2016). The Tier 1 harvest control rule is parameterised as B_{Lim}: B_{Brk}: B_{Targ} (Smith *et al.*, 2008; Fulton *et al.*, 2019). The stock assessment provides an estimate of current spawning biomass, B_y, and the B_{Lim}: B_{Brk}: B_{Targ} HCR computes a target fully-selected fishing mortality, $F_{\mathrm{RBC},y}$, which is related to a limit reference point B_{Lim} (LRP, at which targeted fishing is zero), the control rule breakpoint B_{BRK} (the spawning biomass at which the RBC fishing mortality is reduced below the target level), and the target reference point (TRP), F_{48}. In the current SESSF Tier 1 HCR, F_{48} is the rate of fishing mortality that is estimated to reduce the stock to 48% of its unfished level while B_{Lim} is 0.2 $B_{t=0}$, B_{Brk} is 0.35 $B_{t=0}$ and B_{Targ} is 0.48 $B_{t=0}$.

Under Dynamic B_0, the HCR takes the same 'hockey-stick' form, but the target fishing mortality rate changes as the reference points are now functions of $B_{F=0}$ (for example $B_{\mathrm{Lim},y}$ is 0.2 $B_{F=0}$). Three variants of the dynamic B_0 HCR are evaluated: dynamic B_0; dynamic B_0-target and dynamic B_0-slide. The dynamic B_0-target HCR is identical to the dynamic B_0 HCR except that B_{Lim} is always set to 20% of the static B_0, and B_{Brk} is the maximum of 0.35 $B_{F=0}$ and B_{Lim}. Dynamic B_0-slide allows B_{Lim} to only drop as low as 10% of static B_0 and B_{Brk} is only allowed to drop to 25% of static B_0. The four HCR variants are illustrated in Figure 9-3.

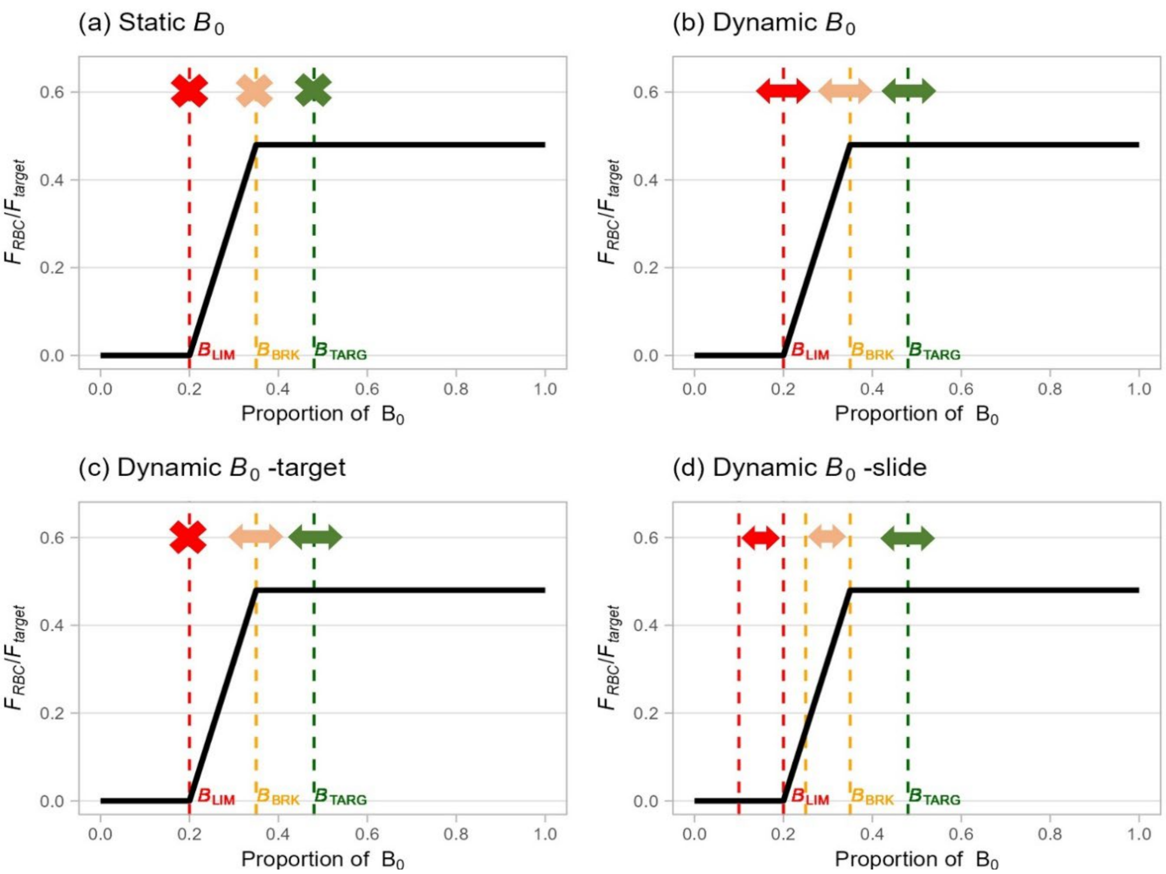


Figure 9-3. Illustration of the four HCRs considered in the MSE: (a) static B_0, (b) dynamic B_0, (c) dynamic B_0-target and (d) dynamic B_0-slide. The solid lines represent the HCR, the dashed red lines show the limit reference point, the dashed orange lines show the breakpoint of the HCR, and the dashed green lines show the target reference point. Coloured crosses represent a part of the HCR that does not change due to time-varying parameters, while arrows represent the ability to change. The two lines for the dynamic B_0-slide HCR (d) represent the range of possible movement for the limit reference point and the breakpoint.

9.3. Results and Discussion

The MSE results presented here (see Bessell-Browne *et al.* 2024, Appendix 17.2) highlight that the use of a dynamic B_0 HCR will, on average, recommend slightly higher and less variable catches than a static B_0 HCR, and there will be a lower probability of zero RBCs. In addition, absolute stock biomass will be smaller than if a static B_0 HCR was adopted.

Stock status (or depletion, expressed as a proportion of estimated unfished biomass) depends on which measure of B_0 is used – relative to static B_0 the status will be lower than relative to an estimate of annual unfished biomass (dynamic B_0). However, a stock with environmentally driven, persistent, lower productivity cannot be expected to rebuild to historical levels over a period of higher productivity.

The SESSF MSE study shows that bias occurs in assessments when parameters are time-varying, but this is not adequately accounted for in the assessment. Even though key assessment outputs are biased when using a static B_0 HCR, this HCR is able to keep the static interpretation of stock status above the limit reference point, while keeping the dynamic interpretation at the target reference point. In contrast, the bias in assessment results for the dynamic B_0 HCRs leads to the static stock status dropping below the limit reference point, and the dynamic stock status not being maintained close to the target reference point.

MSE results also indicate that estimates of static B_0 from the assessment (traditionally assumed to be constant) will vary over time in an attempt to accommodate time-varying changes in R_0 and natural mortality, which are not accommodated in the assessment owing to lack of informative data.

The small difference in median projected catch seen in MSE results between the static B_0 HCR and the dynamic B_0 HCRs partially relates to RBCs under the static B_0 HCR being the same as those under dynamic B_0 when the stock is above the breakpoint biomass level. RBCs decrease faster to zero when stock status is below the LRP using static B_0. RBCs are on average somewhat higher using the dynamic B_0 HCR when stock status is below the breakpoint of the HCR but above the LRP. This is because the dynamic LRP is reduced when declines are attributed to the environment allowing fishing to continue, albeit at lower levels of fishing mortality.

The catches from these two approaches converge to a similar value over the course of the projection period as the stock either recovers, or stabilises at a new lower level, although catches are slightly higher for the dynamic B_0 HCR.

For management purposes, the choice of HCR then depends on management objectives and the intent of the harvest strategy under conditions of changing productivity, particularly declining productivity. The various trade-offs need to be considered when selecting an appropriate harvest strategy. The key trade-offs that managers will need to consider when selecting a HCR for a stock that appears to be environmentally affected relate to catch levels, catch variability, risk of fishery closure (zero RBCs) and expected long-term biomass and any recovery in that biomass. MSE analyses suggest that use of a static B_0 HCR will result in moderately lower catches, higher catch variability and higher risk of fishery closure, but with higher absolute stock size. The opposite trends were found when applying a dynamic B_0 HCR.

10. MSE of static and dynamic HCRs for Redleg Banana Prawn

Biological reference points have long been used in fisheries management to assess stock status relative to desirable and undesirable levels, so that harvest control rules can be developed that help guide the stock towards a target level, or away from a limit level. Traditionally, biological reference points are determined based on historical equilibrium population assumptions. These equilibrium-based 'static' reference points do not account for changes in stock productivity due to e.g. environmental variability, predatory-prey dynamics.

Stock productivity can be highly variable for some marine resources (Rothschild 2000) or is likely to change under a changing climate (Cheung *et al.* 2019, Free *et al.* 2019, Cheung and Frölicher 2020, Kjesbu *et al.* 2022). In these circumstances, static biological reference points, such as the equilibrium-based pre-exploitation biomass B_0, may not be meaningful. Instead, non-equilibrium-based, time-varying reference points, such as a dynamic B_0, or regime-based reference points might provide more appropriate reference indicators of stock abundance (MacCall *et al.* 1985, Szuwalski and Punt 2013, Berger 2019, Maunder and Thorson 2019), particularly under climate change (Szuwalski and Hollowed 2016). Dynamic reference points consider factors other than fishing pressure that might be driving stock size. Thus, instead of setting reference points based on a fixed pre-exploitation biomass (static B_0), a dynamic B_0 could instead set reference points based on a projected unfished biomass for a future year. In this way, future anticipated changes in the environment and hence stock productivity, are implicitly accounted for in the biological reference levels, and any impacts of fishing in the coming period can be evaluated.

Abundance of short-lived, highly variable resources, such as small pelagic fish, squid and prawns, are often driven by the environment (Lehodey *et al.* 2006, Kurota *et al.* 2020, Plagányi *et al.* 2021), with alternating periods of high and low productivity. For these resources, the use of dynamic reference levels could allow increased catches during periods of high stock productivity. During periods of low stock productivity, although catches would be reduced, they could be maintained at even very low stock abundance. Essentially, the use of dynamic reference levels aims to reduce unfairly penalizing fishers if stock levels are low due to underlying environmental conditions, and not because of fishing. Furthermore, it aims to reward fishers with greater effort allocation (fishing mortality) when stock levels are high due to favourable environmental conditions.

The latter is particularly useful for short-lived species in which greater harvests and economic gains may be achievable during these periods. Hence, for short-lived, naturally varying species it might make economic sense to utilise the surplus or "bonus" biomass during environmentally favourable years. However, dynamic reference levels would also allow fishing pressure to be maintained during periods of low stock productivity. In other words, as a stock declines, the limit reference point is reduced, allowing fishing to continue. While this is a less precautionary approach, typical 'boom-bust' dynamics for short-lived species such as forage fish are known to exist in the absence of fishing (Schwartzlose and Alheit 1999) and so it is possible stocks could recover from low levels. Nonetheless, there is still debate around this, given fishing may amplify stock collapse of short-lived species (Essington *et al.* 2015). Moreover, limit reference points are not only implemented to avoid stock collapse, but also for ecological reasons e.g. ensuring a biomass sufficient to maintain ecosystem-based processes (Sainsbury 2008).

The Redleg Banana Prawn *Penaeus indicus* is an example of a short-lived, highly variable species whose abundance has been linked to underlying environmental conditions, specifically El Niño Southern Oscillation (ENSO) cycles and rainfall (Plagányi *et al.* 2021). It is fished primarily in the Joseph

Bonaparte Gulf in northern Australia and contributes to Australia's economically important multispecies northern prawn fishery.

The climate in northern Australia is influenced by large-scale climate features such as ENSO and the Indian Ocean Dipole. Under a changing climate, the variability of extreme ENSO events is expected to increase (Cai *et al.* 2021, Cai *et al.* 2023) and will likely influence the productivity of stocks such as Redleg Banana Prawn. As such, measures are already being taken to ensure fisheries are robust to the anticipated change (Blamey *et al.* 2022, Plagányi *et al.* 2023). Given productivity of Redleg Banana Prawn is expected to change, it is prudent to consider the use of dynamic reference points in management of this stock.

Here, we used an operating model from an existing MSE framework for Redleg Banana Prawn that included a stock-climate relationship (Blamey *et al.* 2022). Using this OM, we tested three harvest control rules based on static, dynamic or a mix of static and dynamic reference levels. We assessed the performance of these rules under a historical climate, a future dry climate (representative of low stock productivity) and a future wet climate (representative of high stock productivity).

10.1. Methods

Redleg Banana Prawn Operating Model

Redleg Banana Prawn (RBP) were modelled using a discrete population model with a monthly timestep and fitted to monthly catch and effort data for the period 1980-2018. The number of prawns in year *y* and month *m* were calculated as follows:

$$N_{y,m+1} = N_{y,m}e^{-M} - C_{y,m} + R_{y,m+1} \tag{1}$$

Where $N_{y,m}$ is the number of prawns in month *m* of year *y*, $C_{y,m}$ is the catch taken that month and $R_{y,m+1}$ is the number of recruits (6-month old prawns) added to the population at the end of each month *m* during year *y*, and M is the monthly natural mortality rate, which is assumed constant. Recruitment is modelled using a Beverton-Holt stock recruitment relationship and is assumed to be related to spawning stock biomass (SSB) six months prior (see Blamey *et al.* (2022) for further details).

Plagányi *et al.* (2021) hypothesised that some major fluctuations in RBP abundance were environmentally driven, specifically related to the Southern Oscillation Index (SOI) and wet season rainfall. Blamey *et al.* (2022) recently incorporated the January SOI and January-February cumulative rainfall into operating models (OM) used for MSE of the Redleg Banana Prawn fishery. In one of the OMs, the January SOI was linked to variability in prawn recruitment, such that during El Niño and La Niña years (defined by an SOI of -7 and 7 respectively), there is an added fluctuation about the expected monthly recruitment as follows:

$$R_{y,m}.\, e^{\varsigma^{e}_{y=ElNino}.\eta + \varsigma_y - (\sigma_R)^2/2} \tag{2}$$

where ς_y reflects fluctuation about the expected recruitment during year *y*, which is assumed to be normally distributed with standard deviation σ_R. In El Niño and La Niña years, a common parameter ($\varsigma^{e}_{y=ElNino}$) is estimated and η is set at -1 in El Niño years and +1 in La Niña years, whereas in neutral years, $\varsigma^{e}_{y=ElNino} = 0$. We use this OM to test harvest control rules based on dynamic and static reference levels under historical and future climate scenarios.

January SOI data were obtained from the Australian Bureau of Meteorology (BOM) (http://www.bom.gov.au/climate/current/soi2.shtml) for the same period as the model, 1980-2018.

Forward projections

The OM was forward projected for 50 years from 2019, and 200 simulations were conducted using the same set of random numbers to generate each simulation (consistent with recommendations of Punt *et al.* 2016). A future exploitable biomass was generated and the monthly future fishing effort was assumed to be similar to recent observed fishing effort during the most recent 5 years and scaled so that the target fishing mortality per month would keep the stock at the target reference level i.e. B_{MEY}^{sp} (Blamey *et al.* 2022). From 2021, we assumed no fishing effort in the first season given recent changes to the Harvest Strategy, and fishing effort in the second season was increased as might be expected with a closure of the first season. The monthly fishing mortality and projected exploitable biomass were then used to calculate the projected number of prawns caught each month. As per Blamey *et al.* (2022), these projected catches were capped at 1.1 x the maximum monthly recorded historical catch, under the assumption there was a limit to what vessels could take.

Using the projected number of prawns, as well as an index of relative spawning occurring during any given month and the average mass of a prawn in that month, the monthly spawning stock biomass $SSB_{y,m}$ could be calculated (see Blamey *et al.* (2022) for details).

Similarly, for calculating dynamic reference levels, the unfished spawning biomass (i.e. a dynamic B_0) was computed based on the unfished projected number of prawns:

$$SSB_{y,m}^{unfished} = f_m \cdot w_m \cdot N_{y,m}^{unfished} \tag{3}$$

where w_m is the average mass of a prawn during month *m*, f_m is a relative index of the amount of spawning during month *m*, assumed to be greatest between October to December given that 95% of recruits arrive between December and April (Loneragan *et al.* 1997) and $N_{y,m}^{unfished}$ is the number of unfished prawns in year *y*, and month *m* (i.e., no fishing applied).

Future CPUE for the projection period was calculated using the projected exploitable biomass, catchability coefficient (*q*), and an assumption regarding future fishing power (Blamey *et al.* 2022). Uncertainty around both the realized future fishing effort (and hence catch) and the predicted CPUE were captured using an implementation error σ_I and observation error σ_{CPUE} respectively. σ_I and σ_{CPUE} were set at levels similar to those estimated from past data (Blamey *et al.* 2022).

Projected ENSO climates

Future SOI projections were generated using the curated CMIP5 sub-set for application-ready data from “Climate change in Australia” (CCiA) (CSIRO and BOM, 2025). Eight of the 40 CMIP5 models assessed in the CCiA project were selected for use in provision of application-ready data (see CSIRO and BOM (2015) for details). A monthly Southern Oscillation Index (SOI) time series for the historical and Representative Concentration Pathway RCP8.5 was generated using the standardized index methodology from the National Centers for Environmental Information (NCEI).

From the eight models used to project SOI, we selected models that represented a historical climate (i.e. 1980s-mid-2000s), a future ‘dry climate’ – a model scenario with more El Ninos than La Ninas and a future ‘wet climate’ – a model scenario with more La Nina’s than El Ninos. We then generated 200 random draws from each of the three model scenarios (historical, dry, wet), each 50 years in length (see example in Figure 10-1).

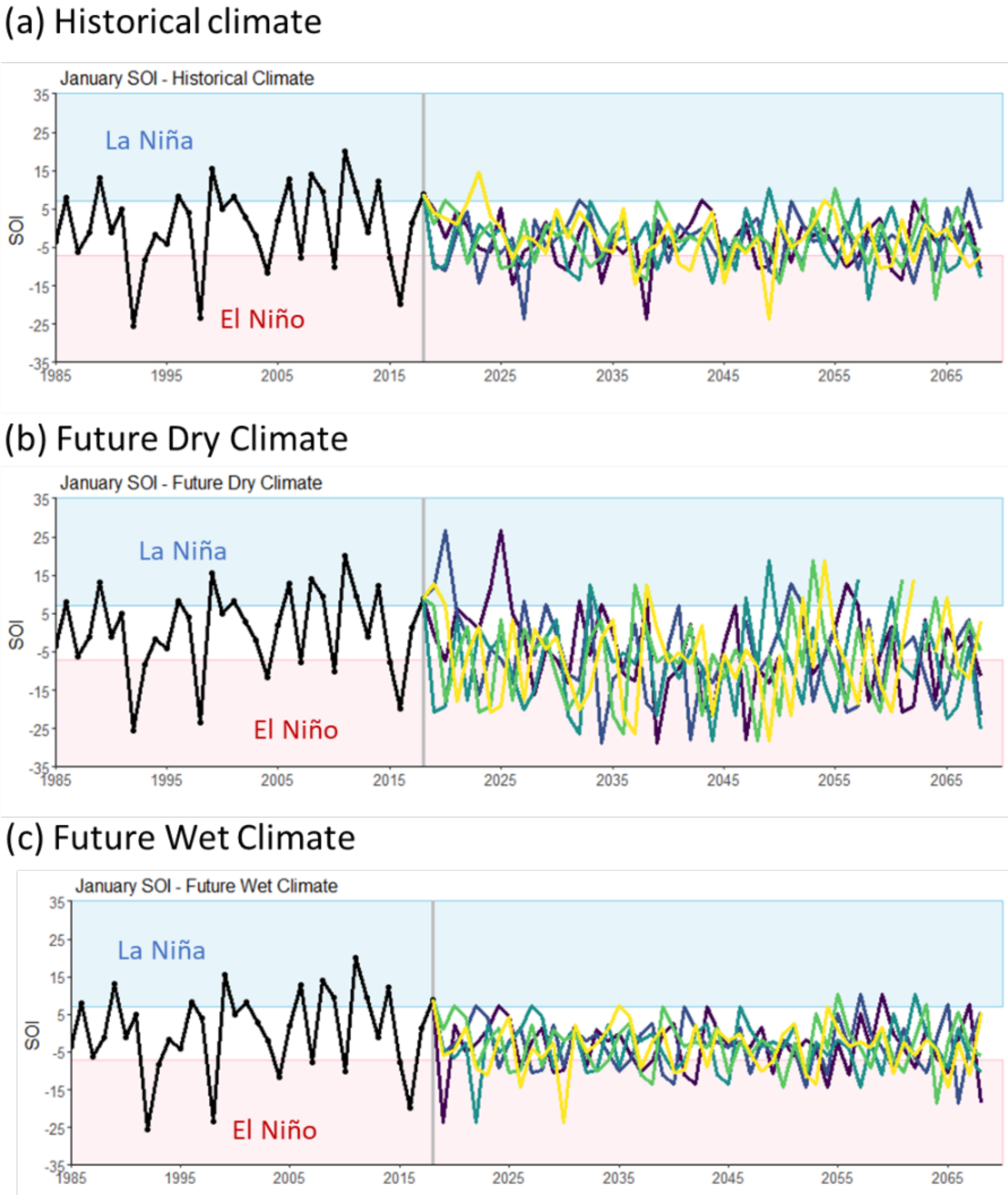


Figure 10-1. Examples of five of the 200 replicate 50-year trajectories of the January Southern Oscillation Index (SOI) for: (a) historical climate; (b) future dry climate; and (c) future wet climate. These forecasts were used for the model projection period (2019-2068) (black lines, observed historical SOI to 2018; grey lines, end of observed historical period 2018; red shading, SOI values corresponding to El Niño years; blue shading, SOI values corresponding to La Niña years).

Reference Levels

The static reference levels were taken from the corresponding operating model – OM2 – in Blamey *et al.* (2022). Thus, B_{MEY} was a proxy that is based on a recent average spawning stock biomass computed over a period when industry were assumed to have been fishing at a level that maximises economic yield, namely average spawning stock biomass since 2000. B_{MSY} was then approximated as $0.8B_{MEY}$, B_{LIM} as $0.5B_{MSY}$ and B_0 as $2B_{MSY}$. The dynamic reference levels were calculated relative to an unfished spawning stock biomass $SSB_{y,m}^{unfished}$ (see Eq 3) instead of the fixed B_0.

Harvest Control Rules

We implemented a hypothetical hockey stick harvest control rule, such that the target fishing mortality F_{Targ} is adjusted based on spawning biomass relative to reference levels (B_{Targ}, B_{Brk} and B_{Lim}). F_{Targ} remains constant when spawning stock biomass is at or above B_{Targ} ($0.6B_0$), F_{Targ} then decreases linearly to 0 at B_{Lim} ($0.25B_0$) when spawning stock biomass drops below B_{Brk} ($0.5B_0$) – i.e. there is no fishing effort when stock size is ≤ B_{Lim}. We varied this harvest control rule such that reference levels were either fixed, dynamic or a mix of fixed and dynamic (Figure 10-2). The three reference levels (B_{Targ}, B_{Brk} and B_{Lim}) were fixed relative to a static B_0 for the static B_0 rule (Figure 10-2a). None of the reference levels were fixed and instead were calculated relative to a fluctuating B_0 (i.e. the annual unfished spawning biomass) for the dynamic B_0 rule (Figure 10-2b). Finally, the limit reference point was fixed and based on a static B_0, whereas the other two reference points (B_{Brk} and B_{Targ}) were calculated relative to a fluctuating unfished biomass for the dynamic B_0-target rule (Figure 10-2c).

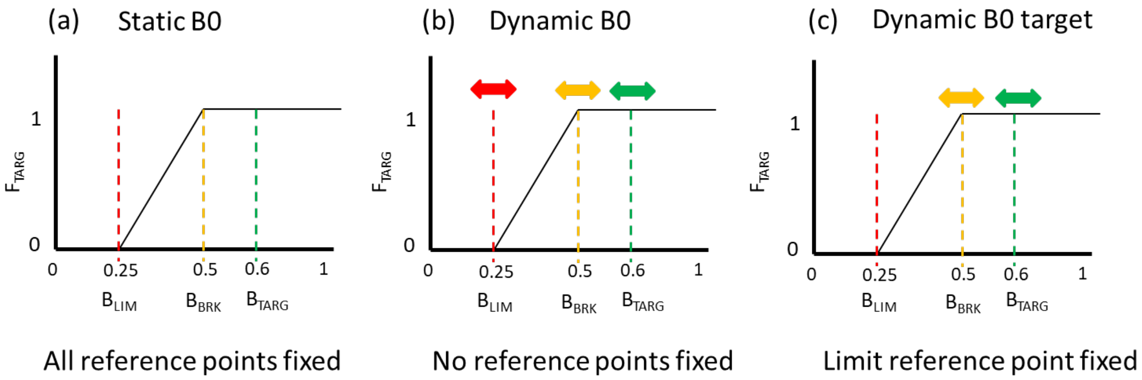


Figure 10-2. The three harvest control rules tested: (a) static B_0 rule with all reference points fixed; (b) dynamic B_0 rule with no reference points fixed and (c) dynamic B_0-target rule with only the limit reference point fixed. Adapted from Bessell-Browne *et al.* (2024), see Appendix 17.2.

Performance Metrics

Performance of the three HCRs under a historical climate, future dry climate and future wet climate was assessed using pre-defined performance metrics. These were:

- Time series showing median ± 90% simulation intervals and example simulations, as well as boxplots showing medians, interquartile ranges and ranges of values over the 200 simulations for spawning stock biomass SSB ;
- Timeseries showing median ± 90% simulation intervals, and example simulations from the 200 simulations for stock status $\frac{SSB}{B_0}$ or $\frac{SSB}{SSB^{unfished}}$,
- Time series showing median ± 90% simulation intervals and example simulations, as well as boxplots showing medians, interquartile ranges and ranges of values over the 200 simulations for predicted annual catch C in tons,
- Timeseries showing median ± 90% simulation intervals, and example simulations from the 200 simulations for predicted recruitment,
- Boxplots showing medians, interquartile ranges and ranges of values over the 200 simulations for the average annual variation (AAV) in catch C over 50 years, calculated as

$$\frac{1}{50}\sum\frac{|C_y - C_{y-1}|}{C_{y-1}}$$

- Probability of SSB falling below the limit reference level (LRP), namely B_{LIM} (equal to $0.25B_0$), at least once during a 50-year projection period. Two variants of this metric were investigated: (a) probability of SSB dropping below a static B_0 LRP of 25% of B_0, and (b) probability of SSB dropping below a dynamic B_0 LRP. This probability is assessed against a 10% threshold level, which is the risk tolerance specified in the Australian Commonwealth Government Fishery Harvest Strategy Policy (CFHSP, Department of Agriculture and Water Resources, 2018);
- Probability of at least one year of zero catch, representing the likelihood of the fishery being closed.

10.2. Results

Spawning stock biomass

There was little difference in median spawning stock biomass between the static B_0 HCR and the dynamic B_0-target HCR whereas median spawning stock biomass was slightly lower under the dynamic B_0 HCR under the historical climate scenario (Figure 10-6a and Figure 10-7a). This pattern was more evident under a future dry climate scenario (i.e., more El Niños and less productive stock), in which there was a greater difference between the dynamic B_0 HCR and the other two HCRs, with the overall trend in SSB declining, but more so under dynamic B_0 because fishing pressure is maintained even when SSB was low due to underlying environmental conditions (Figure 10-6b and Figure 10-7b). Median SSB was similar across all three HCRs under a future wet climate, representative of increased stock productivity (Figure 10-6c and Figure 10-7c).

There was little difference between the three HCRs under historical, future dry and future wet climate considering individual trajectories of SSB (Figure 10-8a-c). However, SSB was projected to dip a bit lower under the dynamic B_0 HCR than under the other two HCRs, particularly for a dry future climate (Figure 10-8b). Variability in SSB was largely maintained across the projection period for the historical and future wet climates, but not the future dry climate, with SSB becoming increasingly reduced over time.

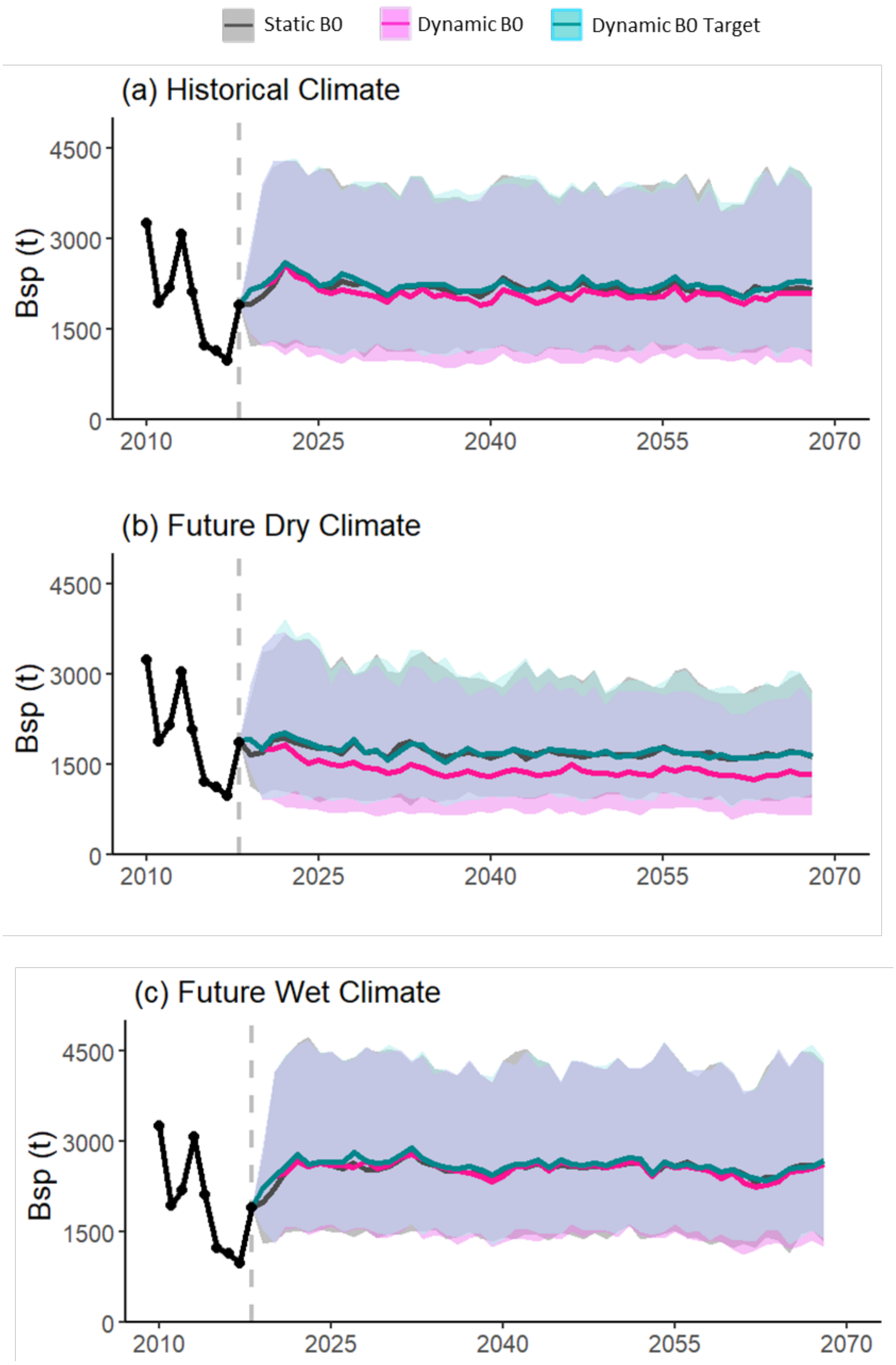


Figure 10-3. Median (with 90% simulation envelope) spawning stock biomass (SSB) projected for 50 years under: (a) historical climate; (b) future dry climate; and (c) future wet climate when applying a static B_0 (grey), dynamic B_0 (pink) or dynamic B_0-target (turquoise) harvest control rule. Black line shows historical estimated SSB and vertical grey dashed line indicates start of the model projection period in 2019.

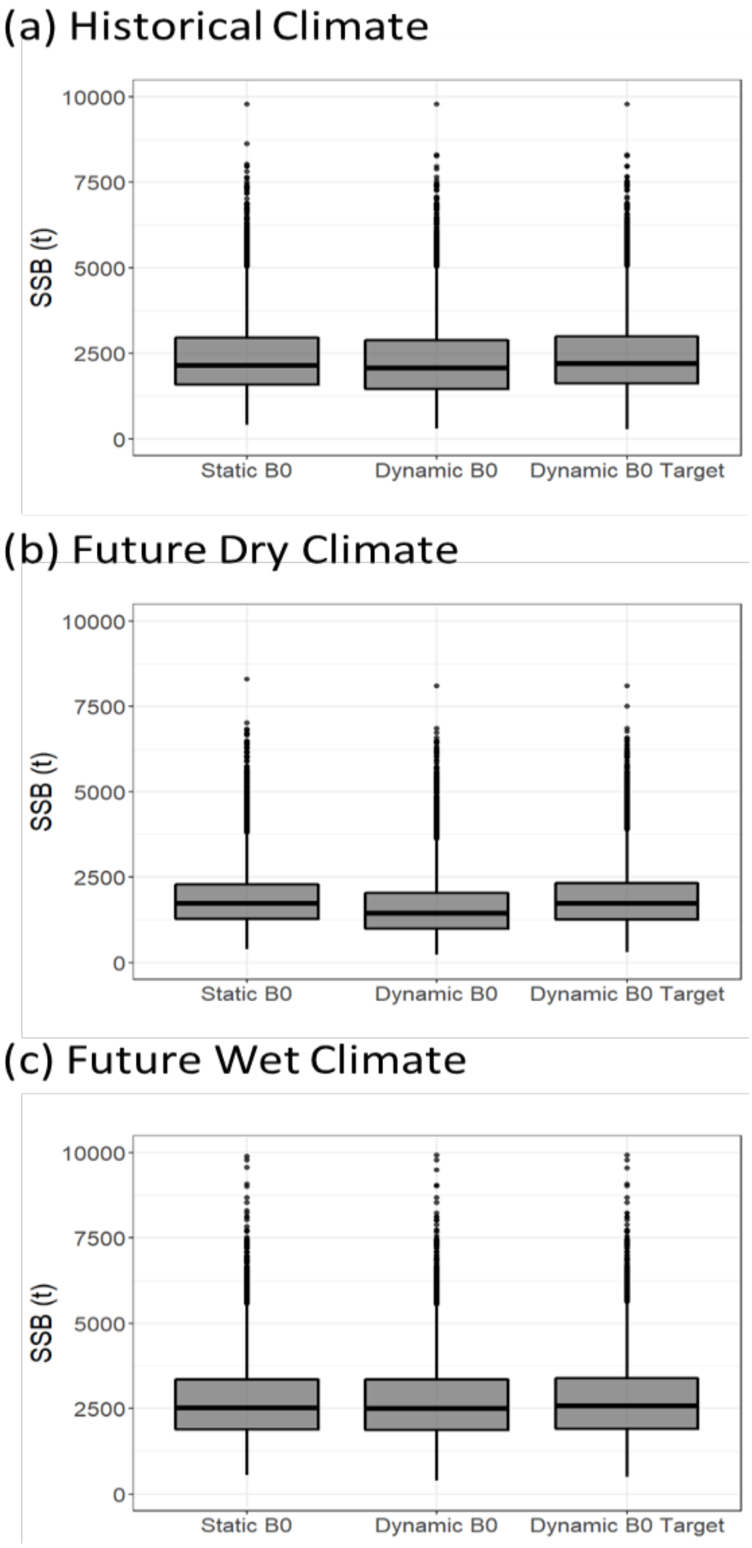


Figure 10-4. Box and whisker plots of spawning stock biomass (SSB, t) under three harvest control rules (static B_0, dynamic B_0 and dynamic B_0-target) for: (a) historical climate; (b) future dry climate; and (c) future wet climate.

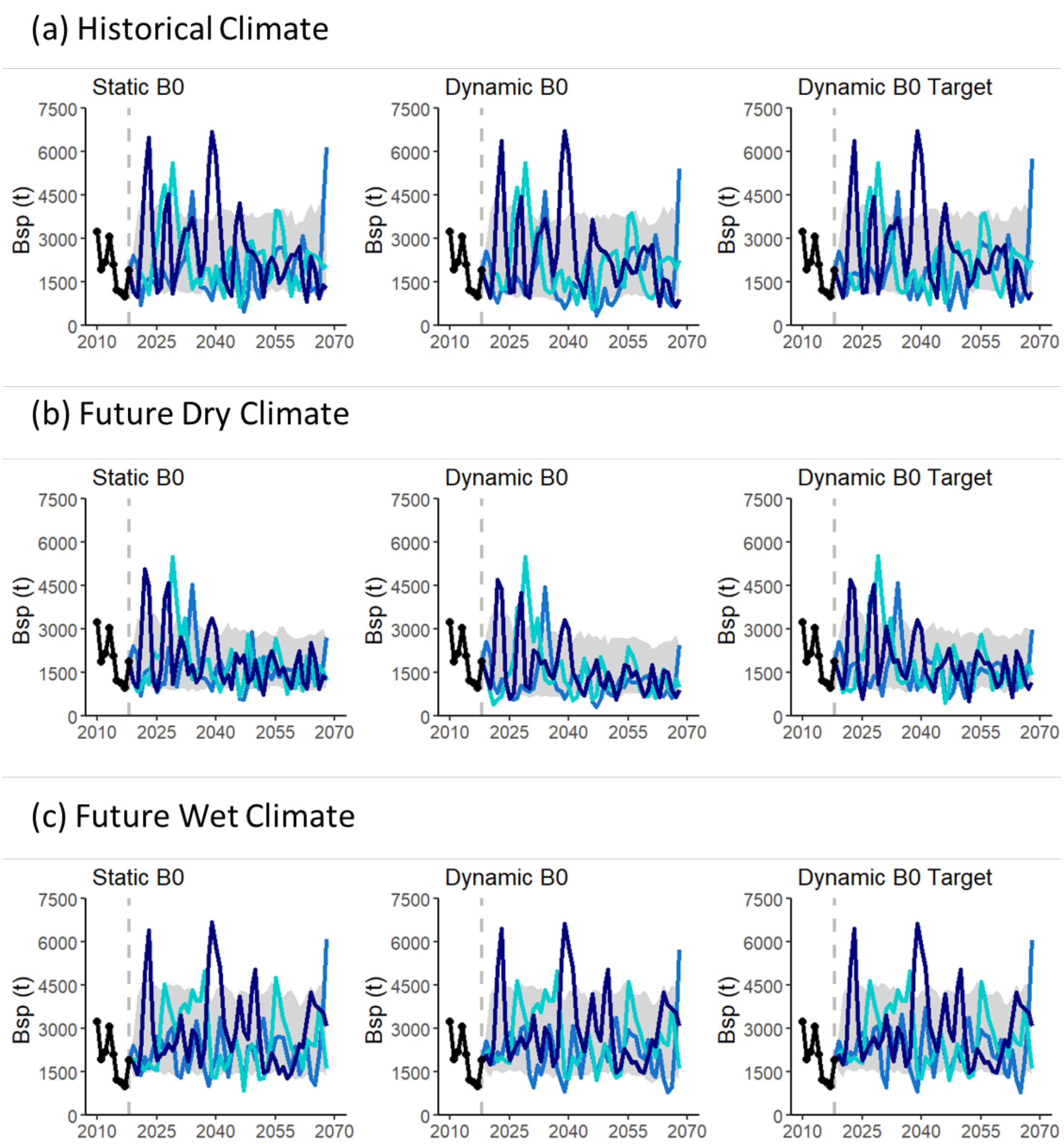


Figure 10-5. Examples of individual trajectories of spawning stock biomass (SSB) for three random model runs (coloured lines) under three harvest control rules (static B_0, dynamic B_0 and dynamic B_0-target) for: (a) historical climate; (b) future dry climate; and (c) future wet climate. Black lines show historical estimated SSB; vertical grey line indicates 2018 – the end of historical model period. Grey shading shows 90% simulation envelope.

Stock status

For the historical climate scenario, projected stock status fluctuated widely under the static B_0 HCR, often dropping below the limit reference level (B_{Lim}) (Figure 10-6a). In contrast, there was less variability in stock status under the dynamic B_0 and dynamic B_0-target HCR, with stock status almost never dropping below the limit reference level. This was because the B_0 for these two HCRs was an unfished spawning biomass that varied from year to year and hence the target reference levels could vary, thus maintaining a more consistent stock status even when the stock was low. Both the dynamic B_0 and dynamic B_0-target rules prevented the SSB dropping below B_{Lim} (Figure 106a). Hence, they are less precautionary under unfavourable conditions / low stock productivity but still allow larger catches when stock abundance is high. However, under the dynamic B_0-target HCR, B_{Lim} is fixed, so fishing cannot continue when stock abundance is very low.

The static B_0 HCR resulted in stock status dropping below B_{Lim} more often under a less productive state (future dry climate scenario), and over time as the stock becomes depleted under unfavourable conditions, B_{Targ} was reached less often. Hence, median stock status declined slightly over time and was much reduced compared to the historical or future wet climate scenarios (Figure 10-6b). The dynamic B_0-target HCR managed to avoid hitting the lower reference level because it enabled fishing pressure to reduce in proportion to stock abundance, but with a fixed lower floor reference level. For this reason, the stock does not decline to the same extent as under the dynamic B_0 HCR. Only the dynamic B_0-target HCR was able to approximately maintain the target reference level on average under the future dry climate scenario (Figure 10-7). The dynamic B_0 HCR resulted in a slight decline in median stock status over time because fishing pressure continues even when the stock is reducing in size (Figure 10-7b).

Under a more productive stock (future wet climate scenario) when the climate is more favourable for prawn recruitment, the three HCRs performed similarly and generally the stock status was maintained at target reference levels (Figure 10-6c and Figure 107c). Nonetheless, under a static B_0 rule there was still the chance of dropping below B_{Lim}. This was likely because even if the stock was low in a particular year, the B_0 remains fixed and hence the reference levels are not adjusted. As such, fishing pressure is maintained and could result in too much catch being taken and the stock hitting B_{Lim} thereafter. When the Redleg Banana Prawn stock is at healthy levels, all three HCRs maintain median stock status at the target reference level (Figure 10-7c).

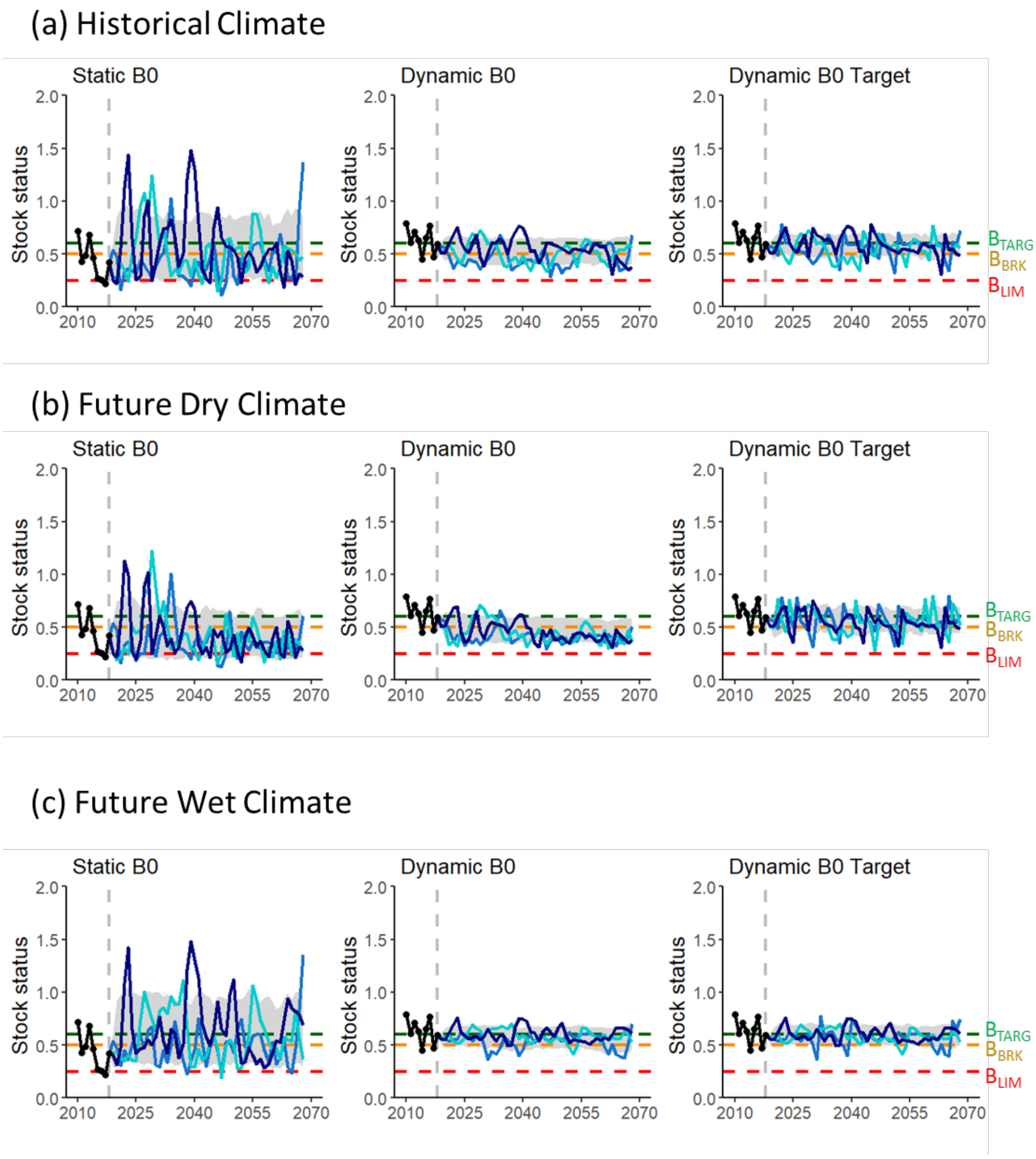


Figure 10-6. Examples of individual trajectories of OM stock status for three random model runs (coloured lines) under three harvest control rules (static B_0, dynamic B_0 and dynamic B_0-target) for; (a) historical climate; (b) future dry climate; and (c) future wet climate. Stock status is calculated as SSB/B_0 (static B_0 HCR) or $SSB/B_{Unfished}$ (dynamic B_0 HCR and dynamic B_0-target HCR). Black lines show historical estimated stock status; vertical grey line indicates 2018 – the end of historical model period. Grey shading shows 90% simulation envelope. Horizontal dashed lines indicated the reference levels: B_{Targ} (green), B_{Brk} (yellow) and B_{Lim} (red). Static reference levels were used for the Static B_0 HCR whereas dynamic reference levels were used for the Dynamic B_0 and Dynamic B_0-target HCRs as per Figure 102. Trajectories show three randomly selected possible outcomes under this OM.

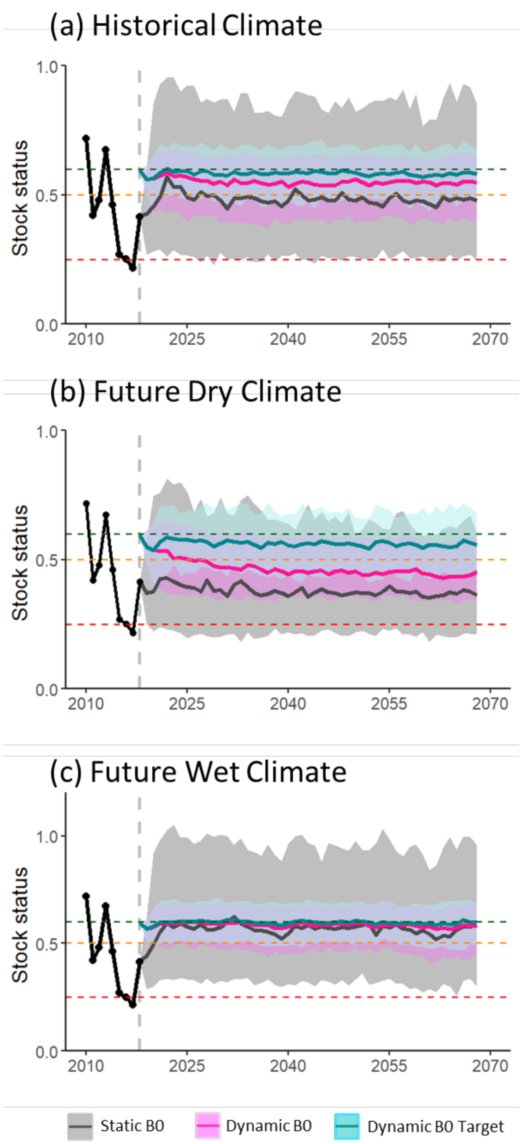


Figure 10-7. Median (with 90% simulation envelope) stock status projected for 50 years under: (a) historical climate; (b) future dry climate; and (c) future wet climate when applying a static B_0 (grey), dynamic B_0 (pink) or dynamic B_0-target (turquoise) harvest control rule. Stock status is calculated as SSB/B_0 (static B_0 HCR) or $SSB/B_{Unfished}$ (dynamic B_0 HCR and dynamic B_0-target HCR). Black line shows historical estimated stock status and vertical grey dashed line indicates 2018 – the end of historical model period. Horizontal dashed lines indicated the reference levels: B_{Targ} (green), B_{Brk} (yellow) and B_{Lim} (red). Static reference levels were used for the Static B_0 HCR whereas dynamic reference levels were used for the Dynamic B_0 and Dynamic B_0-target HCRs

Catch and catch variability

Catches were more variable under the static B_0 HCR for the historical climate, and the static B_0 and dynamic B_0-target HCRs meant that catches sometimes reduced to zero, although this is slightly less under the dynamic B_0-target HCR (Figure 10-8a). Catches were almost always maintained and were less variable across the projection period under the dynamic B_0 HCR (Figure 10-8a). This pattern was more evident under a future dry climate scenario, where catches reduced to zero more often under the static B_0 and dynamic B_0-target HCRs, but were maintained under the dynamic B_0 HCR, even though the stock was being reduced in size (Figure 10-8b). Catches were greater and less variable under all three HCRs under the future wet climate scenario, when the Redleg Banana Prawn stock was elevated because of more favourable environment (La Niñas), and these catches dropped to zero less frequently for the static B_0 and dynamic B_0 target HCRs (Figure 10-8c).

There was little difference across the HCRs in terms of median catch, although the dynamic B_0-target HCR resulted in a slightly lower median catch than the others (Figure 10-9). Median catch under the dynamic B_0 HCR was only slightly greater under the future dry climate scenario because under this HCR, fishing continued even as the stock declined. However, these catches are less variable from year to year and so probably reflect more frequent smaller catches.

Catch variability was greatest under the static B_0 HCR, least under the dynamic B_0 HCR, and somewhere in between with the dynamic B_0-target HCR (Figure 10-9). This pattern was most notable when stock productivity was low (future dry climate scenario) and less obvious when stock productivity was high (future wet climate scenario) (Figure 10-9).

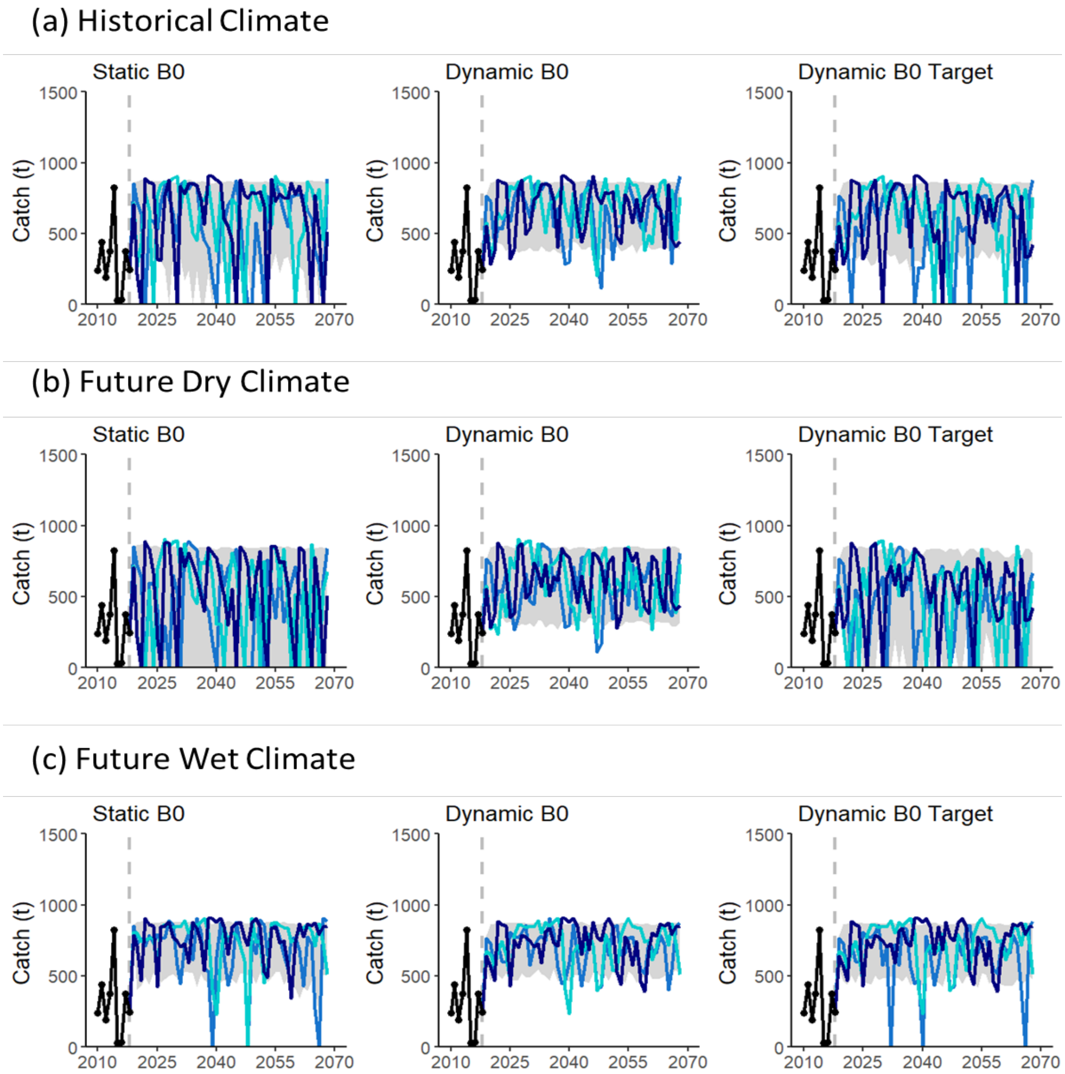


Figure 10-8. Examples of individual trajectories of catch for three random model runs (coloured lines) under three harvest control rules (static B_0, dynamic B_0 and dynamic B_0 target) for; (a) historical climate; (b) future dry climate; and (c) future wet climate. Black lines show historical estimated stock status; vertical grey line indicates 2018 – the end of historical model period. Grey shading shows 90% simulation envelope. Trajectories show three randomly selected possible outcomes under this OM.

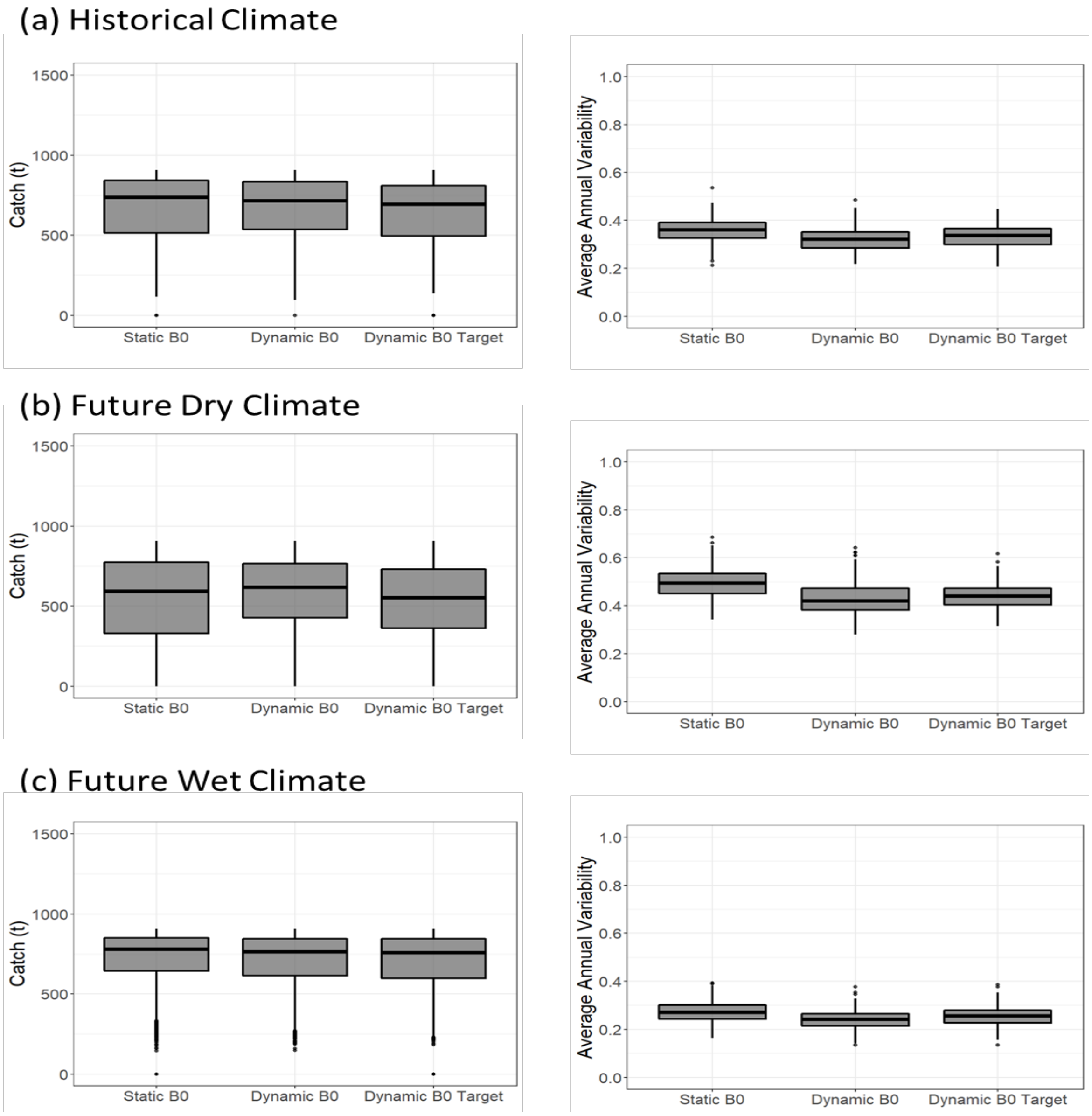


Figure 10-9. Box and whisker plots of catch (t) (left panels) and average annual variability in catch (right panels) under three harvest control rules (static B_0, dynamic B_0 and dynamic B_0-target) for; (a) historical climate; (b) future dry climate; and (c) future wet climate.

Recruitment

There was little difference in median recruitment among the HCRs, which is to be expected as recruitment is largely driven by the environment. Median recruitment differed considerably between the three future climate scenarios, with a much lower recruitment under the future dry climate scenario (more El Niños) and this declined slightly over time. In contrast, recruitment was greatest under the future wet climate scenario (more La Niñas) (Figure 10-10).

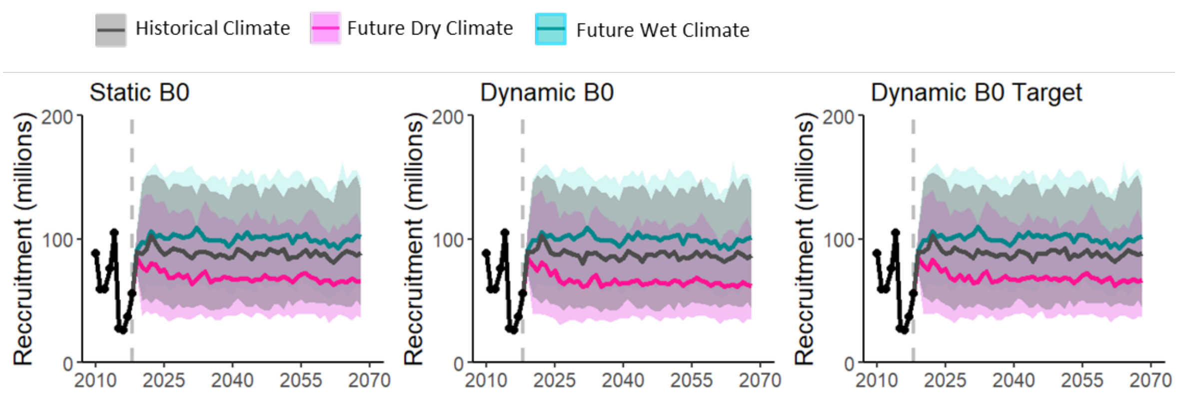


Figure 10-10. Median (with 90% simulation envelope) Redleg Banana Prawn recruitment projected for 50 years under historical climate (grey), future dry climate (pink) and future wet climate (turquoise) when applying a static B_0, dynamic B_0 or dynamic B_0-target harvest control rule. Black line shows historical estimated recruitment and vertical grey dashed line indicates 2018 – the end of historical model period.

Risk of breaching the limit reference point and obtaining zero catch

The probability of dropping below a fixed limit reference point in the OM is greatest under the dynamic B_0 HCR and was > 10%, which is considered unacceptable under the guidelines of the Australian Commonwealth Harvest Strategy. Under the future dry climate scenario, the probability of dropping below a fixed limit reference point is greatly increased for all three HCRs, but most notably for the dynamic B_0 HCR. This probability is reduced under the future wet climate scenario, for all three HCRs with little difference among them (Figure 10-11).

The probability of dropping below a variable limit reference point in the OM, i.e. B_{LIM} changes from year to year, was negligible for both the dynamic B_0 and dynamic B_0-target HCRs (and not applicable for the static B_0 HCR) (Figure 10-11).

The probability of catch being zero at least once was greatest under the static B_0 HCR, less under the dynamic B_0-target HCR and least (almost zero) under the dynamic B_0 HCR. Probabilities of achieving zero catch at least once increased under the future dry climate scenario and decreased under the future wet climate scenario (Figure 10-11).

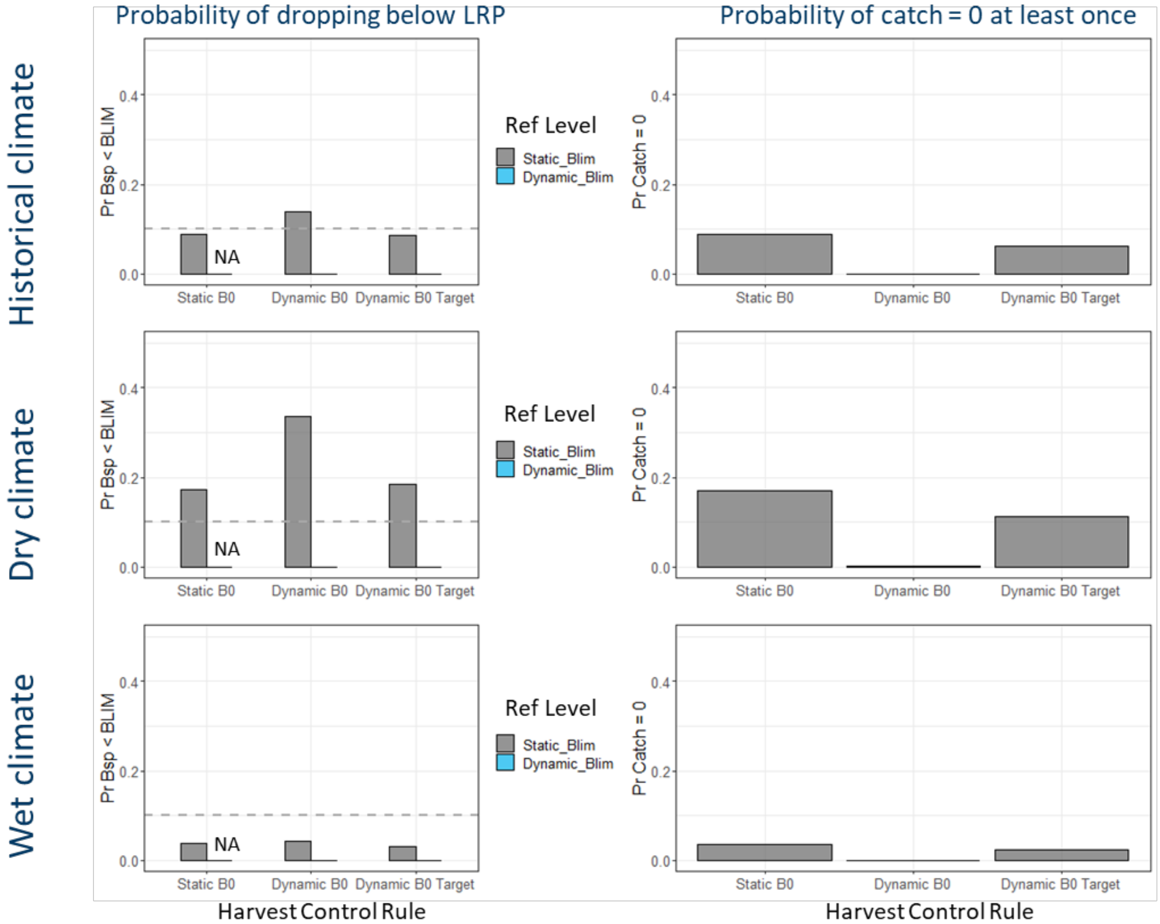


Figure 10-11. Left panel: Probability of dropping below the limit reference point in the OM (B_{LIM}), when B_{LIM} is static (grey bar) or dynamic (blue bar) under three harvest control rules: static B_0, dynamic B_0 and dynamic B_0-target and three climate scenarios: Historical climate, future dry climate and future wet climate. Horizontal grey dashed line indicates probability of 0.1. Right panel: probability of catch being zero at least once in the model simulations under three different harvest control rules: static B_0, dynamic B_0 and dynamic B_0-target and three different climate scenarios: Historical climate, future dry climate and future wet climate.

10.3. Discussion

Fisheries management will need to respond to changing climate and the associated impacts on fish stocks and the marine environment. Changes in stock productivity are one of the anticipated impacts under climate change, leading to increased consideration of alternative reference levels (Berger 2019, Szuwalski *et al.* 2023). Short-lived, fast-growing species are often highly sensitive to fluctuations in environment and consequently can switch between periods of high and low productivity. In this study, we assessed the performance of harvest control rules based on static, dynamic or a mix of static and dynamic reference levels on a short-lived, fast-growing species. We assessed the performance of these rules under a historical climate, a future dry climate (representative of low stock productivity) and a future wet climate (representative of high stock productivity).

Implications in utilising dynamic reference levels

We found little difference in the performance of HCRs based on static, dynamic or a mix of static and dynamic reference levels under a historical climate. Similarly, there was little difference between the three HCRs when the stock was productive (e.g., under a wet climate with more La Niñas), although catches did not dip as low under the dynamic B_0 HCR and catch variability was reduced, similar to findings in Chapter 8 of this report. It was only when stock productivity was low, as might be expected due to unfavourable conditions such as a drier climate (more El Niños), that the greatest difference between dynamic and static-based reference levels was found. This finding is in line with other studies that found the difference between static B_0 and dynamic B_0 HCRs was greatest when productivity declines (Berger 2019, Chapter 8 of this report). Under low stock productivity, we found that the dynamic B_0 HCR, on average, maintained higher catches, but that spawning stock biomass decreased. This is not surprising given that catches can be maintained, even as the stock declines, because the reference levels in the HCR change relative to the unfished spawning stock biomass, which is declining due to deteriorating environmental conditions. Moreover, the dynamic B_0 HCR reduced the probability of breaching a dynamic LRP and achieving no catch. However, there was increased probability of this HCR breaching the static LRP, particularly when stock productivity was low. The gains made in catch under a dynamic B_0 HCR relative to a static B_0 HCR were not considerable and need to be traded-off against increased risk to the fishery and stock. This is in line with Szuwalski *et al.* (2023), who found that biomass gains under static management targets were larger than harvest gains under dynamic management targets.

Limitations and caveats

It is important to note that this study was largely hypothetical. First, all the HCRs that were assessed under this study (including the static B_0 HCR) were hypothetical and the Redleg Banana Prawn are not managed like this in practice. Recent changes have been made to the harvest strategy to ensure that management of the Redleg Banana Prawn fishery is robust to increasing environmental uncertainty (Blamey *et al.* 2022, Plagányi *et al.* 2023). Second, the future climate scenarios were somewhat hypothetical and selected specifically to represent a more productive stock (future wet climate) and less productive stock (future dry climate). We selected SOI forecasts that represented wet and dry futures given there is some uncertainty in future rainfall in northern Australia (Grose *et al.* 2020).

Nonetheless, there are predictions for an increase in the variability and frequency of extreme El Niño events and associated rainfall (Cai *et al.* 2014, Wang *et al.* 2017, Cai *et al.* 2018, Cai *et al.* 2023). Furthermore, we used climate projections from the CMIP5 (Coupled Model Intercomparison Projects) models given we did not have access to the updated CMIP6 models at the time. Although there are differences between the CMIP5 and CMIP6 models, particularly with regards to climate extremes (e.g. Zhang and Chen 2021, Zhu *et al.* 2021), CMIP6 projections for Australia are likely similar to those of CMIP5, albeit with some improved confidence (Grose *et al.* 2020, Deng *et al.* 2021). Given we used SOI projections to portray hypothetical wet vs dry future climate, we do not consider it an issue that the projections are not taken from the most recent CMIP phase. However, in future it would be worthwhile to update the SOI projections.

Another limitation was that only one operating model from the Redleg Banana Prawn MSE framework was used to assess the performance of the HCRs. Ideally, MSE needs to account for a range of uncertainties, including model uncertainty (Punt *et al.* 2016) and in the future, it would be useful to consider other OMs that account for stock-environment relationships and other environmental drivers e.g. rainfall (see Plagányi *et al.* 2021, and Blamey *et al.* 2022).

This chapter only focused on time-varying recruitment as the driver of change in productivity, when other factors such as natural mortality are likely to also vary through time but are not always considered in simulations (although see Chapter 8 of this report). Given Redleg Banana Prawn are extremely short-lived (12-18 months), changes in natural mortality may not have as large an impact as changes in recruitment, but this should be confirmed in future work.

Finally, the analyses did not include any uncertainty or error associated with the SOI-recruitment relationship. In other words, the OM assumed that recruitment is either reduced or boosted respectively in every El Niño or La Niña year. In reality, there is some uncertainty around this relationship (Plagányi *et al.* 2021) and it may not hold every year. This was somewhat overcome by the use of multiple OMs in the study by Blamey *et al.* (2022) in which not all OMs included a stock-environment relationship and the fact that reference levels were not based on this relationship. In this study, the dynamic reference levels used in any given year are based on the unfished SSB (dynamic B_0), which depends on the recruitment-SOI relationship. Hence, in the future, one might want to consider including an error around this relationship.

11. Conclusions and recommendations

Key conclusions reached by the project are summarised below under headings related to sequential stages in the process from data collection –> evidence evaluation –> stock assessment –> management. Bullet points show conclusions reached by the project. Related, numbered recommendations are made after each set of conclusions. The key conclusions below are further summarised in Table 11-1.

These conclusions and recommendations directly address all the project objectives:

- All project components include a review of relevant international literature relating to research and management of fish stocks under conditions of changing productivity.
- Suitable candidate fish stocks were identified showing a range of biological productivity characteristics.
- Several approaches were used to evaluate evidence for non-fishing-driven changes in productivity in these candidate stocks, and which might appropriately be managed using dynamic reference points.
- Assessments for these stocks were updated and retrospective analysis of static and dynamic B_0 was used to compare how recommended biological catch recommendations would have differed applying HCRs static and dynamic reference points.
- Several alternative candidate HCRs were developed using static or dynamic reference points, and the performance of these was evaluated using MSE under this project.
- Based on the results of all these project components, several recommendations are made below on future implementation of dynamic reference points and harvest strategies.

11.1. Data collection requirements

The analyses presented in this project largely depended on the results of integrated catch-at-age stock assessments (referred to as Tier 1 assessments in the SESSF). These assessments are able to estimate annual recruitment deviations, and changes in productivity that can be attributed to those recruitment deviations. Such assessments are required to estimate trends in spawning biomass, recruitment, static and dynamic B_0 and dynamic reference points.

The results of Tier 1 assessments, used to set RBCs for stocks in the SESSF mixed-species trawl fishery, first drew attention to the apparent non-recovery of some of these stocks, such as Jackass Morwong east, Redfish and Silver Warehou, despite reduction in catches to levels that were expected to have resulted in their rebuilding. The assessments estimated persistent low recruitment over the past decade or so; well below the levels predicted by the stock-recruitment curve used in the assessments. The assessments were conducted using *Stock Synthesis* software and a bespoke assessment implemented using AD Model Builder (Fournier *et al.* 2012) for SESSF stocks and northern crustacean stocks respectively.

- Tier 1 assessments able to estimate dynamic B_0 require consistent and representative data on landings, discards, effort, along with catch length and age compositions.
- It is primarily data on annual length- and age-composition that inform estimation of recruitment deviations. Much of the evidence for non-fishing effects is derived from the estimates of recruitment deviations relative to those expected from the (usually assumed) stock-recruitment relationship.

1. **Data collection programs should focus on sampling the spatial distribution of the fishery, with adequate samples to allow robust estimation of recruitment deviations within integrated assessments, and subsequent estimation of trends in unfished biomass. Where**

relevant (e.g., for SESSF stocks; longer-lived species), this sampling should focus on collection of age data as these data more directly inform cohort strength through time and thus estimation of recruitment deviations.

11.2. Evidence for environmental impacts on productivity

Stakeholders placed strong emphasis on the importance of having clear evidence for non-fishing (environmentally driven) effects, before considering management approaches that recognise environmental effects on stock productivity and adjust management actions accordingly.

- This project expanded on the expert-judgement approach of Klaer *et al.* (2013), which ranked evidence for environmentally driven effects to justify the regime shift in productivity implemented in the stock assessment for Jackass Morwong east in 2010.
- This project provided a multi-method approach for quantifying available evidence for fishing and non-fishing effects, rather than using expert judgement ranking. This included development of new methods to calculate and present trends in dynamic B_0 deviations as relative trajectory plots comparing fishing and non-fishing effects over time (see *Chapter 8: Evidence for fishing and non-fishing effects*).
- These analyses predominantly rely on estimates of recruitment deviations derived from Tier 1 assessments to estimate dynamic B_0 deviations over the history of the fishery, and to analyse correlations between recruitment patterns between multiple stocks, and with environmental indices. It also relies on the estimated stock-recruitment relationship being unbiased given systematic deviations about a stock-recruitment relationship are interpreted by dynamic B_0 as non-fishing effects.
- Multiple lines of evidence for fishing and non-fishing effects were evaluated for eight case study stocks: six Southeast Trawl Fishery stocks (Jackass Morwong east, Redfish, Silver Warehou, Blue Grenadier, Tiger Flathead, Eastern School Whiting) and two short-lived northern crustacean stocks (Ornate Rock Lobster, Redleg Banana Prawn).
- Analyses showed a wide range of non-fishing effects in terms of both magnitude and historical duration for the case study stocks, ranging from strong evidence for non-fishing effects but little overfishing on Jackass Morwong east over 1975–2017, to little evidence for non-fishing effects but substantial overfishing for Redfish.
- The Tiger Flathead and Eastern School Whiting stocks show little evidence of non-fishing effects or overfishing, fluctuating close to the management target fishing intensity level from 1975–2017.
- The Blue Grenadier stock shows moderate non-fishing effects in most years, but without trend, with episodic years of stronger, positive non-fishing induced recruitment. This stock is known to show episodic high recruitments between extended periods of lower-than-average recruitment. This stock has remained substantially underfished throughout the analysis period.
- The short-lived Redleg Banana Prawn and Ornate Rock Lobster stocks show strong non-fishing effects, but without trend. There was high inter-annual variability in recruitment driven by environmental factors, including the ENSO cycle and associated changes in sea temperature, rainfall, ocean currents, sea surface height, etc. Recruitment variability has resulted, in turn, in high variability in stock biomass and fishing intensity, again without trend.
- Evidence for strong non-fishing effects on the Jackass Morwong east stock was reinforced in this project, with a continuous and strong negative trend over the entire analysis period. Over 1975–1995 fishing intensity fluctuated around the target, but over 1996–2014 fishing intensity was moderately above target.

- Silver Warehou showed a recent negative trend in non-fishing effects over 2008–2017 when fishing intensity was at or below target. There was an earlier period of positive non-fishing effects from 1994–1999, followed by a period of overfishing over 1999–2006, over which time there was little evidence of non-fishing effects.
- There is evidence of masking of non-fishing effects by strong overfishing effects and *vice versa*. Redfish shows correlated patterns in recruitment deviations with Jackass Morwong east and Silver Warehou that appear, in turn, may be correlated with the ENSO environmental index. This suggests an environmental effect on recruitment patterns in all three stocks. However, whereas Jackass Morwong east and Silver Warehou show evidence of negative trends in dynamic B_0 deviations, there is little evidence for differences between static and dynamic B_0 for Redfish, with strong overfishing depleting the stock to levels at which low recruitment is expected.

2. **For stocks with Tier 1 assessments capable of estimating recruitment deviations and trends in dynamic B_0, presentation of assessment results should include trends in dynamic B_0, so that evidence for non-fishing effects can be evaluated, noting that interpretation depends on the assumed unbiasedness of the stock-recruitment relationship.**
3. **Periodic broader reviews of all evidence for non-fishing effects should be conducted for stocks that remain persistently below target, and near the limit biomass, despite management measures that are expected to reduce fishing mortality to levels that should allow for rebuilding.**

11.3. Evaluation of productivity changes in stock assessments

Assessments that estimate stock status as spawning biomass relative to static B_0 as the measure of initial or equilibrium unfished biomass conventionally attribute changes in expected recruitment and expected biomass to the effects of fishing. However, environmental factors can affect key components of biological productivity, such as growth, spawning and recruitment, to some extent, and have always done so.

In conventional fishery stock assessments, ignoring variation in parameters through time does not result in biased results if the parameters vary without trend. However, if parameters change in a directional manner, the assumption of non-stationarity in parameters is no longer tenable. It is commonly acknowledged that climate change is resulting in directional change in parameters for many stocks, however, most jurisdictions lack the data to estimate time-varying parameters.

- For several stocks in the SESSF, systematic differences between estimated recruitment and that expected from the stock-recruitment relationship have become increasingly evident over the past few decades. These differences may reflect the effects of the environment on recruitment, independent of fishing, leading to a declining trend in recruitment. Under such circumstances, a stock is no longer likely to fluctuate around historical production levels, and reference points based on static B_0 no longer reflect the levels to which a stock could be expected to rebuild if unfished.
- Estimates of stock status based on dynamic B_0 (the estimate of the level to which a stock would be expected to rebuild under recent productivity parameters) permit an evaluation of the relative effect of fishing compared to the environment, where non-fishing effects appear to have caused changes in productivity.
- Assessments that can estimate dynamic B_0 could potentially be used to estimate the apparent impact of non-fishing effects on productivity when there is insufficient data to directly estimate time variation in parameters (e.g. growth, M, recruitment).

- Over the past decade, Tier 1 assessments for stocks showing persistent low recruitment, such as Jackass Morwong east, Silver Warehou and Redfish, have conducted constant catch projections assuming that future recruitment will equal recent low average recruitment as the basis for RBC recommendations. This constitutes a formal response to apparent environmental (non-fishing) effects.

4. **Tier 1 stock assessments should routinely report historical trends in both static and dynamic B_0, and depletion relative to static and dynamic B_0 to identify potential non-fishing effects on stock status.**
5. **For stocks for which there are inadequate data to conduct a Tier 1 assessment, efforts should continue to develop robust lower information assessment methods that are able to estimate inter-annual changes in productivity (such as persistent declines in recruitment or production) that cannot be fully explained by fishing mortality.**

11.4. Performance of static vs. dynamic harvest control rules

In broad overview, the results of the MSE and simulation analysis of static and dynamic HCRs for selected SESSF stocks (*Chapter 9: MSE of static and dynamic HCRs for SESSF stocks, Chapter 7: Retrospective analysis*), demonstrate how RBCs would change when applying HCRs based on dynamic B_0. Under conditions of declining productivity, implemented as a declining trend in R_0, changing reference points result in reduced absolute stock size, slightly higher RBCs using dynamic B_0 HCRs, reduced interannual catch variation and decreased probability of fishery closure. However, MSE analysis identified some unexpected behaviour of stock assessments when using dynamic harvest control rules under conditions of declining productivity.

Previous studies investigating dynamic B_0 have focused on the performance of HCRs given perfect information about stock size and productivity (see studies referred to in *Chapter 7: Retrospective analysis*). The MSE analysis for SESSF stocks incorporated trends in the productivity parameters being manipulated (R_0 or M), observation error and process error in recruitment. This introduced variability around estimated stock size and allowing the trade-offs and associated risk of various HCRs to be quantified.

During MSE testing, the decrease in biological productivity was limited to 50% of the initial values for R_0 and a change in M matching that in R_0 in terms of the impact on spawning biomass, either as a cyclical decline and recovery or a linear decline to an enduring lower level. The hard 'floor' in the dynamic B_0-slide HCR was also set at 50% of the initial (static B_0) level (i.e. 0.1 static B_0).

- From the MSE results in this report, the use of a dynamic B_0 HCR will, on average, recommend slightly higher and less variable catch limits than a static B_0 HCR, and there will be a lower probability of zero RBCs. In addition, the stock biomass (in magnitude) will be smaller than if a static B_0 HCR was adopted given changing productivity (modelled as trends in expected R_0 and M for the SESSF; modelled as recruitment driven by El Niño Southern Oscillation for Redleg Banana Prawn).
- Stock status (or depletion, expressed as a proportion of estimated unfished biomass) depends on which measure of B_0 is used – relative to static B_0 the status will be lower than relative to an estimate of annual unfished biomass (dynamic B_0). However, a stock with environmentally driven, persistent, lower productivity cannot be expected to rebuild to historical levels, even in the absence of fishing. The SESSF MSE study shows that bias occurs in assessments when parameters are time-varying, but this is not adequately accounted for in the assessment, with this bias larger when using dynamic B_0-based HCRs (see *Chapter 9: MSE of static and dynamic HCRs for SESSF stocks; Appendix 17.2*). Even though key assessment outputs are biased when using a static B_0 HCR, this HCR is able to keep the static interpretation of stock status above

the limit reference point, while keeping the dynamic interpretation at the target reference point. In contrast, the bias in assessment results for the dynamic B_0 HCRs leads to the static stock status dropping below the limit reference point, and the dynamic stock status not being maintained close to the target reference point.

- MSE results also indicate that estimates of static B_0 from the assessment (traditionally assumed to be constant) will vary over time in an attempt to accommodate time-varying changes in R_0 and natural mortality, which are not accommodated in the assessment owing to lack of sufficiently informative data.
- The small difference in median projected catch seen in MSE results between the static B_0 HCR and the dynamic B_0 HCRs partially relates to RBCs under the static B_0 HCR being the same as those under dynamic B_0 when the stock is above the breakpoint biomass level. RBCs decrease faster to zero when stock status is below the breakpoint of the HCR using static B_0. RBCs are on average somewhat higher using the dynamic B_0 HCR when stock status is below the breakpoint of the HCR but above the LRP. This is because the dynamic LRP is reduced when declines are attributed to the environment, allowing fishing to continue, albeit at lower levels of fishing mortality.
- The catches from these two approaches converge to a similar value over the course of the projection period as the stock either recovers, or stabilises at a new lower level, although catch limits are slightly higher for the dynamic B_0 HCR (see *Chapter 9: MSE of static and dynamic HCRs for SESSF stocks* and *Chapter 10: MSE of static and dynamic HCRs for Redleg Banana Prawn*).

6. **Further work is required to fully understand the cause of increased bias in estimates of spawning stock biomass when using dynamic B_0 HCRs.**
7. **Investigation of directional retrospective patterns in B_0 between assessments should be undertaken as an additional line of evidence suggesting impacts of non-fishing effects.**

11.5. Management trade-offs under productivity shift

The results of the MSE testing illustrate several clear trade-offs when choosing a management approach and a harvest control rule to be used for stocks that appear to show changing productivity. It is not the role of science to advise on management objectives, but it is the role of science to identify and evaluate these trade-offs and associated risks, so that managers can make informed choices when developing harvest strategies.

- Determining which of the tested HCRs is most appropriate to the biology of the stock, and provides optimal performance in meeting related management objectives, depends on several factors. First, there needs to be strong evidence that environmental drivers are causing a clear and persistent trend in productivity. Second, it must be checked that indications of changes in productivity do not result from misspecification in assessments or inadequate data (resulting for example in incorrect estimates of recruitment deviations).
- A key challenge is to detect that productivity is time-varying, which may be difficult for assessments with varying levels of data quality and quantity. Consistent declining trends in estimates of unfished biomass from an integrated assessment may provide an indication of time-varying productivity if there is confidence that the assessment is not mis-specified.
- Once a stock has been identified and agreed to have been strongly affected by environmental factors, appropriate management objectives need to be established and clearly described, so that a harvest strategy can be designed to meet these objectives under the changed environmental conditions and productivity. (See the process implemented to reduce B_0 for Jackass Morwong east described by Klaer *et al.* (2015)).

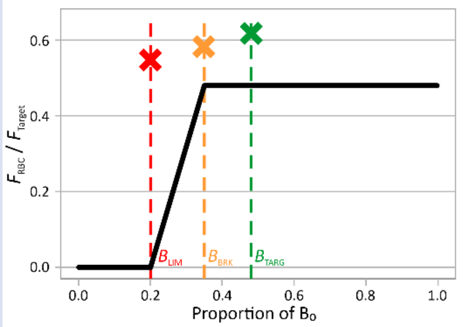
- The choice of HCR then depends on management objectives and the intent of the harvest strategy under conditions of changing productivity, particularly declining productivity. The various trade-offs need to be considered when selecting an appropriate harvest strategy. The key trade-offs that managers will need to consider when selecting an HCR for a stock that appears to be environmentally affected relate to catch levels, catch variability, risk of fishery closure (zero RBCs) and expected long-term biomass and any recovery in that biomass. MSE analyses in this report suggest that use of a static B_0 HCR will result in moderately lower catches, higher catch variability and higher risk of fishery closure, but with higher absolute stock size. The opposite trends were found when applying a dynamic B_0 HCR.
- Under the Commonwealth Harvest Strategy Policy (2018) and harvest strategies developed under that policy, the target reference point (0.48 B_0 for the SESSF and 0.6 B_0 for RBP) relates to the economic objective of maximizing net revenue. The limit reference point (0.2 B_0 for SESSF and 0.25 B_0 for RBP) relates to conservation of the resource and is intended to prevent impairment of recruitment by ensuring an adequate biomass to spawn. The appropriateness of these values and their intended objectives should be developed based on specific fishery characteristics and goals.
- When the default proxy targets and limits were incorporated in the Harvest Strategy Policy, there was no consideration of what an appropriate absolute biomass level might be to prevent recruitment impairment of a stock that is declining for environmental reasons. Environmental drivers can conceivably lead a stock to decline to extremely low levels, in which case management targets and limits become largely meaningless and fisheries management cannot potentially affect the outcome much. However, preserving some absolute biomass, if this can be achieved, would be expected to increase the resilience of the stock to rebuild, should environmental conditions improve.
- The 'hard limit' dynamic B_0-target and dynamic B_0-slide HCRs tested here attempted to achieve a compromise between the static and fully dynamic HCRs. This achieves a compromise along the trade-off axes, by allowing a decrease in reference points to allow for some catches of a lower productivity stock, while preventing the limit reference point from declining to levels that might compromise the resilience of the stock to rebuild. Determining the range of permissible change in these parameters would need to be determined as part of harvest strategy development and would depend on the species biology, and the degree and persistence to which productivity has been negatively affected by environmental drivers.

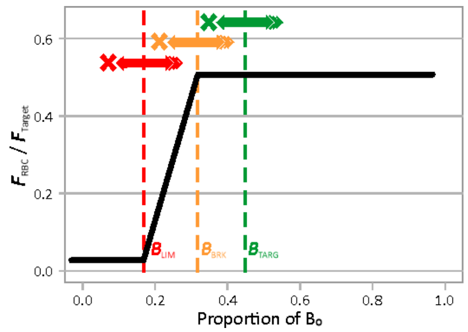
8. **Harvest strategy guidelines and objectives need to be clearly defined. In particular, the intention of the various reference points, particularly the limit reference point, should be clearly defined in the harvest strategy. This definition will need to consider the approach to be taken if a stock has been permanently reduced in productivity and size due to environmental effects.**
9. **Results indicate that using dynamic B_0 is preferable, and more biologically realistic, to the currently implemented step change in productivity for Jackass Morwong east. Analyses showing evidence of productivity decline for this species suggest that there has been an ongoing decline in productivity, rather than a single step change.**

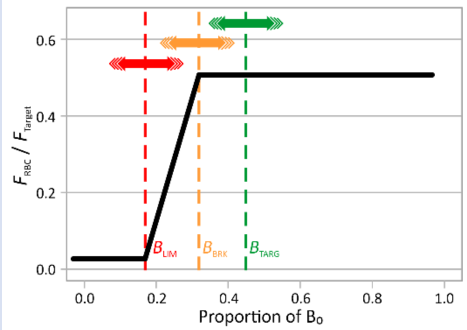
Table 11-1 Summary of key characteristics, performance and management trade-offs of harvest control rules using references points based on static or dynamic B_0.

	Harvest Control Rules Static B_0	Dynamic B_0 with floor (Dyn B_0 target / Dyn B_0 slide)	Dynamic B_0 ($B_{F=0}$)
Estimation of B_0	Assessments estimate a single, fixed 'static' B_0, being the 'virgin biomass' or equilibrium unfished biomass. Under unchanging biological productivity, the stock is expected to be able to rebuild to near this biomass level in the absence of fishing. Variation in estimation of this parameter will occur as assessments are updated.	As for Dynamic B_0.	Assessments estimate annually changing dynamic B_0 ($B_{F=0}$) under changing productivity, calculated as the level the stock would be expected to currently be at had no fishing occurred, while assuming that all other productivity parameters in the assessment (growth, natural mortality and recruitment deviations) remain as they were estimated in each year by the assessment.
Calculation of Reference Points	Reference points are calculated as specified proportions of the unchanging static B_0 value. The SESSF HCR uses a target of $0.48B_0$, a breakpoint of $0.35B_0$ and a limit of $0.2B_0$, with fishing mortality decreasing as stock status decreases between the breakpoint and the limit reference point. Reference points remain unchanged irrespective of trends in stock biomass (see diagram).	As for Dynamic B_0 with no limit to increases in reference points. However, a 'floor' or hard limit is implemented so that reference points cannot decrease below some specified proportion of the static B_0 reference point (B_{Lim}) (see diagram).	Reference points are calculated as the same proportions as in the static B_0 control rule ($0.48B_0$, $0.35B_0$ and $0.2B_0$), but relative to dynamic B_0. Reference points increase or decrease proportionally to the annual change in dynamic B_0 with no limit to how far the reference points can increase or decrease (see diagram).

HCR diagram







Performance measures

Under conditions of unchanged productivity

Under conditions of unchanging productivity, with no evidence of environmentally induced changes in biological productivity parameters, there will be little deviation in the catch limits recommended by dynamic B_0 and by static B_0. There will therefore be little difference between reference points calculated as proportions of static or dynamic B_0, and little difference in performance of the three control rules shown.

Under conditions of decreasing productivity

Dynamic B_0 will decrease over time and so will the reference points calculated from dynamic B_0 under conditions of decreasing productivity (such as a persistent decrease in recruitment deviations from those predicted by the stock-recruitment curve), with clear evidence of non-fishing negative effects on productivity. Depending on stock status in relation to the breakpoint and limit reference points, RBC recommendations will differ using the three control rules shown.

Recommended biological catches	Under decreasing productivity, the static B_0 HCR will recommend reductions in RBCs earlier, as the breakpoint is reached. Below the breakpoint level, the static B_0 HCR will recommend lower catches than the dynamic B_0 HCR, as stock status decreases.	Under conditions of decreasing productivity, dynamic B_0-slide HCR will perform exactly as the dynamic B_0 HCR until the hard limit point is reached. Once the hard limit is reached, the reference points become static at the new lower level and this HCR will revert to performing as a static B_0 HCR at the new lower B_0 level. If productivity and dynamic B_0 increase again to above the floor level, then this HCR will revert again to performing the same as the dynamic B_0 HCR.	Under conditions of decreasing productivity, the dynamic B_0 HCR will recommend reductions in RBCs later than the static B_0 HCR, due to the breakpoint decreasing as dynamic B_0 decreases. As the stock size decreases between the breakpoint and limit reference point, RBCs will be higher. RBCs will, however, still be decreased proportionally to declines in stock biomass as a result of applying the target fishing mortality rate (F_{Targ}) to the decreasing biomass.
Catch variability	RBCs will be more variable under a static B_0 HCR than a dynamic B_0 HCR, if the stock fluctuates between the breakpoint and limit reference level point.		RBCs will be less variable under a dynamic B_0 HCR, with changes in reference points tracking the decrease in dynamic B_0
Risk of fishery closure	There is a higher likelihood of zero RBCs (fishery closure) using the static B_0 HCR, as the limit reference point remains constant as the stock size declines.		There is a lower likelihood of zero RBCs (fishery closure) using the dynamic B_0 HCR.
Stock biomass	When below the breakpoint of the HCR, the static B_0 HCR will maintain a higher spawning stock biomass, as a result of lower catches or earlier catch reductions.		For any given stock size below the static HCR breakpoint, a dynamic B_0 HCR will result in a lower absolute stock size, as a result of higher catches or later catch reductions along with fewer fishery closures as the limit reference point drops with stock size.

	Management trade-offs
RBCs	RBCs (catches) will be slightly higher under a dynamic B_0 HCR when the stock lies between the static breakpoint and limit reference points, as a result of delayed RBC reductions under a dynamic B_0 HCR compared to a static B_0 HCR.
RBC variability	RBCs are likely to be more variable under a static B_0 HCR as the stock fluctuates across static breakpoint and limit reference levels, whereas dynamic reference points adjust to dampen these fluctuations.
Risk of zero RBC	There is a higher likelihood of zero RBCs (fishery closure) using the static B_0 HCR.
Spawning biomass	The absolute spawning biomass will be higher using a static B_0 HCR as a result of the earlier catch reductions, lower catches and increased likelihood of zero RBCs. This may increase the resilience of the stock.
	Justification for applying dynamic HCRs
Evidence for non-fishing effects on productivity	Application of dynamic B_0 HCRs needs to be justified by clear evidence of strong negative non-fishing effects on biological productivity, which cannot be explained by the effects of fishing. This is what occurred for Jackass Morwong east in 2011, when strong and persistent evidence of substantial productivity and decrease, along with a plausible hypothesis for the decline in recruitment, resulted in a step-reduction in B_0 by 70%. In the absence of clear evidence for non-fishing effects on productivity, fishing will likely be the main driver of changes in biomass and static B_0 will be an appropriate basis for setting management targets and limits.

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13. Implications

The purpose of this project was to provide advice to the Australian Fisheries Management Authority (although also relevant to State fisheries management agencies) regarding options for setting management targets and limits for stocks that appear to have been substantially and persistently impacted by non-fishing (presumably environmental) factors. Since at least 1990, several stocks in the multispecies southeast trawl fishery have shown persistent recruitment below that predicted by the stock-recruitment curves in assessments. Repeated reduction in TACs for these stocks to levels that were expected to have resulted in rebuilding failed to result in stock recovery, providing strong indications that the recruitment, and therefore biological productivity, of these stocks has decreased because of non-fishing effects.

For one of these stocks, Jackass Morwong east, this resulted in an evaluation of evidence for environmental effects on productivity that concluded that the stock had undergone a substantial 'regime shift' to a lower productivity level. This was implemented in assessments from 2011 onwards as an (estimated) 70% step-change reduction in 'static' B_0, back-calculated to have occurred in 1998. Analysis of evidence for productivity change for Jackass Morwong east in this project shows that this actually occurred as a steady reduction in productivity from at least 1975. Given the protracted and continual decrease in productivity for Jackass Morwong east, implementation of a dynamic B_0 HCR would have been more appropriate than a step-change regime shift, allowing management measures (RBCs) to track the change in productivity as it occurred.

This project has developed methods and provides guidance on a rigorous, evidence-based approach to identify stocks subject to substantial non-fishing effects and design dynamic harvest control rules to potentially manage such stocks. The main implications of this project relate to guidance provided to fisheries resource assessment and management committees on:

- Data requirements for assessments able to estimate annual recruitment strengths and deviations,
- Detecting and evaluating evidence for non-fishing effects on fish stocks, given assessments that can estimate annual recruitment deviations.
- Estimation of trends in dynamic B_0 and comparison with static B_0, to provide an index of the likely magnitude of non-fishing effects on fish stocks.
- Guidance on options for design of harvest control rules using dynamic reference points, where there is evidence for persistent non-fishing effects.
- Evaluation of risks and trade-offs associated with implementing static vs. various versions of dynamic harvest control rules.

This guidance is intended to assist fisheries managers and stakeholders to determine whether dynamic harvest strategies are appropriate for stocks and, if so, to establish clear management objectives and design appropriate harvest control rules to achieve those objectives.

14. Extension and Adoption

14.1. Extension

Key stakeholders, particularly AFMA, have been kept informed throughout the project through background information documents and presentations of results. Stakeholders were provided with a detailed information document and a presentation on the purpose and methodology of the project, as part of an initial questionnaire sent to stakeholders over February – June 2021. This questionnaire was structured to provide background information and explanation of the use of dynamic reference points, and to canvas opinions, comments, questions and concerns regarding use of dynamic reference points in management of Australian fish stocks. Stakeholders consulted included AFMA, DAWE and AFMA RAG members involved in the SESSF. The report of this 1st Stakeholder Consultation is provided in Appendix 17.4.

An overview of key results and initial conclusion for SESSF stocks was presented to a video meeting of the AFMA Southeast Scalefish and Shark Fishery Resource Assessment Group (SESSF RAG) in August 2021. Participants in this meeting included AFMA managers for the SESSF fishery, SESSF fishing industry representatives and representatives from New South Wales Department of Primary Industries (NSW DPI). NSW DPI provides NSW fisheries data to CSIRO under an agreement to share data for the purpose of joint assessment of stocks shared between Commonwealth and NSW fishers, and communication has been maintained with NSW DPI regarding use of shared data for this dynamic reference points project.

A presentation with additional results was given at a workshop for project 2018-021: *Developing and testing a multi-species Harvest Strategy for the SESSF* in Canberra on 17 March 2022. Participants in the workshop included participants in both projects and representatives of AFMA, ABARES and the Department of Agriculture, Water and the Environment (DAWE).

A 2nd Stakeholder Consultation Workshop was held at AFMA offices in Canberra in May 2023 and again included representatives of AFMA, AFMA RAGs, DAFF and DCCEEW. The report on outcomes of this 2nd Stakeholder Workshop is provided in Appendix 17.5.

Results of this project were presented at an international virtual workshop on *Implication of climate change on harvest strategies* held on 20 September 2023, convened by David Smith, Beth Fulton and André Punt with support from AFMA. The primary aim of the workshop was to examine the implications of climate change on the performances of harvest strategies, how such implications might be addressed, and what had been implemented, through the experiences of several countries and regions, with a focus on the technical aspects of various options and approaches. A report and summaries of presentations were circulated to participants, and it is intended that this will serve as the basis for a scientific paper.

Results of the project were more widely communicated to Australian State fisheries researchers and managers at an FRDC Harvest Strategy Webinar in December 2023, where objectives and key results of all the FRDC projects underway at the time relating to fisheries harvest strategies were shared by project leaders. A summary report of this webinar is available from the FRDC:

Cartwright I (facilitator) (2023) FRDC Harvest Strategy Extension Webinar: Summary Webinar Report. FRDC Project no. 2019-082, 25 pp.

A short media article on *Dynamic approach to improve fisheries management* was published in the FRDC News (https://www.frdc.com.au/dynamic-approach-improve-fisheries-management), outlining how changing population dynamics could usefully be addressed in fisheries modelling and management. Results of the project have also been presented to a wide range of stakeholders at numerous stakeholder consultation meetings, AFMA SESSF RAG meetings and joint project workshops).

The project has resulted in two peer reviewed scientific publications in which the project key findings relating to MSE testing of alternative harvest control ules under conditions of changing productivity have been made available to the scientific community in peer reviewed journals:

Bessell-Browne P, Punt AE, Tuck GN, Day J, Klaer N and Penney A (2022) The effects of implementing a 'dynamic B_0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. *Fisheries Research* 252. https://doi.org/10.1016/j.fishres.2022.106306

Bessell-Browne P, Punt AE, Tuck GN, Burch P and Penney A (2024) Management strategy evaluation of static and dynamic harvest control rules under long-term changes in stock productivity: A case study from the SESSF. *Fisheries Research* 273. https://doi.org/10.1016/j.fishres.2024.106972

14.2. Adoption

Results of *Stock Synthesis* assessments presented at AFMA SESSFRAG meetings now routinely include a comparison of static B_0 and dynamic B_0 on biomass trend plots (e.g. deepwater flathead in 2023), to provide an overview (in terms of dynamic B_0 deviation) of the degree to which the stock being assessed shows evidence of non-fishing effects that cannot be explained by fishing mortality, given the biological productivity specifications of the assessment.

Results of this project will be presented at AFMA Southeast RAG meetings to inform discussions regarding further options for design and implementation of appropriate harvest strategies for stocks affected by environmental drivers.

15. Glossary

The glossary terms below have been selected from the glossary to the 2020 edition of the Status of Australian Fish Stocks (SAFS) reports (https://www.fish.gov.au/) as being relevant to the topics covered in this report.

Acceptable biological catch. See Recommended biological catch.

Age-length (age-length key or curve). Relationship between age and length describing the growth of a species. Growth curves are derived from age-length data. Age-length keys are tables of estimated ages of fish of increasing length, usually derived from otolith age readings (see Otoliths). Age-length keys are used to translate length composition data into conditional age at length data, which can be used when fitting age-structured stock assessment models.

Age-frequency/Age-Composition. Numbers of fish in each age class from samples of the fish captured during a fishing season. Sometimes sampled separately for retained and discarded catch. An important data input for age structured fisheries stock assessments. Usually derived from length-frequency data and age-length keys.

Age-structured assessment. Assessment of the status of a fish stock incorporating length- and age-composition data, as well as indices of relative abundance (such as CPUE), whereby the production (recruitment and growth) and mortality (natural mortality and fishing mortality) of each age class in the population are assessed to estimate the number of fish of each age each year.

Area closure. Closure of a defined area/fishing ground, often for a defined period. Used as a tool in the management of a fishery, to reduce fishing mortality in a chosen area at a chosen time. See also Temporal closure.

Australian Fishing Zone (AFZ). The area extending seaward of coastal waters (that is, from three nautical miles from the territorial sea baseline) to the outer limits of the Exclusive Economic Zone (EEZ). In the case of external territories, such as Christmas Island, the AFZ extends from the territorial sea baseline to the outer limit of the EEZ. The AFZ is defined in the *Fisheries Management Act 1991* (Cth), which also specifies a number of 'excepted waters', notably in Antarctica and the Torres Strait, that are excluded from the AFZ.

B_0 (mean equilibrium unfished biomass). The average biomass level if fishing had not occurred. Usually refers to the historical biomass estimated to have existed before fishing commenced.

Biodiversity. Biological diversity: variety among living organisms, including genetic diversity, diversity within and between species, and diversity within ecosystems.

Bioeconomic model. Method of fisheries stock assessment that models the interaction between the biology of harvested species and the human behaviour of fishers as shaped by economic factors. Seeks to evaluate how economic factors influence fishery performance and economic productivity of a fishery.

Biological reference point. The value of a biological indicator (usually biomass or fishing mortality, but can include surrogate (proxy) indicators, such as length or catch per unit effort) that is used to guide management decisions. Can be either a 'target reference point' that management actions seek to attain, or a minimum biologically acceptable limit ('limit reference point') that management actions seek to avoid. Proxies can be defined and used for hypothetical biological reference points that are difficult to estimate.

Biological stock. Genetically or functionally discrete population that is largely distinct from other populations of the same species and can be regarded as a separate homogeneous group for management or assessment purposes.

Biomass (B). Total weight of a stock or a component of a stock.

Biomass limit reference point (B_{LIM}). Stock biomass below which the risk to the stock is regarded as unacceptably high. Usually expressed as a fraction of B_0, the average adult biomass before the commencement of fishing.

Biomass at maximum economic yield (B_{MEY}). Average biomass corresponding to maximum economic yield. A target reference point that may be estimated using a bioeconomic model.

Biomass at maximum sustainable yield (B_{MSY}). Average biomass corresponding to maximum sustainable yield. A target reference point estimated using a stock assessment model.

Biomass proxy. A relative biomass level used in place of a quantitatively estimated biological reference point when the latter cannot easily be estimated, usually expressed as a fraction of unfished biomass B_0. For example, 0.48 B_0 is used as a proxy for the biomass that sustains maximum economic yield (B_{MEY}) in Commonwealth fisheries.

Bycatch. A species that is (a) returned to the sea either because it has no commercial value or because regulations preclude it being retained, or (b) is affected by interaction with the fishing gear but does not reach the deck of the fishing vessel.

Catch per unit effort (CPUE). The number or weight of fish caught by a unit of fishing effort, such as tonnes caught per day or per fishing operation. Often used as an index of relative fish abundance through time in stock assessments and management decision rules.

Catch projection. Forecasts of estimated future yields (catches) from a fishery, produced using the results of stock assessments.

Catch rate. See Catch per unit effort.

Cohort. Individuals of a stock born in the same spawning season.

Conservation dependent species. The *Environment Protection and Biodiversity Conservation Act 1999 (Cth)* dictates that a native species is eligible to be included in the conservation dependent category at a particular time if, at that time, (a) the species is the focus of a specific conservation program, the cessation of which would result in the species becoming vulnerable, endangered or critically endangered; or (b) the following subparagraphs are satisfied: (i) the species is a species of fish; (ii) the species is the focus of a plan of management that provides for management actions necessary to stop the decline of, and support the recovery of, the species so that its chances of long-term survival in nature are maximised; (iii) the plan of management is in force under a law of the Commonwealth or of a state or territory; and (iv) cessation of the plan of management would adversely affect the conservation status of the species.

Decision rules. Rules that determine agreed management recommendations under predefined circumstances regarding stock status. Also called ‘control rules’ or ‘harvest control rules’. Usually a key component of a Harvest Strategy.

Demersal. Found on or near the benthic habitat (*cf.* Pelagic).

Depletion (stock depletion). A measure of how close or far the biomass of a fish stock is from a reference condition, usually the average unfished spawning biomass; the smaller the number the more depleted a stock is said to be.

Depletion estimation methods. Stock assessment methods that estimate both the spawning biomass of a stock before exploitation began and that remaining after a period of exploitation.

Discards. Any part of the catch that is returned to the sea, whether dead or alive.

Dynamic B_0. Also referred to as B_{Unfished} or $B_{F=0}$ (biomass under conditions of zero fishing mortality). This is calculated in stock assessments as the level the stock would be expected to currently be at had no fishing occurred, while assuming that all other productivity parameters in the assessment (growth, natural mortality and recruitment deviations) remain as they were estimated in each year by the assessment run with the catches as estimated in the assessment. It provides an indicator of non-fishing effects on stock biomass.

Ecologically sustainable. 'Use of natural resources within their capacity to sustain natural processes while maintaining the life-support systems of nature and ensuring that the benefit of the use to the present generation does not diminish the potential to meet the needs and aspirations of future generations'.

Ecologically viable stock. 'Ecologically viable stock refers to the maintenance of an exploited population at high levels of abundance, to maintain biological productivity above target levels, provide margins of safety for uncertainty, and conserve the stocks' role and function in the ecosystem'.

Ecological risk assessment. A process of estimating the effects of human actions on a natural resource.

Ecosystem. A complex system of plant, animal and microorganism communities that, together with the non-living components, interact to maintain a functional ecological unit.

Effort. A measure of the level of fishing activity used to harvest a fishery's stocks. The measure of effort appropriate for a fishery depends on the methods used and the management arrangements. Common measures include the number of vessels, the number of hooks set, number of trawl tows, the duration of trawl tows and the number of fishing days or nights.

Effort restriction. Restriction of the permitted amount of fishing effort (for example, the number of vessels or total number of hooks) in a particular fishery; used as a management tool. One of the input controls that can be used to limit impacts of a fishery (*see* Input controls).

El Niño. The extensive warming of the central and eastern Pacific Ocean with northward and southward expansion of equatorial warm waters that leads to a major shift in weather patterns across the Pacific region (*cf*. La Niña). In Australia (particularly eastern Australia), El Niño events are associated with an increased probability of drier conditions.

Endangered species. A species in danger of extinction because of its low numbers or degraded habitat, or likely to become so unless the factors affecting its status improve. The *Environment Protection and Biodiversity Conservation Act 1999* (Cth) dictates that a native species is eligible to be included in the endangered category at a particular time if, at that time, (a) it is not critically endangered, and (b) it is facing a very high risk of extinction in the wild in the near future, as determined in accordance with the prescribed criteria.

***Environment Protection and Biodiversity Conservation Act 1999* (Cth) (EPBC Act).** Australia's national environment law. The EPBC Act focuses on protecting matters of national importance, such as World Heritage sites, national heritage places, wetlands of international importance (Ramsar wetlands), nationally threatened species and ecological communities, migratory species, Commonwealth marine areas, and nuclear actions.

Exclusive Economic Zone (EEZ). The area that extends from the limit of the territorial sea, which is 12 nautical miles offshore from the territorial sea baseline to a maximum of 200 nautical miles, measured from the territorial sea baseline. The EEZ is less than 200 nautical miles in extent, where it coincides with the EEZ of another country. In this case, the boundaries between the two countries are defined by treaty. Australia has sovereign rights and responsibilities over the water column and the seabed in its EEZ, including the exploration and exploitation of natural resources.

Exploitation rate. The proportion of an exploited fish population caught; usually expressed as an annual rate.

Fishing mortality limit reference point (F_{LIM}). The fishing mortality rate above which overfishing is said to be occurring and the stock biomass would be declining (-depleting). If applied for long enough, this can lead to a stock declining below the biomass limit reference point.

Fishing mortality maximum sustainable yield (F_{MSY}). The fishing mortality rate that, at equilibrium, is expected to produce the maximum sustainable yield.

Fishery-dependent data. Data collected directly from a fishery, from commercial fishers, processors and retailers. Common methods include logbooks, fishery observers and port sampling (*cf*. Fishery-independent data [survey]). May be more prone to bias than fishery-independent data because the fishery-dependent data are influenced by fishers' attempts to maximise economic returns.

Fishery-independent data / survey. Data collected by scientifically planned surveys, carried out by research vessels or contracted commercial fishing vessels, to gather information independently of normal commercial fishing operations, using standard gear and methods (*cf*. Fishery-dependent data [survey]).

Fishing effort. Amount of fishing taking place, usually described in terms of gear type and the frequency or duration of operations (for example, number of hooks, trawl hours, net length).

Fishing mortality (F). The instantaneous rate of fish deaths due to fishing a component of the fish stock. F reference points may be applied to entire stocks or segments of the stocks. Instantaneous fishing mortality rates of 0.1, 0.5, 1.0, and 2.0 are equivalent to annual exploitation rates of 9.5 per cent, 39.3 per cent, 63.2 per cent and 86.5 per cent respectively. *See also* Mortality, Natural mortality.

Growth rate. In population ecology, growth rate is the average change in a population over time. When applied to an individual in the population, growth rate refers to the speed or rate of change in the weight or length of an individual over time. Growth rate may be affected by environmental drivers (such as temperature) and typically decreases over the lifespan of an individual, being rapid when young and slowing as the individual ages. In the von Bertalanffy Growth Formula, growth rate is modelled by the growth coefficient K.

Harvest control rules. *See* Decision rules.

Harvest strategy. An agreed combination of data collection, assessment, decisions rules and management actions intended to achieve defined biological and economic objectives in a given fishery.

Hyperstability. A relationship between catch per unit effort (CPUE) and abundance in which, initially, CPUE declines more slowly than true abundance as a stock declines. Hyperstable CPUE provides a positively biased index of abundance.

Index of abundance. Relative measure of the abundance of a stock (for example, catch per unit of effort).

Indicator. A quantity that can be measured and used to track changes with respect to an objective. The measurement is not necessarily restricted to numerical values, and categorical values may be used.

Individual transferable effort (ITE). Shares of a total allowable effort that are allocated to individuals. They can be traded permanently or temporarily. Analogous to individual transferable quotas in a fishery managed with a total allowable catch [TAC]. Usually issued at the start of a fishing season. One of the input controls that may be used to limit the impacts of a fishery.

Individual transferable quota (ITQ). Management tool by which portions of the total allowable catch quota are allocated to fishers (individuals or companies). The fishers have long-term rights over the quota, but can trade quota with others (*see also* Quota). One of the output controls that may be used to limit fishing mortality.

Input controls. Management measures that place restraints on who fishes (licence limitations), where they fish (closed areas), when they fish (closed seasons) or how they fish (gear restrictions).

Intrinsic productivity. The natural rate of growth of a population, measured as births minus natural deaths per capita in the absence of fishing mortality or environmental constraints on population increase.

Key commercial species. A species that is, or has been, specifically targeted and is, or has been, a significant component of a fishery. Key commercial species provide most of the economic yield of a fishery and may be managed to a MEY bioeconomic target.

La Niña. The extensive cooling of the central and eastern Pacific Ocean. In Australia (particularly eastern Australia), La Niña events are associated with an increased probability of wetter conditions (*cf*. El Niño).

Length and age frequency. *See* Age-length frequency.

Length-frequency distribution; modal size. The number or proportion of individuals in a catch or catch sample in each length group (length interval). The modal size is the length group into which most individuals fall. Some distributions may show several modes, reflecting cohorts of fish of different ages.

Limited-entry fishery. Fishery in which the fishing effort is controlled by restricting the number of operators. Usually requires controlling the number and size or fishing power of vessels, the transfer of fishing rights and the replacement of vessels (*cf*. Open-access fishery).

Logbook. Official record of catch-and-effort and other relevant data completed by fishers. In many fisheries, a licence condition makes the return of logbooks mandatory.

Management strategy evaluation (MSE). A structured procedure to test whether a proposed harvest strategy will achieve the required objectives in the context of, and despite, identified uncertainties in monitoring/observations, stock/fishery dynamics and management implementation. Testing is usually conducted by mathematical simulation modelling, but it can also be applied using qualitative expert judgement.

Maximum economic yield (MEY). The sustainable catch level for a commercial fishery that allows net economic returns to be maximised. For most practical discount rates and fishing costs, MEY is achieved at an equilibrium stock size larger than that associated with maximum sustainable yield (MSY). In this sense, MEY is more environmentally conservative than MSY and should, in principle, help protect the fishery in the event of decreased biological productivity that results from unfavourable environmental impacts.

Maximum sustainable yield (MSY). The maximum average annual catch that can be removed from a stock over an indefinite period under prevailing environmental conditions. MSY defined in this way assumes that fish stocks reach equilibrium and makes no allowance for productivity changes and environmental variability. Studies have demonstrated that fishing at the level of MSY is often not sustainable in such cases.

Maximum sustainable yield rate (MSYR). The ratio of MSY to the biomass at which MSY is obtained (that is, MSY / B_{MSY}).

Model (population). Hypothesis of how a population functions using mathematical descriptions of determinants of fish stock productivity, such as growth, recruitment and mortality.

Mortality. Deaths from all causes, usually expressed as a rate or as the proportion of the stock dying each year.

Multispecies fishery. A fishery using non-selective gear(s) that unavoidably catches a variety of species (for example, trawl nets), or in which fishers' profits depend on the catch of more than one species. Fishery data from multispecies fisheries are more difficult to interpret because of uncertainty around the relative targeting of individual species, and therefore of the extent to which CPUE for the fishery might index the relative abundance of individual species in the mixed catch. Also, the non-selective gear(s) may make it difficult to simultaneously control the catch of each species at intended and/or individually optimal levels.

Natural mortality (M). Deaths of fish from all natural causes, excluding fishing. Usually expressed as an instantaneous rate or as a percentage of fish dying in a year. See also Fishing mortality, Mortality.

Nautical mile (nm). A unit of distance derived from the angular measurement of one minute of arc of latitude at the earth's surface, but standardised by international agreement as 1852 metres.

Nominal catch. The sum of the catches that are landed (expressed as live weight equivalent), as reported, and not scaled up or down by any factor. Nominal catches do not include unreported discards.

Non-fishing effects. Influences on fish stock productivity and abundance that are not related to fishing activities. In the context of SAFS stock status reporting, this particularly refers to substantial impacts that lie outside the normal or expected range of these effects, and which result in substantial and unexpected declines in stock biomass. Examples include, but are not limited to, climatic and oceanographic extremes (cyclones, oceanic heat waves, coral bleaching, floods), disease outbreaks, introduction of exotic species, land-based effects (sedimentation, pollution, eutrophication) and habitat destruction or degradation. To be used as justification that observed declines in biomass are not attributable to fishing, there must be clear defendable evidence that anomalous non-fishing effects have occurred and have caused substantial and unexpected biomass declines.

Non-target species. Species that is unintentionally taken by a fishery while fishing for other species; may not be routinely assessed for fisheries management. See also Bycatch, Byproduct.

Observer. A certified person on board fishing vessels who collects scientific and technical information for the management authority on the fishing operations and the catch. Observer programs can be used for monitoring fishing operations (for example, areas fished, fishing effort, gear characteristics, catches and species caught, discards, collecting tag returns). Observers usually have some degree of independence from the fishing operator and may or may not have legal coercion powers, and their data may or may not be used for non-scientific purposes (for example, enforcement).

Otoliths. Bone-like structures formed in the inner ear of fish. Seasonal variation in appearance of annual rings or layers deposited as otoliths grow can be counted to determine age, similar to growth rings in trees.

Otolith microchemistry. A technique used to delineate fish stocks and characterise movements and natal origin of fish from analysis of the microscopic chemical composition of otoliths, which changes as otoliths grow over time, depending on the chemical composition of the water in which the fish are at the time.

Output controls. Management measures that place restraints on what is caught, such as total allowable catch limits (TACs) and quotas, rather than on the fishing effort put into the fishery (*cf*. Input controls). These usually species-specific but may include limits for mixed catches.

Depleted stock. Spawning stock biomass that has been reduced through catch and/or non-fishing effects, so that average recruitment levels are significantly reduced (recruitment is impaired). Current management is not adequate to recover the stock, or adequate management measures have been put in place but have not yet resulted in measurable improvements. (Referred to as 'Overfished stock' in *Status of Australian fish stocks reports* 2012 - 2016)

Pelagic. Inhabiting waters at or near the ocean surface, rather than in midwater or near the sea floor. Usually applied to free-swimming species, such as tunas and sharks (cf. Demersal).

Performance indicator (performance measure). Measurable parameter used to assess the performance of a fishery against predetermined sustainability objectives (such as current biomass compared to some reference biomass level).

Population modelling. Mathematical description of a population that is designed to simulate the life cycle of animals in that population. Population models form the underlying basis of most stock assessments and can be used to project the effects on the population of various catch levels, or of environmental factors or biological characteristics of these animals.

Possession limit. The maximum number of fish or other harvested organism that a person is allowed to have in their possession at any time. It discourages the accumulation of large quantities of fish by recreational fishers (*see* Bag limit).

Precautionary approach. Approach to fisheries management where the absence of adequate scientific information, or uncertainty in scientific information, should not be used as a reason for postponing or failing to take measures to conserve target species, associated or dependent species and non-target species and their environment.

Pre-recruits. The proportion of a population that has not yet entered a fishery (that is, not yet able to be caught or retained by the fishing gear).

Productivity (biological). A measure of the rate at which a fish stock is capable of producing biomass, as a result of the birth, growth and death rates of the stock. A highly productive stock is characterised by high birth, growth and mortality rates, shorter life span and early maturation, and can usually sustain high harvesting rates.

Productivity (economic). The ability of firms or an industry to convert inputs (labour, capital, fuel, etc.) into output. Economic productivity is often measured using productivity indexes, which show whether more or less output is being produced over time with a unit of input. The index is calculated by comparing changes in total output (fish catch) to changes in total inputs (such as fuel, labour and capital).

Protected species. As per the meaning used in the *Environment Protection and Biodiversity Conservation Act 1999* (Cth).

Quota. Amount of catch allocated to a fishery as a whole (total allowable catch) or to an individual fisher or company (individual transferable quota).

Quota species. Species for which allowable catches are limited by allocation of catch quotas.

Recommended biological catch (RBC). The recommended total annual catch that can be taken by fishing, while achieving the management objectives for that fishery. Under a harvest strategy, the RBC is calculated from the best estimate of current biomass by application of the harvest control rule. The Total Allowable Catch (TAC) for a fishery would usually be derived from the RBC by subtraction of discard mortality and other sources of mortality.

Recruit. Usually, a fish that has just become susceptible to the fishery. Sometimes used in relation to population components (for example, a recruit to the spawning stock).

Recruitment failure. A situation in which a population is not able to naturally produce sufficient viable offspring to maintain itself as a consequence of physical factors (for example, damaged spawning areas or unsuitable water temperatures) or biological factors (for example, inadequate numbers of fish).

Recruitment impaired. The point at which a stock is considered to be recruitment impaired is the point at which biomass has been reduced through catch so that average recruitment levels are significantly reduced. This can occur due to a number of factors, including fishing, environmental effects or other non-fishing effects.

Recruitment overfishing. A level of exploitation that, if maintained, would result in the stock falling to levels at which there is a significant risk of recruitment and stock collapse. The corresponding term for the state of the stock is 'recruitment overfished', in which the average annual recruitment to the stock is significantly reduced as a result of fishing. Where reduction in recruitment has resulted from both fishing and/or other non-fishing effects, the equivalent term is 'recruitment impaired'. Both terms define a limit reference point (for exploitation rate or stock size) beyond which urgent management action should be taken to reduce exploitation and recover the stock.

Reference point. An indicator, typically of the level of stock biomass or fishing mortality rate, used as a benchmark for assessment and as the basis for management objectives set within harvest strategies (*see also* Biological reference point).

Relative abundance. The number of living individuals at a point in time, expressed as a fraction of the average number of living individuals at some other point in time (such as before the beginning of fishing, or some chosen reference year) or under other conditions (such as if no fishing was currently occurring).

Risk analysis. Analysis that evaluates the likelihood (risk) of not achieving chosen objectives under various harvesting strategies or management options.

Size frequency. *See* Length-frequency distribution.

Spatial closure. A method of fisheries management that prevents fishing in a defined area.

Spawning biomass (SB). The total weight of all adult (reproductively mature) fish in a population.

Spawning stock biomass. *See* Spawning biomass.

Species complex. A group of similar species that are often difficult to differentiate without detailed examination.

Species group. A number of species that are grouped together for the purposes of fisheries management, either because they are difficult to differentiate (*see* Species complex), or to show similar biological and productivity characteristics, or because they are caught in association, and it has been decided to manage them as a group.

Standardised data. Data that have been adjusted to be directly comparable to a unit that is defined as the 'standard' one, usually by correcting for the effects of other parameters that might affect the data, other than the parameter of interest. Standardisation might, for example, involve the correction for effects of different vessels to provide indices where inter-annual changes in catch rate are more directly comparable. Standardised catch per unit effort data are often used as an indicator of relative fish abundance.

Static B_0. This term is used to refer to B_0 (see B_0), particularly when it is being contrasted to Dynamic B_0 (see Dynamic B_0).

Statutory fishing right (SFR). Right to participate in a limited-entry fishery. An SFR can take many forms, including the right to access a particular fishery or area of a fishery, the right to take a particular quantity of a particular type of fish, or the right to use a particular type or quantity of fishing equipment.

Stock-recruitment (S-R) relationship. Relationship between the size of the parental (mature or spawning) biomass and the number of recruits it generates. This is often a key determinant of stock productivity, but is difficult to estimate. In the absence of direct estimates of biomass and recruitment (such as might be obtained from fishery independent surveys), these are usually estimated within stock assessments. S-R relationships can be highly variable, particularly at intermediate to larger stock sizes, with a wide range of recruitment possible for a given stock size. Climate induced changes in S-R productivity can result in substantial changes in estimates of sustainable harvest rates.

Stock Synthesis. A statistical framework developed by NOAA (Methot and Wetzel 2013) for fitting of a population dynamics model to a range of fishery and survey data. It is designed to accommodate both age and size composition samples from a fishery, and multiple stock subareas. Selectivity can be modelled as age specific only, size specific in the observations only, or size specific with the ability to capture the major effect of size-specific survivorship. The overall model contains sub-components that simulate the dynamics of the stock and fisheries, derive expected values for the various observed data, and quantify the magnitude of difference between observed and expected data to allow a ‘best fit’ model to be selected as the basis for management advice.

Target biomass (B_{TARG}). The desired biomass of the stock, chosen to be the management target within a harvest strategy.

Threatened species. As per the meaning used in the *Environment Protection and Biodiversity Conservation Act 1999* (Cth).

Torres Strait Protected Zone. An area defined under an agreement between Australia and Papua New Guinea that describes the boundaries between the two countries and how the sea area may be used. A key purpose of the protected zone is so that Torres Strait Islanders and the coastal people of Papua New Guinea can carry on their traditional way of life. For example, traditional people from both countries may move freely (without passports or visas) for the purpose of traditional activities in the protected zone.

Total allowable catch (TAC. An overall catch limit set as an output control on catches (*see* also Output controls). Where resource-sharing arrangements are in place between commercial and recreational fishers, the term total allowable commercial catch (TACC) can be applied to the commercial catch component. The term ‘global’ is applied to TACs that cover fishing mortality from all fleets, including Commonwealth, state and territory fleets.

Total allowable catch (TAC)—actual. The agreed TAC for the species with amendments applied, such as carryover or debits from the previous year.

Total allowable commercial catch (TACC). *The commercial catch component of a* Total allowable catch.

Total allowable effort (TAE). An upper limit on the amount of effort (such as number of vessels, days fished, number of hooks or fishing operations) that can be applied in the fishery.

Total length (TL). The length from the tip of the snout to the tip of the longer lobe of the caudal fin, usually measured with the lobes compressed along the midline. It is a straight-line measure, not measured over the curve of the body (*cf*. Fork length).

Unfished biomass. Biomass that existed, or that would exist, for a stock that has not yet been fished, or if it had not been fished (also called the ‘unfished’ or ‘unexploited’ biomass or unfished level). This may refer to an estimated historical biomass level before fishing commenced, or the current biomass that would have existed had no fishing occurred.

Virgin biomass. *See* Unfished biomass.

Vulnerable species. Species that will become endangered within 25 years unless mitigating action is taken (*see also* Endangered species). The *Environment Protection and Biodiversity Conservation Act 1999* (Cth) dictates that a native species is eligible to be included in the vulnerable category at a particular time if, at that time (a) it is not critically endangered or endangered, and (b) it is facing a high risk of extinction in the wild in the medium-term future, as determined in accordance with the prescribed criteria.

Yield. Total weight of fish harvested from a fishery.

16. Project materials developed

In addition to this project report, the project has resulted in the publication of two peer-reviewed scientific papers, available from the links in the citations below, and attached in Appendices 16.1 and 16.2 respectively:

Bessell-Browne P, Punt AE, Tuck GN, Day J, Klaer N and Penney A (2022) The effects of implementing a 'dynamic B_0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. *Fisheries Research* 252. https://doi.org/10.1016/j.fishres.2022.106306

Bessell-Browne P, Punt AE, Tuck GN, Burch P and Penney A (2024) Management strategy evaluation of static and dynamic harvest control rules under long-term changes in stock productivity: A case study from the SESSF. *Fisheries Research* 273. https://doi.org/10.1016/j.fishres.2024.106972

These publications contain details of the assessment and MSE testing methodology developed during the project. Other than stakeholder information documents (see Section 17 Appendices), the project has not produced any other publications.

17. Appendices

17.1. The effects of implementing a ‘dynamic B_0’ harvest control rule in Australia’s Southern and Eastern Scalefish and Shark Fishery

The following scientific paper, presenting work conducted under this project, is attached in this appendix:

Bessell-Browne P, Punt AE, Tuck GN, Day J, Klaer N and Penney A (2022) The effects of implementing a ‘dynamic B_0’ harvest control rule in Australia’s Southern and Eastern Scalefish and Shark Fishery. *Fisheries Research* 252. https://doi.org/10.1016/j.fishres.2022.106306

The attached paper presents the full analysis and results of the work summarised in Chapter 8.

17.2. Management strategy evaluation of static and dynamic harvest control rules under long-term changes in stock productivity: A case study from the SESSF

The following scientific paper is attached in this appendix:

Bessell-Browne P, Punt AE, Tuck GN, Burch P and Penney A (2024) Management strategy evaluation of static and dynamic harvest control rules under long-term changes in stock productivity: A case study from the SESSF. *Fisheries Research* 273. https://doi.org/10.1016/j.fishres.2024.106972

The attached paper presents the full analysis and results of the work summarised in Chapter 9.

17.3. List of researchers and project staff

Name	Affiliation	Role
Andrew Penney	Pisces Australis Pty Ltd	Principal Investigator
Geoff Tuck	CSIRO	Principal Investigator
Pia Bessell-Browne	CSIRO	Co-investigator
Laura Blamey	CSIRO	Co-investigator
Éva Plagányi	CSIRO	Co-investigator
Paul Burch	CSIRO	Co-investigator
Richard Little	CSIRO	Co-investigator
André Punt	CSIRO, University of Washington	Co-investigator
Neil Klaer	CSIRO, Luggara	Co-investigator

17.4. First Stakeholder Consultation

Responses received from respondents to the 1st Stakeholder Consultation questionnaire are summarised below under the questions numbered as per the questionnaire. Not all respondents responded to all the questions. Out of the ten questionnaires received, only seven ranked their perceptions of the overall effect of the environment on productivity of fish stocks.

Overall, how much of an effect do you consider that environmental drivers and climate change have had on the Australian marine environment and productivity and status of Australian fish stocks?

- There was general agreement across respondents regarding the overall effect of the environment, with all respondents considering that environmental drivers have had a moderate to strong effect on the Australian marine environment and on productivity of fish stocks (Figure 17-1). Interestingly, some respondents that indicated that environmental drivers have had a strong effect then went on to indicate that fishing has had the dominant effect on individual fish stocks.

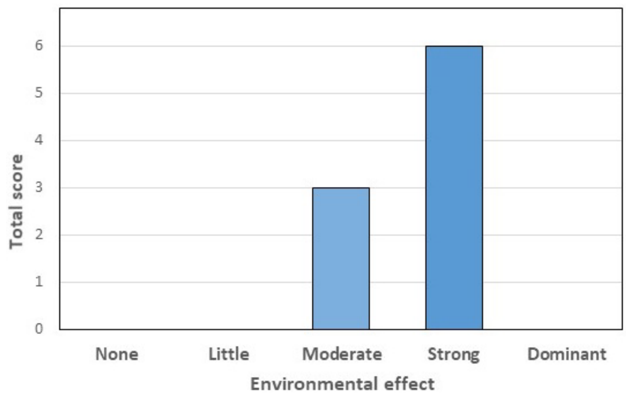

Figure 17-1. Total scores by seven respondents / groups that ranked their perceptions of the overall effect of the environment on the Australian marine environment and productivity of fish stocks.

- This question may have been differently interpreted by respondents, some indicating the relative influence of climate change on the environment, and others indicating the relative effect of environment on fish stocks.

Briefly explain how you think environmental drivers and climate change have affected the Australian marine environment and productivity of fish stocks

- There is a growing evidence base for changes occurring in the marine environment around Australia. Life history parameters of marine organisms are known to be impacted by the marine environment they exist in. There have been demonstrated impacts on water temperature, currents and acidity. These in turn affect abundance, distribution and reproduction, which can manifest as productivity change. Effects may be direct (through recruitment success) or indirect (through food/habitat availability), and different stages of the life cycle may be impacted for different species.
- In temperate Australia, the environmental effects have been mainly to decrease productivity. In the tropics and large pelagics the effects have been more variable and, in some cases, seem negligible. Off southeast Australia there has been an increased influences of the East Australian Current and a decreased influence of the Leeuwin Current. Observed effects include increased water temperatures, decreased eastward larval dispersal (King George whiting, king prawns, rock lobster), major ecosystem changes (e.g. loss of extensive Macrocystis kelp communities), southward species shifts (e.g. *Centrostephanus* urchins, pink snapper, King George whiting); and changed behaviour of pelagic species (e.g. barracouta and gemfish are seldom as accessible to surface trolling or poling as in pre-1970s).
- Climate change is likely contributing to lack of rebuilding for several SESSF species, although current depleted stock status is considered to be largely due to historical overfishing. To what extend climate change is preventing recovery is poorly understood and should be a focus of the project.
- In Northern Australia there have been observable effects of climate change, including significant mangrove dieback in the Gulf of Carpentaria. There is demonstrated correlation between environmental conditions and the strength of recruitment for some prawn species in Northern commercial fisheries, as indicated by correlation between environmental indices and catch trends.
- Causal links between environmental drivers and species production have been observed for some species but demonstrating causal links for most species is hampered by limited availability of data. Nonetheless, some effect is likely even where a causal link between a species and a known change in the marine environment cannot be demonstrated.
- These changes have been largely as expected (with positive, negative and neutral effects at the species/species group level. Most negatively affected species appear to be those that are sedentary, those already heavily fished and those with specific lifecycle/habitat requirements. Few species seem to have been positively affected, although noting that we only really know about fisheries stocks with significant financial value or societal value or are charismatic. This could be skewing our perceptions of climate effects on ecosystems. Broader ecosystem effects need to be examined.

Which fish stocks do you consider have been negatively affected by fishing, by the environment, or by some combination of the two?

- Respondents in eight of the ten questionnaires received ranked their perceptions regarding the effect of environmental factors on productivity of individual fish stocks. The number of stocks ranked by respondents varied greatly, ranging from one stock by one respondent to 18 stocks by another. While most respondents provided a single ranking for each stock (in five categories ranging from 'Entirely Fishing' to 'Entirely Environment'), the AFMA SESSF and Torres Strait respondents indicated more than one ranking for some stocks, with 'Entirely Fishing' or 'Mainly

Fishing' being considered responsible for initial depletion, and 'Equal Fishing and Environment' or 'Mainly Environment' being identified as responsible for lack of recovery of depleted stocks.
- Each ranking was accorded a score of one and rankings were summed across the listed stocks. The minimum score for any nominated stock was therefore one. The maximum score for some stocks was three, indicating that three respondents had accorded those stocks the same ranking. The results are illustrated in the kite diagram in Figure 16-2, with the stocks manually sorted from top to bottom from those entirely or mainly affected by fishing, through those considered to be affected by some combination of fishing and the environment, to those considered by respondents to have been entirely affected by the environment.
- Interestingly, the latter category included some 'stocks' that are not subject to significant fishing, such as stingarees and kelp. Inclusion of these ecosystem components indicates a perception by those respondents that climate / oceanographic factors are having broad-ranging effects on ecosystems, resulting in distributional and abundance changes across many ecosystem components. There are also some interesting anomalies in the ranking of effects, with Redleg Banana Prawn, for example, considered to have been mainly affected by fishing, despite there being a demonstrated causal link between the Southern Oscillation Index (SOI) and prawn recruitment.
- For stocks such as John Dory, Blue Warehou and Gemfish east there are widely divergent views regarding the relative effects of fishing and the environment. These differences of view indicate the need for the project to consider how to demonstrate and estimate the relative effects of fishing, stock structure (parental biomass), environmental drivers and trophic interactions on productivity changes and the failure of stocks to rebuild from a depleted state.
- The stocks selected as example stocks for detailed historical analysis and projections, and for additional historical analysis, span the range of stakeholder perceptions regarding the relative impact of fishing and the environment (see highlighted stocks in Figure 16-2). Stakeholders did not identify Blue Grenadier or Tiger Flathead, also chosen for analysis in the project, undoubtedly because these stocks are assessed to be near or above the management target. Blue Grenadier, in particular, shows widely variable, episodic recruitment, which seems likely to be caused by some environmental factor.

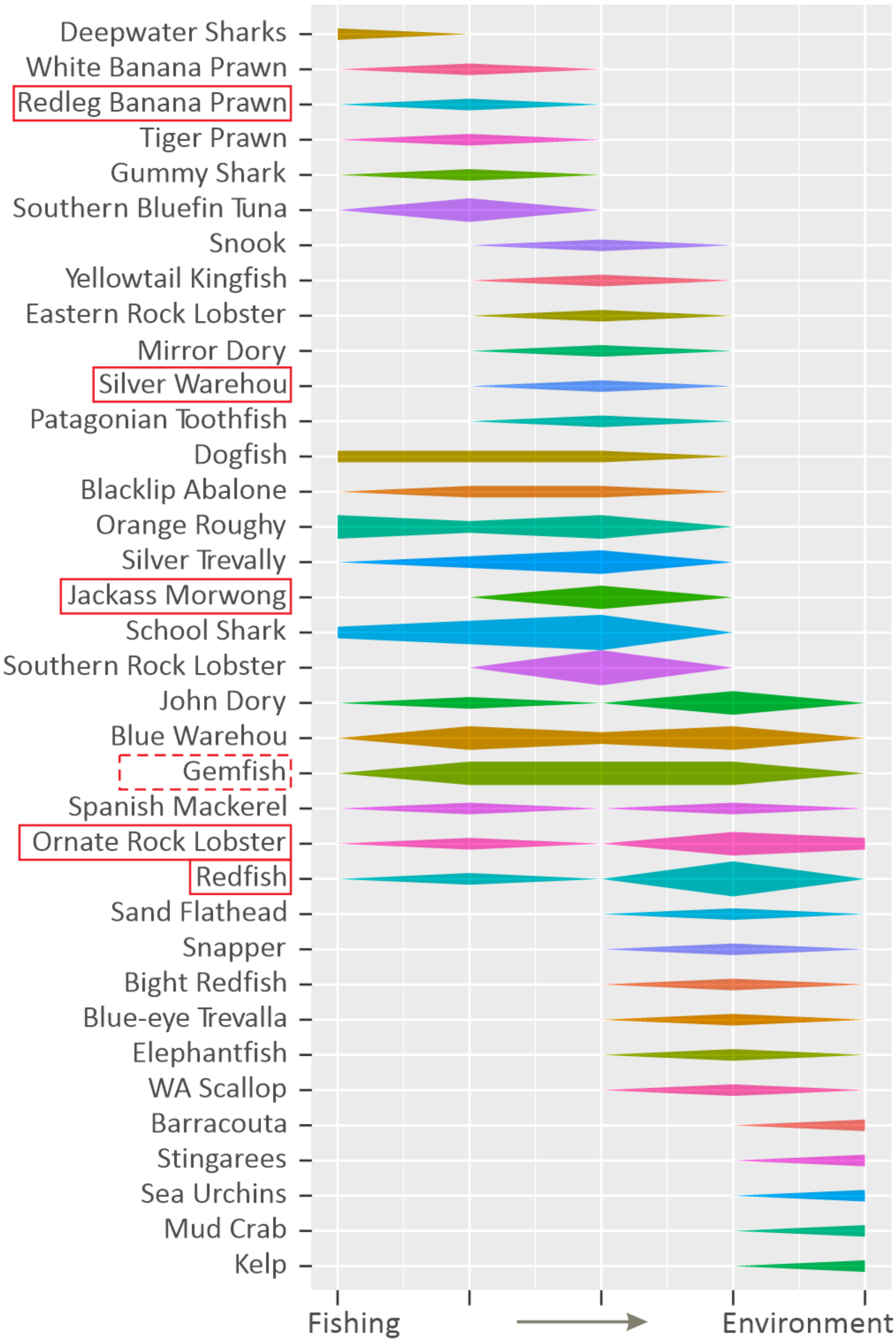

Figure 17-2. Total scores by eight respondents or respondent groups that ranked their perceptions of the effect of the environment on individual Australian fish stocks. Respondents chose which stocks they wished to nominate and allocated each stock to one or more categories ranging from 'Entirely Fishing' to 'Entirely Environment'. Resulting scores range from 1–3. Stocks that have been selected as main case studies for analysis in the project are boxed in solid red, those selected for additional analysis are boxed in dotted red. Respondents did not mention the case study stock Blue Grenadier, or the additional stock Tiger Flathead.

Briefly explain how you think that environmental drivers have affected fish stocks that you consider had an equal or higher effect of the environment

- Environmental drivers probably affect fish stocks by decreasing productivity. Fishing has usually played a role in the decrease in production, often resulting in depletion of the adult stock (e.g.

Gemfish east and School Shark). But the lack of recovery, despite reduced fishing mortality, indicates that either a strong environmental effect has hindered recovery, or that fishing had some serious biological impact from which it cannot easily recover. Major biological impacts on the stocks, including changes in stock structure and genetic impacts, may have occurred with school shark and gemfish.

- Environmental factors have been observed to affect fish stocks in a number of ways:
  - Distributional shifts, particularly towards the poles where habitat allows it.
  - Abundance reductions, driven mainly by productivity reductions and resulting unintended overfishing of a less productive stock.
  - Productivity reductions such as poor recruitment and growth, lower reproductive success and/or higher natural mortality.
- Other anthropogenic impacts such as coastal development and pollution are also likely to negatively impact fish stocks, particularly those that are reliant on coastal habitats. Silt loading in the nearshore environment can be linked to environmental drivers such as rainfall and flood events.
- Off southeast Australia there are several stocks for which fishing was historically the main driver of depletion, but the environment seems to be hampering recovery. For several depleted fish stocks, reducing fishing mortality (by reductions on catch limits, cessation of targeted fishing or spatial closures) does not seem to have resulted in rebuilding. It is not clear to what extent climate change has impacted recruitment, range shift and/or changes in trophic interactions, but factors other than fishing appear to be constraining the rebuilding of stocks such as Gemfish east, Redfish and Blue Warehou. What impact is climate change having on the rebuilding capacity of Orange Roughy, dogfish and School Shark?
- Environmental / oceanographic changes seem to have affected surface feeding, schooling behaviour, distribution and abundance of Barracouta and Gemfish, probably driven by changes in spatial distribution, depth distribution and abundance of prey species. It also seems unlikely that targeted or incidental catches of Sand Flathead in recent years could have had the effect seen.
- Barracuda was a major fishery in southeast Australia but, around the time of WWII it collapsed and, despite limited subsequent fishing, has not recovered. Presumably, another case of fishery plus some mix of environmental/biological impacts. Leatherjacket was also very common in the early southeast Australian fishery, then disappeared for many years and has now begun appearing again. It seems likely that factors other than fishing caused this pattern.
- There seems to have been an extreme version of a productivity shift in that what was the most abundant School Shark stock, but is now functionally extinct, with the fishery now relying on smaller/less productive stock/s. But is this the effect of the 'environment'? What about other possible explanations? For example, if a target species is fished down and other species simply step into the trophic hole.
- Off northern Australia, temperature is known to effect growth rate and survival of Ornate Rock Lobster, with strong negative impacts at water temperatures > 29°C. Ocean acidification may impact the ability to successfully moult and changes to oceanic currents would be expected to affect larval transport and impact larval recruitment on fishing grounds. Spanish mackerel biomass off northern Australia has also declined in recent years, and this cannot be explained by fishing mortality. The environment is considered to be driving changes in abundance, with similar patterns being observed across northern Australia. There are some views that there is a correlation between drought in Papua New Guinea with subsequent reduced abundance.

Do you consider that use of dynamic reference points will be compatible with fisheries policies – Harvest Strategy Policy & Guidelines and the Environment Protection and Biodiversity Conservation Act?

- The Commonwealth Harvest Strategy Policy (HSP) provides for the use of dynamic reference points (s 2.3.2 of the HSP Guidelines) for stocks that undergo natural variations in stock size even in the absence of fishing. Sections 6 and 7 of the HSP Guidelines are also relevant. However, the following point in the guidelines needs to be accounted for: "Where dynamic limit reference points are applied, consideration needs to be given to their consequences during extended periods of high or low productivity/recruitment. During a low productivity period, the limit reference point will equate to a substantially lower level of absolute spawning biomass and the risk of recruitment impairment at 20%BF=0 may be higher when compared with the same reference point in periods of high productivity".
- Similarly, although not discussed in the HSP Guidelines, consideration may need to be given to the appropriateness of using dynamic reference points as targets, particularly maximum economic yield (MEY) targets. The absolute biomass level associated with a dynamic reference point based TRP, may change over time in response to natural variation in stock dynamics and it is unclear whether a dynamic target is consistent with achieving MEY for the fishery. Trophic interactions may also be an important consideration regarding the application of dynamic reference points, with possible consequences for trophic relationships between predator or prey species. While dynamic reference points may be largely consistent with current fisheries policy, the HSP Guidelines may need some revision regarding application.
- The Environment Protection and Biodiversity Conservation Act 1999 (EPBC Act) also imposes requirements on Commonwealth fisheries and their management. Part F refers specifically to depletion relative to "pre-fishing" levels. This may not be possible for some species and changes to environmental law and policy may be necessary. Some are likely to find this difficult to accept. The project should clarify the expectations and assumptions of the EPBC Act, particularly concepts such as 'pre-fished', and how the Threatened Species Scientific Committee (TSSC) operates, as reflected in the TSSC Guidelines (*inter alia* Part C and Part F). Additionally, the EPBC Act and TSSC are interested in identifying key threatening processes. Non-equilibrium or 'dynamic' assessments may provide some valuable information in this regard.
- Regardless of whether excessive depletions can be attributed to (more or less) fishing or environmental shifts, environmental effects play a role in productivity in the shorter-lived species in tropical waters. To this extent, use of these reference points is warranted if they can be demonstrated as being better predictors of productivity. However, openness to the use of dynamic reference points will be challenging for managers and stakeholders, although they have seen that reliance on an 'equilibrium' paradigm has failed in many cases. Persuading fishers of the need for and merit of the dynamic approach will also be a challenge.
- While there is increasing acceptance of the reality of climate change, there is less acceptance that this impacts fish stocks, despite scientific evidence indicating that this is the case. Generating acceptance of the merits of implementing dynamic reference points will require strong evidence, clear analysis, and substantial explanation. There are still views in some sectors that Australia's fisheries management is, or at least was, not conservative enough. A move to use of dynamic reference points would be seen by these sectors as a move in the wrong direction, with fisheries management being "let off the hook" regarding past overfishing.
- There is therefore a strong requirement for "proof" that factors other than fishing are responsible for stock declines, or failure to recover, before a change to targets and limits can be considered. This proof would need to be species-specific to justify changing reference points for particular stocks. Obtaining the data, information and evidence to provide this proof is likely to be costly, particularly if detailed environmental monitoring is required. With Australia's fisheries management largely cost-recovered from industry, AFMA and industry are probably not able to fund this process. Should the fishing industry be required to fund such a process, given that the concerns relate to factors other than fishing?
- Nonetheless, for stocks that do show substantial natural (not related to fishing) variability in

production (such as recruitment), dynamic reference points may be the preferred approach. While current policies do allow for this, but actual implementation may not be easy. Jackass Morwong east is a case in point. It took a new assessment and a 'regime change decision' to implement what clearly appeared to be a reduction in productivity.

Compatibility with requirements for Marine Stewardship Council certification

- Expert respondent Prof Sainsbury provided the advice related to Marine Stewardship Council (MSC) certification requirements in answer to the question: What evidence would be necessary to justify adopting reference points based on dynamic B_0; and if you do adopt dynamic reference points, how and when would you stop decreasing the target and limit if a stock continues to decline, even though you can argue that fishing is now having negligible impact.
- The MSC can and has accepted dynamic reference points in assessments, the first being for Alaskan pollock where $B_{Unfished}$ is a primary indicator. Estimation of this indicator requires an assumption about the stock-recruitment relationship, and processes for estimation of this and other indicators. The first MSC certification for Alaskan Pollock was appealed under the MSC objection mechanism at the time, but the fishery, including the dynamic reference point process, passed the objection review. Contributory factors to this certification were that the assessment process was well documented, it was scientifically defensible, and it met the general requirements of the MSC in achieving MSY (being better than the standard approach because of the variability in pollock recruitment).
- When to stop decreasing the target reference point (TRP) and limit reference point (LRP) as the stock declines, even when fishing becomes a small or non-existent impact, is unclear. The MSC has not yet had to address this issue. Fisheries usually engage the MSC when the stock is in reasonable condition, with management strategies that are reasonably stable, and with established assessment methods and decision rules that have been tested and shown to work. If a stock continued to decrease, or not recover, after it was depleted by the fishery / environment then the MSC would seek understanding of the reasons for this and an estimate of the current MSY.
- If the stock is very depleted and/or had failed to recover for a long period, then the logic and arguments explaining why this is the case would be a major focus of the assessment. There would probably be great reluctance by the MSC and the team doing the assessment to accept loose arguments about the impacts of the environment on the stock compared to those of the fishery. There would probably not be an easy way to justify continued reduction of the TRP and LRP as the stock decreased unless there had been severe impact on structural elements of the environment - for example wholesale habitat loss or climate change.
- The MSC has encountered examples of this, such as the replacement of some native species by introduced species (Nile perch in African lakes, some European lobsters replaced by US lobsters, some Arctic crabs invading different areas and replacing the natives) and some challenging situations where fish species have expanded their geographical range and moved outside longstanding management arrangements (e.g. NE Atlantic Mackerel, causing management problems with ICES, Iceland, Norway and the Faroe Islands; the MSC ultimately removed this species from certification while the management improved).

List and briefly explain any key questions you have regarding the use of dynamic targets and limits as the basis for design of harvest control rules and the management of Australian fish stocks

Questions across the stakeholder submissions have been collated below into categories of similar questions:

- Do equilibrium reference points provide more stable risk thresholds? If so, under what conditions? How can we ensure 'risk equivalency' (consistent levels of risk between dynamic and equilibrium reference points), or risk 'constancy' (non-varying risk over time) when using dynamic reference points? More specifically, how can we ensure that the risk of recruitment impairment does not change with natural variations in stock dynamics?

- What is the required assessment frequency for applying a harvest strategy using dynamic reference points? Is there a requirement for more frequent assessments? Does this change with different biological / life history characteristics of different species? To what extent can we reliably demonstrate productivity shifts for SESSF species given the lack of environmental data or indices? Are there additional data collection requirements for assessments using dynamic reference points? What are the differences in costs between management under dynamic vs. static B_0 reference points, and how would the cost-benefit trade-off change under dynamic reference points?
- Where TACs are used to set fishing mortality levels that are meant to achieve target biomass reference points, how would this process change under dynamic reference points? How will this be applied to stocks that may experience range expansions/ productivity increases due to environmental regime shifts?
- How will the project consider the implications of using dynamic reference points as TRPs? Depending on natural stock dynamics and how a changing marine environment may impact a stock, a MEY proxy $48\%SB_{F=0}$ could represent quite different actual biomass levels, catch rates and therefore economic returns under different circumstances. This may have implications for achieving MEY objectives. Will might use of dynamic reference points result in changed behaviour by fishers and/or quota owners/lessees?
- If it has been determined that a stock has become less productive, should there be rules in place to stop fishing at some level of absolute biomass to protect ecosystem function? How would this level be calculated – could proxies be developed? Using dynamic reference points, do actual biomass levels below 20% static B_0 have implications under the TSSC Guidelines regarding the size at which a stock might become classed as "conservation dependent" and be subject to a rebuilding strategy? When would you abandon harvest controls and the LRP – TRP harvest strategy for some more conservative approach?
- The smaller the actual stock size, the higher the risk that fishing and/or climate change will have stronger short term-impacts - it is easier to overfish a small stock than a large stock. Should HCRs be more conservative for species that are susceptible to climate change?
- Dynamic reference points seem appropriate when a stock moves to a new permanent or semi-permanent state, but not so much when there is a long-term decline and/or when a species becomes so rare as to make estimating biomass difficult, and extinction a plausible result. For a species in long-term decline, how do you set a LRP and TRP that will minimise risk of recruitment failure or stock collapse?
- Is there a case for developing and applying assessment and/or harvest strategy approaches that utilise both types of information? Equilibrium (pre-fished) ref points might offer a better understanding of absolute risk at low population levels whereas dynamic reference points may provide information on the relative contributions of fishing and natural stock (or environment) driven changes.
- Dynamic reference points might be preferable to our current equilibrium reference points, and may be a better way to represent stock status, but does this depend on there being good evidence for a regime shifts or strong environmental influence on the stock? What about other possible explanations than environmental drivers? For example, what if, when a target species is fished down, other species are simply stepping into the trophic hole? Will use of dynamic reference points increase the likelihood of negative effects with choke species in the SESSF?

What if depensation occurs, affecting the ability to rebuild (e.g. for Gemfish). The previous target may never be able to be achieved regardless of fishing pressure. Will dynamic reference points help here?

- Will doing all this actually increase the uncertainty of assessments/management and require greater precaution? Will this create further pressure to reduce incidental catches of species under rebuilding strategies? Will we be under more pressure to close fisheries to prevent the decline of stocks that will disappear regardless?

- How will the project consider the implications of switching management from equilibrium to dynamic reference points, and the information requirements to satisfy stakeholder concerns regarding such a change? There needs to be adequate information available to address stakeholder questions and concerns in the discussion/conclusions in the final report.

- Regarding the dynamic B_0 assessment process itself, there are a number of questions on technical details of the assessment methodology:
  - How will you identify and justify alternative interpretations to construct the unfished biomass.
  - What stock-recruitment alternatives should be used, and their justification.
  - What environmental drivers to use, given that there will be a wide range of options and in fishery management both type I (false positive) and type II (false negative) errors need to be considered.
  - What statistical tests to apply: (i) in deciding what alternative models to include in the overall analysis (or alternatively what alternative models to discard); (ii) to test to thresholds in population behaviour; (iii) to test population behaviour in relation to alternative models; and (iv) to test the performance of alternative decision rules.
  - What harvest strategies to test, recognising that they will need to be tested. Type II errors in the use of environmental variables are critical.
  - How to explain this all clearly to the various stakeholders – including fishery managers, industry, eNGOs, recreational fishers and the general public. Each of these groups will have their own questions and concerns that will need to be addressed.

Briefly describe key concerns you have regarding the use of dynamic targets and limits as the basis for design of harvest control rules and the management of Australian fish stocks

To a large extent, the concerns raised by stakeholders relate directly to the questions raised in the previous section. There was also repetition of some questions in this section on concerns. These duplications have been removed in the summary below. Some pf the 'concerns' raised were actually recommendations on information to be included in the project report and have been moved to the next section on information to be provided by the project.

- One of the key concerns relates to not having a coherent, acceptable and comprehensive package of information to explain the approach. The overall concepts are very much what is needed in fishery management, but it is an area that is easily confused, even by people who have no intention of causing confusion. For example, the approach can be interpreted as giving managers flexibility to simply track an overfished population down while blaming the environment for the problem. Much depends on having a good set of methods and protocols that can be explained to each group.
- It is not clear how the project can achieve a key task under Objective 2: "Identify selected candidate Australian Commonwealth-managed fish stocks, for which integrated stock assessments are available and which show likely environmentally driven productivity change". This was one of the potential explanations in the SMARP project on under caught TACS/non-recovery/declines for SESSF fish stocks but it left the question unanswered. It is unclear how

you can tell which species "show likely environmentally-driven productivity change". It may just be the conclusion that is left after other possible explanations have been discounted.

- There is a risk that adoption of dynamic reference points will simply be seen as 'changing the goal posts'. How can the results of the project, and the justification for dynamic reference points, be communicated in a way that will address this concern and justify the relevance of dynamic reference points, particularly to the broader (non-scientific) community?
- There is specific concern that risk equivalency (compared with a static B_0 approach), or adequately low risk, will not be ensured at low population sizes. Conversely, at the other end of the scale there is concern that objectives relating to achieving maximum MEY (or MSY) under dynamic reference points will not be achieved.
- There are concerns relating to common obstacles to operationalization of a dynamic management approach (from King *et al.* 2015. Shifts in fisheries management: adapting to regime shifts. Phil. Trans. R. Soc. B, 370: 20130277.) including:
  - linkages between environmental variables and recruitment time series eventually break down, either due to spurious correlations or changes in the nature of the relationship;
  - typically, the length of the time series for recruitment data is shorter than the span of at least one regime shift and state;
  - the environmental and recruitment time series typically have high within-regime variability which makes it difficult for stock assessments to detect regime shifts; and
  - without a reliable way to anticipate a regime shift, predictions (even short-term) are not possible.
- It seems that use of dynamic reference points has the potential to result in fluctuations in TACs depending on how frequently the LRP and TRP are revised. This relates to the frequency of assessments and concerns those infrequent assessments will results in infrequent but large changes in dynamic reference points and TACs.
- This may not be the most cost-effective approach under all circumstances. This approach may result in more complex assessments, assumptions regarding environmental drivers and/or data requirements to monitor environmental drivers. It seems unlikely that environmental drivers can be clearly identified and monitored. Research funding required to gather environmental information to monitor potential productivity shifts in species is unlikely to be available. It may be more cost effective for management to respond differently.

What information will the project need to provide to: justify conclusions regarding the occurrence of environmentally driven changes in productivity for example fish stocks, and to address questions and concerns regarding changing fish stock productivity and use of dynamic targets and limits?

- The project needs to provide a consolidated body or work and an evidence base, should management wish to pursue a change from harvest strategies and control rules based on static B_0 reference points, to strategies and control rules based on dynamic reference points. This body of work needs to be publicly available and address concerns from all sectors. This should include worked examples across multiple species with different biological characteristics. A non-technical summary will be required to explain the results and recommendations of the project, and the justifications for use of dynamic reference points, to a non-technical audience.
- There needs to be a government and stakeholder agreed policy/process to discount all other likely factors before claiming an environmental effect, preferably with quantitative evidence to back up that conclusion. Errors in total fishing mortality, poor compliance/monitoring and scientific error in assessments are some of the issues that need to be tested.
- Dynamic reference points have been used in other jurisdictions, ranging from Alaskan Pollock to sub-Antarctic Mackerel Icefish, to various small pelagic species. Many have been in operation

for many years. There is value in describing the approaches taken in these applications.

- The project will need to demonstrate how management approaches using dynamic reference points will have a high probability of satisfying the multiple requirements of the Commonwealth HSP and the EPBC Act in terms of specification and application of target and limit reference points. In particular, the project will need to provide advice on the estimation and implementation of an absolute biomass limit reference point (or proxy) below which a dynamic LRP should not be allowed to decrease when the stock size has been reduced due to changes in productivity.
- Retrospective analysis will be important to demonstrate the degree to which climate change (or other non-fishing effects) have contributed to the decline and/or failure to recover of stocks, and to what extent fishing mortality is playing a role. Results should address the question: Would we be in a better place now had we included environmental drivers in stock recruitment relationships and /or used dynamic ref points and/or different HCR's than we are now? Methods should be tested to ensure their compatibility with short-lived species (annual or close to annual stocks) as well as long-run testing to see where gains and losses may have occurred.
- The project should not just focus on species that are likely to be negatively affected by climate change (depleted or non-recovering stocks) but should also consider application of dynamic management approaches to species that may be positively affected by climate change. The project should provide advice on which Commonwealth fisheries might be able to realistically move to such an approach and how, given limitations in available information.
- Objectives 6, 7 and 8 relate to evaluating options for incorporating environmental regime shifts that effect fish stock productivity into stock assessments and management, as a basis for forming recommendations. It would be useful to clearly spell out the options to be evaluated. For example, do these include: i) embedding environmental drivers in stock recruitment and/or growth relationships, ii) dynamic reference points iii) alternative HCR's, iv) combinations of i, ii and iii, v) formal decision analysis framework approach? What will be the base case? Also, what criteria will be used to evaluate options (and as basis for recommendations)? And what economic metrics will be included? NPV of profits? Average annual profit? Variability of profits?
- There should be a clear demonstration of how the application of traditional approaches have failed, in terms of recovery of catches, catch rates and recruitment, along with plausible and consistent (over time) environmental explanations. This needs to be coupled with demonstration that dynamic reference points do not result in less conservative management and will not leave stocks in a worse state, as well as demonstration that this would be a more appropriate management framework in a changing global environment.
- The project should document a process for establishing the link between a change in some aspect of the marine environment and a change in some aspect of a stock's productivity, with advice on how to determine that dynamic reference points are an acceptable alternative and/or better approach to equilibrium reference points in terms of achieving fisheries management objectives.
- Provide discussion and recommendations relating to the information and data requirements (including data collection systems) necessary to deliver the required evidence base for monitoring and assessments going forward. Provide advice on how frequently we should revisit reference points given the speed of climate change. Consider and provide advice on how you might evaluate the potential costs and benefits of moving to such an approach versus responding with different management measures.

Table 17-1. List of stakeholders consulted during the first stakeholder consultation round, and record of consultation.

Organisation	Person	Presentation & questionnaire	Follow-up email	Questionnaire response	Phone meeting	Video meeting	In-person meeting
AFMA SESSF	Fiona Hill	✓	✓	✓			✓
	Dan Corrie	✓	✓			✓	
	Natalie Couchman	✓	✓				✓
	Sally Weekes	✓	✓			✓	
AFMA TS	Selina Stoute	✓	✓	✓		✓	
	Georgia Langdon	✓	✓			✓	
AFMA NPF	Steve Bolton	✓	✓	✓			
	Darci Wallis	✓	✓				
	Stephen Eves	✓	✓				
ABARES	James Woodhams	✓	✓	✓			✓
	Don Bromhead	✓	✓				✓
	James Larcombe	✓	✓				✓
	Dave Galeano	✓	✓				✓
	Andy Moore	✓	✓				
	Tim Emery	✓	✓				
DAWE	George Day	✓	✓			✓	
	Mariana Nahas	✓	✓			✓	
	Lesley Gidding-Reeve	✓	✓			✓	
	James Butler	✓	✓				
	Michael Le	✓	✓				
	Peter Yates	✓	✓				
	Cassandra Pert	✓	✓				
SETFIA	Simon Boag	✓	✓				
Indigenous	Chris Calogeras	✓	✓				
Recreational	Owen Li	✓	✓				
	Adam Martin	✓	✓				
eNGOs: HSI	Alexia Wellbelove	✓	✓				
AMCS	Darren Kindleysides	✓	✓				
WWF	Jim Higgs	✓	✓				
PEW	Michelle Grady	✓	✓				
SESSF Experts	Sandy Morison	✓	✓	✓			
	Ian Knuckey	✓	✓	✓			
	Sarah Jennings	✓	✓	✓			
	Ross Winstanley	✓	✓	✓			
	Nick Rains	✓		✓			✓
	Keith Sainsbury	✓	✓	✓			
Total	**36**			**10**			

17.5. Second Stakeholder Consultation

The 2nd Stakeholder Consultation was held as a workshop at the AFMA Head Offices in Canberra, with the option for online participation. The list of stakeholders contacted, and those that participated in the workshop either in person or online, is shown in the table below.

Name	Affiliation	In Person	Online
Andrew Penney	Project Team, Pisces Australis	y	
Geoff Tuck	Project Team, CSIRO	y	
Pia Bessell-Browne	Project Team, CSIRO	y	
Laura Blamey Crous	Project Team, CSIRO		y
Eva Plaganyi-Lloyd	Project Team, CSIRO		
Brodie Macdonald	AFMA		
Cate Coddington	AFMA	y	
Daniel Corrie	AFMA		y
Elissa Mastroianni	AFMA		y
Emma Freeman	AFMA		
Sally Weekes	AFMA	y	
Selina Stoute	AFMA	y	
Jennifer Power-Geary	AFMA	y	
Cathy Dichmont	RAG Chair		y
Ian Knuckey	RAG Chair, Fishwell Consulting		y
Paul McShane	RAG Chair, Global Marine		y
Lance Lloyd	RAG Chair, Lloyd Environmental		y
Sandy Morison	RAG Chair, Morison Aquatic		
Sarah Jennings	RAG member, UTAS		
Chris Calogeras	Indigenous, C-Aid Consultants		
Ross Winstanley	Recreational		
Keith Sainsbury	SESSF expert		y
Tony Smith	SESSF expert		y
Beth Fulton	CSIRO		y
Alexia Wellbelove	AMCS		
Darren Kindleysides	AMCS		
Adrian Meder	AMCS		y
Michelle Grady	Pew Trusts		
Geoffrey Muldoon	WWF Australia		y
Dave Galeano	DAFF		
Don Bromhead	DAFF		y
James Woodhams	DAFF		y
Robert Curtotti	DAFF		y
Trent Timiss	DAFF		y
Daniel Wright	DAFF		y
Peter Yates	DAFF		y
Emma McCormick	DAFF		y
Adam Briggs	DCCEEW		y
Josh Davis	DCCEEW		
Lee Georgeson	DCCEEW		y
Lesley Gidding-Reeve	DCCEEW		y
Matt Flood	DCCEEW		y
Neil Garbutt	DCCEEW		y
Adrianne Laird	FRDC		y
Chris Izzo	FRDC		
Crispian Ashby	FRDC		y
Kris Cooling	FRDC		
Toby Piddocke	FRDC		
	Number of workshop participants		33

The purpose of the 2nd Stakeholder Consultation was to present draft-final results of the project and provide an opportunity for stakeholders to ask questions for clarification, suggest improvements to presentation of results and raise concerns regarding results. Prior to the workshop, stakeholders were presented with a draft final report of all results. The main components of the project were then presented during the workshop under the topics below.

- What is Dynamic B_0?
  - Explanation of dynamic B_0 and how it is calculated, retrospectively and in projections, and used to calculate dynamic reference points.
  - Introduction to deviation of historical dynamic B_0 from static B_0 and how this differs between case study stocks.
- Retrospective analysis, Dynamic B_0, depletion and RBCs
  - Effects of using dynamic B_0 reference points on retrospective estimates of depletion and RBCs.
  - Differences between stocks in degree to which retrospective RBCs differ from catches.
  - Results of simulations showing effects of changes in productivity parameters on trends in unfished spawning biomass.
- Evidence for fishing and non-fishing effects
  - Explanation of the variety of approaches taken to evaluate evidence for fishing and non-fishing effects, from expert scoring to trends in dynamic B_0 deviation. All evidence evaluated is reliant on results from Tier 1 stock assessments.
  - There are clear and, for some stocks, surprising differences in the relative degree of fishing and non-fishing effects on the case study stocks.
  - Strong fishing effects will likely mask non-fishing effects, and *vice-versa*.
- MSE testing of alternative harvest control rules
  - Methodology for MSE testing, including alternative HCRs tested and assumed environmental trends in productivity.
  - How do depletion and RBCs differ using static vs. dynamic reference points under productivity decline? Overview of performance measures for depletion and catch variability.
  - What are the risks in terms of depletion of using dynamic reference points if static reference points are more appropriate.

Stakeholders were invited to make written submissions to the project team, particularly in response to the following questions, sent to stakeholders after the workshop.

1. What further explanation, if any, do you think is required to explain the results presented in the report? What additional questions do you have regarding the analyses and results?
2. Based on the results relating to evidence for non-fishing effects on southeast trawl and northern crustacean stocks, what are your observations and conclusions regarding the role of climate-driven, non-fishing effects on the status of each of these stocks?
3. Based on the retrospective (historical) and MSE (projected) results comparing the options and outcomes of using alternative definitions of B_0 and dynamic reference points to manage these stocks, what are your views and conclusions regarding use of dynamic reference points for each of the stocks concerned?

Two responses were received, one from AFMA and one from DCCEEW. The key questions and concerns raised in these responses are summarised in Section 5.5 of this report: Second Stakeholder Consultation. Key questions and concerns raised in these responses are summarised below.

Technical complexity of results

- Several stakeholders observed that the presentations of results provided at the 2nd stakeholder consultation workshop were highly technical, complex, and difficult for non-technical stakeholders to extract key messages and conclusions, particularly the MSE analysis results. This resulted in an inevitable emphasis, in the minds of stakeholders, on uncertainty regarding the results, which translated into perceived high risk of any change to the way that management reference points are currently calculated and used.
- Stakeholders requested that results should be presented, to the extent possible, in a simplified manner, with clear conclusions and recommendations.

Emphasis on need for strong evidence of non-fishing effects

- It needs to be made very clear that the use of dynamic B_0 in managing fish stocks should only be done when there is a high level of confidence in the ability to separate fishing and non-fishing effects on changes in stock productivity and biomass.
- If confidence around separating fishing and non-fishing effects is poor, it may open AFMA and the Australian Government up to criticism by eNGOs and other stakeholders that different representations of reality are being cherry-picked to achieve a particular management outcome.
- This will need to be communicated very clearly to stakeholders due to the conceptual complexity evident in project outputs to-date.

Role of species biology in susceptibility to non-fishing effects

- Does this work tell us anything about the stocks capacity to recover, regardless of the reason for why there has been a decline?
- Is there anything inherent about the biology of the species that makes it subject to influence? Why Jackass Morwong but not Redfish?
- Highlighted differences between Redfish and Jackass Morwong, these are species that exist in the same environment. How can we explain the differences in what these two stocks have experienced?
  - Is based on recruitment deviations – we've seen it for Jackass Morwong but not for Redfish.
  - Redfish is longer-lived, so less susceptible to climate change.

Approach to take moving forward

- How do we go forward from here? Unless we can get a more direct measure of the things we're worried about, stock size for example, increases the risk of getting it wrong.
- Whether we actually go on to implement dynamic B_0 remains to be seen. Regardless, we need to account for evidence of non-fishing impacts contributing to decline or failure to recover, and the system developed here seems to be defensible.
- Moving forward, do we just take the estimate of dynamic B_0 and F *now* (while we have some data) that allows for rebuilding (or at least prevents overfishing), and manage on the basis moving forward?
- What to do when CKMR (or something else) tells you a stock is now 10k t where it used to be 100k t and will never go back to its original size? - Work out F_{MSY} for the new stock and go from there?
- CKMR is unlikely to be an option for most of our depleted species due to the number of samples required. The only species (from this project at least) for which there is a clear influence, is now subject to closure and likely compromised future data collection. Are we setting ourselves up to fail?
- How does this fit in with MSHS indicator approach, noting RBC/TACs for non-indicator species, which presumably sit within a group that are subject to the same non-fishing impacts.
- If we are to implement, what HCRs can we use? Put a safeguard into the control rule that allows for the 'slide' but eventually stops it from going any further. Soft and hard limits – this is being MSE tested?

- This becomes particularly important when implementing rebuilding strategies. Using Jackass Morwong east as an example, scenarios with and without dynamic B_0 should be presented, including evidence for/against non-fishery impacts, and the management responses developed in that context.
- Concerns about [maintaining] catches as absolute stock biomass declines might be addressed by implementing the dynamic B_0 slide HCR. Our understanding is you can pick a threshold (relative to static B_0) beyond which the dynamic B_0-slide HCR will not allow the stock to breach?

Identification of an environmental driver

- Could the SOI be used as an ecosystem trigger in the HSF? Sustained positive SOI values above about +8 indicate a La Niña event while sustained negative values below about –8 indicate an El Niño.

Resources required for dynamic management

- Exploring and implementing dynamic B_0 seems to be resource intensive, difficult to demonstrate, and very risky if we get it wrong. What's the alternative?
  - Adjusting future recruitment (regime shift) like we have for Jackass Morwong without re-estimating B_0?
  - Can dynamic Tier 4 assessments factor into this at all?
- The level of data and the investment required to support such management approaches may not be available or achievable.

Ecosystem requirements

- Some sort of index of ecosystem productivity, or analysis to support a hypothesis of an overall decrease in ecosystem productivity, may help to justify management of stocks using dynamic B_0.
- At some point, the ecosystem considerations take over. If morwong, for example, is so critical to the ecosystem that even catches at 2-5 t aren't sustainable. Is there any linkage with this work and the concept of an ecosystem cap?
- From an ecosystem perspective, we should probably be aiming for resilience, which is often a product of biodiversity due to the ecological redundancy that biodiversity provides.