MARINE AND ATMOSPHERIC RESEARCH/WEALTH FROM OCEAN
www.csiro.au

Quantitatively defining biological and economic reference points in data poor fisheries

Shijie Zhou, Sean Pascoe, Natalie Dowling, Malcolm Haddon, Neil Klaer, James Larcombe,

Tony Smith, Olivier Thebaud, Simon Vieira, Sally Wayte

FRDC Project No. 2010/044

April 2013

Fisheries Research Development Cooperation

FRDC FISHERIES RESEARCH & DEVELOPMENT CORPORATION

Australian Government
Australian Bureau of Agricultural and Resource Economics and Sciences

National Library of Australia Cataloguing-in-Publication entry: (paperback)

Author:	Zhou, Shijie
Title:	**Quantitatively defining biological and economic reference points in data poor fisheries**
ISBN:	978-0-643-10999-5 (print) 978-1-922173-00-3 (online)
Subjects:	Fisheries--Economic aspects. Fisheries--Australia--Databases. Fish stock assessment--Australia.
Other Authors /Contributors:	Pascoe, Sean, author. Dowling, Natalie, author. Haddon, Malcolm, author. Klaer, Neil, author. Larcombe, James, author. Smith, Tony (Anthony David Milne), author. Thebaud, Olivier, author. Vieira, Simon, author. Wayte, Sally, author. CSIRO, Marine and Atmospheric Research, issuing body.
Dewey Number:	639.20994
Project Number:	2010/044

Citation

Zhou, S., Pascoe, S., Dowling, N., Haddon, M., Klaer, N., Larcombe, J., Smith, A.D.M., Thebaud, O., Vieira, S., and Wayte, S. 2013. Quantitatively defining biological and economic reference points in data poor fisheries. Final Report on FRDC Project 2010/044. Canberra, Australia.

The Fisheries Research and Development Corporation plans, invests in and manages fisheries research and development throughout Australia. It is a statutory authority within the portfolio of the federal Minister for Agriculture, Fisheries and Forestry, jointly funded by the Australian Government and the fishing industry.

Contents

List of tables

List of figure

1 Non-technical Summary

2010/044: Quantitatively defining proxies for biological and economic reference points in data poor fisheries

PRINCIPAL INVESTIGATOR: Dr Shijie Zhou

ADDRESS: CSIRO Marine and Atmospheric Research
GPO Box 2583
BRISBANE QLD 4001
Australia
shijie.zhou@csiro.au

OBJECTIVES:

1. Build on current work for species in data poor fisheries under harvest strategies that: (1) identify biological reference points with associated performance measures and proxies, and (2) test harvest strategies and quantitatively defines limit and / or target reference points in line with the settings of the Commonwealth Harvest Strategy Policy.
2. To identify cost-effective methods of incorporating economic indicators into biological reference points that could be determined in Objective 1.
3. To develop case studies that demonstrate how these methods could be implemented in other Australian fisheries.

OUTCOMES ACHIEVED TO DATE

- A means to derive good estimates of economic variable values for use in bioeconomic analyses when some biological models exist but economic data are unavailable.
- A means to estimate fishing mortality that equates to maximum sustainable yield (F_{MSY}) when fisheries data are extremely limited.
- A means to derive estimates of effort (and/or biomass) at maximum economic yield given F_{MSY} and limited information on the type of fishing activity.
- Developed and tested a simple catch rate gradient based harvest control rule for data-poor fisheries.
- Established relationship between fishing mortality-based biological reference points (including F_{MSY}) and fish life-history parameters, particularly the natural mortality rate.

- Developed and applied a statistical method for estimating gear efficiency, biomass, and fishing mortality based on catch data alone.
- Developed methods to estimate catch-based or biomass-based reference points (including virgin biomass, maximum sustainable yield, limit biomass, and depletion) using primarily catch history.

The outputs from this project will guide fishery management agencies in their development of policies and management rules. The final report will be made available to the relevant management agencies and industry, and findings will be communicated to various stakeholders further through seminars, meetings, publications and conferences.

The implementation of the Commonwealth Harvest Strategy Policy requires limit and target reference points for each fishery. These reference points can be both biomass-based (e.g., B_{TARG}, B_{MSY}, B_{LIM} etc.) and fishing mortality-based (e.g., F_{TARG}, F_{MSY}, F_{LIM} etc.). Estimating these reference points typically requires extensive biological and economic data and has only been achieved for a handful of data-rich target species. This project aims to develop innovative approaches to derive reference points using limited information. It involves both economic analysis and biological modelling.

Proxy measures for economic target reference points

The economic component of the project aimed to develop a methodology allowing proxy measures for maximum economic yield to be identified where economic information is limited. The economics component of the project involved three main activities: reviewing the literature on estimating proxy measures for MEY in data poor fisheries; estimating costs structures in fisheries where information was limited; and deriving "rules of thumb" that link fishery characteristics to ratios of B_{MEY} to B_{MSY}.

Relatively few previous studies had attempted to estimate economic target reference points in data poor fisheries. The use of capacity utilisation measures have been proposed as a method in data limited environments as an indication as to the level of excess capacity in a fishery, and also to estimate what a fully efficient fleet may look like for a given target catch level. Capacity analysis ranged from approaches that just relied on catch and effort data, to more detailed approaches that incorporated economic information also (costs of fishing and prices). Other data poor approaches –

aimed more at harvest control rules rather than defining target reference points – involved catch per unit effort indicators.

The second stage of the study aimed at identifying a generic approach to estimating the key economic variables based on the data that are likely to be readily available for fisheries (in the absence of actual economic data). These cost estimates could be incorporated with biological models where available for bioeconomic analysis. The approach was based on econometric modelling of the main cost components of fishing operations, using information on the technical characteristics of fishing vessels and their fishing activity that is generally available. Economic data for a wide range of fisheries (both Commonwealth and South Australian) were used to derive simple relationships between the costs of fishing and the type of fishing activity. The key cost components that were modelled were variable costs (separated into fuel and oil, crew, freight and marketing, and other variable costs), quasi-fixed costs (including repairs and maintenance costs), fixed costs and capital and depreciation costs. Reasonable estimates of most cost components could be made given information on the average size of the vessels, their main fishing gears, the number of days fished, and the type of management under which vessels operate.

The third stage of the research involved determining a methodology to identify proxy measures for E_{MEY} (and B_{MEY}) in fisheries in which only limited data are available. This involved identifying a generic model linking effort and fishing mortality at MSY, which a range of simple methods allow to estimate even with very limited catch and effort data, to effort and fishing mortality at MEY. Based on the static version of this generic model, it was then shown that the cost share of revenue - defined as the cost per unit catch divided by the price per unit catch - at MSY is a feasible proxy measure by which the optimal ratio of biomass and effort can be derived. In the dynamic model, optimal effort and biomass levels are also dependent on the ratio of the discount rate to the growth rate of the fish stock. While these cost shares of revenue at MSY are generally unknown, it was possible to derive reasonable estimates of these from the economic data used in the empirical analysis. The main variables influencing these cost shares were shown to be the vessel length, the fishery types to which they belong, as well as the average beach price of the fish landed by the vessels. Based on knowledge of these variables for a particular fleet, it is thus possible to estimate the likely cost share of this fleet, and from this, using the results of the generic model, to estimate the likely ratio of E_{MEY} to E_{MSY} for a particular fishery.

Development of biological reference points (BRP) for data-poor fisheries

Several methods have been developed, tested, and applied to case study stocks.

We derived fishing mortality-based biological reference points (F_{BRP}) for data-poor fish species by conducting a meta-analysis on 245 fish species worldwide and linked three types of reference points (F_{MSY}, F_{proxy}, and $F_{0.5r}$) to natural mortality M and other life-history parameters (LHP). We used Bayesian hierarchical errors-in-variables models to investigate the relationships and included the effect of taxonomic class and order. We compared various models and found that natural mortality is the most important LHP affecting F_{BRP}. The best model results in F_{MSY} = 0.87 M (SD 0.05) for teleosts and F_{MSY} = 0.41 M (SD 0.09) for chondrichthyans. F_{proxy} based on per-recruit analysis is about 15% smaller than F_{MSY}. Results could be used to estimate F_{BRP} for many data-poor species when some life history parameters are available.

A key feature of the Commonwealth Fisheries Harvest Strategy Policy is a set of biomass-based biological reference points (B_{BRP}), including B_{TARG}, B_{MEY}, B_{MSY}, B_{LIM}, etc. Till now these reference points have only been estimated for TIER 1 data-rich species. We developed several methods to estimate B_{BRP}.

We first attempted to estimate biomass from catch data, which involved a major innovation—estimating gear efficiency. The new method, referred as cross-sampling method, enables us to derive gear efficiency and abundance from catch data alone, circumventing traditional costly field experiments. The exceptional capacity of the cross-sampling method is empowered by utilizing mixed parametric statistical distributions and Bayesian techniques. By applying multiple gears, the method can be applied to difficult situations where individuals may have a non-random, aggregated distribution and where local abundance may vary at each sampling. We applied the cross-sampling method to five fish species (Tiger Flathead, Jackass Morwong, John Dory, Gemfish, and Ruby Snapper) and estimated their vulnerability to several gear types, including longline, trawl, seine, gillnet, fish trap, and minor lines (e.g., dropline, handline, etc.). The only source of data is the commercial logbook. We then modelled fish density using a general additive model (GAM). Together with distribution area, either from an existing distribution map, or from historical logbook data, we were able to derive annual abundance (biomass) for these case-study species. From estimated biomass, annual fishing mortality rates can be readily derived. Fishing mortality in turn can be compared with reference points derived from life-history parameters to signal whether current fishing intensities are sustainable.

We then developed three interconnected methods for estimating B_{BRP}. There have been a few courageous attempts in the vein of stock reduction analysis (SRA) to achieve the unachievable: using catch data and some life-history parameters to derive reference points such as MSY, B_{MSY}, and B_{LIM}. We advanced similar ideas in this report. First, we developed a deterministic chase-catch (CC) method to estimate B_{BRP} using catch history, natural mortality rate, and stock status (either biomass, fishing mortality, or depletion) in one recent year. Second, a conditional stochastic stock reduction analysis (CSSRA) extends the CC method through stochastic simulations controlled by multiple conditions. Systematic simulations show that these approaches can produce reasonably accurate results where the bias in the key output parameters (e.g., virgin biomass B_0, population growth rate r, maximum sustained yield MSY, and depletion ratio B_Y/B_0), is generally smaller than the potential bias in the inputs. However, the form and parameters of the priors can affect the results and it is difficult to choose priors. We applied these approaches to two case study species, Tiger Flathead and Jackass Morwong, because these TIER 1 species have full stock assessment results for comparison. The results from CC and CSSRA appear to be mixed: the estimate of MSY is more robust than other parameters such as B_0 and depletion.

The CSSRA and other similar methods require prior specification of key inputs such as carrying capacity K and population growth rate r, whereas the form of prior distributions and their parameters will affect the results. To resolve the difficulties of determining the priors for many data poor species, we finally developed an innovative “prior-free” approach to avoid these difficulties. We focused on posteriors instead of priors, that is, we used unconstrained priors for K and r, and closely examined the results after retaining viable iterations and excluding unlikely values. Because K and r are negatively correlated and their log-log plot forms a straight line within the viable range of combinations, the retained data points on this line contain the likely true values. We conducted simulations to demonstrate the approach and applied the method to four case study species: Tiger Flathead, Jackass Morwong, John Dory, and Eastern Gemfish. Using primarily catch data, this simple posterior-focused method results in improved biological reference points (B_{BRP}), including B_0, MSY, B_{MSY}, F_{MSY}, and depletion status.

Key words: data-poor, reference point, bioeconomic, life history, gear efficiency, biomass estimation, fishing mortality, harvest control rule

2 Acknowledgments

The project was jointly funded by the Fisheries Research and Development Corporation (FRDC project 2010/044), CSIRO, Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES), and the former Bureau of Rural Sciences (BRS). We thank the following people for their help and contribution in the project. Mike Fuller of CSIRO helped with database management and queries. Geoff Tuck of CSIRO provided stock assessment data and report for target species. Ross Daley provided information on species biology and fishing gears. Shaowu Yin of Nanjing Normal University, China, and James Thorson of University of Washington, USA helped with data collection and analysis in the F_{BRP} section. Tony Courtney of DAFF Queensland reviewed and commented on an earlier draft of the report. We would also like to thank Julian Morrison and Heather Bailey from Econsearch for provision of South Australian data used in the analyses.

2.1 Background

In 2007, the Australian Commonwealth Fisheries Harvest Strategy Policy was developed (DAFF 2007). The objective of this policy is the sustainable and profitable utilization of natural aquatic resources. The Commonwealth Harvest Strategy Policy relies on developing limit and target reference points for each Commonwealth fishery, with the former aimed at ensuring stocks remain above a critical minimum level and the latter aimed at identifying the target stock level that management should aim to achieve. The harvest strategies for each Commonwealth fishery aim to establish a target biomass point B_{TARG} equal to the stock size required to produce maximum economic yield (B_{MEY}) and to ensure fish stocks remain above the limit biomass B_{LIM} at least 90% of the time. There is considerable interest in the harvest strategy policy by many State management agencies, and it is likely that – at some point in the future – similar policies will be in place at the State level.

For many larger Commonwealth and State fisheries, there is a collection of both biological and economic information that can be used to meet the goals of a harvest strategy. For example, the management of the NPF reflects the use of both biological and economic information to set management targets consistent with the MEY principal. However, for many of the smaller fisheries there is limited availability of biological and economic data, precluding the use of sophisticated modelling techniques and analysis, such as bio-economic modelling and profit/productivity analysis in the management of these fisheries. Further, many of the harvested species in Commonwealth and State's fisheries do not have sufficient data to allow formal stock assessment to establish either biological or economic reference points. These fisheries are typically referred to as "data poor". There are some stocks existing in "data poor" fisheries for which some limited biological information is available such as length frequency, weight-at-age, and CPUE time series. These limited data may allow simple analyses such as yield-per-recruit, catch curves, biomass dynamics modelling, etc. However it is the case that many stocks in "data poor fisheries" have even less biological information than this, for example, catch only, and very limited economic information.

In this report, we define data-poor fishery as a fishery where available data are insufficient for conducting a conventional stock assessment and/or bioeconomic analysis, which includes fisheries with few or limited data, as well as poor data quality. For simplicity, we do not intend to explicitly distinguish between the terms of "data-poor" and "data-limited" and may use both terms interchangeably.

BACKGROUND

The Australian Bureau of Agricultural and Resource Economics and sciences (ABARES), and the former Bureau of Rural Sciences (BRS), produces annual "Fishery Status Reports" (Woodhams et al. 2011). However, stock status of many stocks in Commonwealth managed fisheries are uncertain in regard to overfishing or over fished, because many of the fish stocks are "data poor" and have not been assessed using quantitative methods.

Just as the cost of acquiring accurate economic and biological information for data poor fisheries is prohibitive, some management arrangements (such as ITQs) are too costly to implement. Consequently, a different approach is required. For smaller fisheries, a more generic set of information is required that can assist fisheries managers to integrate economic objectives in a practical and cost-effective manner and be useful for monitoring the economic health of these fisheries.

To ensure sustainable exploitation of these data-poor stocks, research is needed to develop suitable quantitative reference points or proxies consistent with the intent of the Commonwealth Harvest Strategy Policy. In addition to biological sustainability, Harvest Strategy Policy requires that the maximum economic yield be achieved for the fishing fleet. Hence, it will be important that any target reference points adopted for fisheries also incorporate economic considerations, so that the MEY objective of maximising the long term economic returns to the fishing industry from the management of the fishery is actively pursued.

In 2009, Commonwealth Fisheries Research Advisory Board (ComFRAB) requested proposals to develop innovative methods for incorporating economics into harvest strategies without bioeconomic models and quantitatively defining proxies for limit and target reference points in data poor fisheries. While identified in the call as potentially two separate projects, there is considerable overlap, particularly in relation to the estimation of target reference points that, under the harvest strategy policy, require an economic focus. As a result, this research project combines two initial projects, “Incorporating economics into harvest strategies without bioeconomic models” and “Quantitatively defining proxies for limit and target reference points in data poor fisheries”.

3 Need

The Commonwealth Harvest Strategy Policy requires the estimation of specific reference points for each stock to which the policy applies. Unfortunately, it is challenging, if not impossible, to estimate directly such reference points for many stocks due to limited, or absence of, economic data as well as biological data. In most cases, this is due to the relatively small size of the fishery or the relatively low economic importance of the species concerned, making the routine collection of appropriate data too costly. The current TIER system of assessment only attends to those fisheries that can either have a detailed quantitative assessment (TIER 1), have limited biological data and some ageing data (TIER 3), or have meaningful catch and catch rate statistics (TIER 4). The methods and proxies already in place provide a means of designating a target and limit in terms of catch rates and catches. However, these reference points are only useful for those species for which catch rate data are a meaningful reflection of stock status. There are many species for which catch rates, even if available, are very poor performance measures. Alternative methods and proxies need to be developed for even lower TIERs that provide for a consistent and defensible approach across all data poor fisheries. In most of these fisheries, economic data will also be absent, so some consistent means of developing meaningful and defensible target reference points needs to be developed.

4 Objectives

1. To build on current work for species in data poor fisheries under harvest strategies that:

- identify biological reference points with associated performance measures and proxies, and

- test harvest strategies and quantitatively defines limit and / or target reference points in line with the settings of the Commonwealth Harvest Strategy Policy.

2. To identify cost-effective methods of incorporating economic indicators into biological reference points that could be determined in Objective 1.

3. To develop case studies that demonstrate how these methods could be implemented in other Australian fisheries.

This report contains two sub-projects: Economic component — target reference points and biological component — developing methods for biological reference points. In the following Methods, Results, and Discussion sections, materials are structured against these two major components.

5 Methods

Economic analysis — target reference points for data-poor fisheries

5.1 Review of the literature on setting economic target reference points in data poor environments

Current experiences in setting economic target reference points were examined by reviewing the available literature. Attention was primarily given to peer-reviewed published journal articles, but "grey literature" (e.g. reports, working papers, conference papers etc) was also examined where appropriate. Key search engines used for finding appropriate references included Google Scholar, Sciencedirect, Scopus and Econlit.

The review was undertaken in three components – a review of the theory underlying maximum economic yield (MEY) as a target reference point and how it has been implemented in practice, a review of alternative decision support approaches in data poor situations, and a review of empirical applications where models have been developed to assess MEY.

The results of the review are presented in the results section.

5.2 Developing generic cost models

5.2.1 EMPIRICAL APPROACH

Critical to even proxy measures or indicators of MEY is some understanding of the cost structure of the fishery. The purpose of this part of the project is to develop a generic model based on fishery characteristics that can be used to estimate likely cost structures for fisheries for which no cost information exists. This includes the data poor as well as data limited fisheries. Given the type of fishery and characteristics of the vessels, the model will be able to indicate – at a minimum – if it is likely to have a high, medium or low unit cost of effort.

There is an a priori expectation that fishing costs are related to the characteristics of the vessel and the type of fishing activity. For example, it would be expected that large boats towing trawl nets would use more fuel than smaller trawlers, as well as more fuel than similar sized vessels deploying more static fishing gear (e.g. gill nets). The targeted species, as well as the type of markets on which the fish are sold may also influence costs of catching and handling fish. The type of management in place may influence the cost structure as well. Given this, it is expected that econometric models of individual vessel costs against the vessel and fishery characteristics can be developed that could be used to provide proxy cost measures in fisheries where actual cost data are not collected.

Information on costs of fishing is currently collected for a limited number of fisheries at the Commonwealth (e.g. ABARES) and State level (e.g. SA). From the ABARES surveys, information exists on the historical costs of fishing of a wide range of vessel sizes, fishing types (trawl, longline, squid jig, gillnet, hook and trap), as well as target species (prawns, multispecies finfish, tuna, squid, and shark). Economic data also exists on inshore fisheries in South Australia that covers prawns, finfish, lobsters, crab and abalone fisheries. These are harvested by smaller boats than those in the Commonwealth fisheries, using a range of methods some of which overlap with the Commonwealth fisheries (e.g. trawl, line and gillnet) as well as some that are restricted to inshore fisheries only (e.g. dive).

In this section, we outline the methods used to estimate generic cost models based on the individual vessel cost data for the range of fishery types covered by the available economic survey data. The key cost components considered were the major variable costs (fuel, crew, freight and other running costs), fixed costs (capital costs and other annual costs), and quasi fixed costs (repairs and maintenance). A number of different functional and structural forms of the models linking the cost to the vessel and fishery characteristics were tested, and the models that best captured the variability in the data while also conforming to a priori expectations about the influence of particular variables were chosen[1].

[1] It is possible that a model may fit the data statistically well in terms of goodness-of-fit statistics, but have estimated coefficients that were nonsensical. For example, if fuel costs were estimated to decrease with the number of days fished then it is likely that there is something wrong with the structure of the model even though it may have a good statistical fit.

5.2.2 DATA

The development of generic cost models required the use of detailed vessel-level cost data sourced from economic surveys of fisheries. Two main survey data sources used were a data set sourced from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) and a dataset sourced from consulting firm Econsearch.

ABARES (formerly ABARE) has been conducting economic surveys of Commonwealth fisheries since the early 1980s and has maintained a regular survey program for selected fisheries since 1992. The current program focuses on the most valuable Commonwealth fisheries. Each individual fishery is surveyed every two years, requiring that data be collected for the previous two financial years. This biannual approach to the survey minimises survey respondent burden while also reducing the risk of recall error.

The ABARES surveys program has allowed the development of a time series of economic information for surveyed fisheries. The number of vessels from each of the major Commonwealth fisheries that have been sampled by financial year since the early 1990s is given in Table 5-1. The aggregated financial and economic performance results generated from each survey are made publicly available through the annual Australian Fisheries Surveys Report series (see George, Vieira and New (2012) for the most recent report).

Given the small number of firms in Commonwealth fisheries, an attempt is made to contact all operators in the fishery. In practice, the full population is never sampled as non-response is relatively high across fisheries, reflecting the difficulty in contacting some operators and a reluctance of others to participate. Sample design and weighting systems have been developed that reduce the effect of non-response on the final survey results.

Table 5-1. ABARES survey sample (number of vessels) by year and fishery.

	BSS	CTS	ETB	GAB	GHT	NPF	SBT	SSh	SSq	SWT	TSP	TOTAL
1990		38	28			65						131
1991		42	40			69		41				192
1992		34	39			58	16	44				191
1993		35	47	4		43	32	31			13	205
1994	18	44	33	5		48		35			14	197
1995	27	44	39	5		59		27			17	218
1996	19	51	33	5		66		40			24	238
1997	28	41	40	4		69		42			21	245
1998	16	46	23	6		70		23	10		26	220
1999	18	37	40		41	57		27	14		20	254
2000		37	20		32	60		23	6	12	23	213
2001		38	32		33	56		25	11	8	18	221
2002		39	32		23	58				12	28	192
2003		20	44		28	41			2		18	153
2004		25	23		13	43					19	123
2005		27	27		16	28					12	110
2006		23	34		17	29					12	115
2007		19	33		17	34					13	116
2008		14	24		16	30					12	96
2009		15	24		16	31						86
2010	8					33						41
2011	7											7
TOTAL	141	669	655	29	252	1047	48	358	43	32	290	3564

BBS: Bass Strait Scallop; CTS: Commonwealth trawl sector; ETB: Eastern tuna and billfish; GAB: Great Australian Bight; GHT: Gillnet hook and trap; NPF: Northern Prawn Fishery; SBT: Southern bluefin tuna; SSh: Southern Shark; SSq: Southern squid; SWT: South West tuna; TSP: Torres Strait prawn.

Survey interviews are generally undertaken with boat owners to obtain financial details of the fishing business, although skippers, bookkeepers and owner spouses may also be interviewed. Further information may also be subsequently obtained from accountants, selling agents and marketing organisations on the signed authority of the survey respondents. Key information collected as part of the survey includes:

- profit and loss statements which summarise all vessel revenues and costs;
- the market value of the vessel, licences and endorsements;
- characteristics of the labour employed by the vessel; and,
- replacement cost, estimated market value and year of manufacture of vessel capital items.

All information obtained is reconciled to produce the most accurate description of the financial characteristics of each boat sampled in the survey.

Similar information is collected by EconSearch as part of their economic surveys of South Australian commercial fisheries. EconSearch has been undertaking these surveys since 1999 (EconSearch 2010a, 2010b, 2010c, 2010d, 2010c). Each fishery is generally surveyed every three to four years and only data from the preceding financial year are collected. For the years between surveys for which survey data are not collected, the most recent survey estimates are imputed using primary and secondary information sources (fishery catch, effort and price data).

As noted by EconSearch (2010a, 2010b, 2010c, 2010d, 2010c), survey definitions and terms have been kept consistent with those used by ABARES where possible. This means that the two datasets are reasonably consistent with each other and can be combined relatively easily. However, minor differences in data collection and recording practices do exist between the two surveys. These differences and how they were resolved for the purpose of the analysis presented here are discussed in the results section below.

5.2.3 DATA USED IN THE ANALYSES

A key aim of the project was to develop an approach to determining harvest strategy reference points for a wide range of data poor fisheries. Therefore, to allow applicability to a broad range of fisheries, it is important to estimate cost models using data associated with a variety of fisheries, fishing methods, target species, management arrangements and any other key characteristics that may affect a fishery’s cost structure.

From the ABARES survey data outlined in Table 5-1, a sub-dataset that included eight Commonwealth managed fisheries was used to estimate the cost models (Table 5-2). These data were combined with catch, effort (days fished) and boat size data sourced from logbook data collected by the Australian Fisheries Management Authority (AFMA). The dataset was limited to vessels sampled post 1998-99 financial year based on the available logbook data. The dataset was further limited to vessels that derived 100% of their fishing revenue from the surveyed fishery.

Data for the seven South-Australian fisheries surveyed by EconSearch are also included in the analysis (Table 5-2). These data were available for financial years between 1997-98 and 2008-09. Given that EconSearch surveys South Australian fisheries every three to four years, survey data for each fishery are not available for all financial years within the latter time period. Further, while data were available at the individual vessel level, information on the identity of the vessels was not recorded by EconSearch to maintain confidentiality. Hence, it was not possible to link data for individual vessels surveyed through time.

Further selection of observations from the combined sample was required to:

- exclude missing values for the variables which were to be used in the estimations (see below, the results section);
- exclude categories of vessels which, while different in their characteristics to the other vessels in the sample, were not represented to an extent which allowed statistical representation in the estimations (e.g. purse seine vessels and polling vessels from the South-West tuna fishery).

Table 5-2. Final sample (number of vessels) by year and fishery.

	Commonwealth fisheries								South Australian fisheries								
	BSS	CTS	ETB	GHT	NPF	SSq	SWT	TSP	AB	BC	L&C	MSF	PSGWC	RLNZ	RLSZ	SAR	**Total**
1998									0	13		35	9	18	28		60
1999	10	34	27	37	57	12		20									45
2000		36	17	26	60	6	11	22									47
2001		38	30	33	55	10	8	18	13	13		64	11	24	26		146
2002		39	32	20	58		12	27								12	172
2003		19	44	26	41			16			27						167
2004		24	23	12	43			15									112
2005		26	27	15	27			11	14	6			22	26	89		116
2006		19	33	17	29			12			22					13	117
2007		19	33	16	34			13				112					222
2008		14	24	13	29			12	15	5			17	21	57		107
2009		15	24	14	31						16					9	66
2010	8				33												
2011	7																
Total	25	277	200	125	255	24	24	100	54	37	65	211					1377

CTS: Commonwealth trawl sector; ETB: Eastern tuna and billfish; GHT: Gillnet hook and trap; NPF: Northern Prawn Fishery; SSq: Southern squid; SWT: South West tuna; TSP: Torres Strait prawn; AB: Abalone; BC: Blue crab; L&C: Lakes and Coorong; MSF: Marine Scalefish PSGWC: Spencer Gulf & West Coast Prawn; RLNZ: Rock lobster northern zone; RLSZ: Rock lobster southern zone; SAR: Sardines.

The characteristics of the final sample used for the analysis are described in Table 5-3.

A key characteristic that will be a strong determinant of a vessel's cost structure is the fishing method it uses. The sample data set covered a total of 13 fishing methods (Table 5-4). Trawl vessels were by far the most dominant vessel type in the sample data set, accounting for 38 per cent of the sample. This was followed by pelagic longline (15 per cent), pots (13 per cent), gillnet (9 per cent) and dropline (8 per cent). Other methods included automatic longline, Danish seine, demersal longline, diving, dropline, jigging, pots and mixed gear (predominantly a mix of gillnet, pots and dropline).

Table 5-3. Characteristics of the vessels included in the final sample

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
freight	0	0	12,109	43,408	50,095	651,036
otherrc	0	909	8,440	18,031	19,363	226,502
fuel	182	20,000	65,000	109,183	166,552	791,048
BRM	0	13,091	38,223	67,706	96,341	1,133,272
GRM	0	0	7,416	18,912	30,225	222,679
overheads	0	30,907	54,400	69,589	90,773	536,174
crew2	424	81,245	159,107	182,783	261,231	1,528,848
boatval	1,806	200,000	461,500	641,860	950,000	7,065,000
replace	0	309,678	644,000	824,992	1,143,877	9,250,000
length	3	12	18	17	22	46
catch	0	15,334	50,735	95,200	99,088	7,467,163
days	1	77	128	126	165	365
age	0	10	18	18	24	67
crewno	1	2.215	3	3.599	5	11

Freight: freight, marketing and packaging costs; otherrc: other variable costs; fuel: fuel, oil and grease costs; BRM: boat repairs and maintenance costs; GRM: gear repairs and maintenance; overheads: overhead costs including administration, accounting, banking, electricity, licensing; crew2: labour costs for crew and skipper including imputed labour costs; boatval: market value of boat; replace: replacement cost of hull and engine; length: vessel length in metres; catch: catch in kilograms; days: days fishing; age: age of the hull in years.; Crewno: the number of crew on the vessel including the skipper (FTEs).

In terms of fishery management arrangements, vessels managed under individual transferrable quotas accounted for the majority of the sample (39 per cent). This was followed by vessels managed under non-transferable effort-based management units (32 per cent) and individual transferable effort controls (29 per cent) (Table 5-5). The remainder of the vessels in the sample were managed under individual transferable effort controls.

Table 5-4. Number of vessel in the sample by year and fishing method.

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Total
Auto longline[a]	0	0	0	0	1	1	2	3	3	3	2	2	0	0	17
Danish seine	0	9	10	6	6	4	6	8	4	4	7	7	0	0	71
Demersal longline	0	7	3	5	5	6	6	9	7	6	5	6	0	0	65
Diving	12	0	0	0	0	0	0	14	0	0	15	0	0	0	41
Dropline	35	11	7	51	0	3	0	0	1	78	0	0	0	0	186
Gillnet	0	19	16	35	15	44	6	6	30	9	8	24	0	0	212
Jigging	0	12	6	10	0	0	0	0	0	0	0	0	0	0	28
Mixed gear	7	0	0	13	0	0	0	2	0	35	1	0	0	0	58
Pelagic longline	0	27	24	38	44	44	23	27	33	33	24	24	0	0	341
Pots	52	0	0	56	0	0	0	119	0	0	82	0	0	0	309
Purse Seine	0	0	0	0	12	0	0	0	13	0	0	9	0	0	34
Dredge	0	10	0	0	0	0	0	0	0	0	0	0	8	7	25
Trawl	0	102	108	105	118	72	76	56	56	62	48	39	33	0	875
Total	115	197	178	330	200	173	117	263	144	227	207	109	41	7	2308

Note: a) Auto longline was only introduced in around 2006, but these vessels had different operation size based characteristic than other vessels in the fishery prior to the introduction of the new gear (enabling them to adopt the new gear)

Table 5-5. Number of vessel in the sample by year and management arrangement.

Year	Non-transferable effort based	Individual transferable quota	Transferable effort units	Total
1998	62	53	0	115
1999	39	81	77	197
2000	34	62	82	178
2001	147	110	73	330
2002	44	71	85	200
2003	71	45	57	173
2004	23	36	58	117
2005	49	176	38	263
2006	54	49	41	144
2007	145	35	47	227
2008	41	125	41	207
2009	40	38	31	109
2010	0	8	33	41
2011	0	7	0	7
Total	749	896	663	2308

5.2.4 VARIABLES INCLUDED IN THE DATA SET USED IN THE ANALYSES

The final sample data set included the following key cost variables:

- Freight – includes freight, marketing, cool storage and packaging;
- Other running costs – includes bait, ice and food;
- Fuel, oil and grease;
- Total repairs and maintenance – includes boat repairs and maintenance and fishing gear repairs and replacements;
- Overheads – includes a range of costs covering administration, accounting, banking, electricity, licensing etc.;
- Crew cost – cost of skipper and crew (two measures: one based on cash cost only and the other including an imputed cost where labour is unpaid);
- Boat and gear market value (representing the capital cost of the vessel).

Other key data included boat length, catch, days at sea fishing, hull age, crew number and boat receipts. Dummy variables were also created to indicate a boat's primary fishing method, the fishery management arrangements it operated under, whether it was likely to freeze its catch at sea and whether a boat's skipper was also its owner.

5.2.5 INPUT PRICE INDEXES

Costs are a function of both the level of input use and input price. Data on input prices in fisheries is generally unavailable, and where input price data has been used, it has either had to be derived based on a range of assumptions (e.g. Pascoe et al. 2011) or been provided by the industry (e.g. Punt et al. 2010). However, there is an a priori expectation that prices of inputs such as fuel, capital and freight in fisheries should be similar to input prices in agriculture.

An advantage of defining the models in terms of the agricultural price paid indexes is that these are annually produced and published by ABARES (ABARES 2010), with a separate index for each major input category. The price indexes used for the analysis are given in Table 5-6.

While it is expected that price changes in the fisheries sector should follow similar trends to that in agriculture, it is possible that they may change at different rates. The estimated coefficients relating to the price indexes in the model can be used to adjust these price indexes to make them more relevant to the fishing industry.

Table 5-6. Prices paid indexes used in the analysis.

	Cost item in the analysis					
	Fuel	Capital	Maintenance	Freight and Marketing	Other running costs	Fixed costs
Indexes of prices paid by farmers in Australia	Fuel and lubricants	Capital items: plant and equipment	Maintenance: plant and equipment	Marketing: total	Total prices paid	Overheads: other overheads
Year						
1998	0.522	0.686	0.690	0.747	0.706	0.712
1999	0.543	0.708	0.706	0.767	0.71	0.734
2000	0.775	0.730	0.733	0.784	0.739	0.741
2001	0.752	0.773	0.773	0.816	0.777	0.774
2002	0.669	0.795	0.795	0.840	0.797	0.797
2003	0.663	0.818	0.818	0.866	0.858	0.821
2004	0.753	0.838	0.838	0.887	0.868	0.841
2005	0.872	0.860	0.860	0.908	0.892	0.861
2006	1.099	0.888	0.888	0.937	0.913	0.889
2007	1.087	0.914	0.914	0.964	0.959	0.914
2008	1.271	0.945	0.945	1.070	1.095	0.946
2009	1.101	0.975	0.975	1.024	1.051	0.976
2010	1	1	1	1	1	1

Note: Derived from ABARES' Australian Commodity Statistics 2010 Table 92 (ABARES 2010)

5.2.6 MODELLING FORMULATION AND ESTIMATION

A key objective of the research was to determine if reasonable estimates of key cost parameters required in bioeconomic analysis could be derived from limited information about the fishery. To this end, an econometric model was developed for each main cost (e.g. fuel costs, crew cost, freight, repairs and maintenance, capital cost, depreciation rates and other fixed and variable costs). In each case, the cost – or some modification to the cost (e.g. crew share rather than crew cost) – was the dependent variable and vessel and fishery characteristics were the independent variables.

A number of different functional forms of the models were tested based on expectations as to how the costs were likely to relate to the various fishery and vessel characteristics. The initial model in each instance was based on assumptions as to how the inputs were likely to interact to affect the cost item. In most cases, a multiplicative assumption was made, and the models estimated in log-linear form. That is, $C \propto \prod_i \beta_i I_i$, such that $\ln C = \beta_0 + \sum_i \beta_i I_i$ .The assumptions underlying each cost model are presented in the results section (Section 7.3) along with the final model formulation. The general principles involved in the development of the models were that they should

- attempt to capture key drivers of the cost items; and
- cover key cost components that are relevant for incorporation into appropriate bioeconomic models.

Ideally, the models would have been run as panel data models to capture any vessel-specific characteristic not captured by the general characteristics considered. However, vessel identifiers were not recorded for the South Australian data and it was not possible to track individual vessels over time in the data.[2] As a result, all observations are considered to be independently distributed. This may have some implications for the parameter estimates, although given the size and breath of the data set any biases introduced by excluding fixed (or random) effects are likely to be small.[3]

Given the limited price information deliberately used in the analysis, there may be periods when relevant input prices for the fishing industry diverged from those of the agricultural sector, which would manifest itself in correlation between residuals from the different models over time. The models were initially estimated as system of equations to allow for the potential for contemporaneous correlation. However, the results of the initial model estimations suggested that the residuals were not correlated so individual models for each cost component were developed.

Different final functional forms were adopted for the different cost components on the basis of what was most theoretically justifiable (i.e. had to have an a priori logic) and also which best fitted the data. The final functional forms are presented in the results section (as these forms are also results

[2] Data stored by Econsearch does not include a vessel identifier to protect the confidentiality of the fisher. The data are not commonly used for the types of analyses we undertook, and problems of not having some form of vessel identified in the data had not previously arisen.

[3] An advantage of panel data is that omitted variable bias (due to unobserved or unmeasurable factors) is reduced. However, with such a diversity of fishing activities included in the analysis, differences between activities is likely to be more influential than unobserved/unmeasured differences between individuals within a given fishing activity. Without a panel data formulation, however, it is not possible to test this assumption.

of the analysis rather than just methodology). Most models include dummy variables representing the different types of fishing gear employed. In these cases, the base gear (i.e. the gear not included in the model but against which everything else is assessed) is fish trawl.

5.3 Proxy target reference points for data poor fisheries

5.3.1 INTRODUCTION

The use of biological reference points as indicators to guide fisheries management has been well established (Caddy 1995, 2004). While numerous types of biological reference points exist (Mace 1994), the most commonly applied are target and limit reference points, usually expressed in terms of either the biomass of the stock or the level of fishing mortality that achieves given outcomes. Limit reference points indicate a point which should be avoided, while the target reference point represents the point that management is aiming to achieve (Mace 1994). While maximum sustainable yield (MSY) is the most commonly applied target reference point (Caddy 2004), there is increasing interest in maximum economic yield (MEY) as an alternative target (Dichmont et al 2010). Maximum economic yield represents the level of fishing effort and catch that maximises the level of economic profits in the fishery (see section 2 of this report). As it generally involves a lower level of fishing effort, it is more conservative in terms of biomass than MSY, and as it generally involves a lower level of fishing effort is often considered to be more environmentally beneficial in terms of bycatch and habitat damage (Dichmont et al. 2008; Grafton et al. 2007).

The Australian Commonwealth Harvest Strategy policy (DAFF 2007) identifies the level of biomass that achieves MEY (B_{MEY}) as the target reference point for Commonwealth managed fisheries. The estimation of MEY requires an understanding of both the key economic and biological parameters relevant to the fishery. In data poor fisheries, some or all of these parameters may be missing. Where economic information is missing, the Policy suggests a default value of 1.2 B_{MSY} as a proxy for the target reference point (DAFF 2007). However, estimation of B_{MSY} also requires information about the biology of the stock, and assumes that each stock in a multi species fishery can be targeted separately (i.e. there are no technical interactions). Further, the default proxy measure does not take into account the effects of prices and costs, as well as the discount rate if a dynamic MEY is the target.

In data poor fisheries, the ability to estimate B_{MSY} is limited. However, a range of simple methods exist to estimate fishing mortality at MSY (F_{MSY}) even with very limited catch and effort data, based on assumptions about some of the biological characteristics of the species (Garcia et al. 1989). Given this, it may be possible to derive proxy target reference points of F_{MEY} based on F_{MSY} as an alternative to the B_{MEY}/B_{MSY} ratio.

In this section, the relationship between B_{MSY} and B_{MEY} is explored through a stochastic simulation using a simple bioeconomic model. Further, and alternative target reference point is examined that compares effort and fishing mortality at MSY with that at MEY. The results of the analysis are synthesized using a regression tree approach to determine if there exists a simple set of criteria for determining an appropriate proxy value for F_{MEY}.

5.3.2 BASIC BIOECONOMIC MODEL OF THE FISHERY AND DEFINITION OF PROXY TARGET REFERENCE POINTS

1.3.2.1 The basic model

The basic bioeconomic model used in the analysis was based on a logistic biological growth model l for a single species fishery (Shaefer 1954, 1957) of the form

$$B_{t+1} = B_t + rB_t(1 - B_t/K) - C_t$$

where B_t is the biomass in time period t, r is the instantaneous growth rate, K is the environmental carrying capacity and C_t is the catch in time period t. Catch is assumed to be a linear function of fishing effort and the level of biomass, given by

$$C_t = qE_tB_t$$

where q is a proportionality constant known as the catchability coefficient and E_t is the level of fishing effort in time t.

At equilibrium, $B_e = B_t = B_{t+1}$ and hence $C_e = rB_e(1 - B_e/K)$ where the right hand side represents the annual growth in the population, also referred to as the surplus production as it is surplus to what is required to keep the population at a stable level of biomass (in the absence of fishing). The maximum equilibrium level of catch (the maximum sustainable yield) is hence given by

$$\frac{dC_e}{dB_e} = r - 2rB_e/K = 0$$

and hence

$$B_{MSY} = K/2$$

That is, MSY is achieved when the level of biomass is half the carrying capacity.

Equating catch to the surplus production in the population also allows the sustainable catch to be expressed as a function of fishing effort, given by

$$C = qEK - \frac{q^2K}{r}E^2$$

From this

$$\frac{dC}{dE} = qK - 2\frac{q^2K}{r}E = 0$$

And hence

$$E_{MSY} = r/2q$$

The simple model assumes prices are independent of the quantity landed and are hence constant. Similarly, the cost per unit of fishing effort is also assumed constant, such that the average cost equals the marginal cost. Costs in the model are economic costs, and represent full opportunity cost of all inputs in the production process (including unpriced labour and a normal return to capital). Given this, the level of economic profits in the fishery can be given by

$$\pi = pC - cE,$$

where *p* is price and *c* is cost. The level of fishing effort that maximises profits is hence given by

$$\begin{aligned}\frac{d\pi}{dE} &= p\frac{dC}{dE} - c = 0\\ &= p\left[qK - 2\frac{q^2K}{r}E\right] - c\end{aligned}$$

From which

$$E_{MEY} = \left(qK - c/p\right)\Big/ 2\frac{q^2K}{r}$$

Given $E_{MSY} = r/2q$, then

$$E_{MEY} = \left(qK - \frac{c}{p}\right) \Big/ \frac{qK}{E_{MSY}}$$

and hence

$$\frac{E_{MEY}}{E_{MSY}} = \left(1 - c/pqK\right)$$ **Equation 5-1**

Given that fishing mortality is given by $f = qE$, then

$$\frac{f_{MEY}}{f_{MSY}} = \frac{qE_{MEY}}{qE_{MSY}} = \left(1 - c/pqK\right)$$ **Equation 5-2**

That is, the ratio of fishing mortality at MEY to fishing mortality at MSY is a function of prices, costs, catchability and the carrying capacity of the stock. This value will always be less than 1 for any value of $c > 0$. By definition, the proportional target reference point expressed in terms of fishing mortality is the same as that expressed in terms of fishing effort.

Similarly, the biomass at MEY is given by

$$B_{MEY} = (K/2)(1 + c/pqK) = B_{MSY}(1 + c/pqK)$$

and hence

$$\frac{B_{MEY}}{B_{MSY}} = (1 + c/pqK)$$ **Equation 5-3**

As with the ratio of fishing effort and fishing mortality at MEY and MSY, the ratio of biomass at MEY and MSY is a function of prices, costs, catchability and the carrying capacity of the stock. This value will always be greater than 1 for any value of $c > 0$.

1.3.2.2. Introducing discount rates

The basic model presented above indicates the optimum level of fishing effort and biomass assuming it can be attained instantaneously. Usually, the process of reaching MEY will involve adjustment delays for stock biomass as well as fishing capacity. In particular, in cases where excess fishing effort is being applied to the stock, adjusting to MEY may involve short term costs in terms of effort reduction (Dichmont et al. 2010), and hence the long term benefits need to be balanced against the short term costs. The functional definition of MEY in the Australian fisheries context is the level of biomass and fishing effort that maximises the net present value of economic profits over time (DAFF 2007). The dynamic version of MEY incorporates the discount rate to allow the trade-off between future benefits and short term costs to be factored into the analysis. Following Clark (1990), the level of biomass that produces the dynamic MEY (B_{DMEY}) is given by

$$B_{DMEY} = \frac{K}{4}\left[\left(\frac{c}{pqK}+1-\frac{d}{r}\right)+\sqrt{\left(\frac{c}{pqK}+1-\frac{d}{r}\right)^2+\frac{8cd}{pqKr}}\right] \qquad \textbf{Equation 5-4}$$

where *d* is the discount rate. When *d* = 0, the value of B_{DMEY} is equivalent to that given in Equation 5-2. Estimating the sustainable level of fishing effort that produces the dynamic MEY (E_{DMEY}) is less straightforward than in the case where the discount rate was zero. Instead, E_{DMEY} needs to be estimated from the value of BDMEY, and the sustainable level of catch at B_{DMEY}. The associated level of catch at MEY is given by $C_{DMEY} = rB_{DMEY}\left(1 - B_{DMEY}/K\right)$ and the level of fishing effort by $E_{DMEY} = C_{DMEY}/qB_{DMEY}$. Consequently, the relationship between E_{DMEY} and E_{MSY} needs to be determined numerically rather than algebraically.

The target reference point, however, needs to be distinguished from the path to achieve it over time. In practice, the pathway to building the biomass to the target level is often subject to a number of constraints (Dichmont et al. 2010; Martinet et al. 2007), which affects the speed of recovery, and, depending on the extent of the constraints, may influence the target reference point also (Dichmont et al. 2010). For data poor fisheries, factoring these considerations into the definition of dynamic target reference points is not possible due to the lack of the detailed dynamic models needed to estimate these reference points taking into account the constraints.

5.3.3 NUMERICAL ANALYSIS

A numerical version of the model was developed to assess the relationship between E_{MEY} and E_{MSY}, and to allow the derivation of a simple framework for determining appropriate target reference points in the case where data are limited. Values of the key parameters were varied stochastically and a range of possible relative target reference points (i.e. E_{DMEY}/E_{MSY} and B_{DMEY}/B_{MSY}) were estimated.[4] These ratios were subsequently linked via regression trees (De'ath and Fabricius 2000) to cost shares and vessel characteristics to determine a set of "rules of thumb" from which appropriates estimates of the target reference points could be derived for particular data poor fisheries.

6.3.3.1 Data underlying the stochastic bioeconomic analysis

The values used in the stochastic analysis and the distributions of the final "acceptable" values are given in Table 5-7. Ten thousand random values were generated for each of the parameters in Table 5-7. However, a set of criteria was established to ensure that the set used for the analysis was relatively realistic. First, any set of parameters containing a negative value was discarded (removing some 250 sets). Second, any set of observations that would have result in negative economic profits at MSY was removed. While it is theoretically possible that MSY is not economically feasible, it is rarely observed for commercially important species. This resulted in only 5897 of the 10000 random sets of parameter values being used in the analysis.

The choice of the initial mean values of the parameters and their standard deviations was aimed at producing sets of widely varying parameter values that were representative of a wide range of fisheries. The instantaneous growth rate (r) ranges from relatively slow growing species (such as shark (Cortes 1998) to fast growing species (such as prawns). The mean price of all wild caught Australian produce in 2008-09 was $8.10 (Figure 5-1), although prices varied widely between (and within) different types of species groups (ABARES 2000). A mean of $10/kg was chosen for the purposes of the stochastic analysis. This is higher than the current average but, with a standard deviation of $4/kg, the distribution largely captured the range of prices observed for Australian wild caught fisheries. Catchability and the carrying capacity are inversely related in terms of scale, as the derivation of the target reference points relies on the value of their product (qK). For the stochastic simulations, mean values of q, K and c were chosen in order to give an estimated cost per unit catch at MSY[5] of approximately $7.50/kg (i.e. 75 per cent of the average price). This implies that economic profits are assumed to be at approximately 25 per cent of the revenue at MSY, on average. This was

[4] While some parameters are generally correlated (e.g. r and K), these correlations were not captured in the stochastic simulations. This contributed to some of the infeasible outcomes detailed above.

[5] Cost per unit catch at MSY is given by $c/(0.5qK)$.

an arbitrary assumption but, as noted above, ensures that a sufficiently high proportion of cases with positive economic profits at MSY are obtained.

Table 5-7. Key parameters used in the stochastic analysis.

	Values used in stochastic analysis		Distribution of "acceptable" values					
	Mean	Standard deviation	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
r	1.4	0.4	0.065	1.140	1.396	1.400	1.661	3.122
q	0.004	0.001	0.001	0.004	0.004	0.004	0.005	0.008
K	1000	400	138.8	901.0	1126.0	1142.0	1365.0	2639.0
c	15	6	0.021	9.517	13.150	13.320	17.030	33.640
p	10	4	0.575	9.017	11.400	11.510	13.860	25.460
d	0.1	0.04	0.000	0.074	0.101	0.101	0.128	0.251

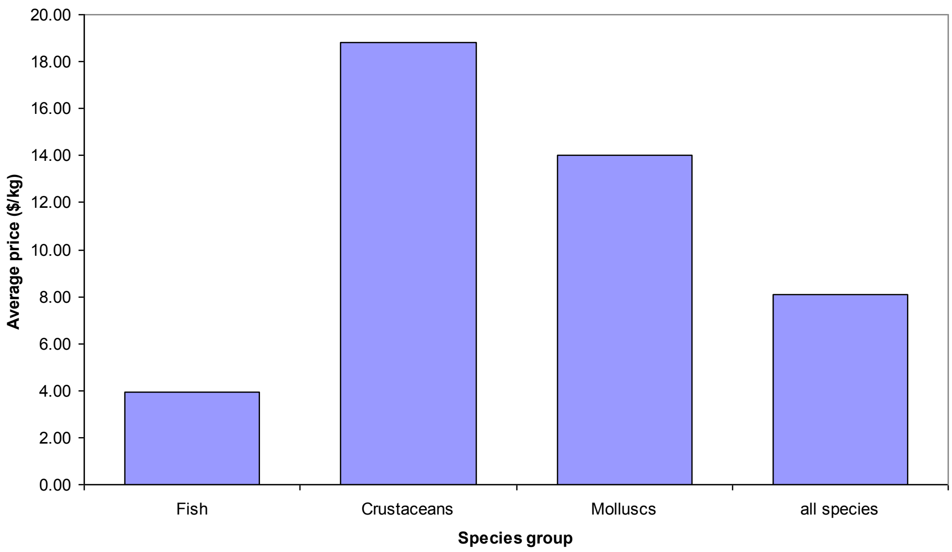


Figure 5-1. Average prices for Australian fish species 2008-09. Source: ABARES (2000)

6.3.3.2 Estimating cost shares

From Equations 6-1 and 6-2, both B_{DMEY}/B_{MSY} and $\underline{E}_{DMEY}/E_{MSY}$ are dependent upon the ratio $c/(pqK)$ where $c/(qK)$ effectively represents the cost per unit catch given an unexploited biomass, which is unknown. However, given that the catch per unit of effort at MSY is given by $0.5qK$ (as $B_{MSY} = 0.5K$), then the cost per unit of catch at MSY is equivalent to $c/(0.5qK)$ which is directly proportional to the cost per unit catch given an unexploited biomass[6]. Consequently, at MSY, the cost share of revenue, defined as the cost per unit catch divided by the price, is a feasible proxy measure by which the optimal ratio of biomass and effort can be derived in a comparative statics context. Multiplying both numerator and denominator by the catch at MSY gives the cost share as the ratio of the total fishing cost to the total revenue.

As noted above, cost and revenue information is currently available at the individual vessel level for a substantial number of fisheries at the Commonwealth (e.g. ABARES) and State level (e.g. SA). The data described above (Section 6.2.3) covered the period 1998 to 2010. Over most of the period of the data, the management target for most fisheries was maximum sustainable yield, although several Commonwealth fisheries were transitioning to a target of MEY from 2008. About 20 per cent of stocks in Commonwealth fisheries were considered overfished in 1999 (Caton and McLoughlin 2000), although this declined to less than 10 per cent in 2010 (Woodhams et al. 2010). For South Australian fisheries, around 20 per cent of stocks were considered over fished during the middle period of the data (2002-2005) (PIRSA 2007). Given this, it can be assumed that most fisheries were at or around MSY for most of the period of the data, and hence the empirical cost shares of revenue are representative of the theoretical shares required for the analysis.

6.3.3.3 Regression tree analysis

A regression tree analysis was undertaken with the B_{MEY}/B_{MSY} and E_{MEY}/E_{MSY} as the dependent variables, and cost share and the ratio of the discount rate to the stock growth as the explanatory variables, based on Equations 6-1, 6-3, and 6-4. A regression tree analysis was also run with cost share as the dependent variable and price, length, and gear types (trawl, dive, long line, purse seine and other static gear) as the explanatory variables.

The results from the regression tree analyses, presented in Section 7.3, provide a set of “rules of thumb” with which target reference points can be estimated for a wide variety of data poor fisheries.

---

[6] The value 0.5qK is equivalent to the catch per unit effort (CPUE) at MSY. Given these relationships, the cost per unit catch at MSY is twice that at the unexploited biomass.

Biological analysis — developing methods for biological reference points for data-poor fisheries

5.4 Simple catch rate gradient based harvest control rules for data-poor fisheries.

5.4.1 INTRODUCTION

Precautionary fisheries management usually includes harvest control rules (HCR) that react to stock assessments by manipulating catches or effort to manage a fishery towards a defined target reference point and away from a related limit reference point (Garcia, 1994; FAO, 1996). Fishing mortality rates or spawning stock size are often the basis for many management reference points (DAFF, 2007), but, estimating such performance measures for data-poor fisheries presents obvious difficulties because of insufficient suitable data, which is a research area where we attempt to develop new methods (see following sections).

Data-poor situations can arise in many circumstances (Haddon *et al*., 2005), including new or developing fisheries (only short time series of data collected, if any), low value fisheries (no facilities or resources to collect data), bycatch or byproduct fisheries (data is only collected on more valuable target species, a common situation in multi-species fisheries), fisheries with Illegal, unreported and unregulated activities (IUU fishing), and fisheries with a high degree of spatial structure (where fishing occurs on many small mostly separate stocks with different characteristics). Despite these difficulties there is growing recognition that fisheries management advice about allowable catch or effort levels is required even for relatively data-poor species (Cadrin & Pastoors, 2008). In response there has been a recent increase in the examination of alternative formal harvest strategies with harvest control rules (HCRs) that only need information regarding catches and/or catch rates (Dichmont *et al.,* 2006; Cope and Punt, 2009; O'Neill *et al*., 2010; Dick & MacCall, 2010, 2011; Little *et al*., 2011).

In Australia, such relatively simple harvest control rules have been implemented, for example, in Australia's Southern and Eastern Scalefish and Shark Fishery, the SESSF (Smith *et al.,* 2008), and the Queensland fishery for spanner crabs (Dichmont & Brown, 2010). One of the simplest strategies is to alter allowable catches in relation to changes in the recent trends in catch rates (Haddon, 2007;

Smith *et al*, 2008); for example a very simple Harvest Control Rule (HCR) converts a catch rate gradient and current catches into a TAC:

$$TAC_{y+1} = \left(1 + \alpha.Gradient_{y-3:y}\right)\bar{C}_{y-3:y} \qquad \textbf{Equation 5-5}$$

where TAC_{y+1} is the total allowable catch in the coming year, α is a scaling factor, $Gradient_{y-3:y}$ is the gradient from a linear regression of the previous four years catch rates against year, and $\bar{C}_{y-3:y}$ is an estimate of the average of all catches (landings plus discards) over the same four years. The management advice, that is the recommended future catch level, is thus produced without a formal stock assessment. Rather, this empirical HCR uses catch rates (in this case standardized catch rates) as a fishery performance measure. Such a performance measure provides the direction in which to move a fishery rather than specifying a target or a limit (though thresholds for special actions can be added to this particular HCR).

One of the guiding principles for the development of the empirical HCRs in the SESSF was that they should be capable of recovering depleted stocks. However, experience with applying this CPUE gradient based HCR (Haddon, 2007, 2009) demonstrated that in its original form it did not appear capable of rebuilding a depleted stock and it was also vulnerable to a downward ratchet in the catches brought about by the industry never quite managing to catch the complete TAC (Appendix 2). As the TAC was based on previous catches this latter was a serious flaw that led to a complete change in the HCR to one which used a comparison of the average catch rates from the last four years with that expressed during a period that acts as a target for the fishery (Little *et al.*, 2009; Little *et al*., 2011). While this change was useful for the relatively data-poor species in the SESSF it does require sufficient years of catch and effort data to provide a target period (the default was ten years) which, ideally, does not overlap with the latest years used to monitor the current state of the fishery. For very data-poor fisheries where only a few years of catch and effort data are available (e.g. less than ten years), different changes are possible to the catch-rate gradient HCR that may allow it to continue to be useful for management despite not having specified target or limit reference points. One of the aims of this present work is to examine the behaviour of simple catch-rate gradient control rules to determine their potential value for data-poor fisheries.

Changes that will be considered to the HCR described by Equation 5-5 will include:

- To use the gradient of the last four year's standardized catch-rates to modify the TAC rather than the current catches. That should prevent the ratchet effect on TACs and related catches.
- In stocks suspected of being in a depleted state the effect of changing the initial catch levels at the same time as introducing the new HCR will be examined.

5.4.2 METHODS

Management strategy evaluation was used to simulation test the performance of the modified catch-rate gradient HCR. Instead of fitting an age-structured model (Appendix 2) to a specific fishery and its history, and have that act as the operating model, the model was conditioned on the biology and fishery for Tiger Flathead (*Neoplatycephalus richardsoni*) so as to behave similar to a flathead species and the population initiated in an unfished state with no harvest and constant recruitment. This simulated population could then be depleted to some desired level by applying a simulated catch history for a given number of years, the HCR is then introduced and the dynamics projected forward for a further period of years. In this way the recruitment dynamics remain as originally defined despite any given level of depletion, thus the average recruitment levels when the stock is in a depleted state will be expected to be lower than when it is put in to a less depleted state. This means that it becomes possible to examine the behaviour of the HCR when the stock has the same biological properties of production but the stock can be in either a depleted state, close to a given target, or above a given target.

The standard Commonwealth proxy target for Maximum Economic Yield (0.48B_0) is intended to be 1.2 x MSY, with the proxy for the B_{MSY} being 0.4B_0; the proxy limit reference point in the Commonwealth is 0.2B_0 (DAFF 2007) In the simulations used here, above the target B_{TARG} was taken as about 60%B_0, the target was taken to be about 32%B_0 (about B_{MSY}), and below the target was taken to be about 15%B_0.

The three depletion options, that is below, at, and above the B_{MSY} target, will be explored using the basic HCR. In addition, instead of starting the TAC at the introduction of the HCR at the same level of catches imposed by the catch history, an array of different TAC levels (75%, 100% and 125% of the status quo TAC) would be examined to determine their impact of the HCR's performance. This would generate nine different scenarios combining different depletion levels with different initial TAC levels. Other depletion levels were also examined where they could improve interpolations between the three main depletion levels.

5.4.3 POPULATION CHARACTERIZATION

The productivity of the simulated stock was determined by taking the unfished equilibrium stock and applying in turn an array of different constant harvest rates, each for 70 years with deterministic recruitment, to achieve equilibrium catch and spawning biomass levels. In this way the production curve that defines the maximum sustainable yield was produced (**Figure 6-16**) along with a determination of the state of depletion (B_{MSY}) that gives rise to the MSY. This was the only time that constant recruitment was used, in all other simulations recruitment variation was included.

5.4.4 DIFFERENT INITIAL DEPLETION LEVELS WITH CONSTANT CATCH

Seven different initial spawning biomass depletion levels were considered ranging from about 15 – 62% of unfished spawning biomass. The constant catch needed to obtain the initial pre-depletion level differed for a number of the lower depletion levels. The constant catches were selected to ensure that catch rates were relatively flat at the inception of the HCR.

Once the initial depletion level was achieved in each scenario the revised Tier 4 HCR was introduced into the dynamics and variation included in recruitment and the estimated catch rates. In each case 1000 runs of each scenario were made and the outcomes summarized graphically and by recording the final TAC and final depletion level.

5.4.5 DIFFERING INITIAL CATCH RATES

The HCR is dependent upon the gradient of catch rates for its operation so it is to be expected that the catch rates over the previous few years before the introduction of the HCR may have an influence over its effectiveness. To examine this potential influence three catch history arrangements were devised to be applied to the unfished simulated population. To illustrate the effect of initial catch rates on the outcome the first scenario considered was designed to have the stock depleted to about 15% at the start of the HCR but have falling catch rates at the same time. The remaining two catch histories were devised to drive the stock to a depletion level of about 25% but one with declining catch rates and the other with increasing catch rates at the time of introducing the HCR.

5.4.6 ALTERING THE INITIAL TAC TO BE DIFFERENT FROM CURRENT CATCHES

If catch rates are stable then it would not be expected that a HCR based on catch rate gradients is likely to be rapid in producing any management interventions to prevent stock declines or rebuild depleted stocks. Three depletion levels were therefore selected to compare the analyses already completed, i.e. initial TAC = 100% current catches, with identical analyses except that the initial TAC would be 75% and 125% of current catches. The depletion levels selected were below the target (and limit), at the target, and above the target, that is, 15.4%, 32.5%, and 60.5%.

This also simulates the possibility of using the HCR with only four year's data as the TAC could be considered to be independent of the previous information. This would be appropriate for any fishery in which data had only just begun to be collected, at least for the minimum period required by the HCR (in this case defaulting to four years).

5.5 Application of cross-sampling method for estimating gear efficiency, biomass, and fishing mortality rate

5.5.1 INTRODUCTION

Fishing gears typically catch only a fraction of the fish that reside within the affected area in each gear deployment. The quantity that links the catch to the true abundance *N* or biomass *B* available to the gear at each gear operation (shot or unit of effort) is called gear efficiency *Q* (also referred to as fishing power, or probability of catching a fish). When we consider the true population size of the whole stock, this quantity is defined as catchability (*q*) in fisheries (Arreguin-Sanchez 1996). Fish availability for a fishing operation is affected by the distribution of the entire fish stock by time, area and depth. Catchability is a combination of both gear efficiency (*Q*) and stock availability. Estimating gear efficiency is necessary when deriving absolute abundance estimates from catch data, as well as when refining estimates of catchability in stock assessment models (Somerton et al. 1999).

The traditional approach used to estimate gear efficiency is by field experiments and is typically applied to trawling. Somerton et al. (1999) categorized four techniques for studying trawl efficiency: (1) gear comparison experiments where *Q* is estimated as the quotient of fish density (catch per area swept) from the trawl to density estimates from a gear type believed to be completely efficient, such as visual transects from a ROV or minisub. (2) Depletion experiments where *Q* is estimated by repeatedly trawling on a small closed population then fitting a model to the decline in catch per unit effort (CPUE) as a function of cumulative catch. (3) Tagging experiments where *Q* is estimated by determining the fate of individual fish, identified with acoustic transponding tags, which were initially positioned in the trawl path. (4) Experiments focused on vertical herding, horizontal herding, and escapement. The estimates of *Q* are then obtained by combining the three components in a mathematical model of the catching process (Dickson 1993). As these approaches are costly, only a few studies have been conducted for a limited number of species and trawl types. In addition, gear efficiency can be affected by many factors, including selectivity, fish behaviour, fisher skills, and environmental conditions (Arreguin-Sanchez 1996). This makes the result for one species in one study difficult to be applied to another species or in a new region.

Estimating gear efficiency is even more difficult for other gear types, such as hook and lines, seine, gillnets, and traps. Studies on these gear types often focus on relative selectivity rather than overall efficiency (Borgström and Plahte 1992; Prchalová et al. 2009). Unlike trawls, clearly defining the gear affected area (or area fished) is not easy for gears that do not physically sweep a measurable area. Absolute abundance estimates using these gear types are rare.

A cross-sampling method has been developed in this and a closely related project[7] to estimate gear efficiency and abundance from catch data alone. The method is suitable in complicated situations where assumptions of random distribution of individuals and constant abundance at each site over time are not appropriate. In these situations, the method only requires repeated shots in an area with more than one fishing gear. The data can come from commercial catches or from scientific surveys. Therefore, the method can be applied to data-rich or data-poor species as long as there are sufficient catch data. In this section, we applied the cross-sampling method to gear efficiency and biomass for several species caught by multiple gears.

5.5.2 METHODS FOR ESTIMATING GEAR EFFICIENCY, BIOMASS, AND FISHING MORTALITY RATE

Data source and preparation

The commercial logbooks provided the primary data in this study. Multiple gear types have been used in the Southern and Eastern Scalefish and Shark Fishery (SESSF), including: longlines (manual and automatic), Danish seine, gillnet, trawls, fish trap, minor lines (handline, dropline, troll) etc. We used data from 2000 to 2012 to estimate gear efficiency, which was then used to estimate biomass in recent years.

We defined and estimated gear affected area a for each gear type in one deployment (shot) as follows:

Longline: $a = wL$

Seine: $a = \pi(L/2\pi)^2$

Gillnet: a = wL

Trawl: $a = 0.7Lh$

[7] FRDC Project Number 2011/029: ERA extension to assess cumulative effects of fishing on species

Where *a* is swept area, *L* is the length of longline, gillnet, seine net, or trawling length in km, *w* is the width in km along the length of the gear within that range fish can be affected, *h* is the headrope length, and 0.7 is the spread factor when the trawl is towed under the water (Milton et al. 2007; Pezzuto et al. 2008). For the longline and gillnet, it is difficult to define the distance from the gear (i.e., 0.5*w*) within which a fish may be likely to be caught. For gears that use baits to attract fish, gear affected area depends on various factors, including type of bait, soak time, physiological state of the fish (duration of food deprivation), current speed, fish swimming speed, body size, etc. (Løkkeborg et al. 1989, 1995). The active space where the odour concentration is present in super-threshold quantities shrinks with soak time. Within the first hour, the maximum length of the active space for sablefish is 925 m, in 2 h is 793 m, and in 6 h is 654 m (Løkkeborg et al. 1995). In a field study using baited gillnet, cod were observed to move directly towards the gear from distances up to 400 m (Kallayil et al. 2003). Near 90% of sablefish were hooked within 3 hours of soak time, which corresponds to the leading edge of the plume of about 800 m from the bait (Sigler 2000). In a baited video experiment, the greatest distance of fish attraction was 48-90 m for a 200 mm fish in a current velocity of 0.1- 0.2 m s^{-1} (Ellis and DeMartini 1995). If the current speed is about 0.2 m s^{-1}, 1 hour soaks of baits may have an effective range of attraction of about 480 m for fish of 200-300 mm length (Cappo et al. 2004). Based on these studies, for baited gears we assumed that the gear affected area was *w* = 1 km from the gear. Similarly, for minor gears, including handline (HL), dropline (DL), trolling (TL), and fish trap (FP), we assumed that *a* for each shot was 1 km^2. Within a reasonable range, the delineation of gear affected area *a* is relatively robust in estimating fish density, because gear efficiency *Q* is a relative scaling parameter negatively correlated to *a* so the effect is mitigated in density or biomass estimation as long as the same *a* is used in estimating *Q* and later in estimating density or biomass (see below). Nevertheless, more accurate definition of gear affected area would be helpful in future studies.

The spatial and temporal resolution of the analysis can be expressed at various scales, for example, space at 0.1 by 0.1 degrees and time by year and month, space at 0.1 by 0.1 degree and time by year only, space at 1 by 1 degrees and time by year and month, space at 1 by 1 degree and time by year only, etc. To increase the number of spatial-temporal units where different types of gears overlap while reducing the variance of CPUE (expressed as catch per unit of area here), we used the resolution of 1 by 1 degree by year. This level of scaling therefore allows that the abundance of a particular species has a non-random annually-varying distribution among 1*1 degree cell and a random (Poisson) distribution within each grid cell is assumed in the following Bayesian cross-sampling model.

Estimating gear efficiency *Q* from Bayesian cross-sampling model

We used commercial logbook data from the SESSF (generally from 2000 to 2012) to estimate gear efficiency. Abundance among unique grid-year units was modelled as a negative binomial distribution

$N_i \sim$ negbin(p, r),

where unit *i* can represent either a unique grid cell or the same grid cell but in different years. The negative binomial distribution (negbin) is parameterized as

$$f_{NB}(N_i; p, r) = \frac{\Gamma(N_i + r)}{\Gamma(r) \times N_i!} p^r (1-p)^{N_i}$$

where p [$\in$ (0, 1)] is the success probability in each experiment. The shape parameter r describes the extent of aggregation and measures overdispersion ($r > 0$). As $r \rightarrow \infty$, the negative binomial converges in distribution to the Poisson so the variance approaches the mean. The mean is $\mu = r(1 - p)/p$ and the variance is $\sigma^2 = r(1 - p)/p^2$. Within each grid-year unit, the local abundance available to each shot was assumed to following a Poisson distribution:

$N_{ij} \sim$ pois(N_i).

Catch data were then modelled as a binomial distribution:

$C_{ijk} \sim$ binom(Q_{ik}, N_{ij}),

where *j* is the number of shots in the same grid-year unit by the same type of gear k. In this equation, N_{ij} is the abundance within the gear affected area, i.e., $N_{ij} = D_{ij}\, a_{ijk}$, where *D* is gear-independent fish density. Hence, for the same gear type, as observed catch C_{ijk} is fixed, *Q* and *a* correlate negatively within a reasonable spatial range. Assuming a larger *a* will result in a relatively smaller *Q*, and vice versa. Weak informative priors were given to *p*, *r*, and Q_{ik} as:

$P \sim$ beta(1, 1)

$r \sim$ lognorm(0, 0.01)

$Q_{ik} \sim$ beta(1, 1).

The probability density function of the beta distribution with shape parameters $\alpha > 0$ and $\beta > 0$ is

$$f_{beta}(x;\alpha,\beta)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}x^{\alpha-1}(1-x)^{\beta-1}$$

With $\alpha = 1$ and $\beta = 1$ in the distribution of beta(1, 1) is essentially a flat line (a non-informative prior). The expected gear efficiency for gear type *k* is the mean over all grid-year units:

$$Q_k = \frac{1}{n}\sum_{i=1}^{n} Q_{ik}$$

In real fishery data, catch is recorded either in weight or counts, or both. The discrete statistical distributions, such as Poison and binomial, are typically applied to count data. If weight is used in the analysis, the unit chosen may have a dispersion issue which will affect the variance estimate but not the point estimate. For serious application, it may be worth correcting the dispersion parameter when weight is used (Zhou et al. 2008).

Estimation of fish density and biomass

After obtaining *Q* for each gear type, we can apply it to all historical data where gear efficiency can be reasonably assumed to be unchanged, and derive gear-independent fish density D_{yij} in each shot by expanding each catch in year *y*, grid cell *i*, shot number *j*, with estimated gear efficiency above:

$$D_{yij} = \frac{c_{yijk}}{a_{yijk}Q_k}.$$

Note that gear affected area a_{yijk} should be the same as that used in estimating *Q* above. This density, which may be referred to as “observed density”, can be sufficient for deriving biomass in a particular year. However, fishing typically takes place in a limited area in a particular year and does not cover all of the stock distribution range. It is desirable to “smooth” the observed density and predict potential density in any year based on all locations where the species has been previously caught. Here we used a simple general additive model (GAM) and only data in the logbooks to model the observed density:

$$\mathbf{log}(\boldsymbol{D}_{\mathbf{yij}}) = \boldsymbol{\beta_0} + \boldsymbol{f_1}(\boldsymbol{lon},\boldsymbol{lat}) + \boldsymbol{f_2}(\boldsymbol{depth}) + \boldsymbol{f_3}(\boldsymbol{year}),$$

where the f_1 , f_2, and f_3 are smoothing splines, and lon and lat are longitude and latitude. We tested alternative splines, e.g., thin plate splines, cubic spline, P-splines etc. (Wood 2006). The GAM model can be affected not only by the type of smoothing function, but also other factors, such as number of knots and degrees of freedom. With a large dataset, computing capacity may become an issue. The model output was in turn used to predict density for any year of interest at each shot location (i.e., with predictors lon, lat, and depth) where the species had been previously caught and recorded in the fishery.

To estimate total biomass in a given year, we used one of the following two approaches depending on data availability. In the first approach, the stock distribution area was defined as its core distribution from refined Bioregional Mapping (Heap et al. 2005). The total fishable biomass in year *y* is then

$$B_y = \sum_{g=1}^{n} \widehat{D}_{yg} A_g$$

where $\widehat{D}_{yg}$ is the median density predicted by the GAM model above within each polygon *g*, A_g is the area size in polygon *g* within the Core range, and *n* is the total number of polygons where the species has been recorded in the history of the logbook. This method can be only applied to species where core range has been previously defined.

The second method assumed that any point location where the species had been caught represents a suitable habitat. This method requires determining the size of each point location. We examined three sizes, i.e., 0.1*0.1 degree, 0.05*0.05 degree, and 0.01*0.01 degree. For example, the size of 0.05 by 0.05 degree grid is derived as:

$$A_g = \left(\frac{0.05\pi}{180} R\right)^2 \cos\left(\left(lat_g + \frac{0.05}{2}\right)\frac{0.05\pi}{180}\right),$$

where *R* (= 6371 km) is the earth radius. In the southeast region, the mean *A* of 0.05*0.05 degree is about 24.2 km^2. The grid size and the total number of 0.05 by 0.05 degree cells where the species has been recorded in the history of logbook can be fed into the equation in the first method above to derive the total fishable biomass in year *y*. For this method, the estimated biomass tends to increase as the size of the unit A_g increases. It appears a grid size of 0.05*0.05 degree is more appropriate, while 0.1*0.1 degree tends to over-estimate the biomass and 0.01*0.01 degree under-estimate the biomass.

Estimating fishing mortality rate F

Fishing mortality in year *y* by gear *k* is:

$$F_{yk} = \frac{C_{yk}}{B_y}$$

The overall fishing mortality in a year is simply $F_y = \frac{C_y}{B_y}$. Note that the ratio of C_y : B_y is closer to instantaneous fishing mortality rate *F* than exploitation rate (commonly represented by *U*) because we have used the catch data over the entire year so the biomass is not the peak biomass but the average over the year. This F_y can then be compared with reference points such as F_{MSY} derived from the natural mortality rate (or other means) to gauge whether fishing intensity is sustainable:

$$F_{MSY} = \omega M,$$

Where ω is a class- and order-specific scaling parameter estimated from a meta-analysis (Zhou et al. 2012).

5.6 Conditional stochastic stock reduction analysis: deriving biomass-based reference points from catch history

5.6.1 INTRODUCTION

Catch statistics are perhaps the easiest data to collect and the most widely available information in many fisheries, including Australian Commonwealth managed fisheries. However, it is difficult to use catch alone in fishery stock assessments to develop reference points and associated indicators for management. Even the simplest population dynamics model—surplus production (aka biomass dynamics) model and depletion models require additional information, at least fishing effort, to derive catch-per-unit-effort (CPUE) as an indicator of relative biomass. Yet, in some fisheries, effort is not available, is difficult to measure or standardize, or CPUE cannot be used as an indicator of biomass because the distribution of fishing effort is not related to species distribution.

Recently, there is an increased interest in stock reduction analysis (SRA) which was first suggested by Kimura and Tagart (1982) and Kimura et al. (1984). Walters et al. (2006) demonstrated the use of Monte Carlo simulation in SRA. Dick and MacCall (2011) proposed Depletion-Based Stock Reduction Analysis (DB-SRA), which merges stochastic SRA with Depletion-Corrected Average Catch (MacCall 2009). Martell and Froese (2012) used similar methods to estimate MSY from catch and resilience that links to population growth rate. The basic idea of these approaches is similar: to reconstruct possible trajectories of stock change from the beginning of the fishery, given historical catch data and known or assumed stock status (either biomass, proportion of depletion, or fishing mortality rate) in one or more recent years. Since the end point is approximately fixed, the biomass trajectories are determined by only two variables: an initial biomass at the beginning of the fishery (B_0) and a population growth rate (for example r in the surplus production model) over time. The combination of these two parameters can be found by tracing back from the end stock status and historical removals.

Although the idea is simple, there is a wide range of B_0 and r combinations that may produce the same historical catch and end in the same stock size (Martell and Froese 2012). Further, it has been shown that these methods are highly sensitive to the end stock status (Dick and MacCall 2009; Wetzel and Punt 2011); e.g. the effect of fishing on the population can be underestimated when an overly-optimistic value for the ratio of the recent to starting biomass is assumed.

We propose several improvements to SRA-based depletion estimation in this report. The first step is a deterministic method to "guess" the initial virgin biomass (referred to as "chase-catch" or CC method for convenient referral in this report). Secondly, we construct a possible distribution of population growth rate from life history traits developed in Appendix 3. We then use the biomass estimated by expanding the cross-sampling method in the section 5.5, instead of assuming a depletion level. Finally, we apply stochastic stock reduction analysis conditioned on multiple rules (referred to as "conditional stochastic stock reduction analysis" or CSSRA for the same reason in this report). Simulations were conducted to evaluate the performance of CSSRA and to compare CC and CSSRA results with data-rich species that have full stock assessments. The methods were also applied to several data-poor stocks that have not been able to be fully assessed previously.

5.6.2 METHODS OF DERIVING BIOMASS-BASED REFERENCE POINTS FROM CATCH HISTORY

Deterministic chase-catch (CC) method

The basic idea of this CC method is to estimate virgin biomass B_0 (AKA carrying capacity K and we may use both symbols interchangeably herein), given the complete catch history, assumed known stock status in one or more recent years (either biomass, fishing mortality rate, or depletion status), and an assumed population growth rate. The stock status should be obtained from auxiliary data or other sources, while the population growth rate can be deduced from life-history traits.

Let B_t be the time series of mean stock biomass in year t (t = 1, 2, … n), B_1 be the biomass in the first year of the time series, G_t the growth, and C_t the observed catch. At any year y ($y \in t$),

$$B_y = B_1 + \sum_{t=1}^{y-1} G_t - \sum_{t=1}^{y-1} C_t$$

Assume at year y, biomass B_y or fishing mortality F_y is known, e.g., from catch-curve analysis or based on aerial overlap, then $B_y = C_y/F_y$ is known. In the above equation, B_1 and G_t are unknown. If fishing continues, B_y (average biomass in year y) must be less than B_1. That is, the summed net growth must be smaller than the summed catch.

Step 1: The amount of catch that is more than growth during the same period is $C_{exc}^{guess} = \left(\sum_{t=1}^{y-1} C_t - \sum_{t=1}^{y-1} G_t \right)$. Let us tentatively assume this excessive catch is equal to the average catch, i.e., $C_{exc}^{guess} = \frac{1}{y-1} \sum_{t=1}^{y-1} C_t$, so the initial biomass at t = 1 can be obtained as

$$B_1^{guess} = B_y + \frac{1}{y-1} \sum_{t=1}^{y-1} C_t \ .$$

Here B_1^{guess} is a biased guess of the true biomass B_1 ($B_1^{guess} \leq B_1$) and B_y is the biomass at year y, which can be the last year n in the time series.

Step 2: Assume the population can be expressed by the general biomass dynamics model:

$$B_{t+1} = B_t + rB_t \left[1 - \left(\frac{B_t}{B_0} \right)^m \right] - C_t$$

where r is the population growth rate, B_0 is the carrying capacity, and m is the shape parameter. Note that including the shape parameter makes the model more flexible but this parameter is difficult to estimate for real data (Clark et al. 2010). In this model, maximum sustainable yield and fishing mortality at MSY are

$$MSY = rB_0 \left(\frac{m}{1+m} \right) (1+m)^{-\frac{1}{m}}$$

And

$$F_{msy} = r \left(\frac{m}{1+m} \right)$$

The estimated B_1^{guess} can be used as B_1. Further, in most cases it is reasonable to assume $B_0 = B_1$ and natural mortality M is known. Natural mortality is certainly a good predictor for F_{MSY}, for example r = $\left(\frac{1+m}{m} \right) F_{msy}$ = $\left(\frac{1+m}{m} \right) \omega M$, where ω is a class- and order-dependent scale from a meta-analysis (Zhou et al. 2012). The adjusted excessive catch is then:

$$C_{exc}^{adj} = \sum_{t=1}^{y-1}(C_t - G_t)$$
$$= \sum_{t=1}^{y-1}\left[C_t - \frac{1+m}{m}\omega MB_t\left(1-\left(\frac{B_t}{B_0^{guess}}\right)^m\right)\right]$$

The adjusted biomass at the beginning (year 1) is

$$B_1^{adj} = B_y + C_{exc}^{adj}$$

Step 3: repeat this step by replacing B_1^{guess} with B_1^{adj}. The estimated excessive catch is:

$$C_{exc}^{adj} = \sum_{t=1}^{y-1}(C_t - G_t)$$
$$= \sum_{t=1}^{y-1}\left[C_t - \frac{1+m}{m}\omega MB_t\left(1-\left(\frac{B_t}{B_0^{adj}}\right)^m\right)\right]$$

The estimated biomass at year 1 is

$$B_1^{est} = B_y + C_{exc}^{est}$$

Step 2 and Step 3 can be repeated until the difference between B_1^{adj} and B_1^{est} is small enough, for example, $\frac{B_1^{est} - B_1^{adj}}{B_1^{est}} < 0.001\%$.

Sensitivity analysis

If the population process can be described by the biomass dynamics model (3), the accuracy of the estimated biomass is affected by three variables: the population growth rate, the estimated biomass in one particular year *y* B_y, and the shape parameter *m*. For the general Graham-Schaefer model, it is the growth rate and biomass in a particular year that are important for estimating B_0. We test the sensitivity of the method by multiplying the true *r* by a range of values from 0.2 to 2.0, i.e., a relative bias from -0.8 to 1 of the true value (0 means the true value of *r* is used). The bias in *r* may result from uncertainty in M and its relation with F_{MSY}. We also vary the estimated B_y by multiplying it by a range of values from 0.2 to 2.0. The relative error in the estimated B_0 is:

$$RE[B_0] = \frac{B_0^{est} - B_0^{true}}{B_0^{true}}$$

Because estimated biomass for a single year B_y may be inaccurate, it may be desirable to use average biomass from several years $\{B_{y-x}, \ldots B_{y-1}, B_y\}$.

We call this method "chase-catch" for two reasons. First, the method requires catch history as the key data. Second, the process is similar to the game of chase-and-catch where an initial guess of the biomass is fed into a population dynamic model. The model produces an improved estimate. In each reiteration, the process "chases" the true value closer and closer and eventually "catches" the true value.

Conditional stochastic stock reduction analysis (CSSRA)

This method is similar to the stochastic stock reduction analysis (Walters et al. 2006) and the depletion-based stock reduction analysis (Dick and MacCall 2011). We make several improvements and modifications. 1. Derive initial biomass B_0 from chase-catch method; 2. Apply parameter ω from a meta-analysis of hundreds of species; 3. Instead of assuming a relative depletion level (B_y/B_0), we estimate B_y^{est} based on auxiliary information or using the method described in the previous chapter (cross-sampling method); 4. Use multiple rules (so conditional SSRA) to retain a plausible stochastic sample i. These rules may include but are not limited to:

a) $B_{y,i} > 0$

b) $B_{y,i} > B_{0,i} - \sum_{t=1}^{y-1} C_t$;

c) $B_{y,i} < B_{0,i}$; and

d) $\frac{B_{y,i} - B_y^{est}}{B_y^{est}} <| \alpha |$.

where precision scale α is specified by the user to allow uncertainty in estimated biomass in year *y*, for example 0.1 (i.e., 10% deviation from B_y^{est}). The priors for the two key parameters are assumed to have $B_0 \sim \log normal[\log(B_0^{est}), \sigma_{B_0}^2]$ and $r \sim \log normal[\log(2\omega M), \sigma_r^2]$.

Simulations

We carried out simulations with various known input parameters to evaluate the performance of the CSSRA. These simulations involved three steps: data generation, parameter estimation, and evaluation of estimation performance. We used the Graham-Schaefer surplus-production model (i.e., m = 1 in the general biomass dynamics model) to generate each time series of B_t. The catch history was selected to mimic that of typical fisheries: relatively low catch at the beginning of the fishery, increasing to a peak and then flattening out or declineing in recent years (e.g., Figure 5-2). We carried out the following sensitivity analyses:

1. Effect of variability in σ_{B0}, and σ_r on posterior (retained) B_0, r, MSY, and B_y/B_0 by changing cv[B_0] or cv[r] from 0.1, 0.2, …to 1.0.
2. Effect of bias in priors r and B_0 on posterior B_0, r, MSY, and B_y/B_0 by changing relative error from -0.8, -0.6, -0.4, …to 1.0 (relative bias 1.0 means the assumed value is twice as large as the true value).
3. Effect of bias in final biomass B_y on posterior B_0, r, MSY, and B_y/B_0 by changing relative error in B_y from -0.8, -0.6, -0.4, …to 1.0 (relative bias 1.0 means the assumed value is twice as large as the true value).

For each combination of parameter set, we ran Monte Carlo simulations until 1000 iterations met all rules *a* to *d* above.

The performance of the method was evaluated by the mean and distribution for the relative error of the posterior medians for parameter θ (i.e., B_0, r, MSY, and B_y/B_0). For example, the relative error of the final estimate of B_0 from simulation *i* is:

$$RE_i^{\theta} = \frac{\theta_i^{est} - \theta^{true}}{\theta^{true}}$$, i = 1…1000.

The mean relative error of θ is:

$$MRE^{\theta} = \frac{1}{1000}\sum_{i=1}^{1000} RE_i^{\theta}$$

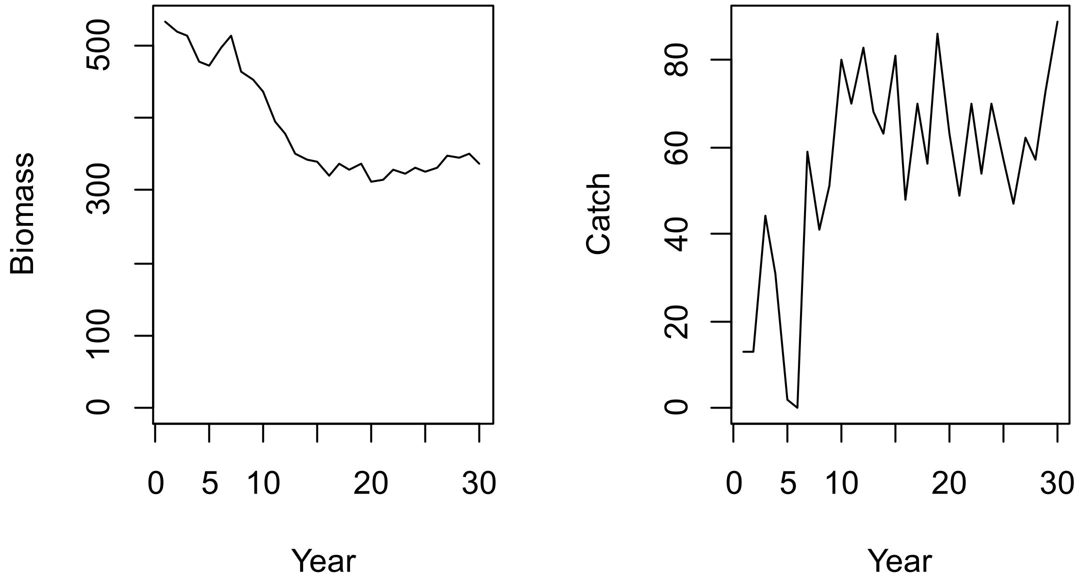


Figure 5-2. General pattern of catch and biomass trends used as input in the simulations.

Application of CC and CSSRA methods to selected stocks

To estimate the robustness of these methods we apply the chase-catch and conditional stochastic stock reduction analysis to selected stocks that have been assessed using full quantitative methods.

The Southern and Eastern Scalefish and Shark Fishery (SESSF) is a multi-species and multi-gear fishery that catches over 80 species of commercial value. More than 20 commercial species or species groups are currently under quota management. Full quantitative stock assessments have been conducted annually for most of these species. The quantitative assessments produce time series of annual biomass for species that fall under TIER 1 management, along with other biological and management quantities (Tuck 2011). Because the CSSRA method produce two key parameters: virgin biomass B_0 and population growth rate r, and from them MSY can be derived. For the purpose of comparison, we fit a biomass dynamics model to these estimated time-series biomasses to produce "true" B_0, r, m, MSY, and B_y/B_0.

We also compared the general and hybrid surplus production models. To facilitate the comparison, we re-parameterize the general surplus production model as in the Fletcher (1978) formulation of the Pella-Tomlinson model (PTF):

$$\frac{dB_t}{dt} = gm\frac{B_t}{K} - gm\left(\frac{B_t}{K}\right)^n - C_t$$

where $g = \frac{n^{\frac{n}{n-1}}}{n-1}$ and m = MSY. The peak production occurs at $\frac{B_{MSY}}{K} = \left(\frac{1}{n}\right)^{\frac{1}{n-1}}$. The popular Schaefer model is a special case of this Fletcher model when *n* = 2.

This general model may overestimate production when the curve is considerably skewed (Fletcher 1978, Dick and MacCall 2011). McAllister et al. (2000) and Dick and MacCall (2011) used hybrid Schaefer-PTF model and we adopted similar idea here. The hybrid production model is a combination of the Shaefer model and PTF model:

- Use Shaefer model when n < 2 and $B_t < B_{join}$ or when n > 2 and $B_t > B_{join}$;
- Use PTF model when n < 2 and $B_t > B_{join}$ or when n > 2 and $B_t < B_{join}$.

The join point for the Shaefer and PTF models is obtained by numerically solving

$$rB_{join}\left(1 - \frac{B_{jion}}{K}\right) - gm\frac{B_{join}}{K}\left(\frac{B_{join}}{K}\right)^{n-1} = 0$$

Additional input values and assumptions are provided in the result section.

5.7 Posterior-focused Catch-biological reference points (Posterior Catch-BRP)

5.7.1 INTRODUCTION AND METHOD

The CSSRA and other similar methods require priors on carrying capacity *K* and population growth rate *r*, as well as assumed known stock status in one or more recent years (biomass, fishing mortality rate, or depletion). The choice of prior distributions (for example, uniform, lognormal) and their lower and upper ranges will affect the results. It is difficult to determine these priors for many data poor species. In attempting to deal with these issues, we developed an innovative approach to avoid such difficulties in prior selection.

The idea is to use unconstrained priors for *K* and *r*, that is $0 < K < \infty$ and $0 < r < \infty$. After retaining viable iterations where $B_t > C_t$, $B_t > 0$, and $B_t <= K$, we examine the results and exclude unlikely values. In another word, this approach focuses on "posterior" rather than "prior". If fact, because *K* and *r* are negatively correlated, the maximum *K* is constrained by $r = 0$ and is much smaller than infinity, while the maximum *r* value is constrained by the minimum viable *K*. The typical log(*r*) ~ log(*K*) plot is a straight line at the middle and curves at the two ends. At one end is high *r* low *K* values where high values of *r* cause chaotic dynamics of the population dynamics model (Quinn and Deriso 1999). To maintain a population, *K* has to change rapidly. At the other end is high *K* low *r* values where a small change in *K* requires an enormous change in r in the opposite direction in order to sustain the population. Therefore, a population with *r* ~ *K* pairs at the two ends is unlikely to be viable. The challenge in this approach is to identify the likely range and the most likely *r* ~ *K* combination on the curve that make the population viable. When the most likely *r* and *K* values are identified, biological reference points (BRP), such as MSY, B_{MSY}, F_{MSY} can all be derived. As catch is the primary required data, we refer to this approach as posterior-focused catch-BRP. We first demonstrate this approach by a simulation, and then apply the method to four case-study species and compare the results with other methods.

In the simulation, we assumed a stock with true $r = 0.5$ was fished for 30 years where catch increased to a peak and then flattened out with a slight decline. The carrying capacity is 6 times the maximum catch in the 30-year history, which is 324 t in this case. The population follows the Graham-Shaefer production model. The biomass at year 30 is assumed to be known and equal to the true biomass of 288 t. The priors for *r* and *K* cover all possible values: *r* ~ dunif(0, 20), *K* ~ dunif(0, 10000).

The posterior retained iterations encompass only a fraction of the wide prior ranges (Figure 5-3). Many randomly generated values for *r* and *K* are simply too large or too small to be possible combinations. To determine the most likely region within the retained *r* ~ *k* curves, we propose several alternatives.

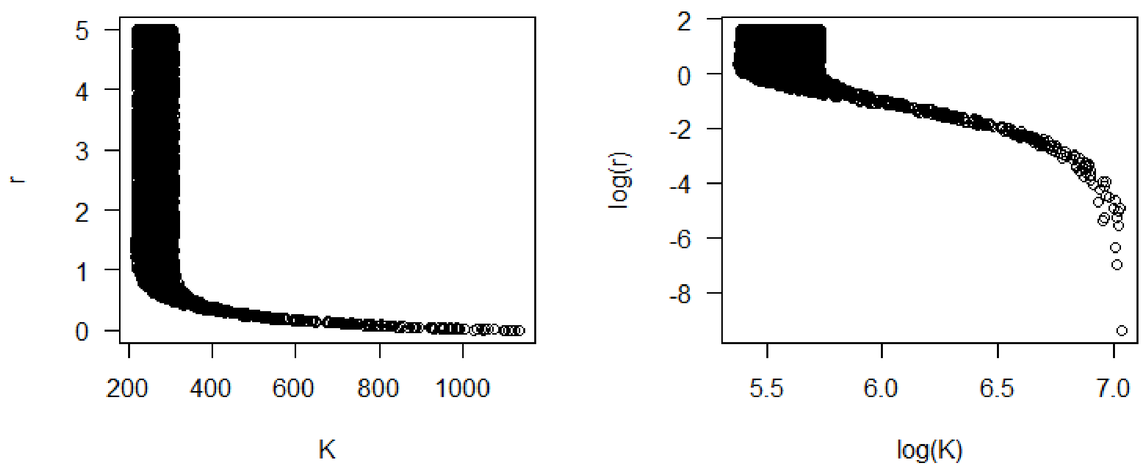


Figure 5-3. Plots of growth rate r and carrying capacity K for all retained iterations. The true r = 0.5 and K = 324. Prior use: r ~ dunif(0, 20), K ~ dunif(0, 10000).

Visual inspection

In the Graham-Schaefer production model, at equilibrium where biomass remains unchanged, growth equals fishing mortality, $rB\left(1-\frac{B}{K}\right)=C$. Hence,

$$r=\frac{CK}{B(K-B)}=\frac{C}{\Delta(1-\Delta)K}$$

Where $\Delta = B/K$ is the depletion ratio from virgin biomass. In this equation, log(r) and log(K) form a straight line with a slope of -1. When the population is not at equilibrium, i.e., biomass changes from one year to the next year, the slope will be smaller than -1 when the population declines and greater than -1 when it increases. From the log~log plot in Figure 5-3, it is apparent that data points that do not fall in on the narrow linear band are unlikely to be viable, i.e., log(r) > 0 and log(K) > 6.6 are not possible values. By excluding the data points at the two ends, we obtained the plots in Figure 5-4. Panel D compares the key parameters from resulting *r*-*K* pairs in panels B and C with true input values. Generally, the relative biases are reasonably small and the section chosen appears to be fairly robust for inference as long as the selected region does not include the extreme data at the two ends. In fact, this can be further improved by excluding additional data points at the two ends in panel C.

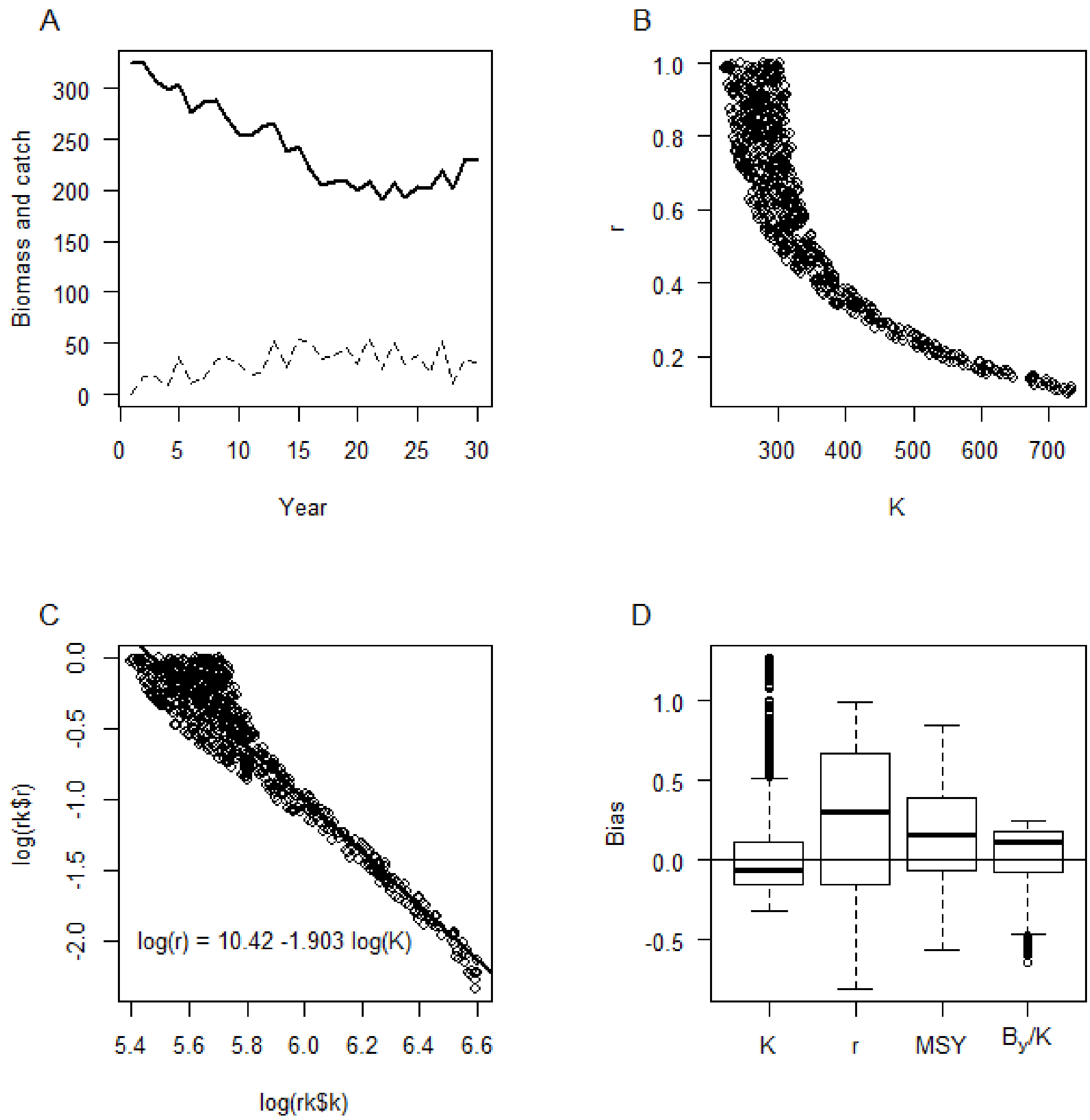


Figure 5-4. Result of visual identification by excluding iterations with r > 1 and log(K) > 6.6 in Figure 5-3.

Search mid point

In Figure 5-3 and Figure 5-4, there is an inflection region in the middle of the *r* ~ *K* curves, which is the most likely area containing the point values of true *r* and *K*. Alternative techniques may be used to identify the inflection point. We used the following steps to find out this point:

Standardize the *r* and *K* as: $K' = \frac{K - \min(K)}{\bar{K}}$ and $r' = \frac{r - \min(r)}{\bar{r}}$;

Scale K' and r' to the same breadth:

$$K'' = \begin{cases} K' \dfrac{\max(r')}{\max(K')} & if \max(r') > max\,(K') \\ K' & otherwise \end{cases}$$

$$r'' = \begin{cases} r' \dfrac{\max(K')}{\max(r')} & if \max(K') > max\,(r') \\ r' & otherwise \end{cases}$$

Calculate the distance to the origin at (0, 0): $d = \sqrt{K''^2 + r''^2}$;

The most likely r and K locate at min(d);

Use 10% data points surrounding [r|min(d)] and [K|min(d)] for inference.

The results are shown in Figure 5-5. The shape of $d \sim K$ plot looks similar to a typical likelihood profile. Relative bias is less than 10% for all key parameters.

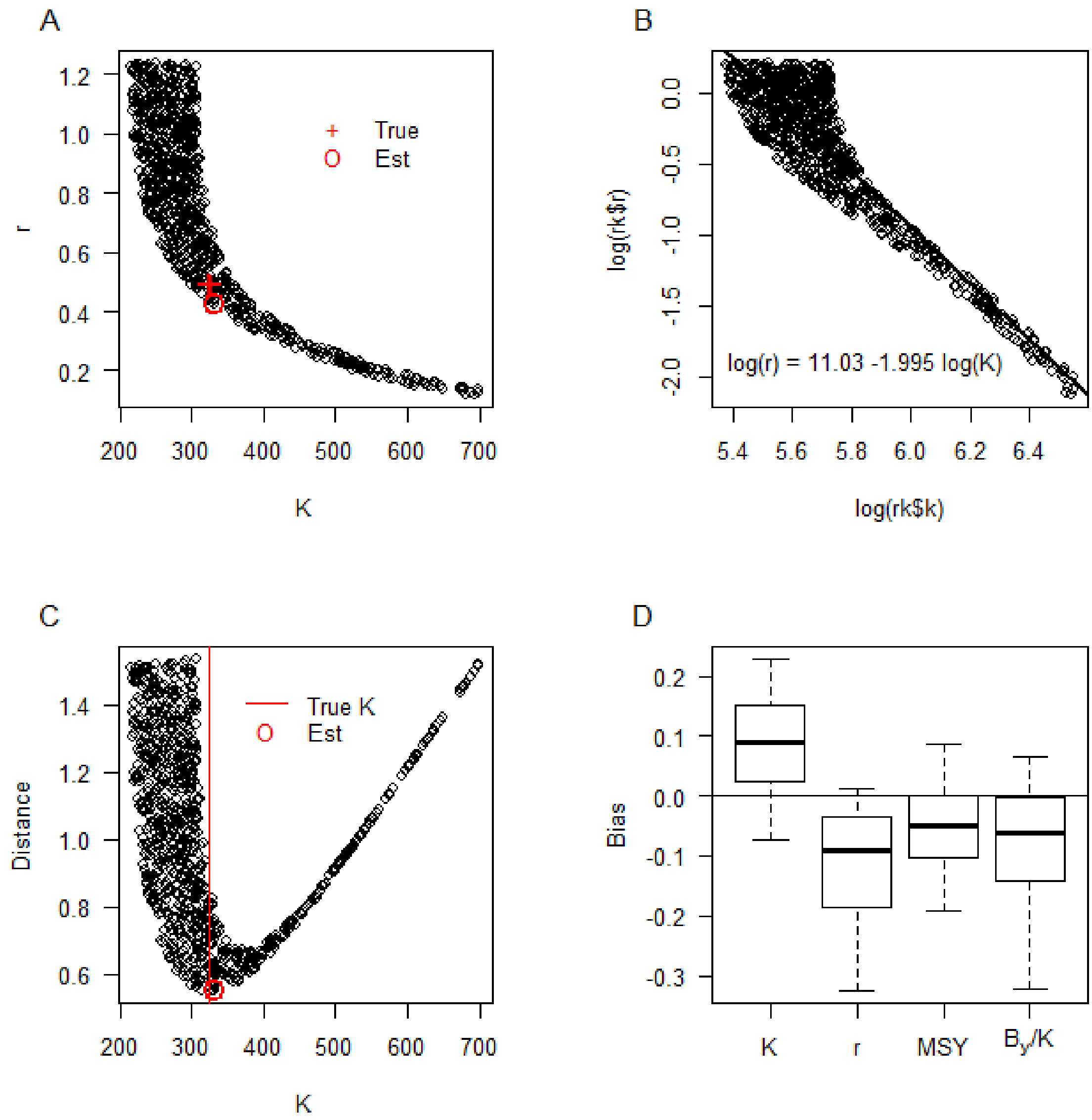


Figure 5-5. Simulation with true r = 0.5 and K = 324. Prior r ~ unif(0, 5), k ~ unif(0, 10000). Use iterations that result in a line with -2 < slope < 0.

5.8 Testing Stock Reduction Analysis through Management Strategy Evaluation (SRA MSE)

5.8.1 INTRODUCTION

Stock reduction analysis (SRA) was first described by Kimura and Tagart (1982) and Kimura et al. (1984). Recent interest in the procedure has been for data-poor situations, leading to further developments. Walters et al. (2006) demonstrated use of Monte Carlo simulation in SRA, Dick and MacCall (2011) proposed Depletion-Based Stock Reduction Analysis (DB-SRA), which merges stochastic SRA with Depletion-Corrected Average Catch (MacCall 2009). These approaches essentially reconstruct possible trajectories of stock change from the beginning of the fishery, given historical catch data and known or assumed stock status (either biomass, proportion of depletion, or fishing mortality rate) in one or more recent years.

Section 5.5 describes a method that provides an estimate of biomass in a recent year using estimated fishing gear efficiency and the spatial distribution of fishery catch rates. Use of such a biomass estimate in combination with SRA (CCSRA) allows the full historical biomass series to be determined. This therefore provides a stock assessment that can be used in combination with a harvest control rule (HCR) to set fishery catch levels.

It is unknown how well such a stock assessment and HCR performs according to expectations of the Commonwealth harvest strategy policy (CHSP) introduced in 2007. Management strategy evaluation (MSE) has become a globally accepted method of testing fishery harvest strategies (HS) – the combination of a stock assessment with a HCR, with performance measures developed in accordance with policy goals. This chapter describes the application of MSE to test the performance of CCSRA in terms of the objectives of the CHSP.

The guidelines for implementation of the CHSP encourage a tiered approach to cater for varying levels of knowledge about a stock. In the Southern and Eastern Scalefish and Shark Fishery (SESSF), the Tier 1 harvest strategy uses a fully-integrated quantitative stock assessment to estimate the current biomass level, which is input into a target- and limit-based harvest control rule (HCR). The Tier 3 HS (Wayte and Klaer, 2010) uses information on the age frequencies of annual catches, annual total catch, and basic biological parameters to estimate current fishing mortality, which is then used in an HCR to calculate the subsequent year's intended fishing mortality. A new harvest strategy (Klaer and Wayte 2012) has been developed that is similar to Tier 3, but uses average length in the estimation of current fishing mortality. Tier 4 stocks are assessed by an empirical rule based on trends in standardized catch rates combined with target catches (Little et al., 2011).

5.8.2 METHODS

Two species were examined: Tiger Flathead and Jackass Morwong. These species are data rich, Tier 1 species in the SESSF. MSE testing is normally carried out using data rich species, plausible operating models can be developed. The estimates of 2009 biomass for these species were available from Section 6.5 (Table 5-8). The estimated SSB0 (virgin spawning biomass) from Tier 1 full assessment was 21,856 tonnes for Tiger Flathead and 25,065 tonnes for Jackass Morwong, respectively. Hence, the target spawning stock B_{48} was 10,491 tonnes for Flathead and 12,031 tonnes for Morwong. Two scenarios were considered for each species: where the assumed "true" stock status at the start of the projection period was below or above the target stock status of B_{48}. These levels were obtained by manipulating the initial stock size in the operating model so that the below-target and above-target starting SSBs were 35% and 60% respectively, of the unfished SSB, which is smaller than the recruited biomass. We can see from Table 1 that the ratio of estimated to "true" recruited biomass was 232% and 99% for Flathead, and 126% and 23% for Morwong.

Table 5-8. The estimated recruited biomass (not SSB) in 2009 used to MSE assessment, and the 'true' value for each of the initial stock status scenarios, for fleets that had the highest proportion of catch in the previous 5 years. For both species this was NSW/Vic trawl. The numbers in parentheses are the ratios between estimated biomass and "true" biomass.

	Estimated	Below target	Above target
Flathead	21,798	9,411 (2.32)	21,971 (0.99)
Morwong	12,744	10,152 (1.26)	54,752 (0.23)

Note: these values will be slightly different for each simulation as recruitments are only fixed until 2005 for Flathead and 2004 for Morwong. The values here are from one of the 100 simulations.

SRA was implemented as in Klaer (2006). This model allows different biological characteristics by sex, but was mostly based on the procedure described by Francis (1992). To generate recommended biological catch (RBC) levels, the MSE framework requires that an assessment method uses particular sources of simulated data provided by the operating model, and also a fixed HCR appropriate to that assessment method. The CCSRA implementation used the 2009 absolute biomass values given in Table 1, and the catch history to estimate B0, current depletion, and fishing mortality (F) (with a constraint that F in any year is no greater than 2.0). As it has the same input requirements of current depletion and current F, the standard SESSF Tier 1 HCR was used to generate RBC values from the CCSRA assessment.

The MSE framework was implemented as described in Wayte and Klaer (2010), with the operating model dynamics described in Fay et al. (2009).

The aims of harvest strategies as specified in the Australian government Commonwealth Harvest Strategy Policy are to: maintain fish stocks, on average, at a target biomass point equal to the spawning stock biomass (SSB) required to produce maximum economic yield (B_{MEY}); ensure fish stocks remain above a limit biomass where the risk to the stock is regarded as too high; and, ensure that the stock stays above the limit biomass level at least 90% of the time (DAFF, 2007). The limit biomass level is set as half of the SB required to produce maximum sustainable yield (BMSY). The use of proxies of B_{40} (40% of unfished equilibrium SSB) for B_{MSY}, and $1.2B_{MSY}$ for B_{MEY} result in a limit SB reference point of B_{20}, and a target SB reference point of B_{48}. Stock status in any particular year *y* is defined as the ratio of that year's SSB (B_y) compared to the unfished equilibrium SSB (B_0). The harvest control rule calculates the exploitation rate as a function of the current stock status, and a RBC is calculated by applying this exploitation rate to the estimate of exploitable biomass at the start of the quota year for which the RBC is required.

6 Results and Discussion

Economic analysis — target reference points for data-poor fisheries

6.1 Estimating maximum economic yield in data poor fisheries – a brief review

Maximum Economic Yield (MEY) in a fishery can be defined as the point at which the sustainable fishing effort level and catches in the fishery entail maximum profits, or the greatest difference between total revenues and total costs of fishing (Kompas 2005). The main determinants of MEY are illustrated in Figure 6-1. The point will change with input and output prices, as will the associated level of profits, and identifying MEY in any given fishery requires an assessment procedure allowing to track these changes (Kompas et al 2009). The dynamic nature of the MEY objective should be fully accounted for in such assessment procedures (Dichmont et al. 2010; Grafton et al. 2010).

While the concept has long been identified by fisheries economists as a target that should drive fisheries management (Gordon 1954), its identification had largely remained a theoretical exercise until recent years, as it had not been formally adopted as a policy objective internationally. With its inclusion in the Australian Commonwealth fisheries policy[8], and growing debates on its relevance as an operational management objective in other parts of the world (Christensen 2010; Norman-Lopez and Pascoe 2011; Bromley 2009; Dichmont et al. 2008), the problem of estimating MEY in real fisheries has attracted growing attention. First attempts at identifying MEY as an actual management target have highlighted the empirical difficulties which need to be addressed in doing so, and relate in particular to the alternative treatments of prices and costs, which may result in differing estimates of MEY and associated adjustment trajectories (Dichmont et al. 2010).

[8] Ministerial Direction to the AFMA under Section 91 of the Fisheries Administration Act 1991 issued by the Australian Government Minister for Fisheries, Forestry, and Conservation in December 2005.

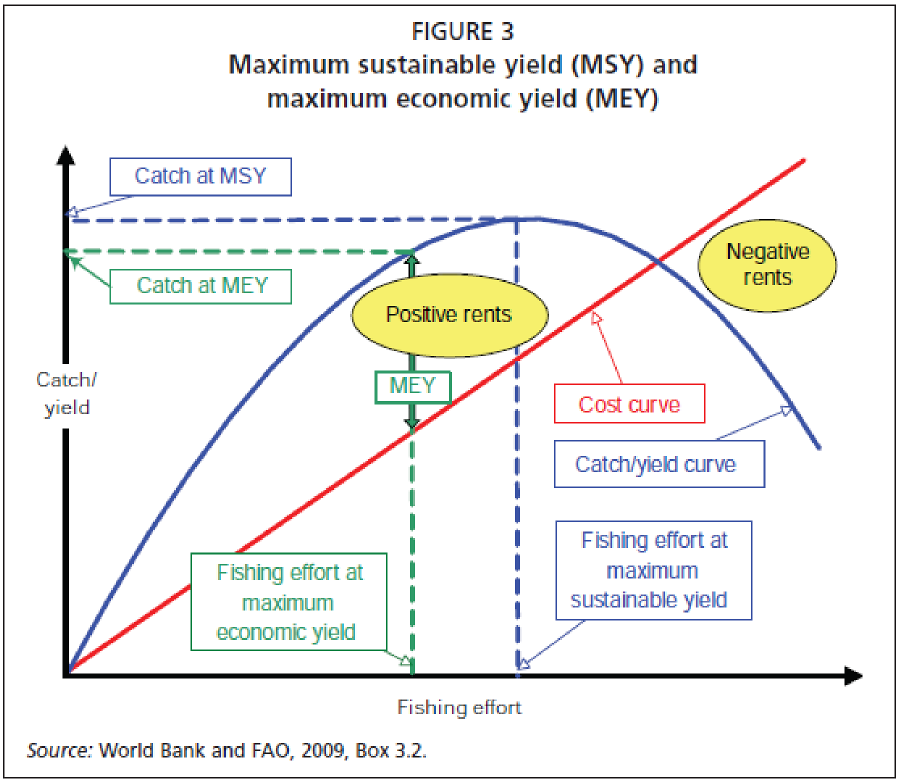


Figure 6-1. Main determinants of Maximum Economic Yield in fisheries (Source: [6, 7])

It has been possible to overcome these difficulties in the context of data rich fisheries, to which the analysis was first applied. However, MEY is also to be applied as a management objective in a broader set of fisheries, including some which are less well monitored and researched. This requires identification of possible approaches to applying this objective in data poor contexts.

In this section of the report, we provide a brief review of the literature on the identification of harvest objectives and management strategies in data poor contexts.

6.1.1 DECISION SUPPORT APPROACHES FOR FISHERIES MANAGEMENT IN DATA POOR CONTEXTS

There has been growing recognition that specific decision support methods and tools for fisheries management are needed in data poor contexts, both in the developed (Kelly and Codling 2006) and the developing world (Johannes 1998). Using the case of New Zealand fisheries (see figure below), Bentley and Stokes (Bentley and Stokes 2009a, 2009b) explain that the amount of detailed assessment information available for fisheries is often limited to non-existent as regards biological status of the fish stocks, and is usually driven by the value of the fishery. In the face of these limitations, the authors call for a shift of focus from assessment to procedural approaches, and for the identification of generic management procedures that depend on easily observed characteristics of a fishery, including biological, economic and social attributes.

Smith et al. (2009) illustrate the approach which has been adopted in the context of Australian Commonwealth fisheries to achieve such a procedural approach using Harvest Control Rules (HCR). These apply across a broad range of contexts, including data poor fisheries. In their conclusions, the authors stress the paucity of economic data in data-poor fisheries. Given that it will usually not be possible to collect detailed economic data for specific fisheries, the authors call for a formal evaluation of the proxies which may be considered for the MEY management target in data-poor contexts.

Dowling et al. (2008) stress the fact that when determining harvest strategies in data poor fisheries, uncertainty creates a trade-off between the risk of setting proxy reference points that would be too conservative, and the cost associated with improving the information needed to allow for reference points to be set closer to levels at which industry profits can be maximised. In a specific research project conducted with the Australian Commonwealth Fisheries Management Agency, the authors worked with fishery managers and stakeholders to develop a set of Harvest Strategies that would apply in data poor contexts. The approach is based on the definition of trigger levels associated with the biological status of the resources. An application to three Australian fisheries is presented. Economic dimensions are however not included in the analysis.

Dichmont et al. (2010) present an example of developing Harvest Control Rules in a Management Strategy Evaluation (MSE) framework applied to the data poor and low value spanner crab fishery in Queensland, Australia. The authors stress that while the economic circumstances of the fishery were considered important, they were never factored explicitly into the analysis, other than through the imposition of constraints regarding, e.g. the stability of Total Allowable Catches. This constraint is further examined by O'Neil et al. (2010) who present a revision of the initial MSE that was adopted to reduce chances of large fluctuations in Total Allowable Catch, which would be negatively perceived by the industry. The economic condition of the fishery was however not directly considered in their analysis.

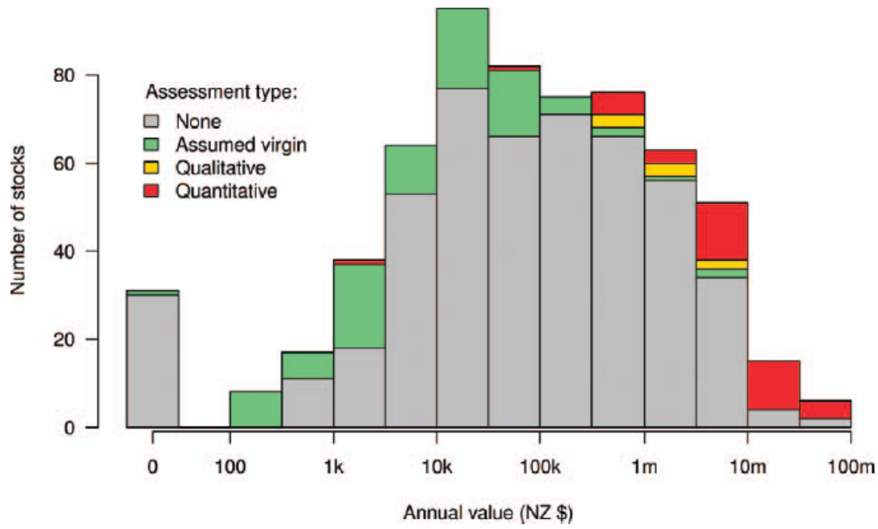


Figure 6-2. Types of assessments for NZ fish stocks according to their annual value. (Source: Bentley 2009b)

Kelly et al. (2006) propose an approach based on harvest rules and simple empirical indicators, to develop management strategies for fisheries in which data are unreliable or unavailable, and complex analytical models cannot be applied. They suggest that this approach, which would also rest on the definition of Harvest Control Rules, should be applied to North Atlantic fisheries management.

Overall, while there have been increasing research efforts dedicated to the development of harvest strategies under data poor conditions, to date, none of these have explicitly attempted to address the issue of identifying approaches which could be used to drive fisheries towards Maximum Economic Yield.

6.1.2 EMPIRICAL APPROACHES.

Empirical estimations of MEY in fisheries are only rarely encountered, and if they are, it is largely as a negative image, in terms of lost rent. This has been the case at the scale of both global fisheries, and local fisheries, as researchers have attempted to measure the extent of excess capacity at both levels, and to demonstrate the need for management changes.

The range of empirical approaches from data rich to data poor situations are illustrated in Figure 6-3. Empirical analysis of MEY in fisheries has largely focused on the development of bioeconomic models. These have been developed for a wide variety of fisheries and for fisheries in most regions of the world (Armstrong and Sumaila 2001; Doole 2005; Kar and Chakraborty 2011; Kompas et al.

2010; Ulrich et al. 2002). Such models require, at a minimum, some underlying stock dynamics models as well as information on costs of different fishing activities and prices of the main species. Models range in type from static equilibrium based models assuming a single homogenous fleet (Chae and Pascoe 2005; Kompas et al. 2010) to complete ecosystem based approaches (Fulton et al. 2007) or multi-species and multi-fleet models (Punt et al. 2011; Pelletier et al. 2009; Ulrich et al. 2007). These models are case specific, such that general rules cannot readily be derived that could be applied in data poor contexts. While the models themselves could be adapted to other fisheries, these would require sufficient appropriate data to populate the model parameters. For management purposes, the reliability of these models is intrinsically linked to the data on which they were based, and acceptance of these models by industry and managers is also greatly influenced by data quality (and quantity) (Dichmont et al. 2010).

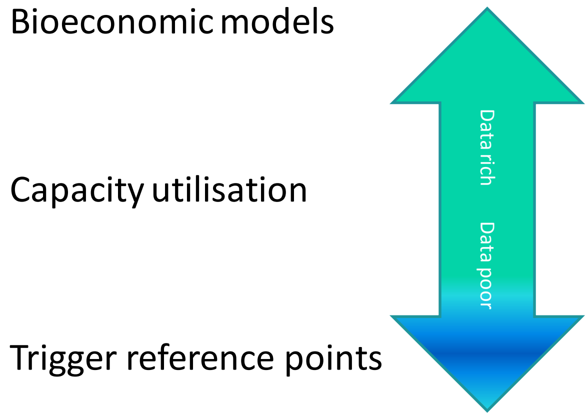


Figure 6-3. Empirical approaches to estimating target reference points.

Non-model based approaches to estimate optimal fleet size in fisheries have largely focused on the estimation of fishing capacity and capacity utilisation (Felthoven and Morrison 2004). These can be derived using vessel level catch and effort data, but require assumptions as to what catch levels may be appropriate at MEY. At best, they can identify how much excess capacity may exist in the fishery, but do not provide an indication as to what may be an optimal level of either effort or catch.

Several attempts at developing indicators of economic performance exist that can be used to assess whether or not fisheries are improving or deteriorating. These include information on licence values (Arnason 1990), although most approaches require more detailed cost and earnings information

(Whitmarsh et al. 2000). As with the capacity measures, these indicators alone do not provide information on where an optimal level of fishing effort or catch may be.

Harvest Control Rules (HCR) (Smith et al. 2009) have been applied across a broad range of fisheries, including data poor fisheries. One such approach is based on the definition of trigger levels associated with the biological status of the resources that also reflect economic performance (Dowling et al. 2008). Several examples of trigger-based management systems exist that have an implicit economic consideration but no explicit economic analysis. These include the data poor and low value spanner crab fishery in Queensland, Australia (Dichmont and Brown 2010; O'Neil et al. 2010), and the banana prawn fishery component of the Northern prawn fishery – a relatively data rich fishery but one in which modelling approaches have proven unreliable. In both cases, appropriate triggers are determined through a co-management arrangement involving industry, scientists and managers. Similar approaches have been proposed for definition of Harvest Control Rules for North Atlantic fisheries management for fisheries in which data are unreliable or unavailable, and complex analytical models cannot be applied (Kelly and Codling 2006).

Much of the attention in these analyses has been on either identifying the potential economic output from a fishery. Munro (2010) presents a synthesis of recent studies commissioned by the World Bank and the Food and Agricultural Organization of the United Nations, which aimed to assess rent losses in global fisheries, and a selection of individual fisheries. The so-called "Sunken Billions report" estimated that the annual lost rent due to global fisheries being sub-optimally managed amounted to approximately US$50 billion over the 1974–2008 period, taking 2004 as the base year World Bank and FAO 2009). Of this lost rent, US$45 billion is due to the fact that fisheries generate rents but that these could be higher, but US$5 billion is estimated to be due to negative rents being generated in some of the world's fisheries, due to over-harvesting and depletion of higher valued stocks.

The estimation is based on an approach which could to some extent be considered a data poor approach, as it is based on highly aggregated data of heterogeneous nature, and seeks to develop an estimation method which is based on a contained number of parameters. The authors of the study construct an aggregate model which assumes a global stock and biomass growth function (assuming either Schaefer-type or Fox models), and an aggregate fishing fleet with unique production, cost and profit functions. It takes into account the dynamic nature of fisheries and the rents they generate, and makes several assumptions in defining the concept of lost rents, particularly as regards the selection of a reference year from which to assess these, but also concerning reversibility of biological overfishing in the long run, and the treatment of transition costs to MEY (Munro 2010 p8).

As stressed by Munro (2010) in the conclusion of his report, while the results of the study clearly illustrate the need for change in world fisheries if they are to produce increased wealth, they do not provide a way forward in addressing the question of how to achieve high economic returns in global fisheries.

At the fishery level, there have been growing efforts at estimating excess capacity in fisheries (e.g. Felthoven and Morrison 2004; Tingley et al. 2003; Szakiel et al. 2006; Eggert and Tveteras 2007; Asche and Egger 2008)). Kompas et al. (2010) assess the lost rent from over-harvesting of the tunas of the Western and Central Pacific. As for the global estimates above, while these studies have help identify the potential to improve the economic performance of the fisheries studied, they do not focus on the identification of possible approaches to MEY.

Kompas et al (Kompas 2005) review possible approaches to the assessment of the economic status of fisheries, and illustrate their application to selected Australian Commonwealth managed fisheries. The authors provide MEY estimates for the northern prawn fishery (NPF) and the south east trawl fishery (SETF), and show that most current stock levels are much smaller than stock levels at MEY, leading to lost rents in these fisheries (see also Kompas et al. (2010) and Dichmont et al. (Dichmont et al. 2010; Dichmont et al. 2008) for further details on the NPF case). The study also estimates vessel-level efficiency in these fisheries, which show considerable efficiency losses, as well as productivity indexes and profit decompositions (applied to the SETF and the eastern tuna and billfish fishery). While the indicators produced are directly relevant as support tools for the identification of management strategies aimed at MEY, they require significant data and data analysis, which precludes their application in data poor contexts.

Szakiel et al. (1990) reviewed possible methods and metrics to assess the status of Commonwealth fisheries, including some economic indicators (Figure 6-4). The methods they discuss range from detailed bio-economic models required extensive data, to what they call “nonmetric approaches”, requiring only limited information. They warn that although these nonmetric indicators can be relatively easy to obtain, they may be biased and provide limited information on which to base assessments of the status of a fishery. Whitmarsh (2000) emphasized the importance of distinguishing between the financial profitability of fishing fleets and their economic performance, and how care should be taken in interpreting financial indicators that are estimated based on current cost and earning surveys.

1 Nonmetric indicators of excess capacity for selected Commonwealth fisheries

	Biological indicators	Management indicators	Profitability trend indicators
Northern prawn fishery	Not overfished Declining CPUE for banana and tiger prawns Some indication of localised expansion of the fishery	Input controls and limited entry	Relatively constant fishing costs since 1992-93 Relatively constant net returns (apart from the 2000-01 outlier year)
South east trawl fishery	Five key species overfished, a further two species where overfishing is occurring 13 species with a declining CPUE	Combination of ITQs and input controls Average of 70 per cent of TAC actually landed	Fishing costs consistently high percentage of net returns with declining trend in net returns since 1998-99
Torres Strait prawn fishery	Fully fished	Limited entry, effort controls and transferable fishing access rights 24 per cent of allocated fishing days not used in 2002	Fishing costs trending upwards since 1992-93 Net returns trending upwards since 1995-96
Eastern tuna and billfish fishery	Not overfished but observed localised depletions of swordfish Declining CPUE for swordfish Expanding geographic area	Input controls Average of 60 per cent of permits used in the fishery and only 30 per cent used full time	Fishing costs trending upwards since 1992-93 representing a large percentage of net returns Net return trending downwards since 1998-99 with a number of years experiencing negative returns
Caveats on the use of specific indicators	Short term fluctuations in stock size may influence current biological assessment and CPUE measure with no impact on excess capacity levels	The management regime of a fishery should provide a good indication of the incentives faced by operators but to gain a fishery wide assessment of excess capacity, other indicators should also be considered.	There are many influences on the profitability indicators that are not necessarily related to excess capacity. Care must be taken to understand underlying market effects that may be causing changes in profitability.

Sources: Caton and McLoughlin (2004); Galeano et al. (2003, 2004); Campbell (2005).

Figure 6-4. Non-metric indicators proposed to assess the status of Commonwealth fisheries. (Source: Szakiel et al 2006)

6.2 Deriving proxy measures of costs based on vessel and fishery characteristics

A key component of the study was to determine the extent to which cost components could be estimated based on characteristics of the vessels and fisheries within which they operated. Bioeconomic analysis requires estimates of costs and cost structures. However, these are often unavailable and expensive to collect. As outlined in the methods section, available economic data for a range of fisheries for which regular surveys were undertaken were used to test the relationship between costs and simple indicators such as vessel size and gear type used. Costs were disaggregated into variable costs, fixed costs and quasi-fixed costs. The results of the analysis are given below

6.2.1 VARIABLE COSTS

Fuel costs

Fuel costs were considered separately from other operating costs as they represent a significant component of these, and are usually well identified in the survey data. The importance of fuel costs in the overall cost structure of a fishing vessel however varies with the type of fishing gear used. Fixed gear fleets will use relatively less fuel per nominal unit of fishing effort than fleets using mobile gears. Hence, fuel costs were estimated in two separate models for vessels using mobile gears (trawl, dredge, Danish seine) and vessels using fixed gear (pot, net, line).

The models were estimated on the assumption that fuel costs vary with (i) nominal fishing effort, measured in days fished in our sample; (ii) size of the vessel as larger boats have larger engines which use more fuel per unit of time; (iii) types of fleets within each category of gear (fixed or mobile) and vessel size, as some vessels will spend more fuel than others in a given day of fishing depending on the type of fishing gear they use, which may itself depend on the species targeted. Other explanatory variables tested in the estimation of the models included the nature of access regulation which applied to the fishery in which the fleets operate, and whether regulations are based on input controls, which could impact the way in which the fleets operate and affect their fuel costs. We also considered the age of vessels as this could affect their fuel efficiency, with technological innovations improving the fuel efficiency of newer vessels.

A generic multiplicative model was chosen as the most appropriate structural form, given by

$$FL = e^{\beta_0} p_{FL}^{\beta_{pFL}} L^{\beta_L} E^{\beta_E} A^{\beta_A} \left(\prod e^{\beta_D D} \right) \tag{1}$$

where FL is the total fuel cost of the vessel over the year, p_{FL} is the price index for fuel, L is the length of the boat using mobile gear, E is the level of fishing effort (measured in terms of days fished), A is the age of the vessel (in years), and D is a set of dummy variables representing type of fishing gear used within the set of mobile gears, management type and other vessel characteristics.

The model was estimated as a log-linear regression model, the function form given by

$$\ln FL = \beta_0 + \beta_{pFL} \ln p_{FL} + \beta_L \ln L + \beta_A \ln A + \sum \beta_D D \tag{2}$$

The model was estimated in two parts given the very different fishing practices. All mobile gear (i.e. trawl) fleets were included in one model and static gear (nets, line, dive and pots) in the other. For the mobile gear model, fish trawl was considered the base fishing method (the default base in all the analyses), while for the static gear vessels, gillnets was chosen as the base fishing method (as it was the most common in the data set).

The results of the estimations for the best model are presented below. The agricultural fuel price index appeared to slightly overestimate the fisheries fuel price trend (as the coefficient is less than, but is not significantly different from, 1), so an adjustment to this needs to be made when estimating costs in data poor fisheries. Fuel costs increased at a less than proportional rate with vessel length, suggesting economies of scale in terms of fuel usage. As would be expected, static gear boats generally had lower fuel costs than mobile gear boats, ceteris paribus.

Fuel costs also increased at a less than proportional rate with days fished. An a priori assumption was that fuel costs would be linearly related to days fished for a given size/gear type. As steaming time is not included in the days fished measure (other than steaming time on the same day as fishing tool place), this result may be an artefact of the data. For example, the smaller vessels mostly operated on a day basis, and had a large number of days fished relative to total days at sea. For the larger vessels operating further offshore, the number of days fished may have been substantially less than the total days at sea (Table 6-1). The restricted model (where some non-significant variables were removed) was derived through backwards stepwise regression, with the Akiake Information Criterion (AIC) used to determine the most appropriate functional form. The model was able to explain a relatively high proportion of the variation in the data (79 per cent).

The agricultural fuel price index appeared to slightly overestimate the fisheries fuel price trend (as the coefficient is less than, but is not significantly different from, 1), so an adjustment to this needs to be made when estimating costs in data poor fisheries. Fuel costs increased at a less than proportional rate with vessel length, suggesting economies of scale in terms of fuel usage. As would be expected, static gear boats generally had lower fuel costs than mobile gear boats, ceteris paribus.

Fuel costs also increased at a less than proportional rate with days fished. An a priori assumption was that fuel costs would be linearly related to days fished for a given size/gear type. As steaming time is not included in the days fished measure (other than steaming time on the same day as fishing tool place), this result may be an artefact of the data. For example, the smaller vessels mostly operated on a day basis, and had a large number of days fished relative to total days at sea. For the

larger vessels operating further offshore, the number of days fished may have been substantially less than the total days at sea.

Table 6-1. Estimated model for fuel costs.

	Initial model				Restricted model			
	Estimate	Std. Error	t value		Estimate	Std. Error	t value	
Constant	7.134	0.250	28.542	***	7.099	0.231	30.798	***
Fuel price index	0.921	0.057	16.107	***	0.931	0.057	16.371	***
Length	0.875	0.067	13.028	***	0.932	0.055	16.854	***
Days fished	0.410	0.032	12.845	***	0.389	0.030	13.046	***
Gear type dummy variables								
Danish seine	-1.158	0.097	-11.902	***	-1.182	0.094	-12.587	***
Gillnets	-1.444	0.083	-17.486	***	-1.482	0.079	-18.800	***
Longline demersal	-1.296	0.162	-8.011	***	-1.265	0.123	-10.255	***
Longline pelagic	-0.424	0.475	-0.893		-0.687	0.048	-14.340	***
Longline automatic	0.229	0.506	0.453					
Trawl roughy	0.169	0.496	0.340					
Trawl prawn tropical	0.263	0.474	0.554					
Trawl prawn temperate	-0.165	0.141	-1.175		-0.330	0.102	-3.242	**
Dropline	-1.973	0.100	-19.670	***	-2.056	0.087	-23.611	***
Dive	-0.701	0.141	-4.956	***	-0.706	0.135	-5.232	***
Pots	-1.186	0.071	-16.746	***	-1.200	0.067	-17.933	***
Purse seine	0.199	0.132	1.507					
Jigging (squid)	-0.700	0.275	-2.542	*	-0.864	0.258	-3.347	***
Multiple Gear	-1.608	0.116	-13.901	***	-1.672	0.109	-15.306	***
Freezer dummy	0.427	0.471	0.907		0.547	0.055	9.971	***
Effort control dummy	-0.110	0.080	-1.379					
$\bar{R}^2$	0.790				0.790			
F	388.6			***	527.3			***
AIC	-1606.44				-1610.46			

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Crew

Crew costs are a particularly difficult cost component to estimate as they will vary according to the conventions adopted by the vessel owners and crews in determining crew payments, which can vary significantly across fisheries and types of fishing firms. Variability can also arise from the diversity of labour costs which can in principle be considered part of a fishing firm's cost structure, including on-land labour costs which may reflect a range of activities supporting the catching component of the firm's activity. Further, the extent to which these costs are included in the data collected through the surveys is not always clear. For both the Commonwealth and South Australian surveys, this has led to the estimation of imputed labour costs, which attempt to assess the total crew costs, including items not accounted for in the raw information collected through the surveys.

The share system is common in fisheries both within Australia and internationally (Arnason 1990). However, the way this system operates may differ from fishery to fishery. In Commonwealth fisheries, the general approach is to pay crew (and any employed skipper) a share of the total revenue. In at least some Australian State fisheries, and in most European (Whitmarsh et al. 2000) and US fisheries (Arnason 1990), crew are paid a share of the revenue less running costs (varying combinations of fuel, food, ice and bait). In order to estimate a generic model, we defined crew share as the ratio of crew payments to gross returns from fishing (but net of any marketing and freight charges due to the inconsistency in the way these were recorded in the data).

The median crew share across fisheries was relatively constant at around 30 per cent (Figure 6-5), although this varied considerably between vessels. Lower crew shares most likely represent a higher proportion of unpaid labour, although substantially higher crew shares were also observed. In the smaller scale South Australian fisheries which all had owner-operator labour and many with only a part time crew, median crew payments were substantially lower than their Commonwealth counterparts (Figure 6-5).

We tested estimations of crew costs using both cash costs only and also adding the imputed measures for the different fleets. However, the imputed values displayed large variability, probably due to the existence of different conventions regarding imputation. In the case of the South Australian fisheries, all were owner-operated and had a high proportion of unpaid labour.

The final model was estimated using raw measures of crew costs (i.e. cash payments to employed crew and skippers only). From this, given the mix of employed and owner-operator skippers, it was possible to impute a consistent opportunity cost (in share terms) for owner-operator labour (see model results below).

Several alternative forms of the model were tested. Here, we describe the variables which were used in the final model estimation. To capture the fact that crew share might not increase proportionally to gross returns, the size of the vessel's activity (in terms of net returns from fishing) was included as an explanatory variable. We also considered the possible influence of the type of firms on crew share. It has been shown that owner operated vessels tend to have smaller crew shares than vessels operated by a paid skipper, as owner-operators will pay for the time they spend running their vessel, through firm profits (Whitmarsh et al. 2000). A dummy variable capturing the owner-operator status of the vessel was added to measure the possible influence of this factor on crew shares in the Commonwealth fleets (all South Australian vessels in the sample being owner-operated).

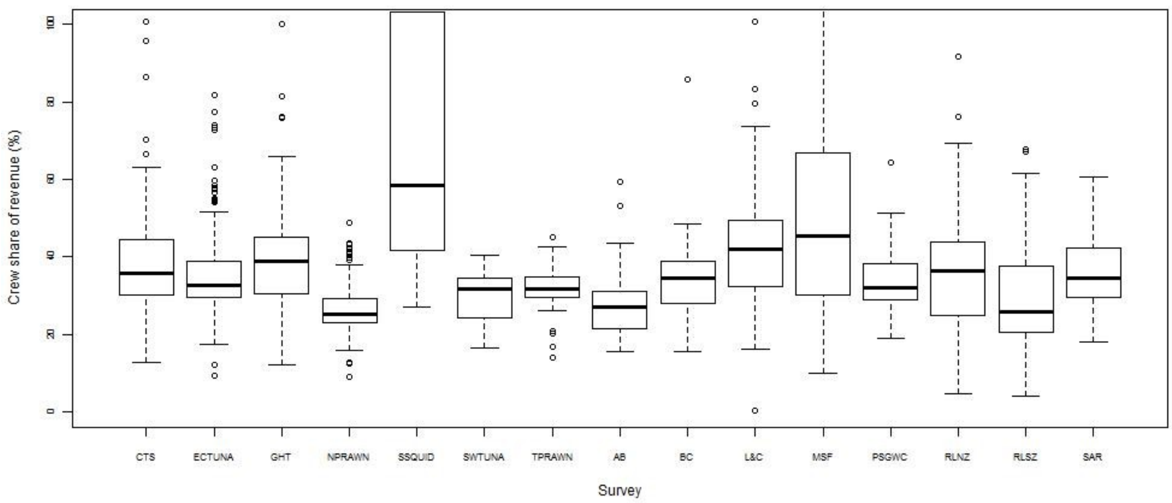


Figure 6-5. Distribution of the crew share of revenue for each fishery.

In addition, recent research on the impacts of catch share systems in fisheries have shown that crew share could be reduced in fisheries managed under ITQs (Eggert and Tveteras 2007; Asche and Eggert 2008). A dummy variable describing whether the vessel operates under an input control regulatory system was added to capture this effect.

The structural form of the final model was:

$$CS_v = \beta_0 + \beta_1 I_v + \beta_2 O_v + \beta_3 NR_v \qquad (3)$$

where CS_v is the crew share NR_v is the net annual return from fishing (i.e. the difference between gross returns and freight costs), O_v is a dummy variable stating whether the vessel is owner operated (1 if it is; 0 otherwise) and I_v is a dummy variable stating whether the vessel operates under an output control regulatory system (1 if it does; 0 otherwise).

Given the large variability observed in crew shares within most of the fisheries included in the sample (Figure 6-5), extreme values (crew shares that were above 0.5) were excluded from the estimation. The results for the final model are presented below (Table 6-2.) for the aggregate sample, and separately for the Commonwealth (Table 6-3.) and South Australian (Table 6-4.) components of the sample.

Table 6-2. Estimated model for crew share: total sample.

Coefficients	Estimate	Std. Error	t value	
Constant	0.351	0.005	77.836	***
Output control (*I*)	0.011	0.002	4.218	***
Owner (*O*)	-0.048	0.004	-10.924	***
Net returns (*NR*)	-5.63E-08	4.72E-09	-11.909	***
$\bar{R}^2$	0.126			
F	79.55			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Given the large variability in observations of crew share within fisheries, the explanatory power of the model is limited, with an adjusted R^2 of 0.126. As is reflected in the descriptive representation of observations presented in Figure 6-5, the estimated crew share over the entire sample averages at around 35%, with crew payments lower for owner-operated vessels averaging around 30 per cent (implying that the opportunity cost of an unpaid owner-operator skipper is around 5 per cent). The marginal increase in crew share with net returns is also negative, although the estimated effect appears very small. However, as this is a linear model and the units of net return often run into the hundreds of thousands (or in some case millions) of dollars, then this effect may be substantial. In the aggregate sample, the nature of the regulatory system under which the vessel operates (i.e. ITQs or effort controls) appeared to have a significant influence on the estimated crew share, with crew in ITQ fisheries having a slightly higher share than vessels operating in input control fisheries.

Application of the model to the sub-sample of Commonwealth vessels only results in a similar estimation (Table 6-3), although average crew share was estimated to be slightly lower – approximately 25% on average. Owner operated vessels reduces the crew share by 5%, leading to average catch shares of approximately 20% on vessels with an unpaid owner-skipper. Contrary to the recent literature on the effects of ITQs on labour contracts in fisheries (Eggert and Tveteras 2007; Asche and Eggert 2008), vessels under output controls had slightly larger crew shares than the reference fleet which is managed under an input control system.

Table 6-3. Estimated model for crew share: Commonwealth fleets

Coefficients	Estimate	Std. Error	t value	
Constant	0.249	0.008	31.659	***
Output control (*I*)	0.010	0.004	2.252	**
Owner (*O*)	-0.051	0.008	-6.779	***
Net returns (*NR*)	3.02E-08	8.47E-09	3.565	***
$\bar{R}^2$	0.061			
F	38.22			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

When applied to the South Australian sub-sample, which is composed of only owner-operated vessels (although some operations may be leasing the quota they need to fish), the model estimates that catch shares are approximately 30% (Table 6-4), which is higher than that in the estimation from the Commonwealth sub-sample, but lower than the combined sample. The regulatory dummy variable in this case has the expected influence on crew share (based on the key literature in the area), which decreases in output controlled fisheries. This may be due to the longer history of ITQs in the SA fishery, as compared to the Commonwealth fisheries. The crew share appeared to be less influenced by the net returns (the coefficient of which was not significantly different to zero) than in the Commonwealth fishery, but this may also reflect the substantially lower, and more homogeneous, revenues on many of the State vessels. While the key explanatory variables were significant, the overall explanatory power of the model was extremely low suggesting that other factors may affect the variability in crew shares.

Table 6-4. Estimated model for crew share: South Australian fleets.

Coefficients	Estimate	Std. Error	t value	
Constant	0.306	0.007	44.378	***
Output control (*I*)	-0.029	0.008	-3.771	***
Net returns (*NR*)	1.97E-09	1.19E-08	0.165	
$\overline{R}^2$	0.0228			
F	7.334			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Based on pooled analysis, an assumption of an average crew share of around 35 per cent (including an allowance for the skipper) decreasing by 6 per cent for every million dollars of revenue of the vessel may be a reasonable assumption for data poor fisheries. This is fairly consistent with current bioeconomic models used for estimating MEY in Australian fisheries. For example, the NPF model uses a crew share of 23 per cent (Tingley and Pascoe 2005), while average revenues in the fishery are around $1.5 million (Kompas et al. 2010).

Freight

Freight costs included not only the costs associated with the freight of catch, but also costs associated with the marketing, selling and packaging of catch. These costs were expected to be dependent on a variety of factors including market proximity, fishery management structure and fishing business structure. Generally, the cost per unit output was relatively low, although it varied considerably within and across the fisheries (Figure 6-6). For the South Australian fisheries, these costs were not identified as they were negligible. The catch was generally landed at the local fisheries co-operative that dealt with subsequent marketing costs, and hence the price paid to the fisher was the price net of any subsequent freight and marketing costs.

A multiplicative model was chosen as the most appropriate structural form, given by

$$FR/C = e^{\beta_0} p_{FR}^{\beta_{pFR}} OP^{\beta_{OP}} M^{\beta_M} \left(\prod e^{\beta_D D}\right)$$

where FR is the freight cost per vessel, C is catch, p_{FR} is an index for the price of freight, OP is the average output price received by a vessel, M represents approximate distance to market for the fishery the vessel operates in and D represents a set of dummy variables. Output prices were included as a potential explanatory variable as it is likely that greater care would be taken for more valuable species. Dummy variables included vertical integration of the fishing firm, export focus, whether the vessel operates under ITQs, and has onboard freezing facilities.

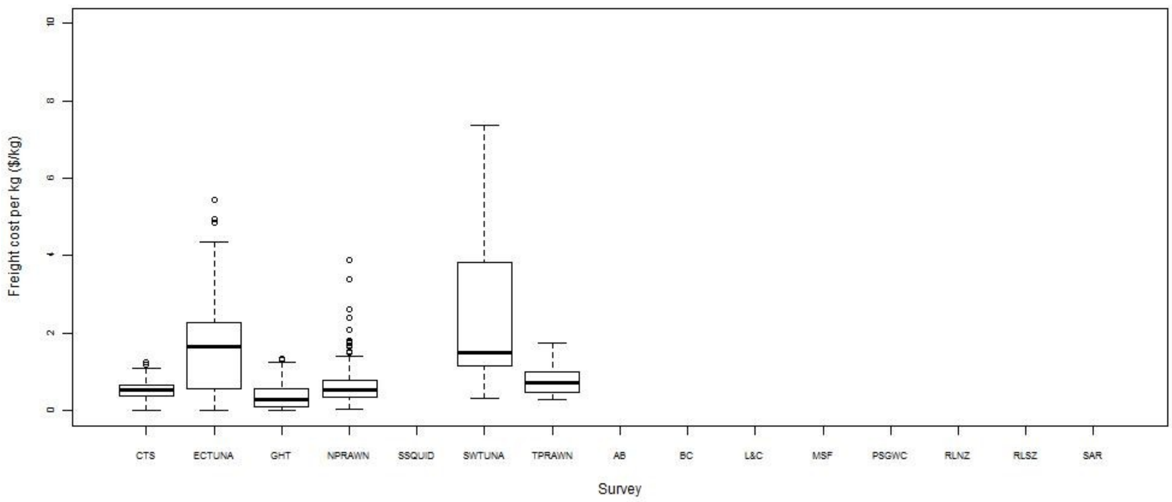


Figure 6-6. Distribution of freight costs ($/kg).

The model was estimated as a log-linear model, with the functional form

$$\ln\left(FR/C\right) = \beta_0 + \beta_{pFR} \ln p_{FR} + \beta_{OP} \ln OP + \beta_M \ln M + \sum \beta_D D$$

Initial models were found to have a low explanatory power. This was improved to a degree by estimating the model using only data for boats that had non-zero values for this cost variable. Collinearity problems also arose with the vertical integration dummy variable and market distance.[9] Various forms were attempted but the final model excluded both variables. While the remaining variables were significant and had the expected signs (Table 6-5), the explanatory power of the final model was still low with an adjusted R-squared value of 0.28 (Table 6-5).

[9] The market distance was average for the fishery rather than each individual vessel, so it is likely that this was a poor indicator of the actual cost to the individual.

The inability to estimate a strong relationship for this cost item simply reflects the random variation in these costs across both fisheries and vessels as reflected in Figure 6-6. Across vessels, this variation is likely to reflect not only variation in the costs that vessels are actually incurring but also variation in reporting practices. In some cases, vessels will report a gross receipts amount in their financial statements and, therefore, report all freight, marketing and packaging costs. For other vessels, the revenue reported reflects the price received from fish buyers after a deduction of freight, marketing and packaging costs (i.e. net receipts) and, therefore, these costs will not be reported in their financial statements. For this reason and for the purpose of the overall study, freight costs may best be excluded in the treatment of costs for the stage of the project (MEY modelling). This requires that net revenues (net of freight, marketing and packaging) as opposed to gross revenues are used for the analysis of MEY.

Table 6-5. Estimated model for freight costs.

Coefficients	Estimate	Std. Error	t value	
Constant	-2.859	0.161	-17.73	***
Price index for marketing costs	2.120	0.287	7.374	***
ITQ fishery (dummy)	1.142	0.076	14.976	***
Freezer (dummy)	-0.608	0.205	-2.972	***
Export (dummy)	2.223	0.227	9.805	***
Average price of outputs ($/kg)	0.758	0.077	9.821	***
$\overline{R}^2$	0.277			
F	80.21			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Other variable costs

Variable costs are those costs that vary with changes in a boat's effort input into a fishery. The *other variable cost* variable here captures those variable costs not captured in the other estimated cost models and included three cost items: bait costs, ice costs and food costs. The model was estimated on the assumption that variable costs will vary uniformly with days fished. It was also expected that these costs would be higher for larger boats.

The first attempts to run the model were not very successful. A key problem was that the three cost items that defined other variable costs will not occur for all fishing methods and operation types. Of the three cost items, food is the only item that can be expected to occur for all vessel types, although it is less likely to occur for boats that primarily engage in day trips. Bait costs are only incurred by vessels that use hook (longline and dropline) and pot based fishing methods. While ice costs are typically incurred by vessels that take short fishing trips and that are not fitted out with onboard freezers.

To deal with this issue, three dummy variables were defined: a food dummy was defined for boats that were expected to have food costs (given their typical trip length); an ice dummy was defined for boats that were not fitted with freezers; and, a bait dummy was created for vessels that used bait based fishing methods.

The model was also run on a subset of the sample data which only included boats that had a positive value for other variable costs as the large number of zero values was impeding the models explanatory power.

The structural form of the model was given by:

$$OV_v = E_v\left[B_0 p_{oth} + \beta_1 L_v + \sum_j \beta_j D_{vj}\right]$$

where p_{oth} is the price index for other variable costs, L_v is the length of the boat, E_v is the level of fishing effort (measured in terms of days fished), CR_v is the number of crew and D_{vj} is a set of dummy variables. Specifically, these dummy variables include the food, ice and bait dummies mentioned above as well as dummies for vessels that use pelagic longline and also owner-operator dummies. These pelagic longline dummy variable effectively reflects the methods that use large number of hooks and therefore use large amounts of bait relative to the size of the vessel. Owner operator vessels were a priori assumed to be more cost efficient in regard to these costs than skipper operated vessels (who had less of an incentive to reduce their costs).

The agricultural price index for running costs (Table 6-5) was assumed to be a reasonable proxy measure for the input prices related to these variable costs. Initial model estimates suggested that the coefficient on this variable was not significantly different to 1 (one). Restricting this to a value of one did not reduce the model performance. Similarly, early results suggested that the coefficient on days fished was also not significantly different from one, and again restricting this to one did not have an adverse effect on the model.

Given this, the final functional form of the model was:

$$\ln\left(\frac{OV_v}{p_{oth}E_v}\right)=\beta_0+\beta_l\ln(L_v)+\beta_{CR}\ln(CR_v)+\sum_j\beta_jD_{vj}\ \frac{OV_v}{E_v}=B_0p_{oth}+\beta_1L_v+\sum_j\beta_jD_{vj}$$

The final estimated model parameters are given in Table 6-6.. Costs increased slightly with length, although this was not significant. A priori, it might be expected that length would be positively related to these costs as larger vessels tend to spend longer at sea (so use more food), although are also more likely to have freezers (so use less ice). The effect of crew number on running costs was significantly different from zero, but also very small. Costs were higher for both multiday trip boats and boats using bait based fishing methods as expected, although boats that did not use freezers had no significant increase in their costs. Owner operator vessels had lower other running costs as expected.

Table 6-6. Estimated model for other variable costs.

Coefficients	Estimate	Std. Error	t value	
Constant	2.070	0.221	9.387	***
Length	0.133	0.086	1.535	
Multiday trips (use food)	1.638	0.090	18.297	***
No freezer (use ice)	0.119	0.079	1.509	
Bait based fishing method	0.614	0.069	8.920	***
Longline pelagic dummy variable	1.208	0.102	11.890	***
Crew number	2.0E-06	2.8E-07	7.179	***
Owner operator	-0.216	0.071	-3.036	**
$\bar{R}^2$	0.565			
F	298.3			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

6.2.2 REPAIRS AND MAINTENANCE (QUASI-FIXED COST)

Repairs and maintenance is a major cost component for many fleets, although it presents several challenges for modelling. The costs of repairs and maintenance was not collected consistently at the State and Commonwealth levels, with the former combining repairs to boat and gear while the later separated boat repairs from gear repairs and replacement. For the purposes of model development to provide cost structure estimates in a data poor fishery, the boat and gear repair costs were combined to fully utilise the data available.

The treatment of repairs and maintenance in bioeconomic modelling varies considerably, with some studies assuming that they are all fixed costs (Lleonart et al 2003; Guyader et al. 2004; Hoff et al. 2012) while others treat them as variable costs (Dichmont et al. 2008; Punt et al. 2010; Hupper and Squires 1987). The implications of how they are treated in the analysis for MEY estimation can be considerable, with treatment as a variable cost resulting in lower optimal effort levels than if treated as a fixed cost (Dichmont et al. 2010). From discussions with industry, repairs and maintenance costs have both a fixed and a variable component. Some maintenance is required each year on the vessels irrespective of how much it fished. Similarly, gear needs replacement regularly even if used infrequently as it often starts to deteriorate once it has been exposed to salt water. However, the more a vessel and its gear is used, the more the need for repairs and maintenance increases due to wear and tear. Gear costs may also have a highly random component as gear can be lost or damaged irrespective of how many trips have been made. Similarly, boats periodically undergo major refits, with much of this cost being included in the boat repairs category and appearing as greater than normal expenditure.

The development of the model for repairs and maintenance costs was based on several a priori expectations. First, the model would need both a fixed and variable cost component, with the input price proxy variable applied to both components. Second, repairs costs were expected to increase with boat size, and as larger boats tend to use more gear, it was expected that gear repairs and replacement costs would also be related to vessel size.

The structural form of the model was given by

$$RM_v = p_{rm} L_v \left[(\beta_0 + E_v)(\beta_1 + \sum_j \beta_j D_{vj}) \right]$$

where p_{rm} is the price index for repairs and maintenance, L_v is the length of the boat, E_v is the level of fishing effort (measured in terms of days fished), and D_{vj} is a set of dummy variables representing gear type, management type and other vessel characteristics. The particular fishery and vessel characteristics are assumed to affect the fixed component of the cost category, while the variable component of the cost was a function of just boat size and effort level. The price index was also assumed to be a reasonable proxy measure for the input prices related to gear and boat repairs and maintenance.

The functional form of the model was given by

$$\frac{RM_v}{p_{rm}L_v} = \beta_0 + \beta_1 E_v + \sum_j \beta_j D_{vj} + \sum_j \beta_{j2} E_v D_{vj}$$

Initial runs of the model identified a number of outliers (Figure 6-7) that were assumed to represent either refits or unusually large gear replacement costs (positive outliers), or observations where owners reduced usual repair and maintenance expenditure (negative outliers). Dummy variables were added to the model representing observations with positive or negative outliers (defined as having standardised residuals with a value greater than 2 or less than -2).

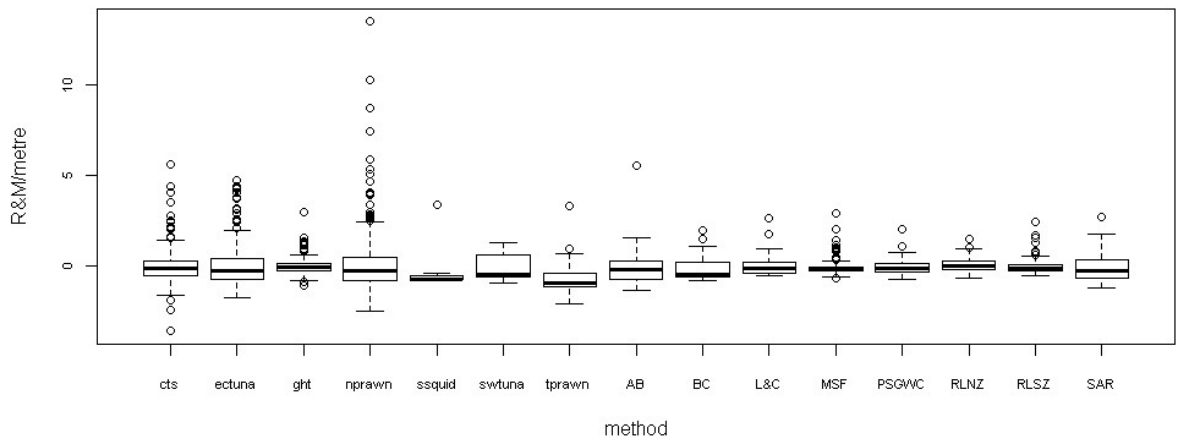


Figure 6-7. Distribution of normalised residuals of cost per metre by survey.

The final estimated model parameters are given in Table 6-7. Most of the parameters are significant and the model is able to explain around 70 per cent of the variation in the data. The signs on the coefficients of the model conform to a priori expectation, namely that repairs and maintenance increase with both length (as indicated by the constant term that is modified upwards or downwards by the gear specific dummy variables) and days fished. Generally (with the exception of the automatic and pelagic longliners), boats using static gear tended to have lower repairs, maintenance and gear replacements costs that the more mobile vessels.

Table 6-7. Estimated model for repair and maintenance costs per metre.

	Initial model				Restricted model			
	Estimate	Std. Error	t value		Estimate	Std. Error	t value	
Constant	-8.02	759.85	-0.01		609.66	323.19	1.89	*
Days fished	32.26	4.37	7.38	***	28.58	2.05	13.94	***
Gear type dummy variables								
Danish seine	1412.97	1707.17	0.83		795.29	1560.21	0.51	
Gillnets	1956.92	934.52	2.09	**	1319.71	631.22	2.09	**
Longline demersal	-1057.17	1649.01	-0.64					
Longline pelagic	2426.54	927.14	2.62	***	1792.30	251.10	7.14	***
Longline automatic	7064.44	2184.88	3.23	***	4805.28	685.95	7.01	***
Trawl roughy	5449.29	2254.93	2.42	**	4433.85	765.11	5.80	***
Trawl prawn tropical	7469.16	1020.65	7.32	***	7036.04	680.13	10.35	***
Trawl prawn temperate	570.12	1558.08	0.37					
Dropline	863.08	929.45	0.93		397.41	564.77	0.70	
Dive	3704.13	1151.68	3.22	***	2627.07	532.43	4.93	***
Pots	1078.40	871.43	1.24		463.23	534.74	0.87	
Purse seine	236.56	2540.64	0.09					
Jigging (squid)	1343.70	1870.10	0.72		2270.22	563.91	4.03	***
Multiple Gear	3076.93	1194.78	2.58	**	2465.48	975.62	2.53	**
Effort control dummy	183.50	322.20	0.57					
Outlier dummy	15289.46	367.74	41.58	***	15279.79	365.82	41.77	***
Days fished*gear dummy								
Danish seine	-26.58	14.24	-1.87	*	-22.90	13.69	-1.67	*
Gillnets	-33.06	5.21	-6.34	***	-28.81	3.36	-8.59	***
Longline demersal	9.24	17.99	0.51					
Longline pelagic	-5.43	5.53	-0.98					
Longline automatic	-17.68	20.18	-0.88					
Trawl roughy	-6.18	13.19	-0.47					
Trawl prawn tropical	-22.75	6.01	-3.78	***	-19.07	4.61	-4.14	***
Trawl prawn temperate	0.37	24.28	0.02					
Dropline	-33.27	5.48	-6.07	***	-29.45	3.88	-7.59	***
Dive	-16.78	21.34	-0.79					
Pots	-25.73	5.08	-5.07	***	-21.90	3.28	-6.67	***
Purse seine	-23.02	66.05	-0.35					
Jigging (squid)	28.79	34.59	0.83					
Multiple Gear	-42.56	8.06	-5.28	***	-37.91	6.86	-5.53	***
$\bar{R}^2$	0.696				0.697			
F	145.4			***	237.7			***
AIC	31366.5				31348.5			

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The distribution of the repairs and maintenance costs between fixed and variable cost categories, varies considerably by gear type. From the coefficients in Table 14 and using a common days fished measure (200 days), for some gears the cost is completely fixed (e.g. gillnets) while for other gears the costs are completely variable (e.g. temperate prawns) (Figure 6-8). However, for most gear types/fisheries, the cost share varies (Figure 6-8).

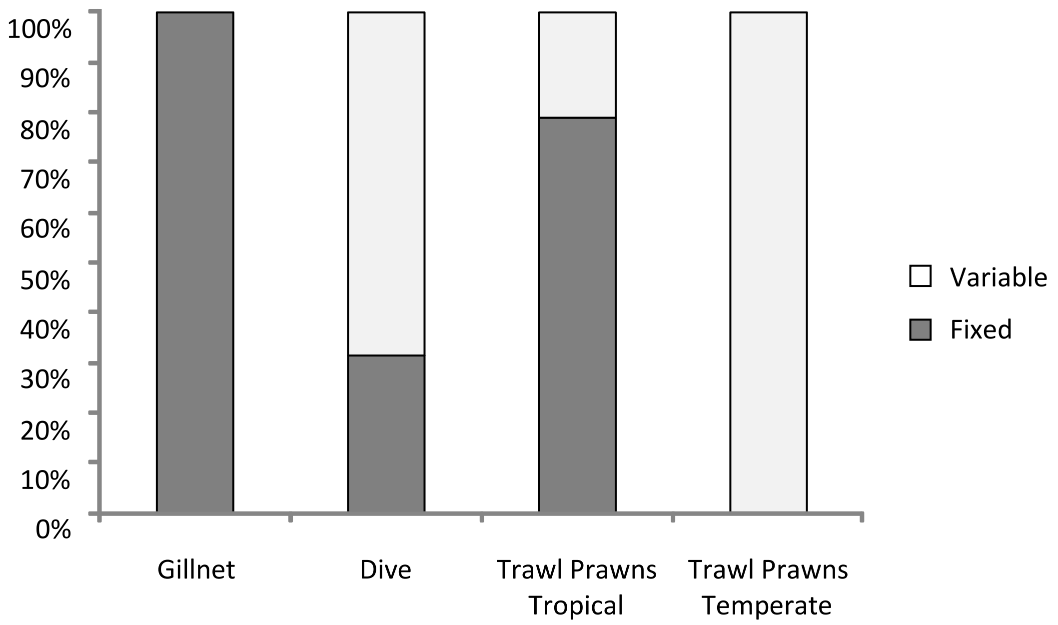


Figure 6-8. Examples of distribution of repairs and maintenance costs between fixed and variable cost categories.

6.2.3 FIXED COSTS

Fixed costs are often a major component of total costs of a fishing firm, and include a wide range of largely administrative cost items (e.g. management levies, accountancy fees, bank charges, etc) as well as insurance costs, wharfage fees, licence fees and a wide range of other costs that do not vary directly with the level of fishing effort or catch. Some of these costs are likely to be fishery specific (e.g. management cost related), while others are likely to vary with the size of the boat (e.g. insurance costs, wharfage fees, protective clothing, which is indirectly related to length through the number of crew).

A multiplicative model was chosen as the most appropriate structural form, given by $FX = e^{\beta_0} p_{FX}^{\beta_{pFX}} L^{\beta_L} \left(\prod e^{\beta_D D} \right)$ where *FX* is the vessel total fixed costs, p_F is the price index for fixed (derived from the agricultural price index for overheads, Table 6-8), *L* is the length of the boat, and *D* are the set of fishery and other characteristics dummies. The model was estimated as a log-linear model, the functional form given by

$$\ln FX = \beta_0 + \beta_{pFX} \ln p_{FX} + \beta_L \ln L + \sum \beta_D D$$

The results of the model estimation are given in Table 6-8. Most of the coefficients were significantly different from zero, with the model explaining roughly half the variation in the data. From the results, the coefficient relating to the price index is less than 1, although is not significantly different to 1. This suggests that the agricultural price index for overheads is a reasonable approximation of the price index for fisheries fixed costs, but may, on average, underestimate the price change. The coefficient on length is less than 1, suggesting that fixed costs increase at a less than proportional rate with boat length. According to the model, effort control fisheries have lower fixed costs, on average, than ITQ fisheries.

Table 6-8. Estimated model for fixed costs.

Coefficients	Estimate	Std. Error	t value	
Constant	9.702	0.188	51.694	***
Price index for overheads	0.692	0.144	4.807	***
Length	0.481	0.061	7.879	***
Gear type dummy variables				
Danish seine	-0.581	0.088	-6.593	***
gillnets	-0.394	0.075	-5.241	***
Longline demersal	-0.723	0.146	-4.964	***
Longline pelagic	-1.020	0.432	-2.363	**
Longline automatic	-1.078	0.461	-2.336	**
Trawl roughy	-0.622	0.452	-1.375	
Trawl prawn tropical	-0.555	0.432	-1.286	
Trawl prawn temperate	0.288	0.118	2.437	**
Dropline	-1.365	0.089	-15.400	***
Dive	0.496	0.121	4.087	***
Pots	-0.329	0.064	-5.110	***
Purse seine	0.491	0.115	4.259	***
Jigging (squid)	-1.118	0.243	-4.608	***
Multiple Gear	-0.707	0.104	-6.789	***
Freezer dummy	1.202	0.429	2.799	***
Effort control dummy	-0.107	0.071	-1.511	
$\overline{R}^2$	0.614			
F	174.2			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

6.2.4 CAPITAL COSTS AND ECONOMIC DEPRECIATION

The level of capital invested in the vessel (including the engine, electronics and gear) is expected to vary with the length of the vessel and the type of fishery. Estimating capital values in fisheries is complex as vessels are constantly repaired and ungraded (through refits), and vessels have widely varying configurations in terms of specifications and on-board equipment. As with many other studies, capital values are based on the owner's estimated market value of the vessel in each time period.

Capital value is expected to decrease over time due to depreciation, but at a lower rate than standard accounting depreciation as ongoing repairs and maintenance (which are also included as costs) is likely to help maintain the value of the capital asset. The rate of economic depreciation, therefore, represents the rate of net loss of capital value, as indicated by changes in the resale value of the capital asset over time (also adjusting for general price changes) (Hulten and Wykoff 1996).

Several different modelling approaches exist to estimate the rate of economic depreciation (Jorgenson 1996). As the objective of this study was aimed at estimating a general model for capital values in fisheries that included economic depreciation, a multiplicative model was chosen of the form (dropping vessel subscripts for simplification):

$$K = e^{\beta_0} p_K^{\beta_{pk}} L^{\beta_L} \left(\prod e^{\beta_D D} \right) e^{-\beta_A A}$$

where K is the capital value, p_k is the price index for capital (derived from the agricultural price index), L is the length of the boat, D are the set of fishery and other characteristics dummies and A is the age of the boat in each time period. The estimated coefficient β_A represents the rate of economic depreciation.

The functional form of the model is given by

$$\ln K = \beta_0 + \beta_{pk} \ln p_k + \beta_L \ln L + \sum \beta_D D + \beta_A A \qquad \textbf{Eq 6-1}$$

The results of the model are given in Table 6-9. The model was able to explain around 73 per cent of the variation in the data, and most of the coefficients were significantly different from zero. From the table, the rate of economic depreciation is estimated to be 2.3 per cent a year. This comparable to what is currently being used in the Northern Prawn Fishery analysis (2.9 per cent (Punt et al. 2010), although this value was based on earlier European studies (Pascoe and Mardle 2001) as no equivalent Australian analysis had previously been undertaken.

Table 6-9. Estimated model for Capital costs.

Coefficients	Estimate	Std. Error	t value	
Constant	9.584	0.187	51.376	***
Price index for capital	1.050	0.129	8.146	***
Length	1.325	0.059	22.378	***
Gear type dummy variables				
Danish seine	-0.216	0.085	-2.530	*
gillnets	-0.320	0.073	-4.370	***
Longline demersal	-0.400	0.142	-2.828	**
Longline pelagic	-0.729	0.420	-1.737	.
Longline automatic	-0.457	0.449	-1.018	
Trawl deep water	-0.129	0.439	-0.293	
Trawl prawns tropical	-0.416	0.419	-0.993	
Trawl prawns temperate	0.488	0.115	4.256	***
Dropline	-1.109	0.086	-12.882	***
Dive	0.254	0.121	2.091	*
Pots	0.302	0.064	4.680	***
Jigging (squid)	-0.653	0.235	-2.774	**
Multiple Gear	-1.174	0.101	-11.593	***
Purse seine	1.020	0.113	9.054	***
Freezer dummy	0.750	0.417	1.797	.
Effort control dummy	0.405	0.070	5.812	***
Vessel age	-0.023	0.002	-14.968	***
$\bar{R}^2$	0.749			
$F_{19,1941}$	309.5			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The coefficient on the price index for capital is not statistically different from one (1) as would be expected. However, as the price index is for agricultural capital, then some divergence from the a value of one is reasonable if the cost of building fishing vessels has generally increased at a faster rate than capital costs in agriculture in general.

Capital costs also appear to increase at an increasing rate as vessel size increases. Again this is not unexpected, as length is a one dimensional measurement whereas vessels are three dimensional objects. Larger boats would also be able to use more crew, increasing the need for accommodation on board but also allowing proportionally more gear to be held on board. More and larger engines are also required to run the larger vessels and the larger vessels are also likely to use proportionally more electronics than their smaller counterparts. While it would be expected that larger vessels would have a freezer, this is captured separately in the model, as a factor that increases capital costs.

The effort control dummy suggests that – length for length – vessels operating in effort control fisheries have higher capital costs than those in ITQ fisheries. Incentives exist for “capital stuffing” in input controlled fisheries where as ITQs create incentives to reduce costs, including capital costs (Asche and Eggert 2008).

6.2.5 DISCUSSION

The model results suggest that reasonable estimates of several key cost components may be made for data poor fisheries given some information on the average size of the vessels, their main fishing gears, the number of days fished, the type of management under which vessels operate, and the business structure of the fishing firms. While input price data are generally unavailable for fisheries, agricultural prices paid indexes provide a guide to changes in fisheries input prices, and the models provide an indication as to how much these need to be adjusted (up or down) to reflect price trends in fisheries.

The two models that were the weakest were freight and crew shares. Freight costs appear to be very fishery specific, depending on the distance of the market, level of vertical integration, type of market (export or domestic), product form and value of the species. However these variables explained only a small proportion of the variation in freight costs, suggesting that there is considerable heterogeneity in fisheries as to how fishers sell their product, and also considerable variability in the way in which these costs are accounted for and reported by fishing firms. Given this, it is unlikely that a generic model will adequately be able to estimate freight and marketing costs, but fishers in data poor fisheries may be able to provide information on prices net of these charges. Since most data poor fisheries in Australia involve sale of product to a processor with price recorded at that point, this may not be a significant problem in practice.

Crew shares also had relatively low goodness of fit measures as a result of differences in the proportion of paid and unpaid labour in the different sectors. However, the models were generally consistent in that a base assumption of 30-35 per cent modified by the level of average vessel revenue appears to be a good assumption for most fisheries. Within this, the opportunity cost of an owner-skipper's labour appears to be around 5per cent of revenue.

The analysis also provided an indication of the level of economic depreciation that can be used in bioeconomic analysis in both data poor and data rich fisheries. The estimated value of 2.3 per cent is slightly lower than is currently being used in the NPF analysis, which was based on studies overseas. This provides a more appropriate measure for use in Australian fisheries.

The analysis also confirmed the existence of capital stuffing in effort controlled fisheries, suggesting that it is important to take the management context into account in developing estimates of MEY in data poor fisheries, as well as the potential effect on these estimates of current moves to output controls, which may result in lower capital costs in the longer term.

6.3 Proxy target reference points for data poor fisheries

The bioeconomic model detailed in the methods section was run 10000 times, although only 5897 results were useable as 1) some resulted in negative economic profits as MSY and 2) others used negative parameter values (a consequence of the randomly generated variables).

The target reference points were regressed against the key variables to ensure that the variables were having the appropriate effects (Table 6-10). As expected, the ratio of $B_{\mathrm{DMEY}}/B_{\mathrm{MSY}}$ increased with growth rate and cost per unit effort, and decreased with increasing values of the other parameters. Also as expected, increasing the discount rate reduced the ratio of $B_{\mathrm{DMEY}}/B_{\mathrm{MSY}}$. Conversely, the ratio of $\mathrm{E}_{\mathrm{DMEY}}/\mathrm{E}_{\mathrm{MSY}}$ decreased with growth rate and cost per unit effort and increased with increasing values of the other parameters.

Table 6-10. Meta analysis of the simulation results for theoretical consistency check.

	B_{MEY}/B_{MSY}			E_{MEY}/E_{MSY}		
	Coefficient	Std. Error	t value	Coefficient	Std. Error	t value
Constant	2.750	0.011	244.67	-0.750	0.011	-66.79
r	0.019	0.003	6.48	-0.019	0.003	-6.47
q	-128.50	1.36	-94.26	128.50	1.36	94.33
K	-0.0005	0.0000	-123.77	0.0005	0.0000	123.83
c	0.016	0.000	123.24	-0.016	0.000	-123.33
p	-0.047	0.000	-127.00	0.047	0.000	127.09
D	-0.142	0.029	-4.83	0.143	0.029	4.84
$\bar{R}^2$	0.8808			0.8807		
F	5381			5388		

See section 5.3.2 for the definition of the variables and parameters included in this table

The model was also run with the discount rate fixed at various levels. The distribution of the target reference points at the 5 and 10 per cent discount rate is illustrated in Figure 6-9. From Figure 6-9, in most cases, B_{DMEY}/B_{MSY} >1, while E_{DMEY}/E_{MSY} < 1, with the former being distributed mainly between 1.1 and 1.4 and the latter between 0.6 and 0.9. At higher discount rates, the distribution of B_{DMEY}/B_{MSY} shifts to the left, and that of E_{DMEY}/E_{MSY} shifts to the right.

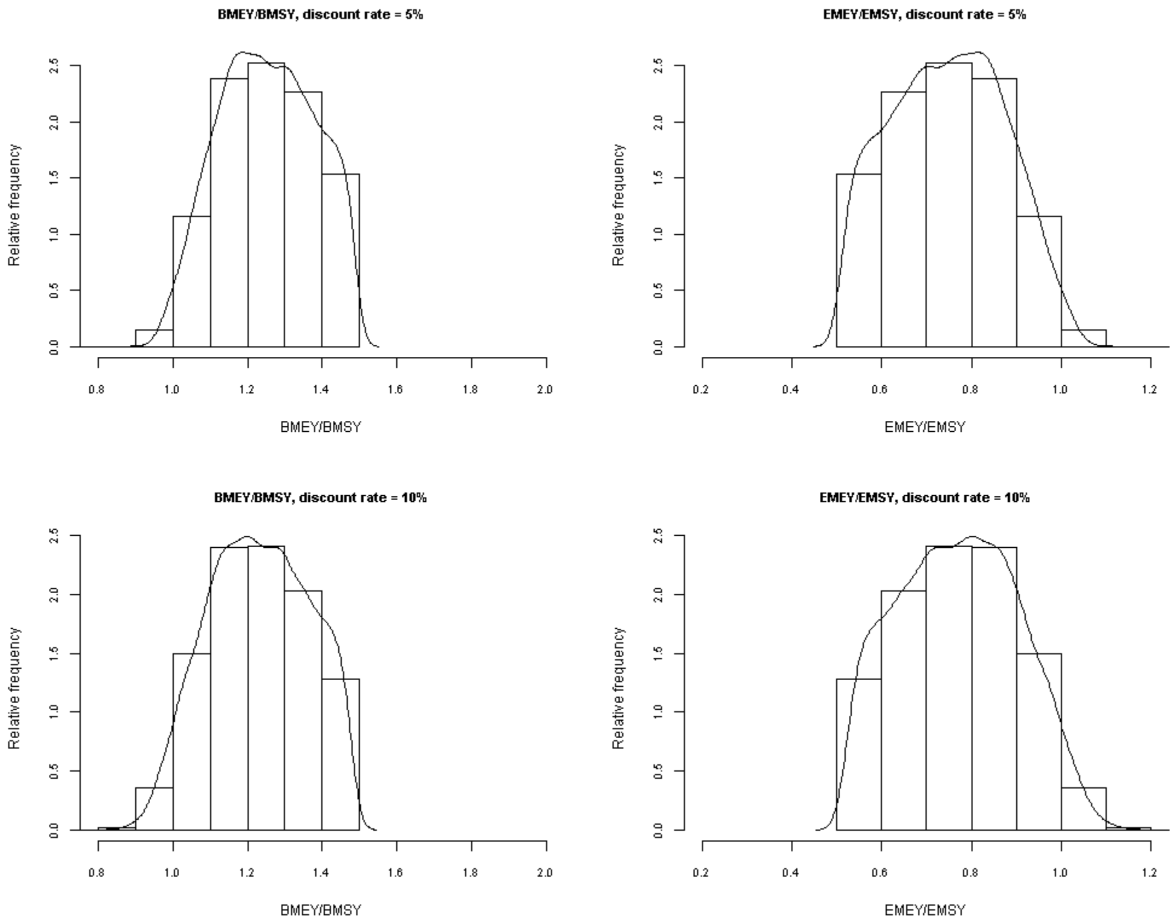


Figure 6-9. Distribution of dynamic target reference point ratios.

6.3.1 FRAMEWORK FOR DETERMINING APPROPRIATE ECONOMIC TARGET REFERENCE POINTS WITH LIMITED INFORMATION

In data poor fisheries, it is unlikely that the values of the key biological and economic parameters will be known. Garcia et al (1989) demonstrated that reasonable estimates of B_{MSY} and E_{MSY} can be made with very limited data, based on a few assumptions about the characteristics of the fishery. Similarly, reasonable estimates of cost per unit of effort and prices could be obtained through a similar approach.[10]

[10] The earlier section of this report demonstrated that reasonable estimates of costs can be obtained based on limited information on the characteristics of the fishing fleet and its activity. Prices are more readily observed from market transactions.

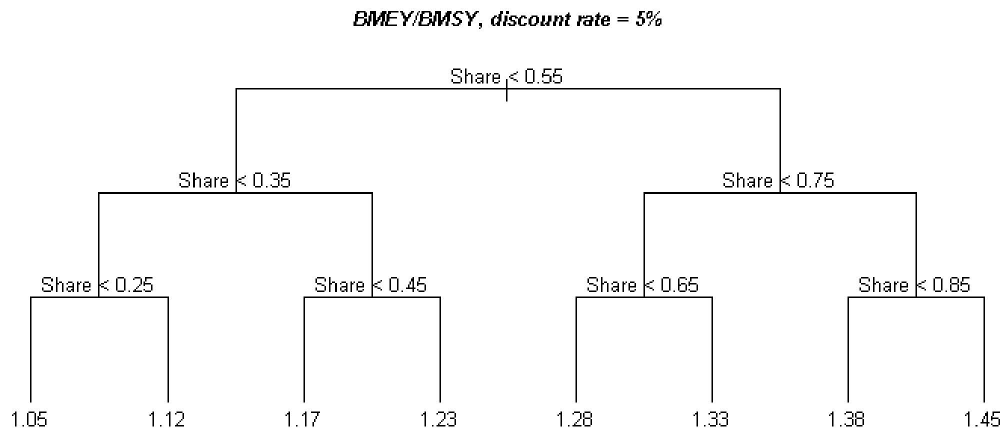
From Equation 5-1 and Equation 5-2, both B_{DMEY}/B_{MSY} and E_{DMEY}/E_{MSY} is dependent upon the $c/(pqK)$ where $c/(qK)$ effectively represents the cost per unit catch given an unexploited biomass, which is unknown. However, given that the catch per unit of effort at MSY is given by $0.5qK$ (as $B_{MSY} = 0.5K$), then the cost per unit of catch at MSY is equivalent to $c/(0.5qK)$ which is proportional to the cost per unit catch given an unexploited biomass.[11] Consequently, the cost share of revenue, defined as the cost per unit catch divided by the price,[12] at MSY is a feasible proxy measure by which the optimal ratio of biomass and effort can be derived. In the dynamic model, B_{DMEY}, and hence E_{DMEY}, is also dependent on the ratio of the discount rate to the growth rate (from Equation 5-3).

A regression tree analysis was undertaken with cost share and the ratio of the discount rate to the growth as the explanatory variables. These were undertaken for a given discount rate as this is generally determined exogenously for all fisheries (and public policy) analyses. For the analyses using four standard discount rates (0, 0.05, 0.1 and 0.5), the tree was split only in terms of the cost share component. This is illustrated for the 5 per cent discount rate case in Figure 6-10 (and the other discount rates in Annex). The residual mean deviance of both models was extremely low (0.0004726 for the 5 per cent discount rate model) indicating that the regression tree provided a good representation of the characteristics of the data. The distribution of the error terms (Figure 6-11) also suggests that the model captures most of the variation in the ratios. The current proxy value for B_{DMEY}/B_{MSY} adopted in Australian fisheries management is 1.2 (DAFF 2007), and the commonly adopted discount rate for MEY estimation is 5 per cent (Punt et al. 2010). From the tree in Figure 6-10, this figure is appropriate for fisheries where the cost share is expected to fall between (roughly) 45 and 55 percent. That is, expected economic profits at MSY are also between 45 and 55 percent of revenue. According to this analysis, a B_{DMEY}/B_{MSY} ratio of 1.2 would appear to be conservative in fisheries with a cost share greater than 65%, where a ratio of 1.33 to 1.45 would appear to be more appropriate.

---

[11] The value 0.5qK is equivalent to the catch per unit effort (CPUE) at MSY.

[12] This can also be estimated as total cost divided by total revenue, which was the approach used in the subsequent analysis.



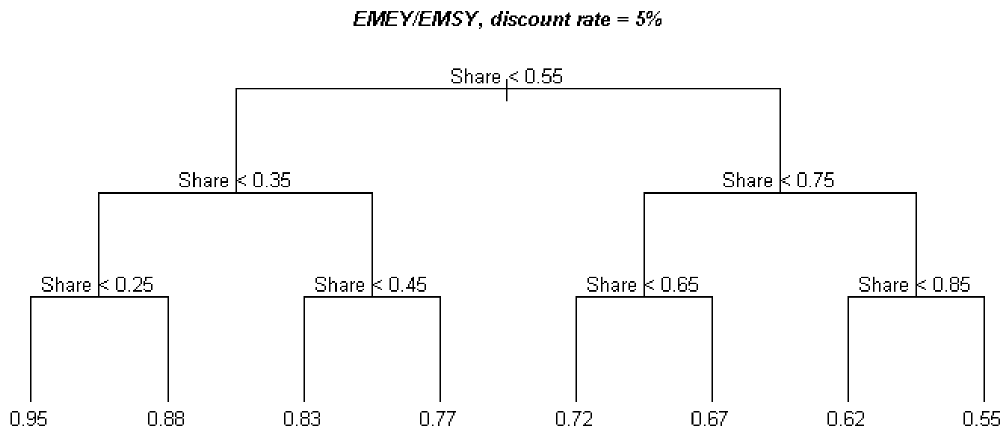


Figure 6-10. Predicted B_{DMEY}/B_{MSY} and ED_{MEY}/E_{MSY} ratios as a function of the economic characteristics (cost share) characterizing the fishery, at a 5 per cent discount rate.

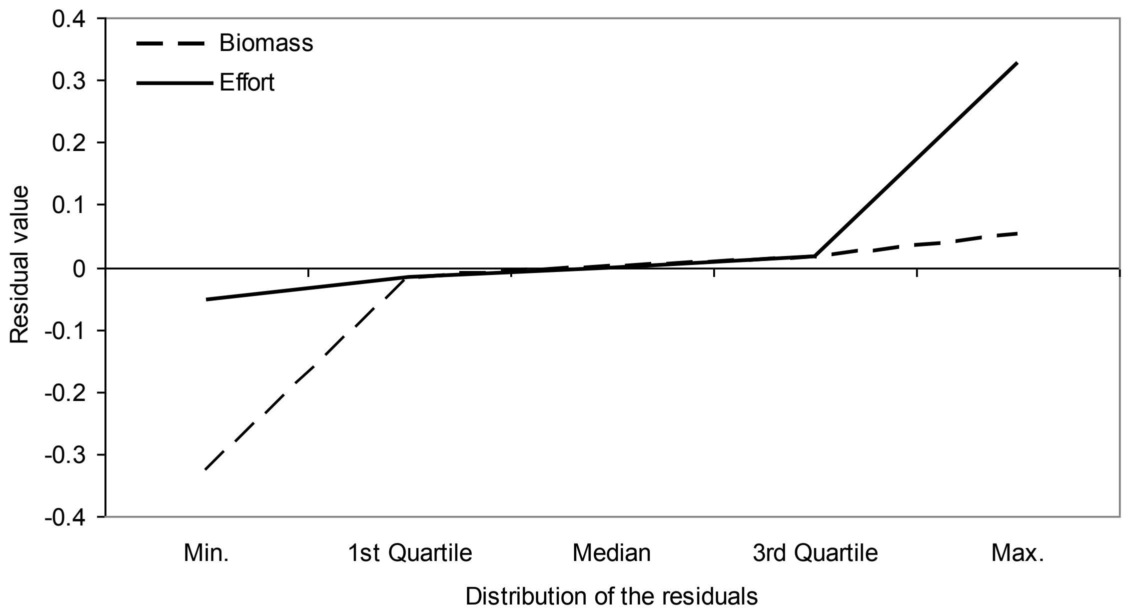


Figure 6-11. Distribution of residuals from the regression tree analysis.

6.3.2 RELATIONSHIP BETWEEN COST SHARES AND FISHERY CHARACTERISTICS

The theoretically derived model results above require some estimate of the cost share of revenue at MSY in order to derive an appropriate proxy for E_{MEY}/E_{MSY}. While these cost shares are unknown, a reasonable estimate of them may be made based on the economic data used in the previous analysis. The objective of MEY has only been implemented since 2007, and only one fishery (the Northern Prawn Fishery) has had an active policy of moving to MEY (Dichmont ea al. 2010), although to date this has not been realised. For the other fisheries, and prior to 2007, the main management objective remains linked to maximising sustainable yields. While these were not necessarily achieved each year and in each fishery (Woodhams et al. 2012), on balance it could be assumed that the observed cost share of revenue was roughly equivalent to the costs shares at or near MSY for most of the period of the data.

The distribution of cost share of revenue in each of the fisheries for which economic data were available is given in Figure 6-12. Median cost shares for the SA fisheries appeared lower than those of the Commonwealth fisheries, although they were subject to considerably greater variability.

A priori there is an expectation that cost shares in ITQ fisheries would be lower than those in input control fisheries due to the different incentives faced (Asche and Eggert 2008). This is supported to some extent by the data, although there is not a clear significant difference between the cost shares solely on the basis of management type (Figure 6-13).

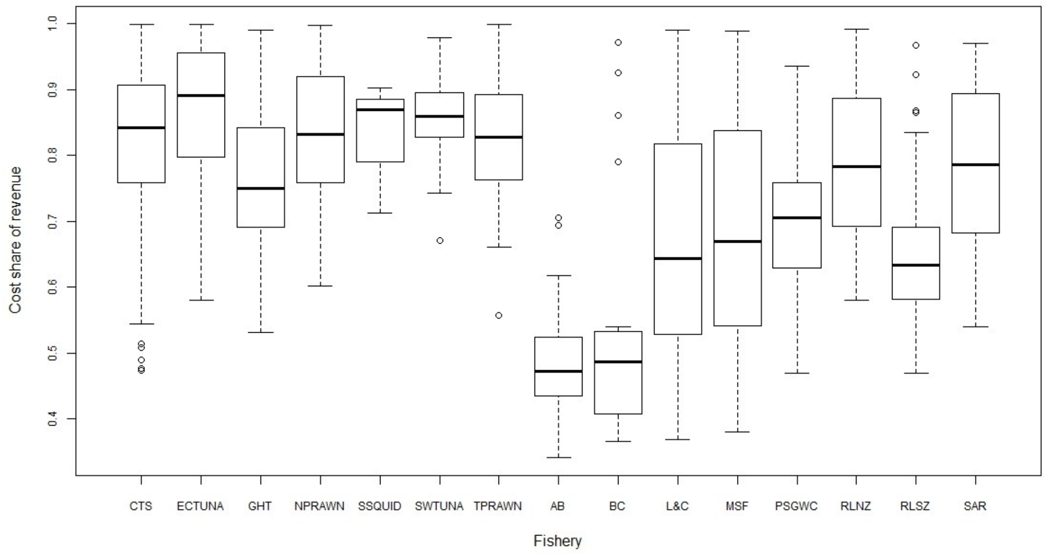


Figure 6-12. Distribution of cost share of revenue in fisheries with economic survey data.

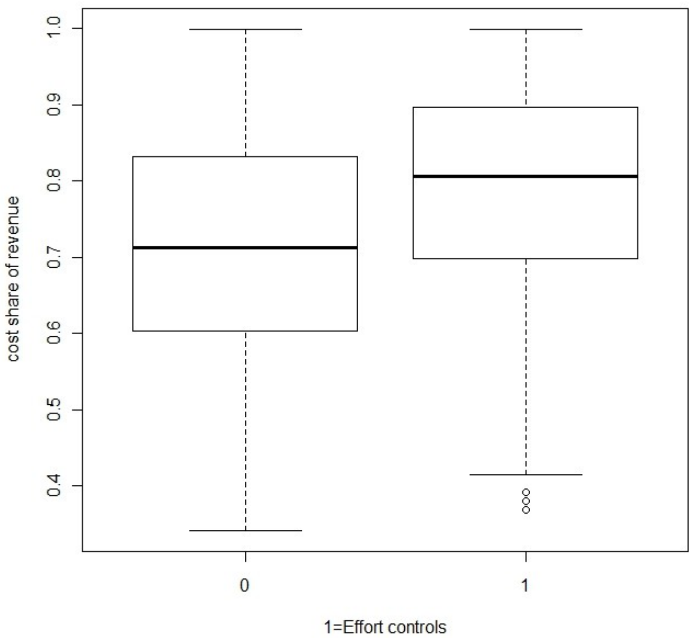


Figure 6-13. Cost share by management type.

The relationship between cost share of revenue and fishery characteristics was examined through simple regression analysis. A priori, it was expected that boat size, fishing method (expressed as dummy variables with trawl as the base), management method (i.e. ITQ or effort controls), and potentially average price would affect the cost share of revenue. A log linear form of the model was assumed.

The results of the model are given in Table 6-11. The explanatory power was relatively low (33%), although this is as expected given the considerable variability between individual observations in the data. However, most of the signs on the coefficients were as expected: fisheries with higher prices are likely to have a lower cost share (as revenues are higher, ceteris paribus); larger boats are likely to be higher cost than smaller boats relative to revenue, and cost share differed by main fishing method. The coefficient on the effort control was negative, although this was not significantly different from zero suggesting that effort control fisheries do not have a significantly higher cost share than output control fisheries (consistent with the distribution in Figure 6-13).

Table 6-11. Regression results for lnCostShare

	Estimate	Std. Error	t value	
Constant	-0.365	0.059	-6.149	***
lnPrice	-0.045	0.010	-4.450	***
lnLength	0.078	0.018	4.245	***
Method dummy variables				
Dropline	-0.083	0.027	-3.049	***
Trawl prawn	0.029	0.026	1.122	
Gillnet	-0.125	0.023	-5.437	***
Pots	-0.101	0.027	-3.725	***
Dive	-0.369	0.042	-8.824	***
Longline	0.061	0.020	3.067	***
Danish seine	-0.091	0.028	-3.197	***
Purse seine	-0.166	0.043	-3.868	***
Effort control dummy	-0.001	0.017	-0.047	
$\bar{R}^2$	0.338			
F	61.38			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The coefficients on dropline, gillnets, pots and Danish seine were not significantly different from each other. While Danish seine is a trawl based method, it is very different to other trawl methods so a cost share similar to other static gears is not surprising. For the subsequent analyses, these four gear types were amalgamated into an “other static gear” variable. Prawn trawl was not significantly different than other (fish) trawls.

As the aim of the study was to develop proxy estimates of MEY from limited data, a regression tree analysis was run with cost share as the dependent variable and price, length, and gear types (trawl, dive, long line, purse seine and other static gear) as the explanatory variables. The resultant tree is illustrated in Figure 6-14, and the distribution of residuals given in Figure 6-15. The residual mean deviance was 0.014, and in most cases the residuals were less than 0.1. Given individual variability in the fisheries between vessels and between years, this degree of “error” is relatively low, as factors such as individual skipper/crew efficiency and random variations (“luck”) in catch also affect the output and hence cost share of revenue.

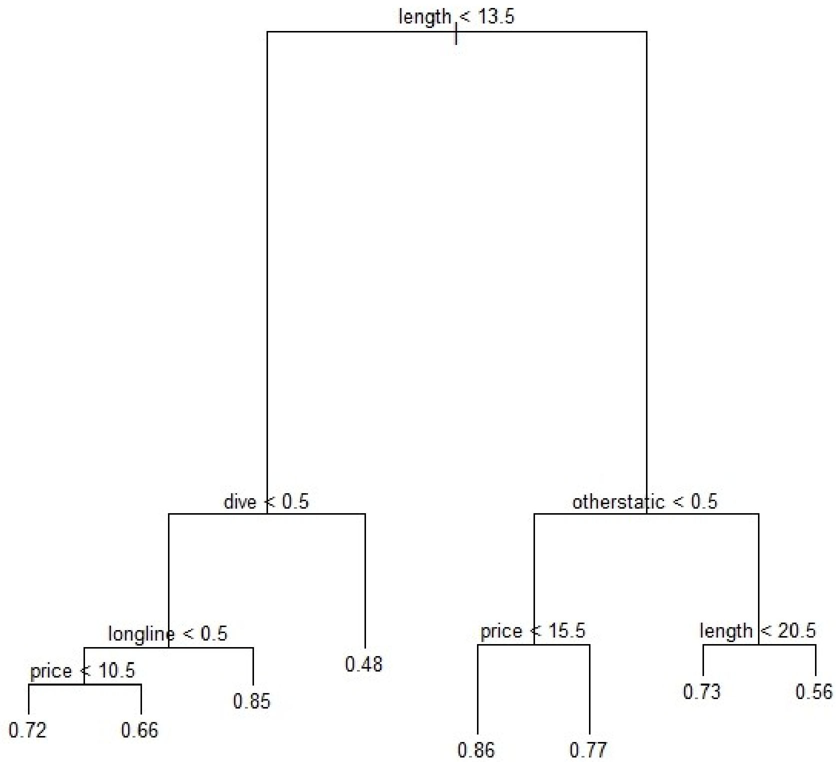


Figure 6-14. Predicted cost share of a fishery, as a function of the its technical and economic characteristics.

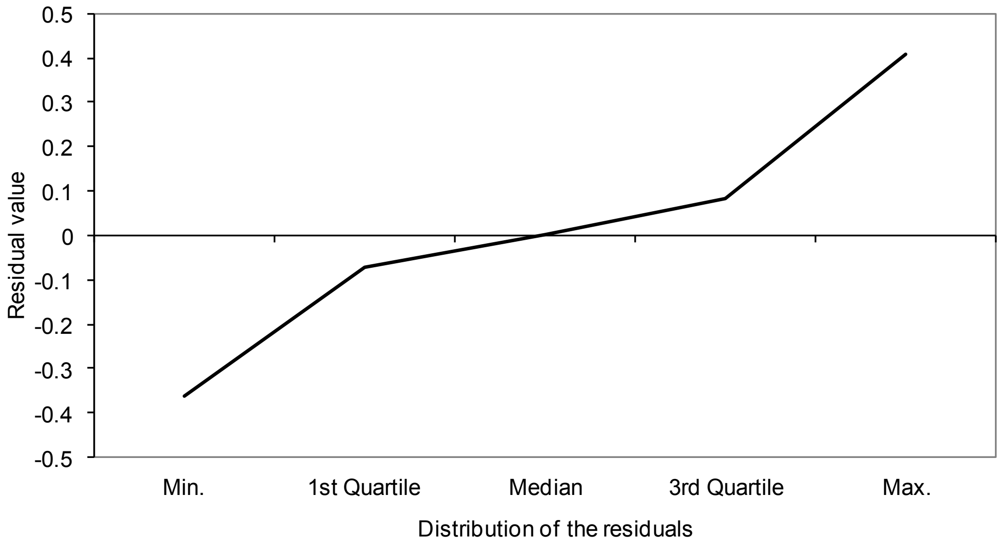


Figure 6-15. Distribution of cost share residuals.

From Figure 6-14, larger boats tend to have higher cost shares than smaller boats, although this is not always the case. For example, based on the data available, small longline vessels and small vessels targeting low valued fish species tend to have comparable cost shares to the larger trawl vessels.

Combining Figure 6-10 and allows an estimate of the ratio B_{DMEY}/B_{MSY} or E_{DMEY}/E_{MSY} to be derived based on limited information on the fishery – effectively some indication of the average price, average boat size and the main fishing methods. From the two figures, for example, a trawl vessel targeting relatively high valued species (i.e. > \$15.50/kg) would have an average cost share of around 0.77 (Figure 6-14), which would imply a B_{DMEY}/B_{MSY} ratio of around 1.38 at a 5% discount rate. A summary of the relationships between fishing gear type, size and price and the ratio E_{DMEY}/E_{MSY} is also presented in Table 6-12.

Table 6-12. Determination of a proxy target E_{DMEY}/E_{MSY} ratio based on the results of our empirical analysis.

Main fishing gear#	Vessel Length Class#	Average first sale price of fish landed ($)#	Estimated cost share of revenue at MSY#	Cost share class*	EMEY/EMSY at 5% discount rate*
Longline	< 13.5m	Any	0.85	> 0.85	0.55
Active gear	> 13.5m	< $15.5	0.86	> 0.85	0.55
Active gear	> 13.5m	> $15.5	0.77	[0.75, 0.85[	0.62
Active gear	< 13.5m	> $10.5	0.66	[0.65, 0.75[	0.67
Active gear	< 13.5m	< $10.5	0.72	[0.65, 0.75[	0.67
Other static gear	> 20.5 m	Any	0.73	[0.65, 0.75[	0.67
Other static gear	[13.5m - 20.5m]	Any	0.56	[0.55, 0.65[	0.72
Dive	< 13.5m	Any	0.48	[0.45, 0.55[	0.77

* See Figure 6-10; # See Figure 6-14

6.3.3 COMPARISON WITH EXISTING ESTIMATES OF E_{MEY} AND B_{MEY}

Relatively few studies have attempted to quantity the revenue share of economic profits at MSY although several studies have looked at the potential share of profits in the fishery at MEY. Dupont (1990) found that in the Canadian Pacific salmon fishery, potential economic profits were about 42 per cent of total revenue. Potential economic profits were estimated to be between 20-30 per cent of revenue for Denmark, Sweden and the UK, and even higher for Iceland and Norway (Asche and Eggert 2008; Pascoe and Mardle 2001). Assuming that economic profit at MSY is around half that at MEY[13] such that the ratio of economic profits to revenue at MSY ranges between 10-20 per cent, then more appropriate "default" proxy values for B_{MEY} may be 1.3-1.4 times B_{MSY}. Similarly, it might be expected that optimal effort levels are most likely to fall between 55 and 65 per cent of those at MSY.

[13] This relationship varies substantially depending on the relative costs and prices. For some fisheries economic profits at MSY may be small relative to those at MEY whereas in other fisheries the difference in economic profits may be small.

MEY has been assessed for the Northern Prawn fishery (Punt et al. 2011). This is a relatively high cost per unit effort fishery, and with a low catch is a relatively high cost per unit catch fishery also. Based on the most recent published economic survey estimates, total costs were roughly 84 per cent of revenue for the fishery as a whole in 2008-09 (Vieira et al. 2010). Estimates of B_{MEY}/B_{MSY} for the three primary species in the fishery were 1.15, 1.255 and 1.38, with the stocks in 2009 (the reference year for the analysis) for the latter two believed to be close to, but above, MSY (Punt et al. 2011). From the regression tree, a proxy value of 1.38 would have been selected (i.e. 0.75< cost share < 0.85) as appropriate for the fishery, reasonably consistent with at least one of the key target species and not substantially greater than the bioeconomic model estimates for the other two species. This also corresponds to the illustration given above based on the combination of both regression trees, where a trawl vessel targeting high value species on average would have a cost share of around 0.77 and a proxy value of 1.38.

Estimates of the ratio B_{MEY}/B_{MSY} have also been undertaken for several species in the South East Trawl fishery, with values ranging from 1.06 for flathead (taken primarily by Danish seiners) to 1.53 or orange roughy (taken primarily by large trawlers), with an average of 1.26 for the set of species considered (Kompas). Published economic survey results for the fishery as a whole suggest that, in 2009-10, economic profits and total costs were roughly 21 per cent and 79 per cent of the total revenue respectively (Perks and Vieira 2010). Based on the cost share regression tree model, the optimal ratio of B_{MEY} to B_{MSY} would again be 1.38, substantially overestimating the optimal values of some species and underestimating them for others. However, several of the species are overfished or are subject to overfishing, and hence lower costs per unit of catch would be expected at higher stock levels (such as B_{MSY}). Adjusting for this would result in a lower optimal biomass ratio (or higher effort ratio) using the regression tree model.

The example fisheries above are all multispecies fisheries, which add an extra complexity to the analysis. The models used in this analysis were based on a single species fishery. In multispecies fisheries, the optimal harvest rate of any individual species in a fishery subject to joint production may differ from the optimal harvest rate of the species if it was a single species fishery. Nevertheless, the proxy values for the relative target reference points based on the single species model were closer to that estimated using a multispecies bioeconomic model than the base assumption of B_{MEY}=1.2B_{MSY}.

Modifying the models to allow for multispecies fisheries with joint production is the subject of a follow on project, the preliminary results of which should be available next year. From the more detailed models, the optimal ratio of B_{DMEY}/B_{MSY} varies by species. However, in multispecies fisheries where the species are caught jointly, there will be only one measure of effort that maximises profits across the fishery (E_{MEY}), and one measure of effort that maximises overall sustainable catch (E_{MSY}), so effort based target reference points may be of more value as a fisheries management tool than biomass based measures in multispecies fisheries.

6.3.4 DISCUSSION

Proxy measures for economic target reference points

The 2007 Australian Commonwealth Fisheries Harvest Strategy Policy established that levels of commercial fish stocks should be managed such that they equal the stock size required to produce maximum economic yield (B_{MEY}). For many fisheries where there is limited availability of biological and economic data, detailed modelling techniques are not available to assess the likely value of this reference point. There is thus a need to develop innovative methods for incorporating economics into harvest strategies without bio-economic models.

The economic component of the project aimed to develop a methodology allowing proxy measures for maximum economic yield to be identified where economic information is limited. The economics component of the project involved three main activities: reviewing the literature on estimating proxy measures for MEY in data poor fisheries; estimating costs structures in fisheries where information was limited; and deriving “rules of thumb” that link fishery characteristics to ratios of B_{MEY} to B_{MSY}.

Literature review

Relatively few previous studies had attempted to estimate economic target reference points in data poor fisheries. Most studies in data rich environments developed bioeconomic models from which target reference points could be developed. The use of capacity utilisation measures have been proposed as a method in data limited environments as an indication as to the level of excess capacity in a fishery, and also to estimate what a fully efficient fleet may look like for a given target catch level. Capacity analysis ranged from approaches that just relied on catch and effort data, to more detailed approaches that incorporated economic information also (costs of fishing and prices). Other data poor approaches – aimed at more harvest control rules – involved catch per unit effort indicators. For example, with falling catch rates the allowable (or target catch) is reduced and vice versa. An explicit economic target is often not possible except through stakeholder agreement.

Estimating cost structures in a data poor environment

The use of bioeconomic models is the most appropriate means of deriving economic target reference points, although these require information on both biological and economic features f the fishery. Simple biological models can be developed from catch and effort data (e.g. surplus production models or biomass dynamics models), but some indication of costs of fishing is still required.

The second stage of the study aimed at identifying a generic approach to estimating the key economic variables determining the profitability of fishing operations, based on the data that are likely to be readily available for fisheries (in the absence of actual economic data). The approach was based on econometric modelling of the main cost components of fishing operations, using information on the technical characteristics of fishing vessels and their fishing activity that is generally available. Economic data for a wide range of fisheries (both Commonwealth and South Australian) was used to derive simple relationships between the costs of fishing and the type of fishing activity. The key cost components that were modelled were variable costs (separated into fuel and oil, crew, freight and marketing, and other variable costs), quasi-fixed costs (including repairs and maintenance costs), fixed costs and capital and depreciation costs. Modelling prices was also considered, although discussions with a range of stakeholders and managers suggested that reliable estimates of prices could be obtained from industry with minimal complexity, and hence there was little value added in developing models for these.

Results of the analysis suggest that reasonable estimates of several key cost components may be made for data poor fisheries given some information on the average size of the vessels, their main fishing gears, the number of days fished, the type of management under which vessels operate, and the business structure of the fishing firms. While input price data are generally unavailable for fisheries, indexes of agricultural input prices provide a guide to changes in fisheries input prices, and the models provide an indication as to how much these need to be adjusted (up or down) to reflect price trends in fisheries.

The two models that were statically the weakest were freight and crew shares. Freight costs appear to be very fishery specific, depending on the distance of the market, level of vertical integration, type of market (export or domestic), product form and value of the species. However these variables explained only a small proportion of the variation in freight costs, suggesting that there is considerable heterogeneity in fisheries as to how fishers sell their product, and also considerable variability in the way in which these costs are accounted for and reported by fishing firms. Given this, it is unlikely that a generic model will adequately be able to estimate freight and marketing costs, but fishers in data poor fisheries may be able to provide information on prices net of these charges.

Crew shares also had relatively low goodness of fit measures as a result of differences in the proportion of paid and unpaid labour in the different sectors. However, the models were generally consistent in that a base assumption of 35 per cent modified by the level of average vessel revenue appears to be a good assumption for most fisheries. Within this, the opportunity cost of an owner-skipper's labour appears to be around 5 per cent of revenue.

The analysis also provided an indication of the level of economic depreciation that can be used in bioeconomic analysis in both data poor and data rich fisheries. The estimated value of 2 per cent has already been adopted for use in bioeconomic models of major Australian fisheries.

The analysis also confirmed the existence of capital stuffing in effort controlled fisheries, suggesting that it is important to take the management context into account in developing estimates of MEY in data poor fisheries, as well as the potential effect on these estimates of current moves to output controls, which may result in lower capital costs in the longer term.

Proxy measures for MEY

The third stage of the research involved determining a methodology to identify proxy measures for E_{MEY} (and B_{MEY}) in fisheries in which only limited data are available. This involved identifying a generic model linking effort and fishing mortality at MSY, which a range of simple methods allow to estimate even with very limited catch and effort data, to effort and fishing mortality at MEY. Based on the static version of this generic model, it was then shown that the cost share of revenue - defined as the cost per unit catch divided by the price per unit catch - at MSY is a feasible proxy measure by which the optimal ratio of biomass and effort can be derived. In the dynamic model, optimal effort and biomass levels are also dependent on the ratio of the discount rate to the growth rate of the fish stock.

While these cost shares of revenue at MSY are generally unknown, it was possible to derive reasonable estimates of these from the economic data used in the empirical analysis. The main variables influencing these cost shares were shown to be the vessel length, the fishery types to which they belong, as well as the average beach price of the fish landed by the vessels. Based on knowledge of these variables for a particular fleet, it is thus possible to estimate the likely cost share of this fleet, and from this, using the results of the generic model, to estimate the likely ratio of E_{MEY} to E_{MSY} for this particular fishery. Given that E_{MSY} can be readily estimated in data poor contexts, this provides a set of tools by which proxy targets for achieving maximum economic yield can be identified in these fisheries.

Biological analysis — developing methods for biological reference points for data-poor fisheries

6.4 Simple catch rate gradient based harvest control rules for data-poor fisheries

In this section, we demonstrate the method described in section 5.4, Simple catch rate gradient based harvest control rules for data-poor fisheries., using Flathead (*Neoplatycephalus richardsoni*) as an example.

6.4.1 POPULATION CHARACTERIZATION

The constants used to condition the operating model were based on the latest Flathead assessment for the Australian east coast down to the north of Tasmania in the SESSF (Klaer, 2011), these included details of weight at age, maturity, steepness, and related parameters (Table 6-13; Figure 6-16).

Table 6-13. Series of constant input into the operating model (see Appendix 2) to condition it to be similar to a Flathead (*Neoplatycephalus richardsoni*). See Klaer, 2011.

Parameter	Value	Parameter	Value
M	0.27	Age @ 50% Maturity	2
L_∞	55.9	0.5 Interquartile Distance	0.75
K	0.175	SSB0	36000
t0	-1	SigmaR – recruitment	0.35
Growth CV	0.096	SigmaCE – catch rates	0.1
Weight at Length a	0.00000588	catchability	1.51E-06
Weight at Length b	3.31	age at 50% selection	3
Steepness	0.62	0.5 Interquartile Distance	0.5

Given the assumption of an unfished spawning biomass of 32,000t and the other parameters relating to productivity this led to an expected Maximum Sustainable Yield (MSY) of 2,356 t at a depletion level of 32.9%*SSB*0. The steepness of 0.62 implies a significant decline in average recruitment as the stock size declines (Figure 6-16). This implies that there would be a decline in the number of fish at ages and sizes below those that would be selected by the fishery (Figure 6-17).

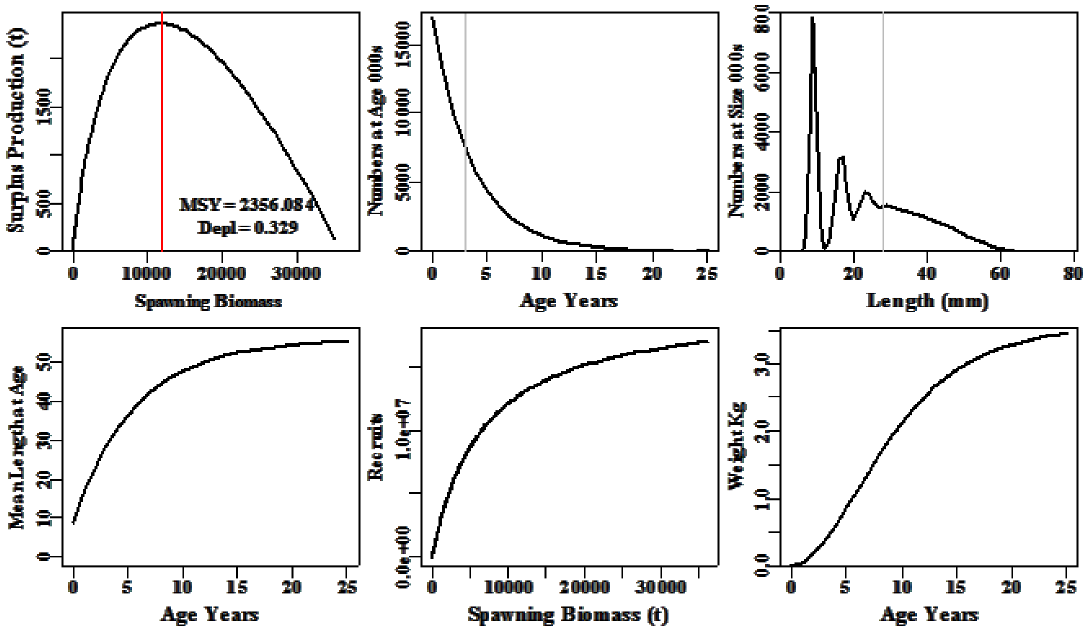


Figure 6-16. Characteristics of the unfished simulated population used in the management strategy evaluation. The top left graph depicts the production curve with an MSY of 2,356t at a depletion level of 32.9%SSB_0. The cohort structure of the unfished stock in the top left graph omits the 0 year old fish for clarity. The vertical grey line in the top right graphs is the age and size at 50% selection. The spawning stock – recruitment relationship is illustrated in the middle of the bottom line of graphs.

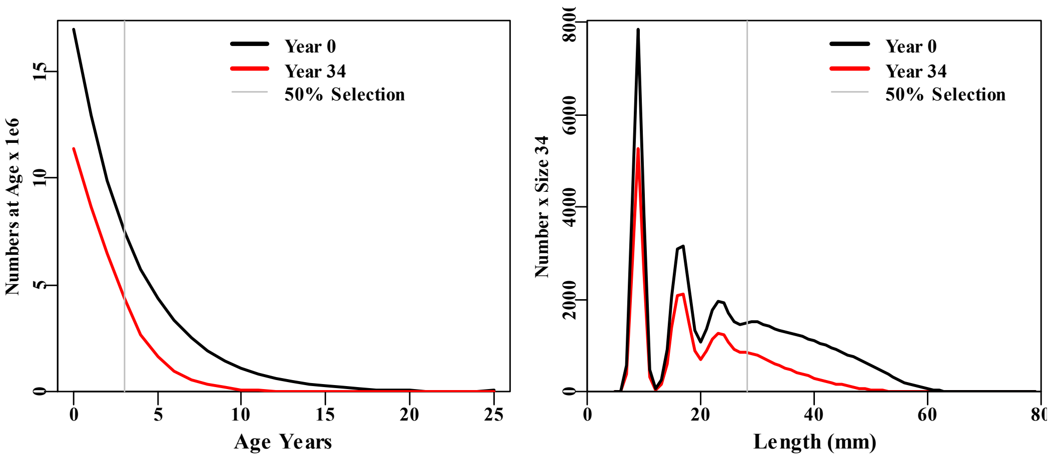


Figure 6-17. By fishing the unfished population with a constant catch of 2,300t for 35 years the stock is depleted to a level of 26.95% SSB0. The vertical grey lines are the age and size at 50% selection.

6.4.2 DIFFERENT INITIAL DEPLETION LEVELS WITH CONSTANT CATCH AND CATCH RATES

The outcome from applying a constant catch to the fishery and then applying the HCR is at least partially dependent upon what catch rates are exhibited in the last few initialization years. If catch rates are essentially flat and the TAC is set initially at the constant catch being applied, then the outcome is effectively the status quo in terms of catches, catch rates, and TAC (Figure 6-18, Figure 6-19, and Figure 6-20; Table 6-14). When the initial depletion level is above about 20%*B*0 the outcome of applying the HCR is usually a slight reduction in the final TAC and a slight increase in the spawning biomass (Figure 6-20). If the initial depletion is below 20%*B*0 the end result of applying the HCR changes to involve a slight increase in TAC and in the spawning biomass, however, these changes only appear to begin after about 15 – 17 years of applying the HCR. The increase in spawning biomass, however, is only a little more than 2% and so it could not be claimed that this HCR is capable of rebuilding depleted stocks.

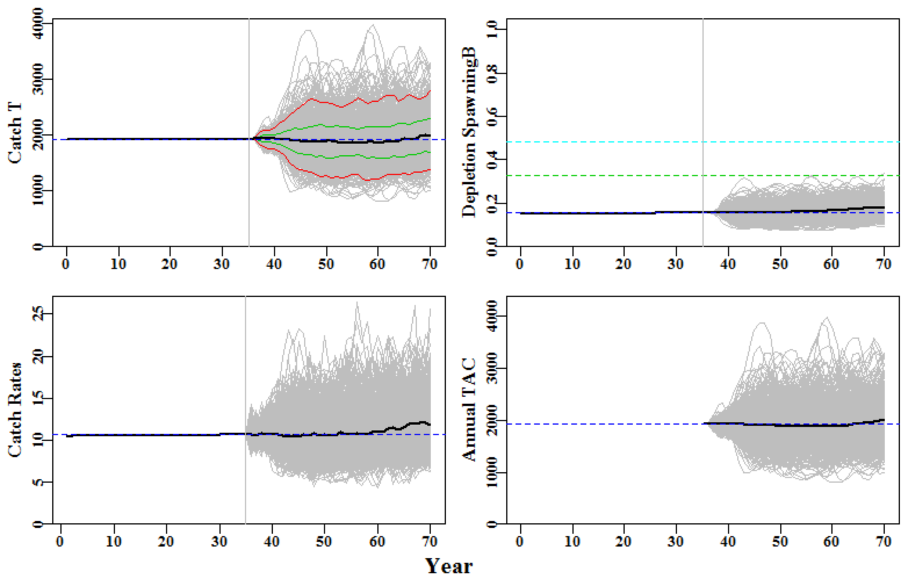


Figure 6-18. The simulation outputs when the unfished fishery is first depleted to 15.4%*B*0, then fished for 35 years at 1,927t, and then fished for a further 35 years under control of the HCR. The TAC begins at 1,927t and ends at 2,000 and a depletion level of 17.8%*B*0t. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated *B*MSY.

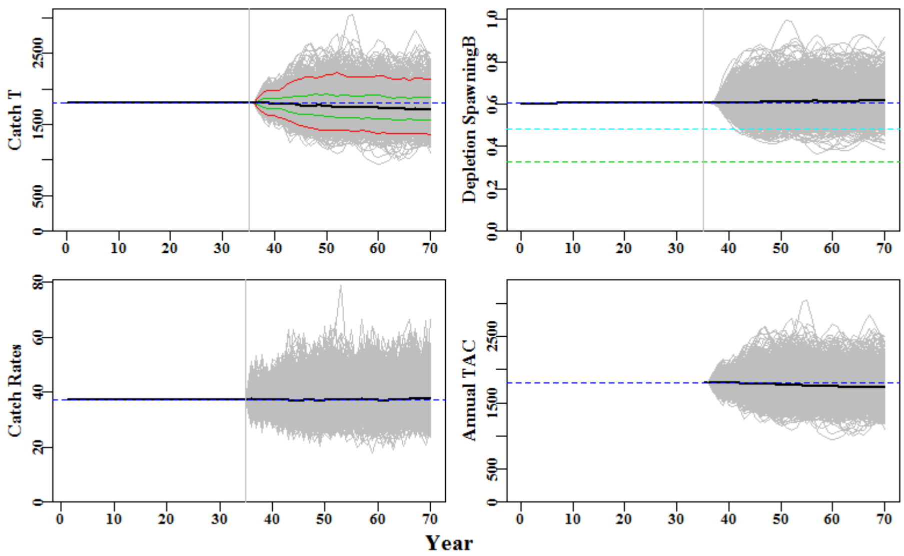


Figure 6-19. The simulation outputs when the unfished fishery is first depleted to 60.5%*B*0, then fished for 35 years at 1,800t, and then fished for a further 35 years under control of the HCR. The TAC begins at 1,800t and ends at 1,729t. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated *B*MSY.

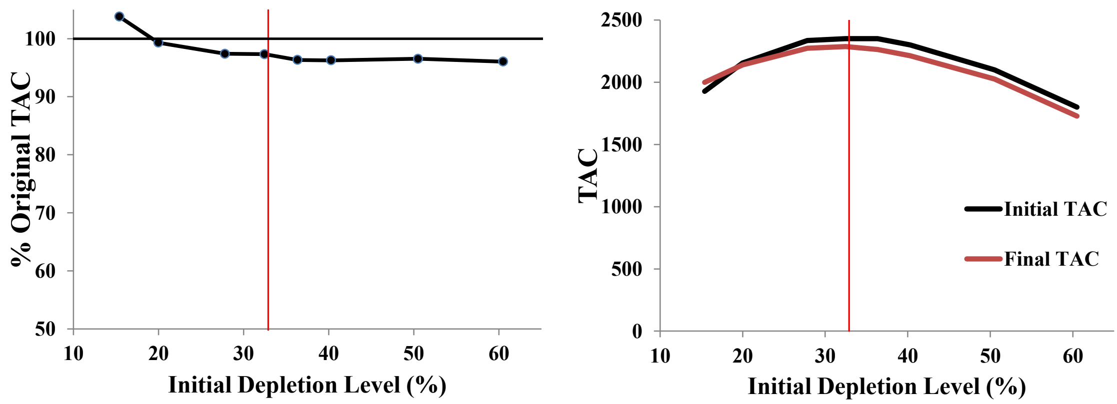


Figure 6-20. The outcome of applying the HCR for 1000 runs. At spawning biomass levels above the *B*MSY and down to about 25%*B*0 the mean TAC in the final year is about 96.5% of the original TAC. At and below 25%*B*0 the final TAC moves closer to the initial TAC until below about 20%*B*0 the final TAC is proportionally greater than the initial TAC. The absolute amount of the initial TAC needed to vary in order to achieve the different initial spawning biomass depletion levels with relatively flat catch rates. The vertical red line in each graph denotes the *B*MSY.

Table 6-14. Simulation outcomes from applying a constant catch to a stock at a given depletion level when catch rates are relatively flat at the time when the HCR is introduced.

Initial Depletion	15.4	19.99	27.82	32.48	36.35	40.29	50.51	60.5
Final Depletion	17.77	21.91	29.53	34.26	38.01	41.85	51.93	61.64
Catch History	1927	2155	2335	2350	2350	2300	2100	1800
Initial TAC	1927	2155	2335	2350	2350	2300	2100	1800
Final TAC	2000	2140	2274	2287	2264	2214	2027	1729
∆Depletion	2.37	1.92	1.71	1.78	1.66	1.56	1.42	1.14
%InitialTAC	103.79	99.30	97.39	97.32	96.34	96.26	96.52	96.06

6.4.3 DIFFERING INITIAL CATCH RATES

The outcome of apply the HCR is at least partially a function of conditions immediately prior to initiating the HCR. If catch rates are flat and catches are maintained then, in effect, the status quo is maintained (Figure 6-20; Table 6-14). However, if catch rates are declining when the HCR is introduced there will be an immediate decrease in the TAC until the catches approximately match the productivity of the remaining spawning biomass and catch rates stabilize again (Figure 6-21). While this doesn’t lead to a stock recovery the effect of the HCR is that further declines in the spawning biomass can be mostly avoided (Figure 6-21). This also operates when the depletion is not so marked, although the changes to the TAC and other variables are not so dramatic (Figure 6-22).

In addition, when the catch rates are increasing, reflecting increases in the spawning biomass, the introduction of the HCR has the effect of slowing and eventually stopping this increase by stabilizing the spawning biomass level (Figure 6-23). However, in both cases where catch rates were initially declining the decline in spawning biomass was very rapid and stable. In contrast, when catch rates were initially increasing there is a rapid change but only in the rate of change. Spawning biomass continues to increase slowly until it becomes much closer to B_{MSY} (Figure 6-23).

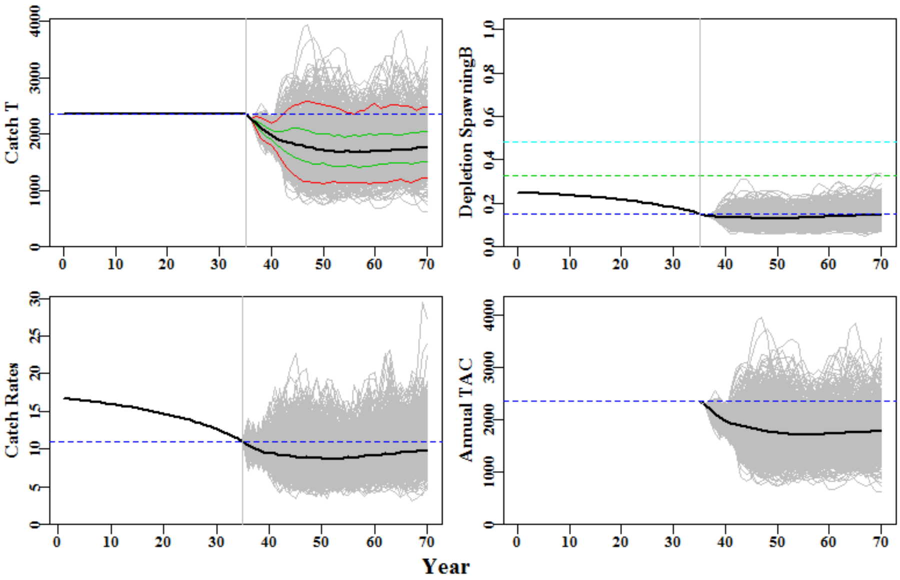


Figure 6-21. The simulation outputs when the unfished fishery is first depleted to 24.77%*B*0, then fished for 35 years at 2,350t, which further depleted the stock to 15.12%*B*0, and then fished for a further 35 years under control of the HCR and an initial TAC of 2,350t, leading to a final TAC of 1,782t. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the central 50% quantiles and the red lines are the central 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated *B*MSY.

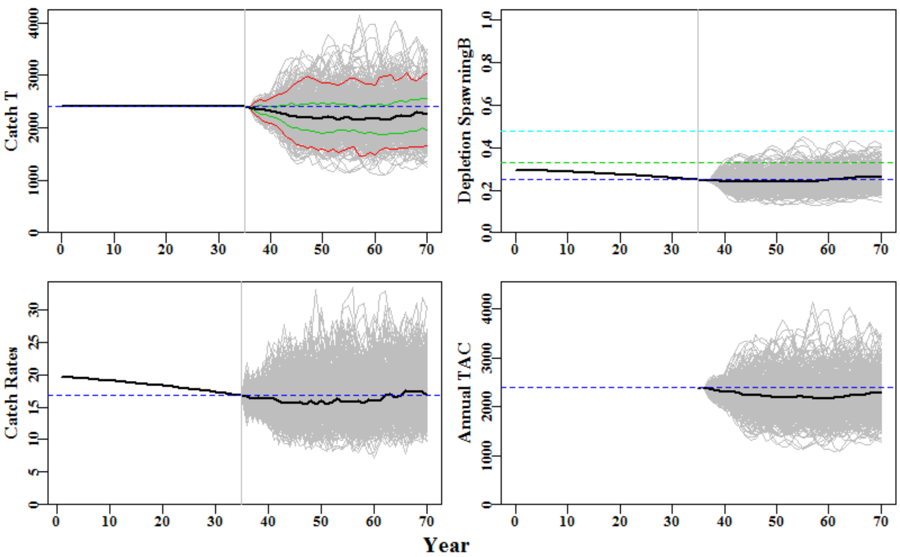


Figure 6-22. The simulation outputs when the unfished fishery is first depleted to 29.56%*B*0, then fished for 35 years at 2,400t, which further depleted the stock to 24.84%*B*0, and then fished for a further 35 years under control of the HCR and an initial TAC of 2,400t, leading to a final TAC of 2,283t. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated *B*MSY.

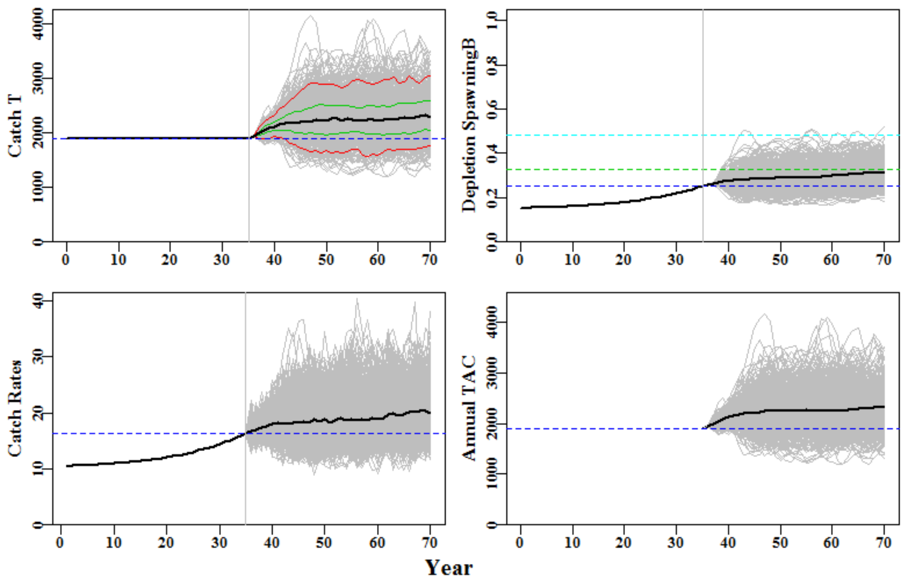


Figure 6-23. The simulation outputs when the unfished fishery is first depleted to 17.56%*B*0, then fished for 35 years at 1,900t, which allows the stock to recover up 25.09%*B*0, and then fished for a further 35 years under control of the HCR and an initial TAC of 1,900t, leading to a final TAC of 2,328t and a depletion level of 31.04%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green solid lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green dashed line is the estimated *B*MSY.

In the case of an initial depleted state but with increasing catch rates it appears as if the HCR slows stock recovery but continues that recovery until the spawning biomass becomes close to the B_{MSY}. While catch rates would continue to increase with stock biomass any increases in TAC beyond the MSY would act to reduce catch rates and hence the HCR would find it difficult to lead to the stock increasing beyond B_{MSY}. When this scenario is run without variation in recruitment or catch rates the effectively deterministic outcome is that some stock recovery still occurs but that it is more limited than when there is variation present.

Thus, in all cases, where catch rates are declining the HCR appears to act to halt the decline in both catch rates and spawning biomass. This reflects that the HCR responds to declining catch rates with decreases in the TAC, which will in turn stop the decline in stock biomass which will stabilize catch rates. The HCR, in its current form, cannot turn the catch rate trend around so that they increase and thus maintain the status quo with regard the state of spawning biomass depletion, but the impact on catches, catch rates, and TACs is dependent upon the manner in which catch rates are changing at the time of introducing the HCR. When the stock is depleted and recovering the maintenance of spawning biomass is not as constrained as when the stock is declining.

6.4.4 ALTERING THE INITIAL TAC AWAY FROM CURRENT CATCHES

Even though the three trials used all had stable CPUE at the onset of the new HCR the alterations to the TAC away from contemporary catches had the effect of introducing contrast into the catch rates, which, in turn, led to significant changes away from the status quo. By comparing Figure 6-18 with Figure 6-24 the dynamics of the fishery changes from barely moving away from the status quo to a significant recovery of the stock biomass.

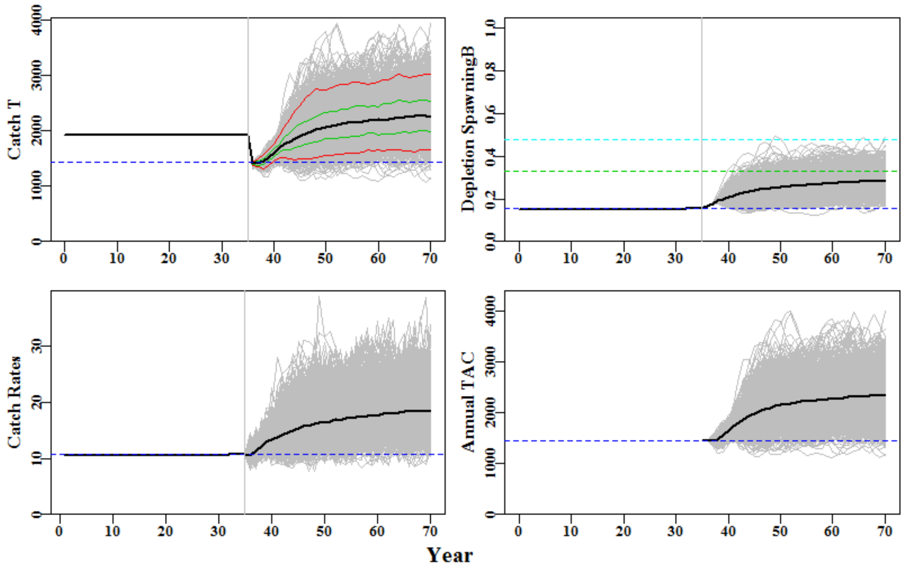


Figure 6-24. The simulation outputs when the unfished fishery is first depleted to 15.4%*B*0, then fished for 35 years at 1,927t, and then fished for a further 35 years under control of the HCR. The TAC begins at 1,445t and ends at 2,340t and a depletion level of 28.3%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green solid lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green dashed line is the estimated *B*MSY.

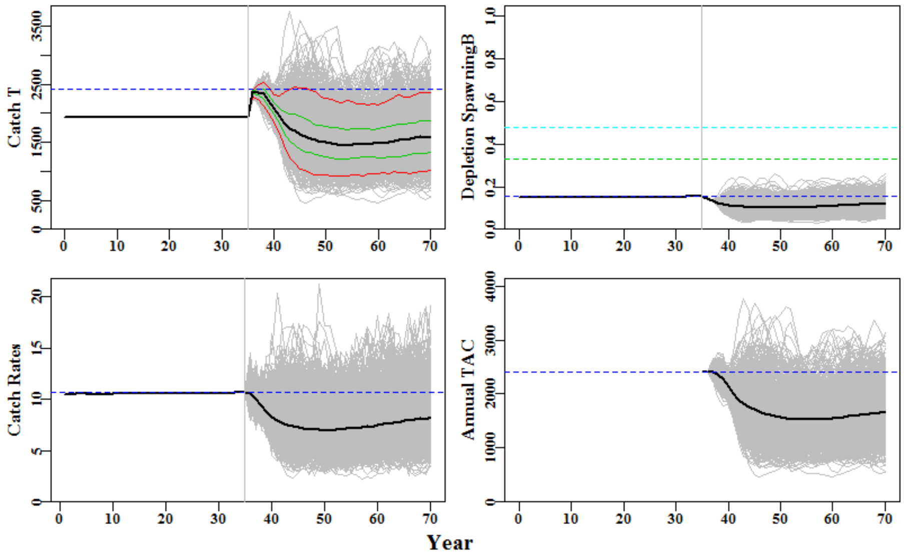


Figure 6-25. The simulation outputs when the unfished fishery is first depleted to 15.4%*B*0, then fished for 35 years at 1,927t, and then fished for a further 35 years under control of the HCR. The TAC begins at 2409t and ends at 1653t and a depletion level of 12.0%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green solid lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green dashed line is the estimated B_{MSY}.

Most of the changes to the stock biomass occur in the first 15 years after which increases in the spawning biomass and in the average catch rate slow markedly. The spawning biomass fails to achieve B_{MSY} but nevertheless, the initial 25% cut in catches leads to almost double the initial spawning biomass with an increase of 12.9% and about an 80% increase in catch rates. If, however, initial catches are increased by 25% the changes in the dynamics occurs more rapidly with most of the changes occurring in the first five – seven years following the introduction of the HCR (Figure 6-25).

By increasing the initial catches when the stock is relatively depleted, the spawning biomass declines further, though only by about 3.4%, however, the TAC and total catches decline significantly through time and while they exhibit slow signs of recovery in the last 10 years of the projections catch rates remain at about 75% of those at the introduction of the HCR.

If the stock is initially depleted to a state very close to B_{MSY}, then, once again, if the initial TAC is set equal to the conditioning catches the status quo is effectively maintained with a final drop in TAC of only about 80 t and the spawning biomass depletion level increasing by 1.8%. However, if the initial

TAC is reduced by 25% to about 1,760 t with the introduction of the HCR then, once again, the spawning biomass level increases along with catch rates while the catches rebound but do not increase above the MSY. The spawning biomass increases from an initial 32.5%*B*0 to 45.0%*B*0, a 12.5% increase (Figure 6-26).

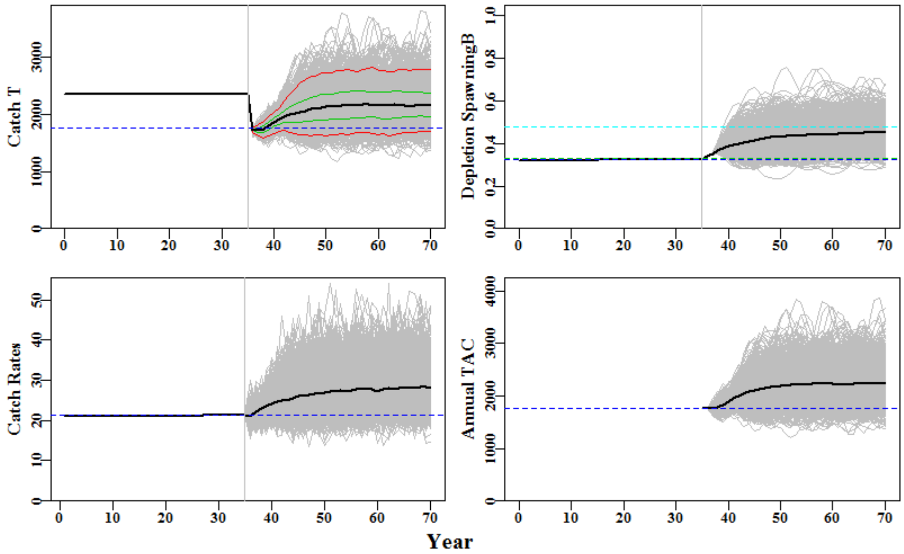


Figure 6-26. The simulation outputs when the unfished fishery is first depleted to 32%*B*0, then fished for 35 years at 2,350t, and then fished for a further 35 years under control of the HCR. The TAC begins at 1762.5t and ends at 2233t and a depletion level of 45.0%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated B_{MSY}.

In contrast, if the initial catches at the introduction of the HCR are 125% of the historical catch levels, once again, the dynamics of the fishery react over between five – seven years and limit the decline in the spawning biomass and catch rates (Figure 6-27).

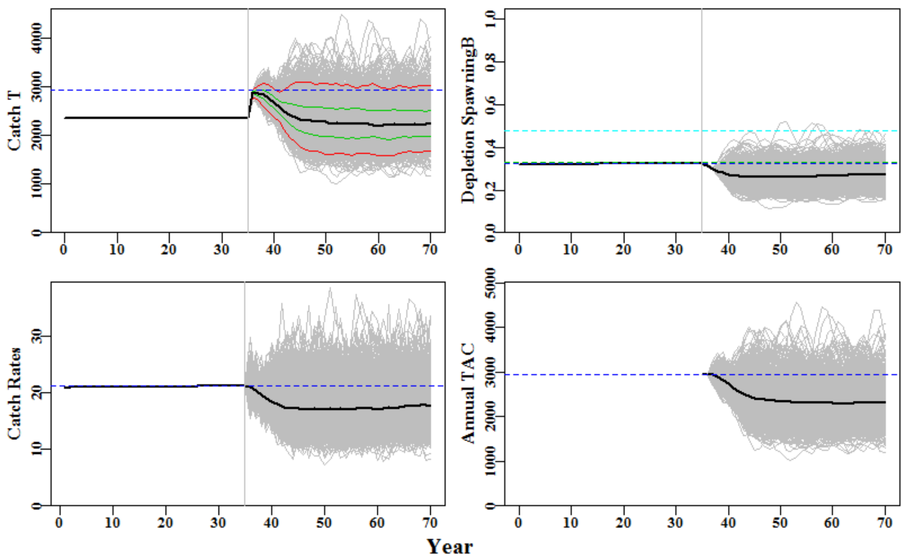


Figure 6-27. The simulation outputs when the unfished fishery is first depleted to 32%*B*0, then fished for 35 years at 2,350t, and then fished for a further 35 years under control of the HCR. The TAC begins at 2937.5t and ends at 2133t and a depletion level of 27.27%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated B_{MSY}.

Finally, if the stock is depleted to a depletion level of about 60.5%*B*0 and fishing continues at the same catch levels that led to the initial state then the depletion level only changes by 1.1% to 61.6%*B*0 and the TAC only declines from 1,800t to 1,729t, a decline of about 70t (Figure 6-19), thereby effectively maintaining the status quo. In this case, if the initial TAC is only 75% of the historical catches there is a rapid but small rise in spawning biomass and catch rates, with associated small rises in catches and TAC (Figure 6-28).

If the initial TAC is 125% of historical catches then over a 15 year period catches (TAC), catch rates, and spawning biomass all decline though only by relatively small proportions (Figure 6-29).

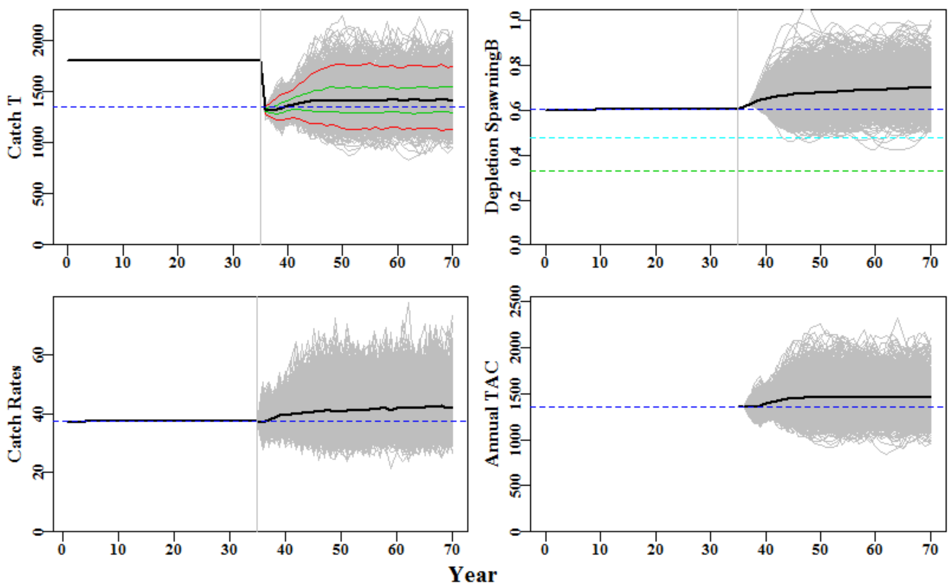


Figure 6-28. The simulation outputs when the unfished fishery is first depleted to 60.0%*B*0, then fished for 35 years at 1,800t, which leads to a depletion state of 60.5%*B*0, and then fished for a further 35 years under control of the HCR. The TAC begins at 1,350t and ends at 1,458t and a depletion level of 69.8%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated *B*MSY.

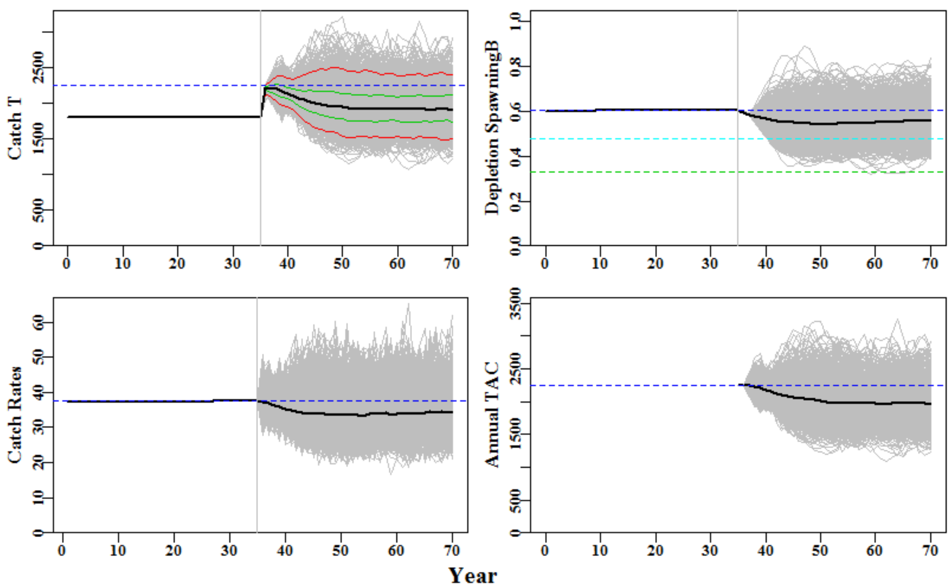


Figure 6-29. The simulation outputs when the unfished fishery is first depleted to 60.0%*B*0, then fished for 35 years at 1,800t, which leads to a depletion state of 60.5%*B*0, and then fished for a further 35 years under control of the HCR. The TAC begins at 1,350t and ends at 1,458t and a depletion level of 69.8%*B*0. The blue dashed line is the value of the variable concerned at the introduction of the HCR. In the catch graph the green lines are the inner 50% quantiles and the red lines are the inner 90% quantiles. In the depletion graph the light blue line is the 48%*B*0 target used in the Commonwealth and the green line is the estimated B_{MSY}.

6.4.5 CONCLUSION

The maximum TAC that can be taken on a continuous basis is the MSY. Catch rates can be expected to decline steadily with stock biomass, however, the surplus production decreases either side of B_{MSY}. The significance of this is that if the TAC is greater than the surplus production then the stock will become more depleted and catch rates will decline leading to a decrease in the TAC. Conversely, if the TAC is smaller than the surplus production then the stock will become less depleted and the cpue will increase leading to an increase in the TAC. The effect of the HCR is to find the balance between these two opposing directions. This is what arrests the increase in stock depletion level when catch rates are declining. The effect in the case of increasing catch rates with a depletion level below B_{MSY}, catches below the surplus production lead to some recovery rather than rapid stability in depletion level because as both the catch rates increase and the stock becomes less depleted the surplus production also increases. Thus achieving the balance of the TAC and the surplus production takes longer than when the stock is declining below B_{MSY}. When the stock is below B_{MSY}, the rate of decline in catch rates accelerates as the depletion becomes worse so the decline in TAC is also faster. These dynamics are what is behind the effects brought about by lowering the initial TAC at the introduction of the HCR. Generally there are other sources of information about the state of depletion in the stock; catches may now be far less than fishers remember. But even if there has been relative stability for a long period, if a drop in catches leads to a large increase in catch rates this can be taken as evidence for significant depletion, especially if the catch rates are maintained once the catches are slowly increased again.

6.5 Results of application of cross-sampling method for estimating gear efficiency, biomass, and fishing mortality rate

In this section 7.5 we use the methods developed in section 5.5 to estimate gear efficiency, biomass, and fishing mortality rate. We applied the methods to five case study species: Tiger Flathead, Jackass Morwong, John Dory, Gemfish, and Ruby Snapper.

6.5.1 TIGER FLATHEAD

Five gear types have caught Tiger Flathead (*Neoplatycephalus richardsoni*): automatic longline, demersal longline (mainly manual longline), Danish seine, gillnet, and trawls. We used data from 2000 to 2012 for estimating gear efficiency. The sampling unit was 1 degree by 1 degree by year. This treatment resulted in a total of 53 unique spatial-temporal grid-year cells and 765 data points. The majority of the cells (50) had only two gear types while 3 cells had 3 gear types.

Gear efficiency

The cross-sampling model using all 5 gear types converged well and there was no abnormal behaviour of the MCMC (estimation) process.

Significant differences in Q existed among gear types (Table 6-15). Danish seine and trawl were the most effective gears for Flathead (median Q_{DS} = 0.84 and Q_{TW} = 0.71), while gillnet was the least effective (Q_{GN} = 0.004). Longlines had similar catchability, with Auto longline (Q_{AL} = 0.03) slightly higher than demersal longline (Q_{BL}= 0.01). The two gears with the highest Q values (trawl and Danish seine) are also the gears that take the bulk of the catch of this species.

Table 6-15. Summary of Bayesian posteriors for gear efficiency of Flathead from logbook data.

Q_k	mean	sd	2.5%	median	97.5%
Auto longline	0.03	0.02	0.01	0.03	0.10
Demersal longline	0.01	<0.01	0.01	0.01	0.01
Danish Seine	0.83	0.09	0.63	0.84	0.97
Gillnet	<0.01	<0.01	<0.01	<0.01	<0.01
Trawl	0.71	0.04	0.62	0.71	0.80

Population size

A total of 126,086 gear deployments (shots) from 2000 to 2012 were included in modelling fish density. Location (lon and lat), depth, and year in the GAM model all had a significant effect on the distribution of fish density (Figure 6-30).

We used year 2009 as an example because this was the latest year with stock-assessment results. Catches of Tiger Flathead occurred in only two large polygons in 2009 (Figure 6-31). The total area of these two polygons was 250,011 km^2. We expanded the predicted log density in each location in the specified year by the area of each polygon to derive biomass. The total biomass in year *y* is the sum across all polygons in the Core distribution area within the SESSF region. This resulted in median fishable biomass B_{2009} = 21,798 t in 2009 with a log scale σ = 0.94. As a comparison, the estimated biomass from the full stock assessment (Klaer 2011) was 23,070 t in 2009, i.e., about 6% higher than our median estimate.

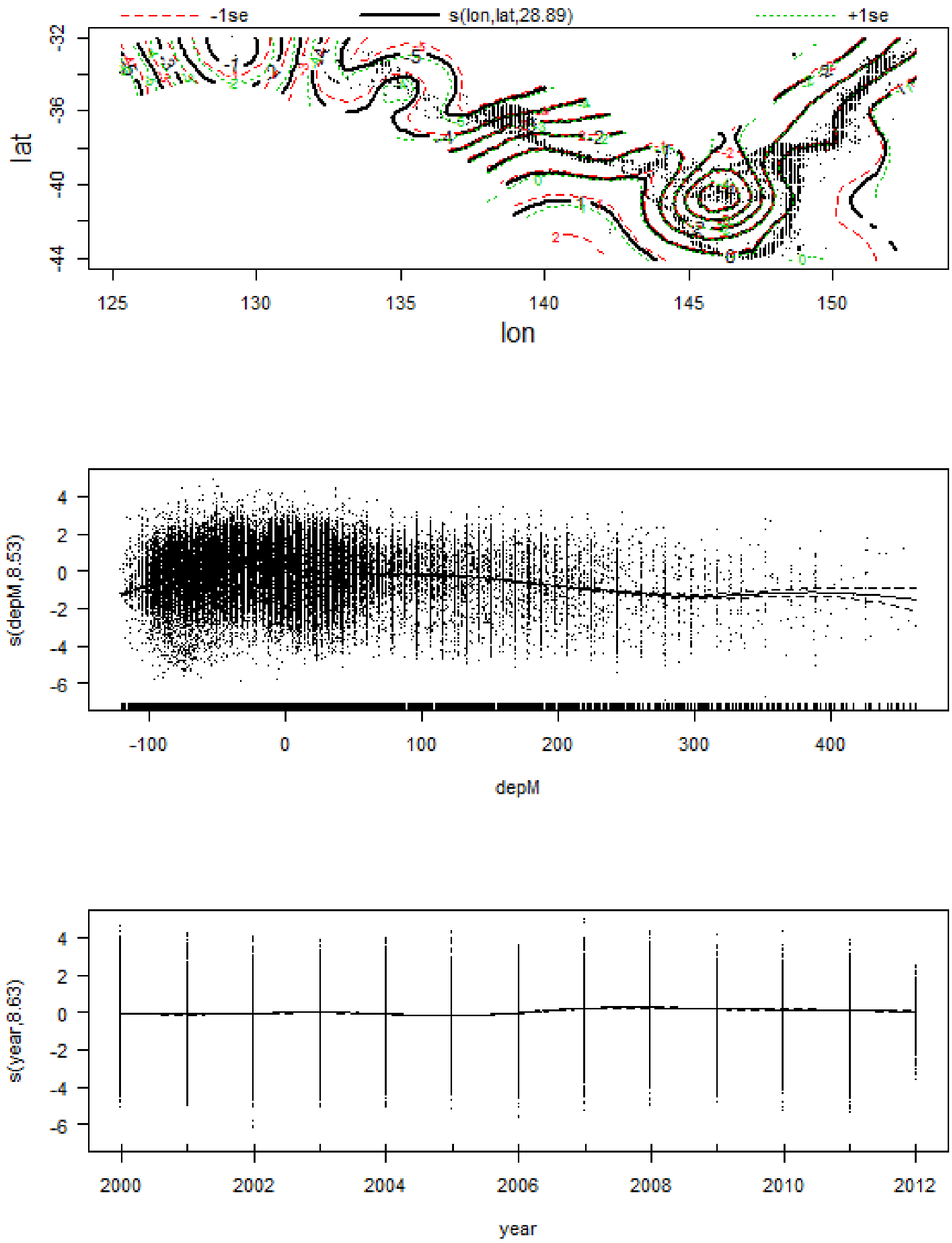


Figure 6-30. Estimated smooth terms for the Flathead density GAM model. The upper panel shows the smooth of location, the middle panel is the smooth of depth expressed as deviation from mean depth of all sample locations, and the lower panel is the smooth of year.

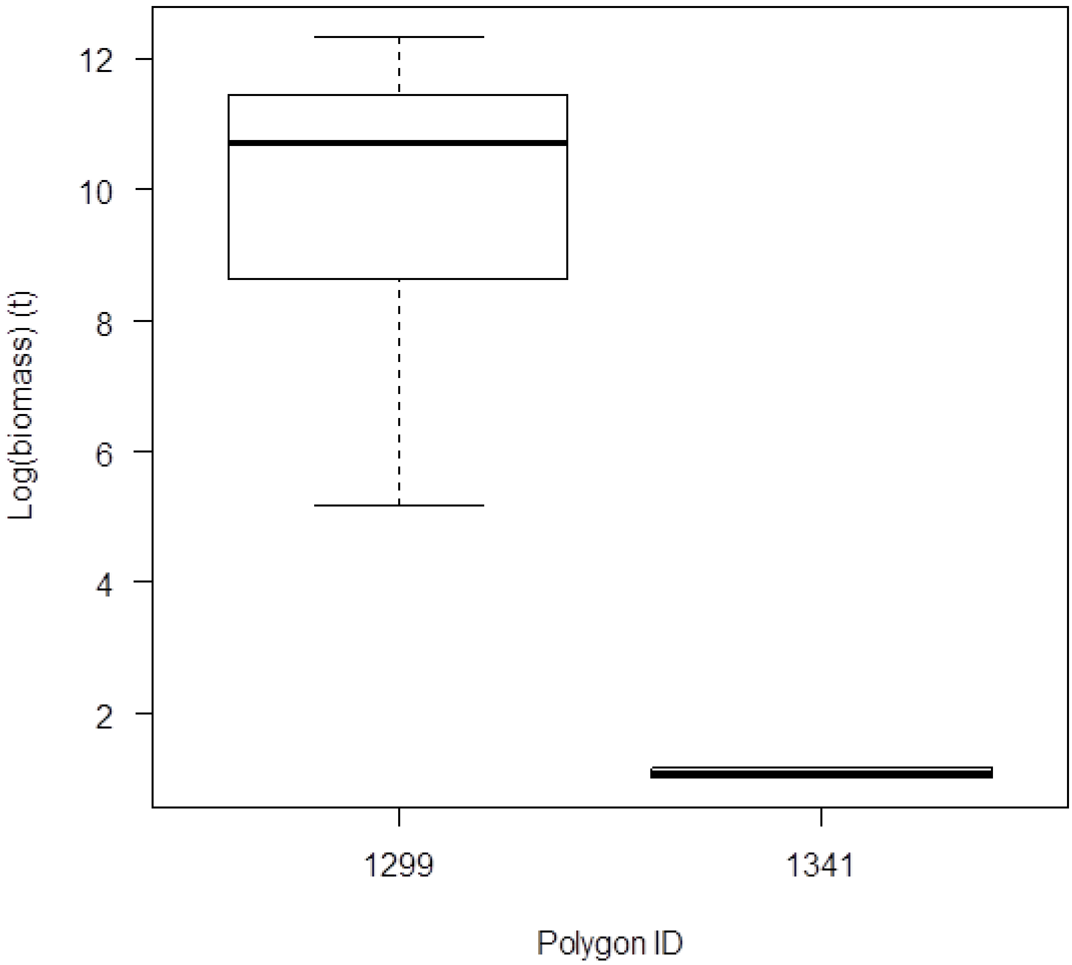


Figure 6-31. Boxplot of estimated log(B_{2009}) for Tiger Flathead in each polygon within the Core distribution range in 2009.

6.5.2 JACKASS MORWONG

Gear efficiency

From 2000 to 2012, the following gear types have caught Jackass Morwong (*Nemadactylus macropterus*): auto longline (AL), demersal longline (BL), Danish seine (DS), gillnet (GN), trawl (TW), fish trap (FP), dropline (DL), handline (HL), rod and reel (RR), and troll (TL). Gear affected area for the last five gear types was assumed to be 1 km^2 per deployment. To increase sample size, we combined AL and BL as longline, and all minor lines (DL, HL, RR, and TL) as one group. This resulted in a total of 117 grid-year cells fished by at least two gear types. The cross-sampling model involving these 6 gear types converged well and there was no abnormal behaviour of the MCMC process.

Significant differences in *Q* existed among gear types (Table 6-16). Trawl was the most effective gear for Morwong (Q_{TW} = 0.71), while fish trap was the least effective (Q_{GN} = 0.04). Longlines, Danish seine, gillnet, and minor lines had similar catchability (Figure 6-32).

Table 6-16. Summary of Bayesian posteriors for gear efficiency of Jackass Morwong from logbook data.

Gear	mean	sd	2.5%	median	97.5%
Longline	0.08	0.01	0.06	0.08	0.11
Danish seine	0.11	0.02	0.07	0.11	0.16
Gillnet	0.11	0.02	0.06	0.10	0.15
Trawl	0.71	0.03	0.65	0.71	0.76
Fish trap	0.04	0.02	0.01	0.04	0.10
Minor lines	0.15	0.03	0.09	0.15	0.21

Population size

A total of 163,967 gear deployments (shots) from 1977 to 2012 were included in modelling fish density. These shots have sufficient data allowing estimation of gear affected area (with length recorded) and hence fish density. The GAM model in section 5.5.2 fit the data fairly well. Location (lon and lat), depth, and year all had a significant effect on the distribution of fish density (Figure 6-33).

There were four polygons where Jackass Morwong were predicted (Figure 6-34), with a total area of 172,936 km^2. The fishable biomass was estimated to be 12,744 t in 2009, using the median predicted fish density and the Core distribution area within SESSF jurisdiction. In comparison, the total biomass was 10,551 t (Morwong and Morwong West) from the full stock assessment (Wayte 2011), a 17% lower than our estimate. The gear efficiency analysis shows trawling as the most efficient gear, again corresponding to the gear that takes the bulk of the catch.

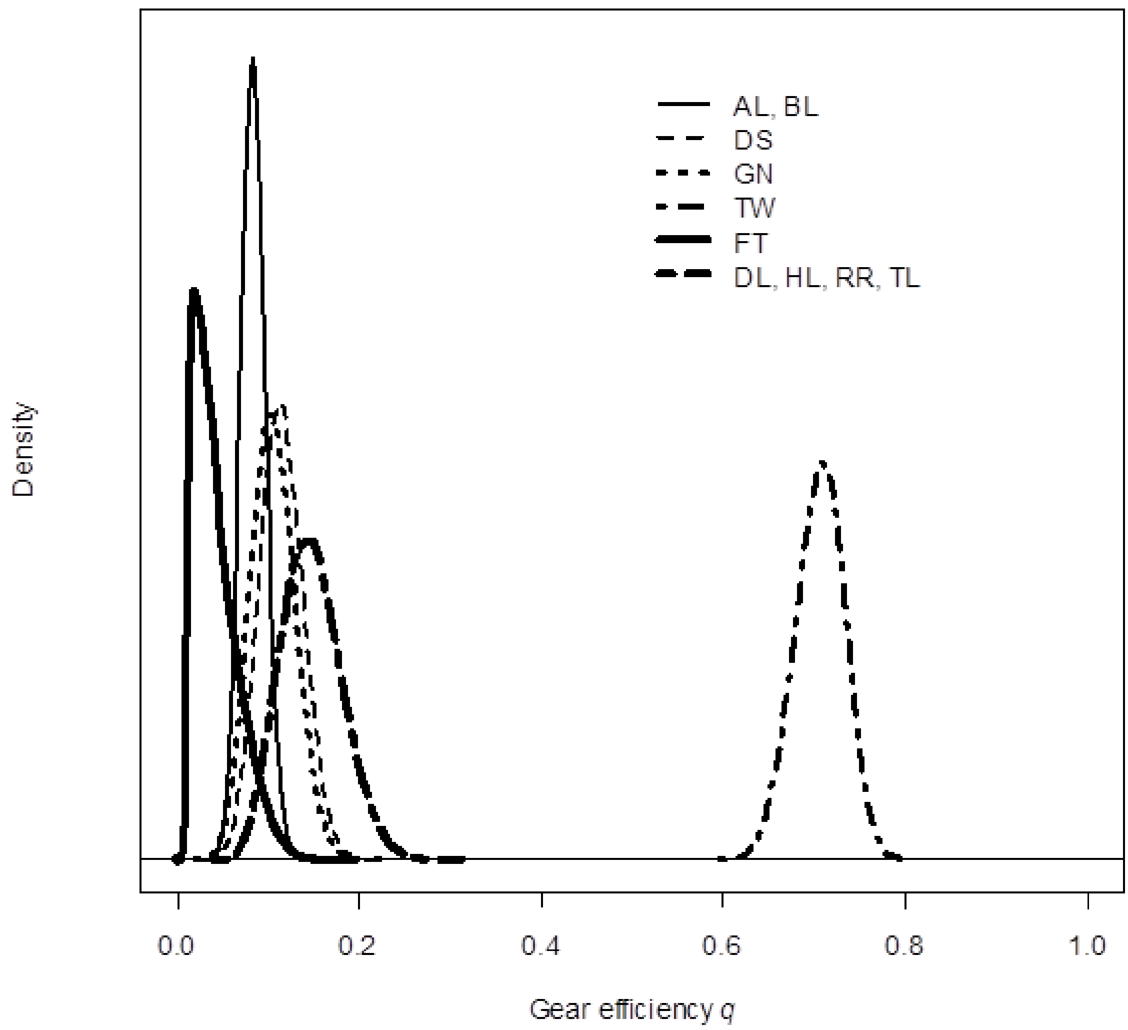


Figure 6-32. Probability distribution of gear efficiency for six gear types for Jackass Morwong.

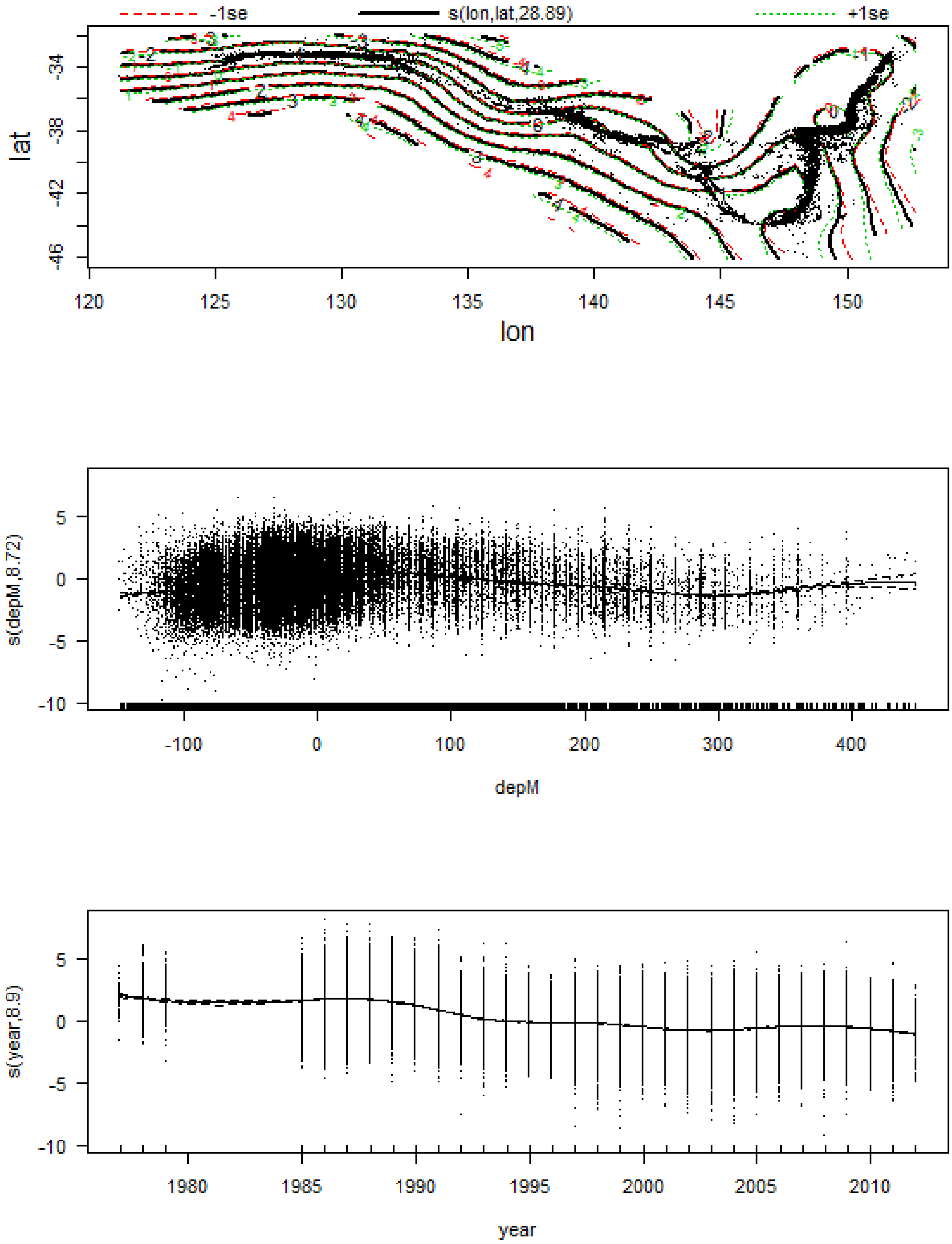


Figure 6-33. Estimated smooth terms for the Jackass Morwong density GAM model. The upper panel shows the smooth of location, the middle panel is the smooth of depth express as deviation from mean depth, and the lower pane is the smooth of year.

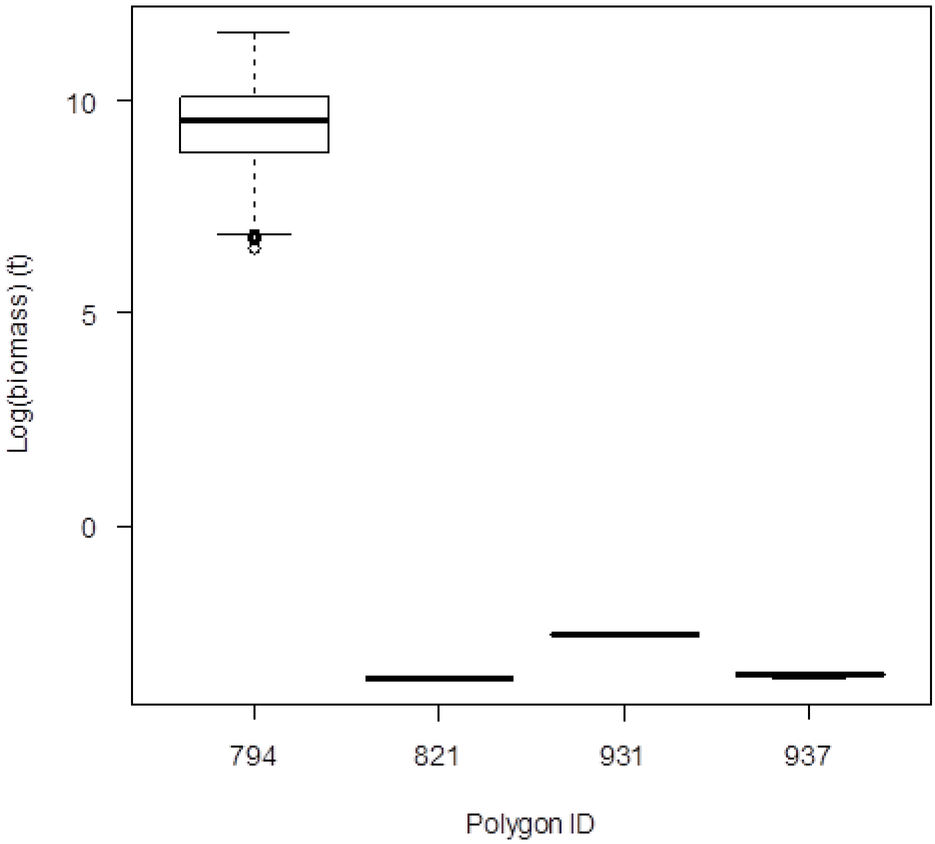


Figure 6-34. Boxplot of estimated log(B_{2009}) for Jackass Morwong in each polygon within the Core distribution range in 2009.

6.5.3 GEMFISH

Gear efficiency

From 2000 to 2012, the following gear types caught Gemfish (*Rexea solandri*): AL, BL, DS, GN, and TW. A total of 146 grid-year cells were fished by at least two gear types. The cross-sampling model involving these 4 gear types converged well and there was no abnormal behaviour of the MCMC process.

Significant differences in Q existed among gear types (Table 6-16). Again, trawl was the most effective gear (Q_{TW} = 0.61), followed by Danish seine (0.49), while longline was the least effective (Q_{GN} = 0.05).

Table 6-17. Summary of Bayesian posteriors for gear efficiency Q of Gemfish from logbook data.

Gear	mean	sd	2.5%	median	97.5%
Longline	0.05	0.01	0.04	0.05	0.06
Danish seine	0.49	0.04	0.41	0.49	0.58
Gillnet	0.15	0.03	0.09	0.15	0.23
Trawl	0.61	0.02	0.57	0.61	0.66

Population size

A total of 89,784 gear deployments (shots) from 1977 to 2012 were included in modelling Gemfish density, which include both Eastern and Western stocks. These shots had sufficient data to allow estimation of gear affected area (with length recorded) and hence fish density. The GAM model in section 5.5.2 fit the data fairly well. Location (lon and lat), depth, and year all had a significant effect on the distribution of fish density (Figure 6-35).

There were 23 polygons where Gemfish density was predicted to be greater than zero (Figure 6-36). These polygons have a total area of 34553 km^2. The fishable Gemfish biomass was estimated to be 6650 t in 2009, using the median predicted fish density and the Core distribution area within SESSF jurisdiction. Gemfish is divided into Eastern and Western stocks in full stock assessment. Only the Eastern stock has estimated biomass, which was 4177 t from in 2009 (Little and Rowling 2011). If our estimate is correct, the Eastern stock makes up about 63% of the total biomass.

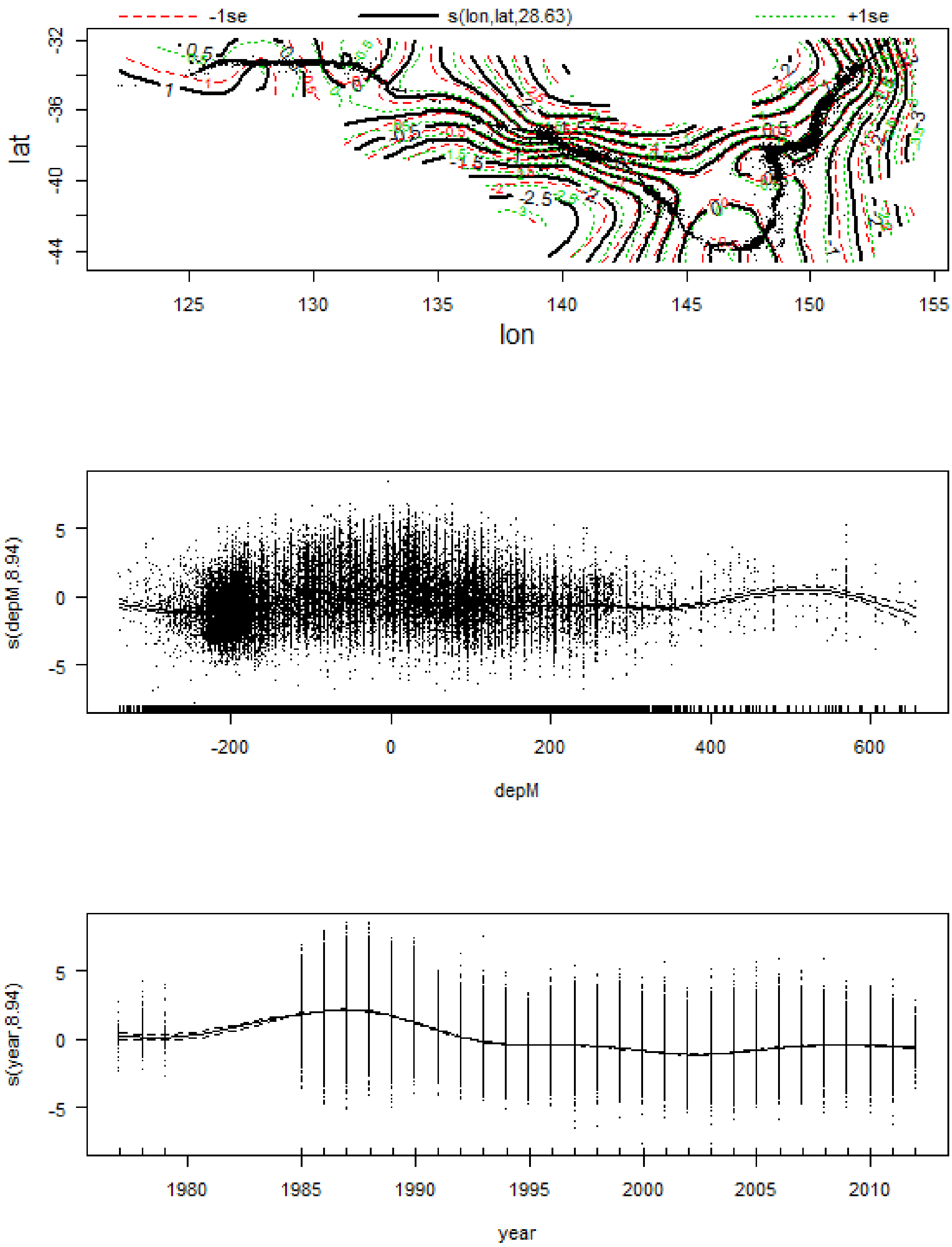


Figure 6-35. Estimated smooth terms for the Eastern Gemfish density GAM model. The upper panel shows the smooth of location, the middle panel is the smooth of depth express as deviation from mean depth, and the lower pane is the smooth of year.

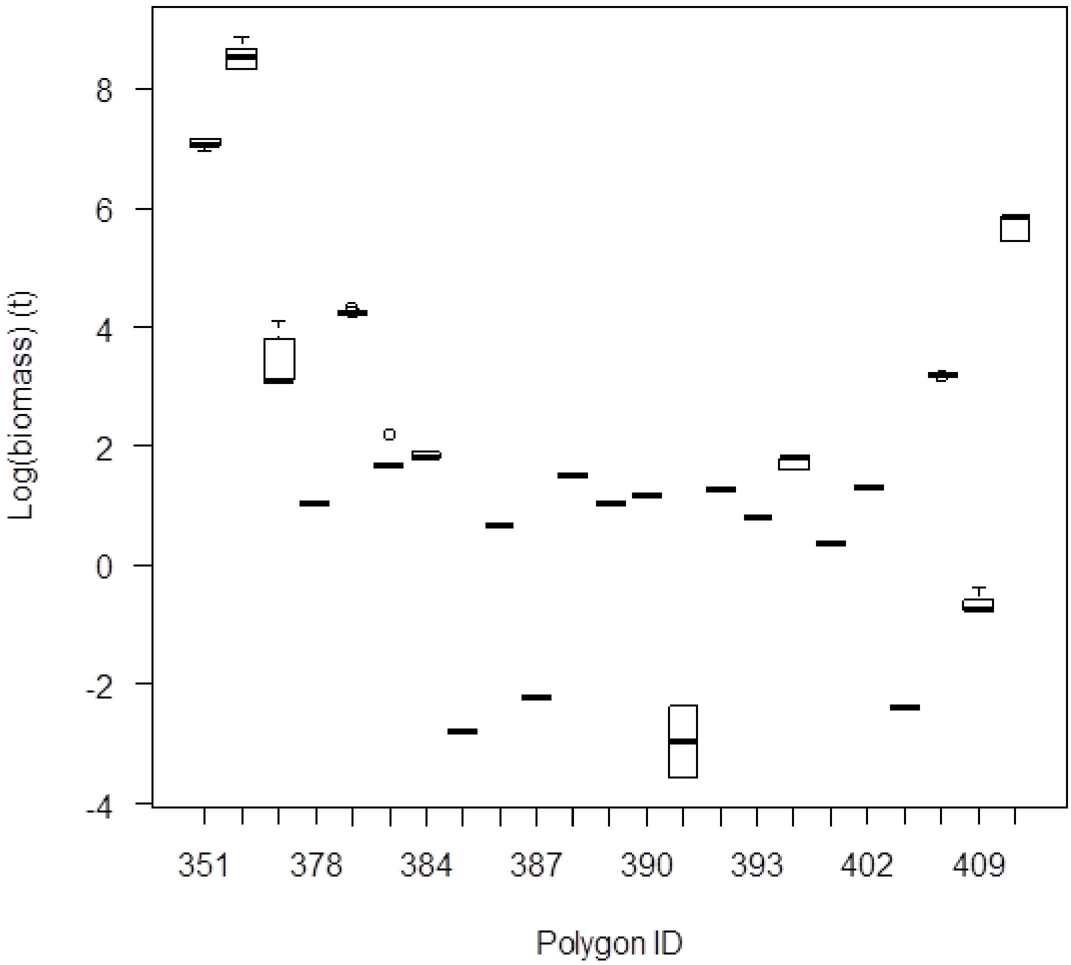


Figure 6-36. Boxplot of estimated log(B_{2009}) for the Eastern Gemfish in each polygon within the Core distribution range in 2009.

6.5.4 JOHN DORY

Gear efficiency

John Dory has been caught by three major gear types: Danish seine, gillnet, and trawl. Danish seine and trawl simultaneously fished in 62 grid-year cells while gillnet and trawl fished together in 1 grid-year cell. Gillnet occurred in a total of 299 grid-year cells and we included these cells with Danish seine and trawl overlapping cells. The cross-sampling model involving these 3 gear types converged well and there was no abnormal behaviour of the MCMC process.

Significant differences in *Q* existed among gear types (Table 6-18). Again, trawl was the most effective gear (Q_{TW} = 0.59), while seine and gillnet had similar efficiency (Figure 6-37).

Table 6-18. Summary of Bayesian posteriors for gear efficiency Q of John Dory from logbook data.

Gear	mean	sd	2.5%	median	97.5%
Danish seine	0.21	0.02	0.18	0.21	0.25
Gillnet	0.24	0.01	0.21	0.24	0.27
Trawl	0.58	0.03	0.52	0.59	0.65

Population size

A total of 112683 gear deployments (shots) from 1978 to 2012 were included in modelling fish density to increase sample size. These shots have sufficient data allowing estimation of gear affected area (with length recorded) hence fish density. The GAM model in section 5.5.2 fit the data fairly well. Location (lon and lat), depth, and year all had a significant effect on the distribution of fish density (Figure 6-38).

Because John Dory's distribution area has not been appropriately defined in the Core map, we opted to use the historical catch location to derive total abundance. From 1978 to 2012, John Dory were caught in 2458 0.05 by 0.05 degree grid cells with location and depth recorded. The total area sums to 60,896 km^2. The fishable John Dory biomass was estimated to be 1935 t in 2009, using the median predicted fish density and the actual distribution area within the SESSF jurisdiction. There is no biomass estimate for comparison for this species using other methods.

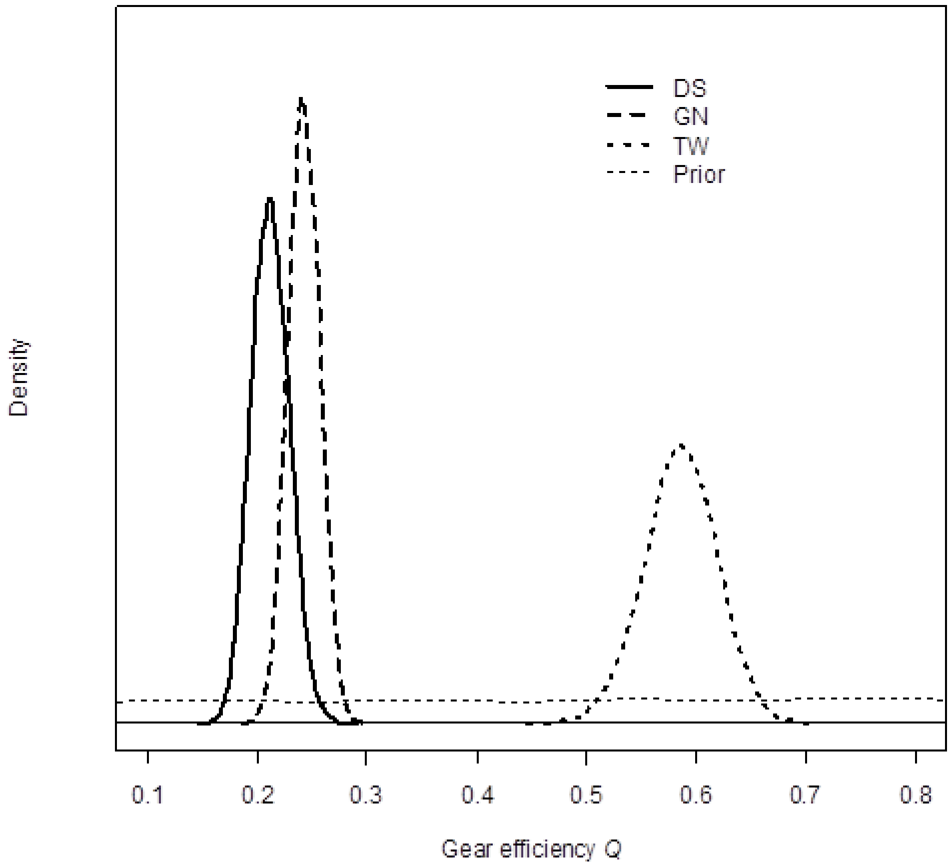


Figure 6-37. Probability distribution of gear efficiency of three gear types for John Dory.

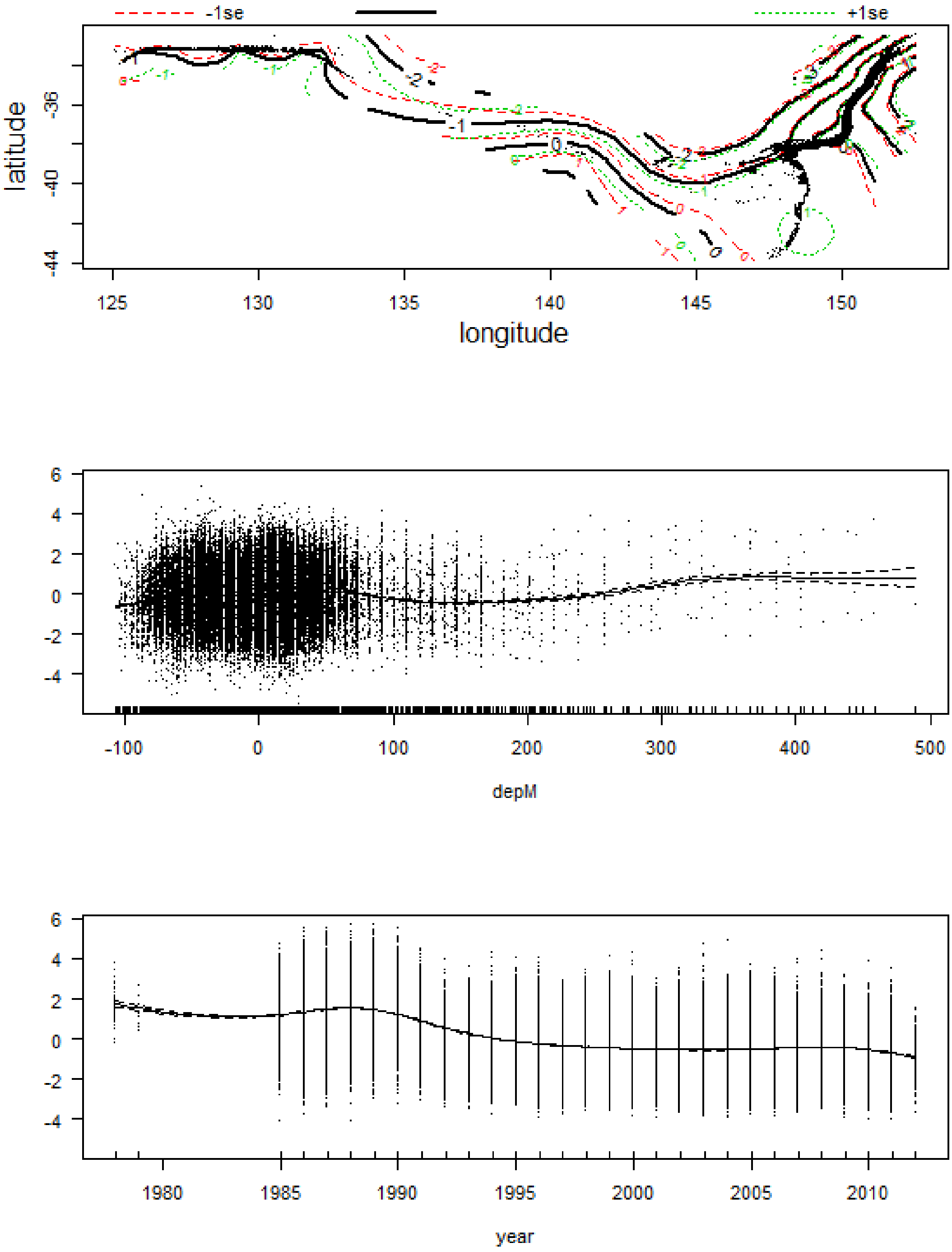


Figure 6-38. Estimated smooth terms for John Dory density GAM model. The upper panel shows the smooth of location, the middle panel is the smooth of depth express as deviation from mean depth, and the lower pane is the smooth of year.

6.5.5 RUBY SNAPPER (ETELIS CARBUNCULUS)

Gear efficiency

Ruby Snapper is a target species in the Western Deepwater Trawl Fishery. Trawl is the major gear catching the species, but other gears also caught them, including longlines, dropline, fish trap (FT), and minor hook and lines. From 2000 to 2010, few grid-year cells were fished simultaneously by multiple gears. To increase the sample size, we included 499 grid-cells and 612 records that had repeated samples by single gear but not necessary by overlapping multiple gears. The cross-sampling model involves 5 gears (Table 6-19).

Table 6-19. Summary of Bayesian posteriors for gear efficiency Q of Gemfish from logbook data.

Gear	mean	sd	2.5%	median	97.5%
Longline	0.38	0.03	0.32	0.38	0.44
Drop line	0.31	0.02	0.27	0.31	0.35
Fish trap	0.16	0.07	0.04	0.15	0.32
Trawl	0.50	0.02	0.47	0.50	0.54
Minor lines	0.36	0.07	0.23	0.36	0.52

Population size

A total of 1287 gear deployments (shots) were included in modelling fish density. These shots have sufficient data to allow estimation of gear affected area (with length recorded) and hence fish density. Location (lon and lat), depth, and year all had a significant effect on the distribution of fish density (Figure 6-39).

Ruby Snapper's distribution range has not been appropriately defined. We used the actual locations where this species has been caught to derive biomass. From 1994 to 2010 Ruby Snapper were caught in 148 0.05 by 0.05 degree grid cells with a total area of 4173 km^2. The median fishable Ruby Snapper biomass was estimated to be 2069 t in 2009.

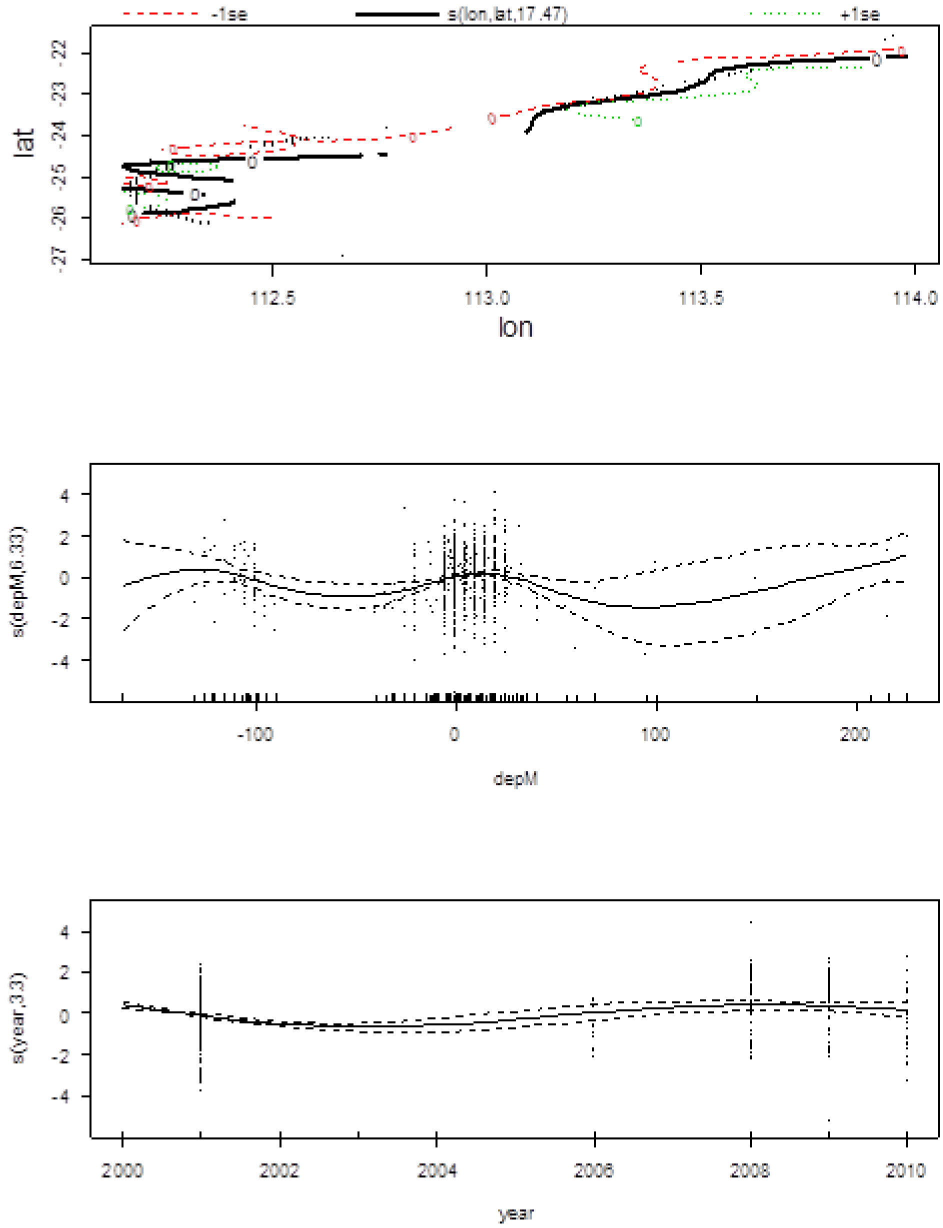


Figure 6-39. Estimated smooth terms for Ruby Snapper density GAM model. The upper panel shows the smooth of location, the middle panel is the smooth of depth express as deviation from mean depth, and the lower pane is the smooth of year.

6.5.6 ESTIMATED FISHING MORTALITY RATE

From the catch data and the estimated biomass, we were able to derive fishing mortality rates for the five case study species examined above. Using the natural mortality rate, as well as the scaling parameter ω between F_{MSY} and M, it was possible to compare the estimated F with the reference point F_{MSY} (Table 6-20). For the five species we examined, we also list the fishing mortality rate estimated by the corresponding stock assessment. The results appear to be very close to each other. It is important to keep in mind that the key data required for the method we described were catch statistics only.

Table 6-20. Comparison of estimated fishing mortality rates and reference points F_{MSY} for the case study species.

						F_{2009}	
Species	M	ω	F_{MSY}	B_{2009}	C_{2009}	Cross-samp	Full assess
Tiger Flathead	0.27	0.69	0.19	21798	3031	0.139	0.131
Jackass Morwong	0.15	0.92	0.14	12744	478	0.038	0.045
John Dory	0.36	0.90	0.32	1935	129	0.067	0.089
Gemfish	0.33	0.92	0.30	6650	406	0.061	0.064
Ruby Snapper	0.33	0.92	0.30	2069	13	0.006	

Note: natural mortality rate *M* is adopted from the stock assessment for Tiger Flathead, Jackass Morwong, and John Dory, while it is adopted from the ERA study by Zhou et al. (2011a) for Gemfish and Ruby Snapper. Catches are combined for Eastern and Western stocks for Jackass Morwong and Gemfish. For Gemfish, full assessment *F* is for the Eastern stock only.

6.5.7 DISCUSSION

We applied cross-sampling method to estimate average gear efficiency for five case-study species, some of which have full stock assessment while others do not. There is no reference for direct comparison of gear efficiency for all these species, as this is a very difficult parameter to estimate and is traditionally obtained from field experiments. However, our results for different gear types fall within sensible ranges. For example, Dickson (1993) compared trawl gear efficiency for catching cod (*Gadus morhua L.*) and haddock (*Melanogramrnus aeglefinus L.*) and found that gear efficiency typically ranged from 0.1 to 0.8 for different size groups. When no information is available for gear efficiency, it is often assumed that $Q = 1$ or $Q = 0.5$ (Pauly 1979; Somerton et al. 1999; Pope et al. 2000). We believe that the method described here provides more realistic estimates than the default assumption.

Gear efficiency is not only essential in converting survey or commercial catch to abundance, but it can also be useful in stock assessment for estimating catchability. When individuals are assumed to be randomly or evenly distributed in stock area *A*, the relationship between gear efficiency *Q* and common catchability *q* in stock assessment is (Somerton et al. 1999):

$$q = Q \, a/A$$

where *a* is the average swept area in each tow (for trawl). When the data needed in a stock assessment model are insufficient, or when there is large uncertainty in the stock assessment, gear efficiency based on the cross-sampling method can improve the assessment and reduce the likelihood of large biases in the biomass estimates.

The results from the application of the cross-sampling method show that the estimated biomass (or fishing mortality rate) for the five species is by and large comparable with the corresponding values from the stock assessment. However, such a direct comparison should be treated with some caution. Besides many other factors, the populations assessed by the two methods may not be the same. Our method uses annual varying density expanded by distribution area that generally does not change much from year to year. In contrast, stock assessment uses annual fishery catch data and only infers the population affected by the fishery. If the fleet did not explore the entire stock areas within the jurisdiction in a particular year and the fish between fished and unfished areas did not mix (migrate) well, there might be sub-populations that were not available to the fishery and this proportion of the population will be missed out in the stock assessment result (Zhou et al. 2011b).

Our objective in this chapter is to derive average gear efficiency for each gear type and each species. This new method uses easily available commercial logbook data, which avoids costly field experimental approaches. We have not explored the effects of many factors that possibly influence gear efficiency, including fish size, fishing season and time, habitat, and other environmental conditions (Arreguin-Sanchez 1996). Although we treat these variables as random effects, they can be incorporated into the model if deemed appropriate.

It is interesting to note the similarity in estimated fishing mortality rates between our method and those derived from conventional stock assessment. Comparing to the reference point, the fishing intensity is relatively conservative for all five case-study species. The method can be applied to species where only catch data are available.

6.6 Results of conditional stochastic stock reduction analysis

6.6.1 DETERMINISTIC CHASE-CATCH (CC) METHOD

The deterministic chase-catch method can produce exact B_0 (and other biomass-based reference points such as B_{MSY} and MSY) if the assumptions are met (including correct population dynamic model, an estimate of biomass in one year B_y, M, m, and the relationship between F_{MSY} and M known). Biases in B_y, M, and the F_{MSY} ~ M relationship cause bias in estimated B_0 (Figure 6-40). However, the relative errors in estimated B_0 are generally smaller than the errors in the input predictors. For example in this instance, when input growth rate r or biomass in year y (B_y) is twice as large as the true value (relative error = 1), B_0 is underestimated by or overestimated by -0.19 or +0.63, respectively. When input r or B_y is 0.4 of the true value (relative error = -0.6), B_0 is overestimated by 0.6 or underestimated by -0.25, respectively.

Estimates of B_0 and r are sensitive to errors in input parameters. However, the estimate of MSY is rather stable (Figure 6-41). This is because the bias in r and B_0 are in the opposite direction. For example, when the assumed B_0 is too large, in order to end at the correct B_y after the series of catch removals, r will need to be biased low. Such a combination of opposite bias results in relatively accurate estimates of MSY.

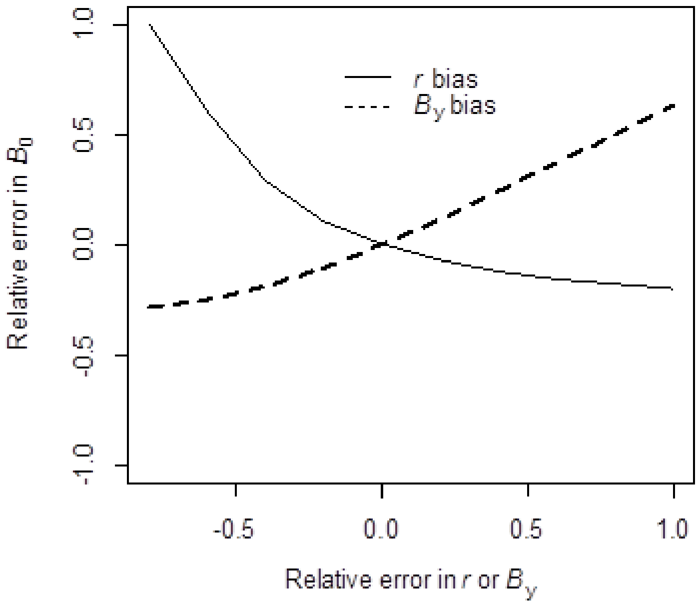


Figure 6-40. Relative error in estimated B_0 caused by relative error in growth rate r or biomass in the year y, B_y.

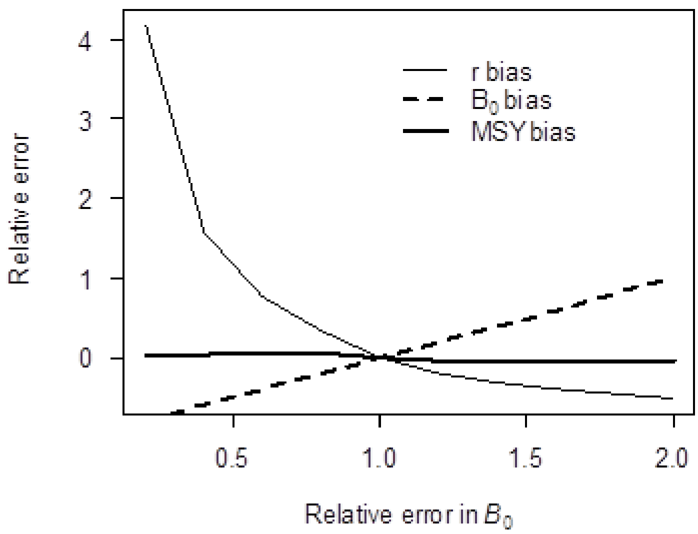


Figure 6-41. Effect of relative error in prior *B*0 on posterior retained r, *B*0, and MSY.

6.6.2 CONDITIONAL STOCHASTIC STOCK REDUCTION ANALYSIS (CSSRA)

The results of the CSSRA method are affected by many potential variables, including the distributions of priors and their parameters, the assumed shape of the production model, and the accuracy of the estimate of biomass in year y, B_y. The effect of growth rate *r* works through its predictors, the natural mortality *M* and the relationship between F_{MSY} with *M*. In the results below, rules *a* to *d* in the Method section are applied. In rule *d*, $\frac{B_{y,i}^{simul} - B_y^{est}}{B_y^{est}} < |\alpha|$, we assume estimated biomass in year *y* is known and set α =0.2.

Effect of prior variability

We conducted simulations by varying prior standard deviation σ_{B0} and σ_r. Both B_0 and *r* were assumed to have a lognormal distribution:

$$B_0 \sim lnorm[log(B_0^{est}), \sigma_{B_0}^2]$$

$$r \sim lnorm[log(2\omega M), \sigma_r^2]$$

The standard deviation is based on $\sigma = \sqrt{log(cv^2) + 1}$. Apparently, increasing the CV results in high variance in the posterior retained key parameters (Figure 6-42, Figure 6-43). This change also causes bias to some extent in addition to imprecision. The reason is because of the skewed distribution of lognormal density where mean increases with the CV (Figure 6-44). Nevertheless, the bias is not too large even at high CV. The bias for the estimated MSY and depletion B_y/B_0 are typically smaller than those for the B_0 and r.

Effect of bias in priors *r* and B_0

In these simulations, we fix σ= 0.5 for both B_0 and *r*. Changing relative error in B_0 and *r* from -0.8, to 1.0 causes some systematic errors in posterior retained key parameters (Figure 6-45 to Figure 6-48). This is expected. However, when there is no bias (bias = 0) in priors B_0 and *r*, the posterior retained B_0, *r*, MSY, and B_y/B_0 are still biased. This bias is caused by the skewed lognormal distribution of the priors, as shown above. Even so, all biases are smaller than the input bias in the priors.

Effect of bias in the estimated biomass B_y

In the CC and CSSRA methods, it is necessary to have an estimate of the biomass in at least one year B_y, or fishing mortality F_y, or depletion ratio B_y/B_0. Compared to priors for B_0 and r, the assumption about the current stock status seems to have a higher impact on other parameters (Figure 6-49 and Figure 6-50). The effect on MSY and B_y/B_0 is of more concern, as the bias can be higher than 50% at extreme cases, even though it is still smaller than input bias in B_y.

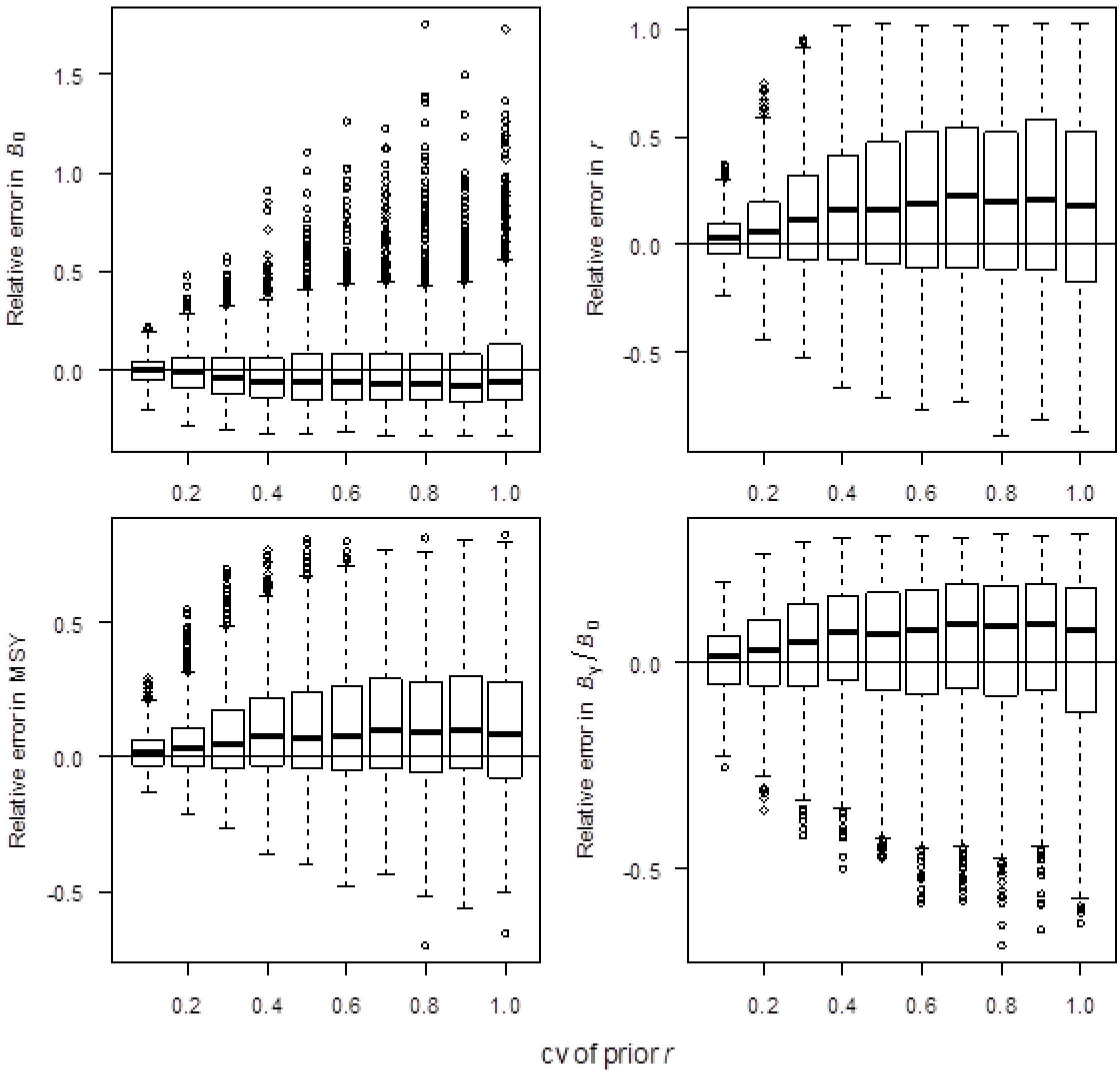


Figure 6-42. Effect of prior variability in growth rate *r* (expressed in coefficient of variance) on posterior B_0, *r*, MSY, By/B_0 ratio when cv[B_0] is fixed at 0.5.

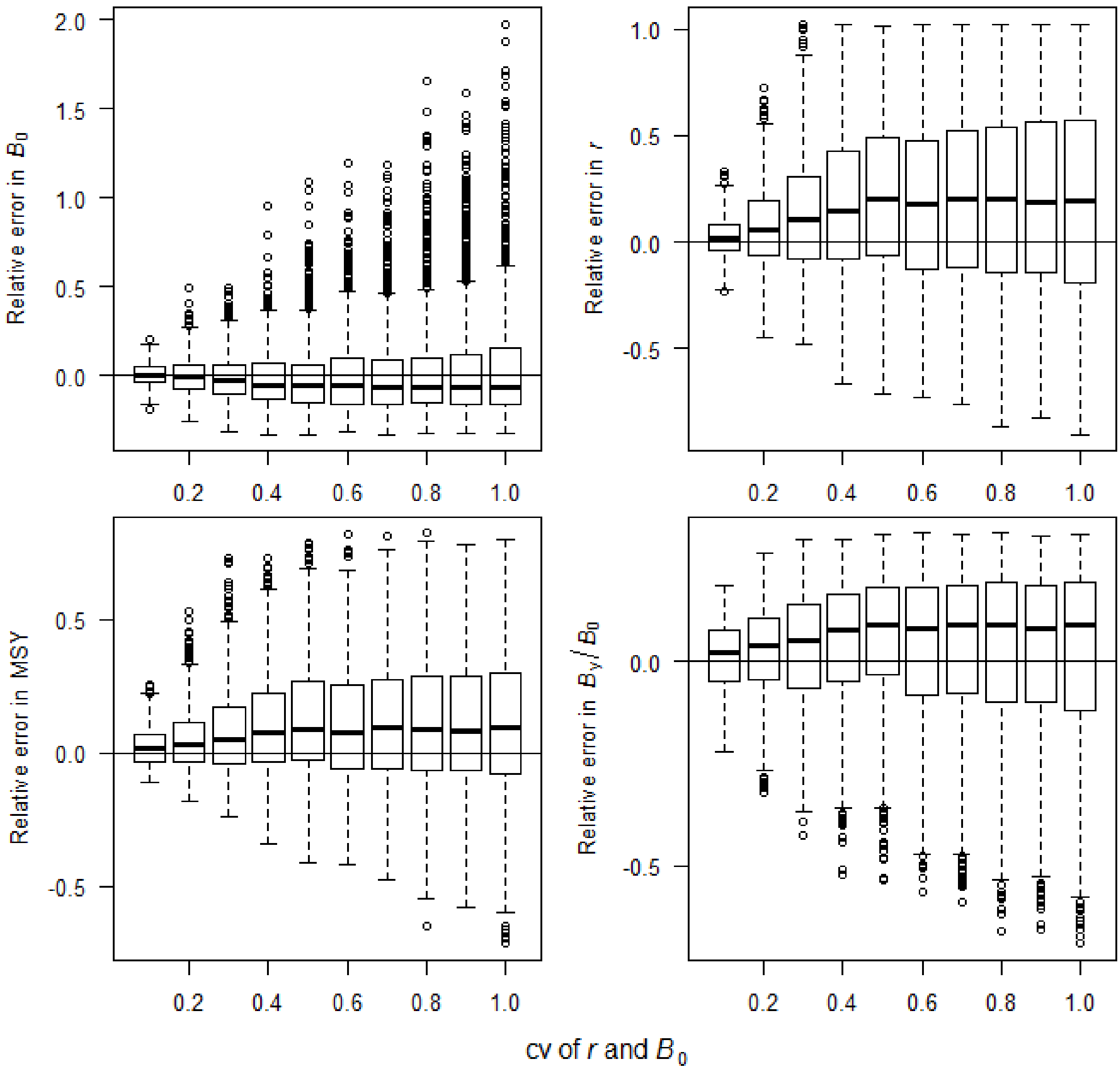


Figure 6-43. Effect of variability (expressed in coefficient of variance) in both growth rate *r* and initial biomass B_0 from 1000 simulations. The priors are centred at the true values derived from the CC method. Increasing CV increases variance of relative error in these four parameters, as well as their median values.

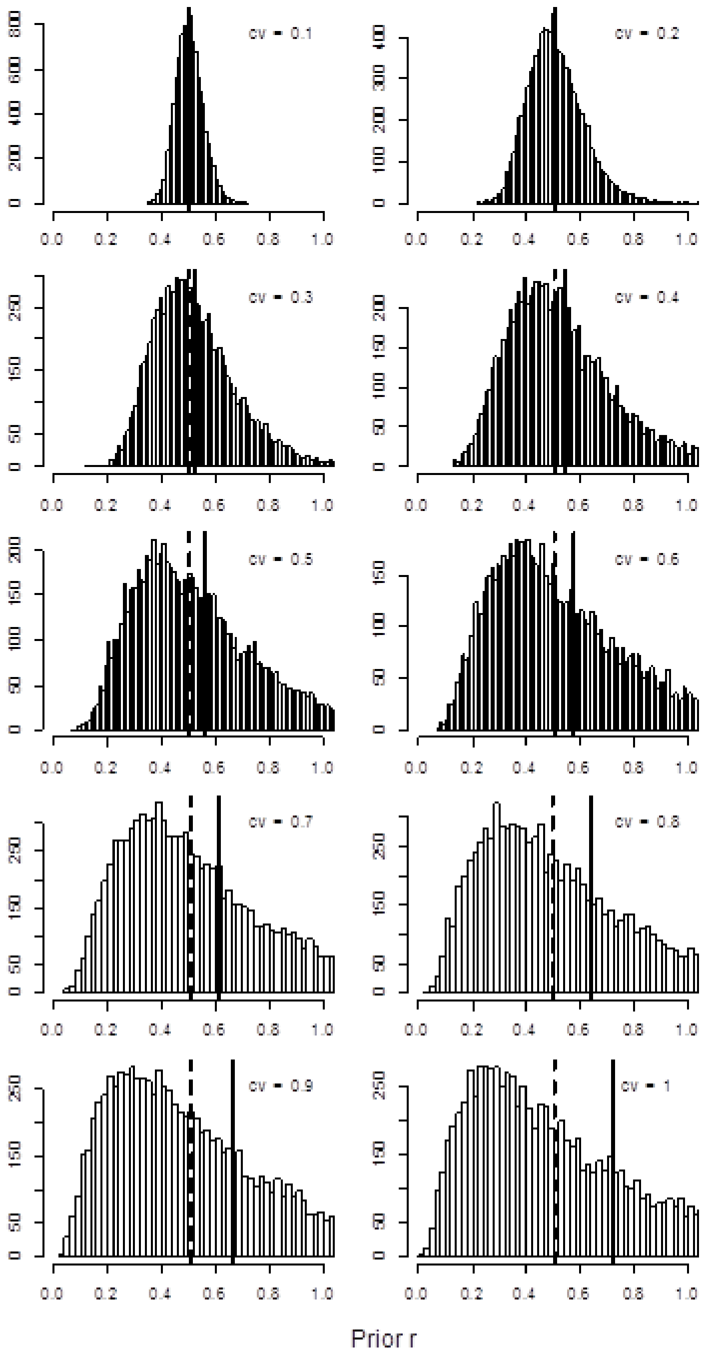


Figure 6-44. Density of log-normally distributed prior r. The dashed lines are the medians and the solid lines are the means.

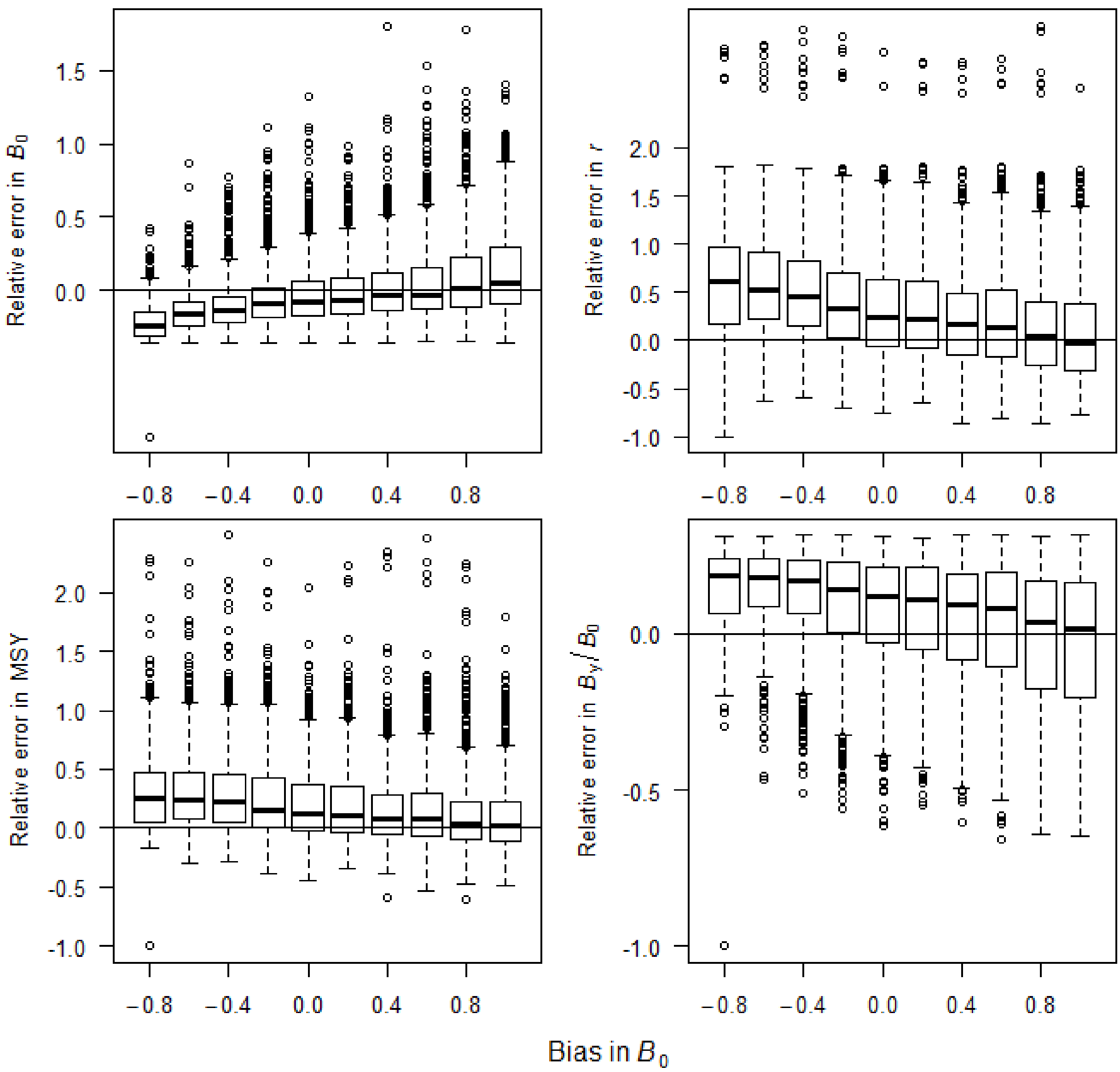


Figure 6-45. Effect of bias in initial biomass prior B_0 on estimated B_0, *r*, MSY, and depletion level B_y/B_0. A standard deviation of σ = 0.5 are used for both priors B_0 and *r*. Bias = 1 in prior B_0 means that the assume biomass is centred at twice the true value.

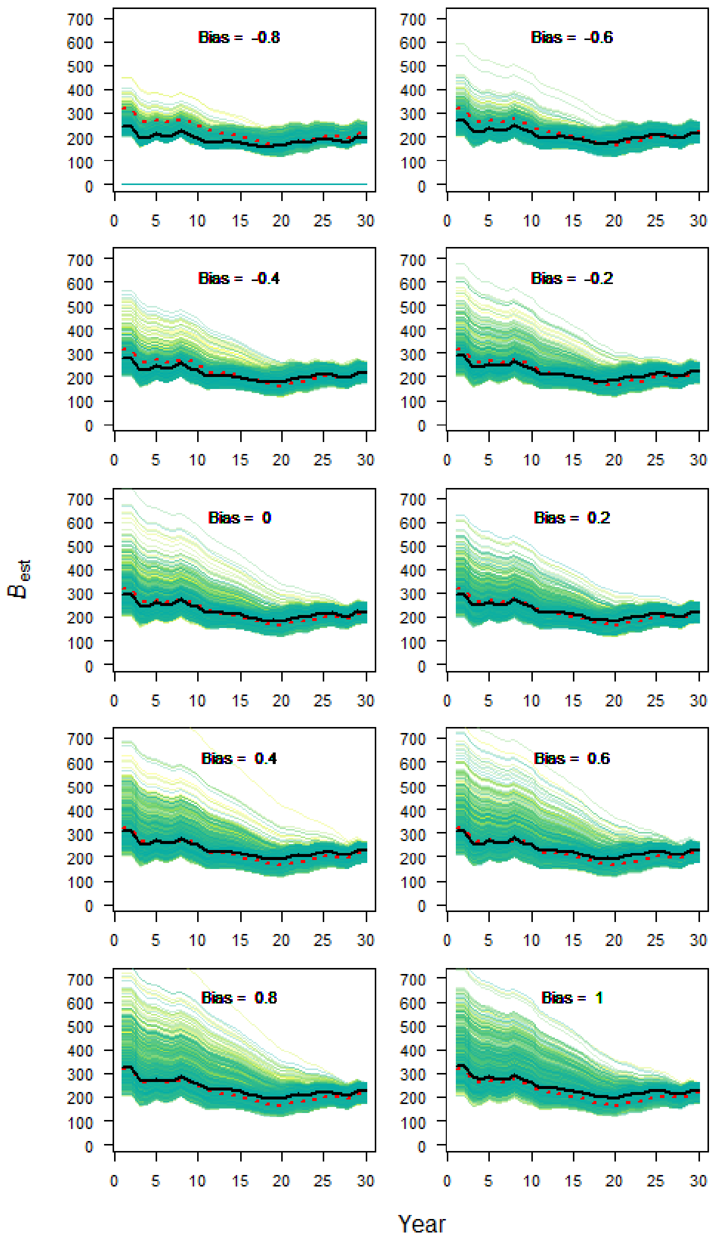


Figure 6-46. Effect of B_0 bias on trajectories of estimated biomass. The solid thick green lines are the median of the 1000 simulations and the dashed red lines are the true biomass.

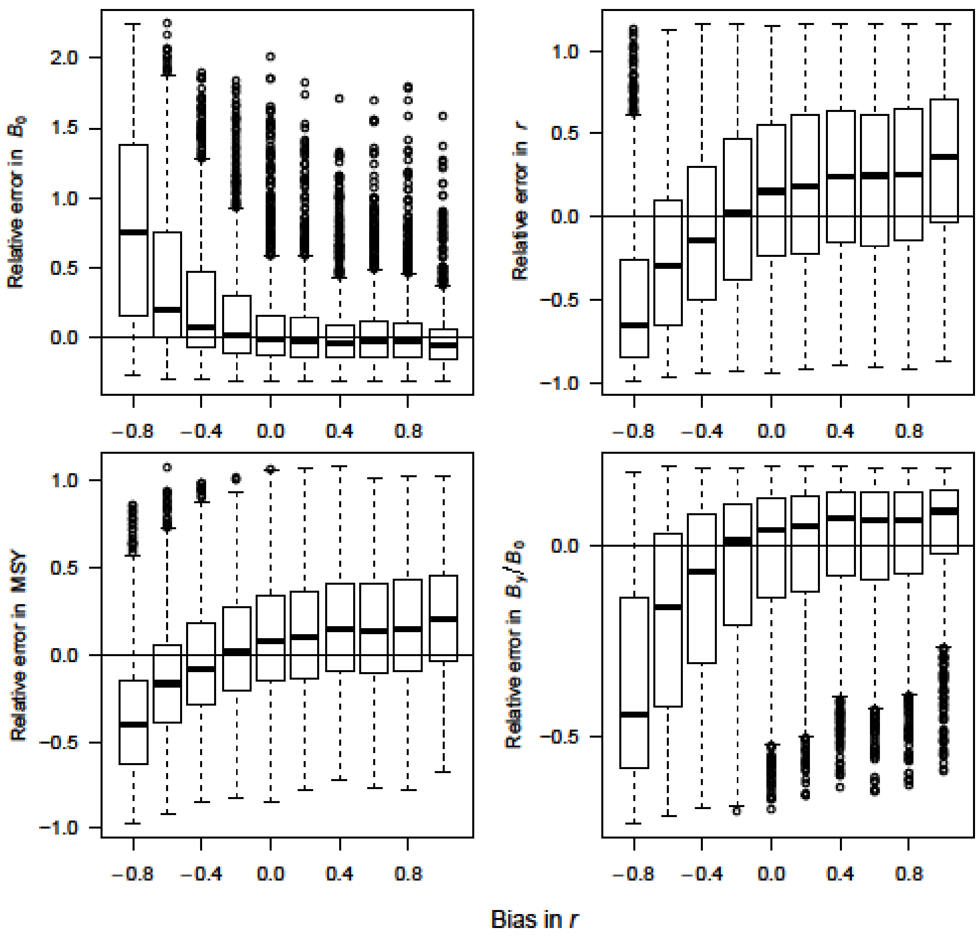


Figure 6-47. Effect of bias in assumed growth rate *r* on estimated B_0, *r*, MSY, and depletion from 1000 simulations. Both *r* and B_0 are assumed to be lognormally distributed with sd = 1. Bias = 1 in *r* means that the assumed *r* is centred at twice the true value. Increase in *r* bias has systematic effect on these four parameters. For example, B_0 tends to be overestimated while *r*, MSY, and depletion underestimated when bias in *r* is negative (i.e., the assumed *r* is smaller than true *r*).

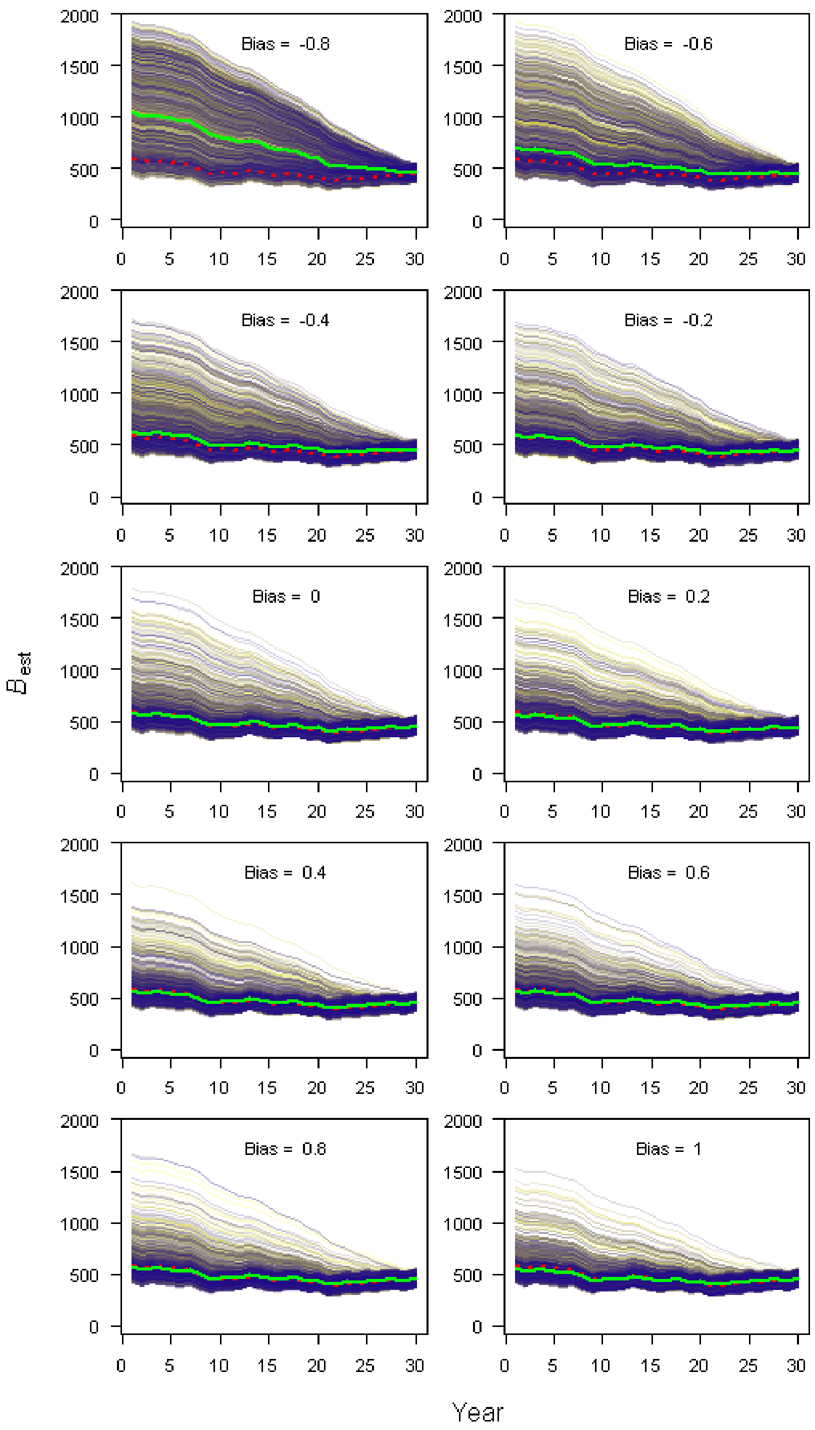


Figure 6-48. Effect of *r* bias on trajectories of estimated biomass. The solid thick green lines are the median of the 1000 simulations and the dashed red lines are the true biomass.

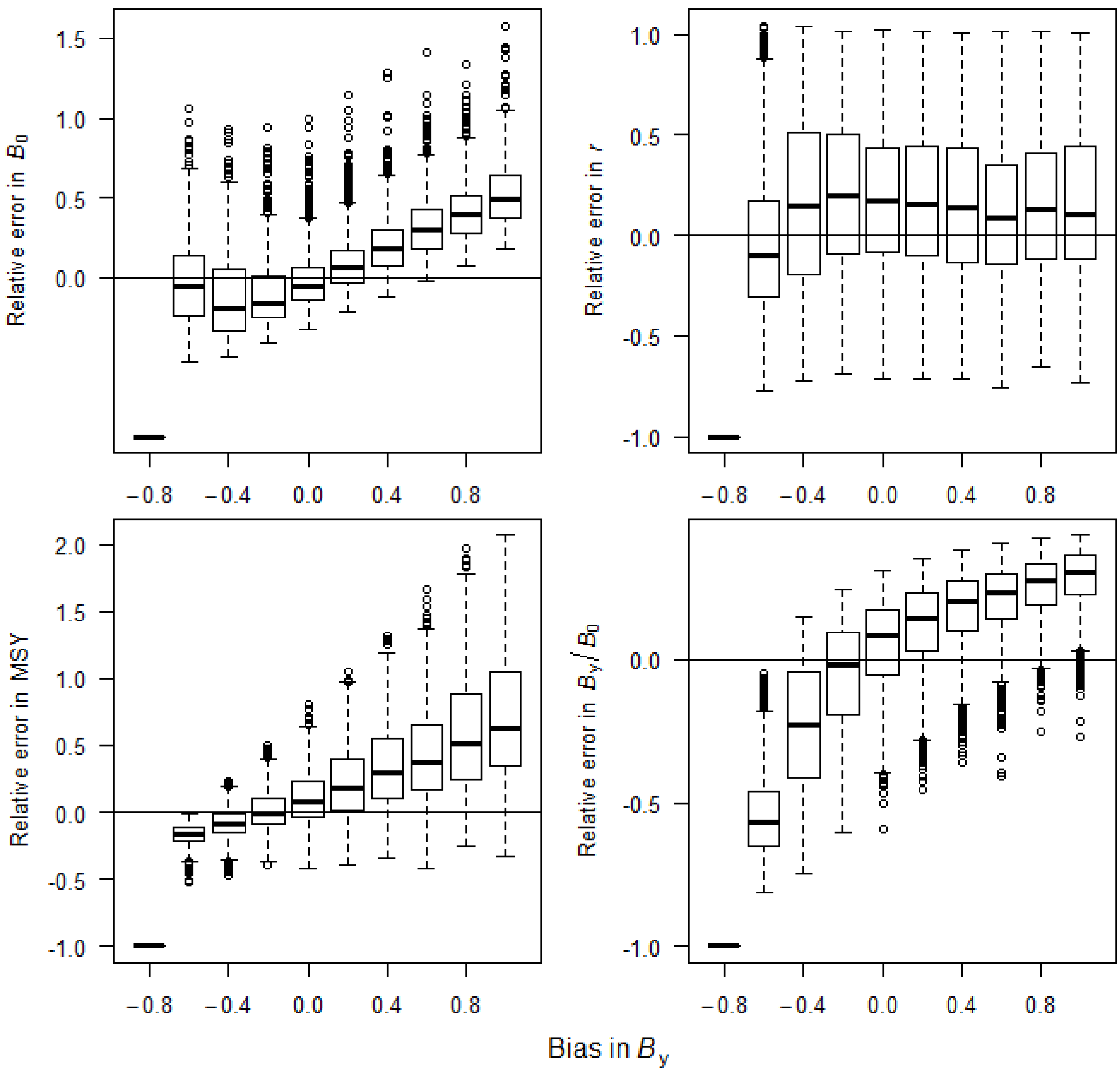


Figure 6-49. Effect of bias in biomass B_y on estimated B_0, r, MSY, and depletion level B_y/B_0. The priors B_0 and r are log-normally distributed with σ = 0.5. Bias = 1 in B_y means that the assume biomass is centred at twice the true value. Too few iterations are retained at bias = -0.8.

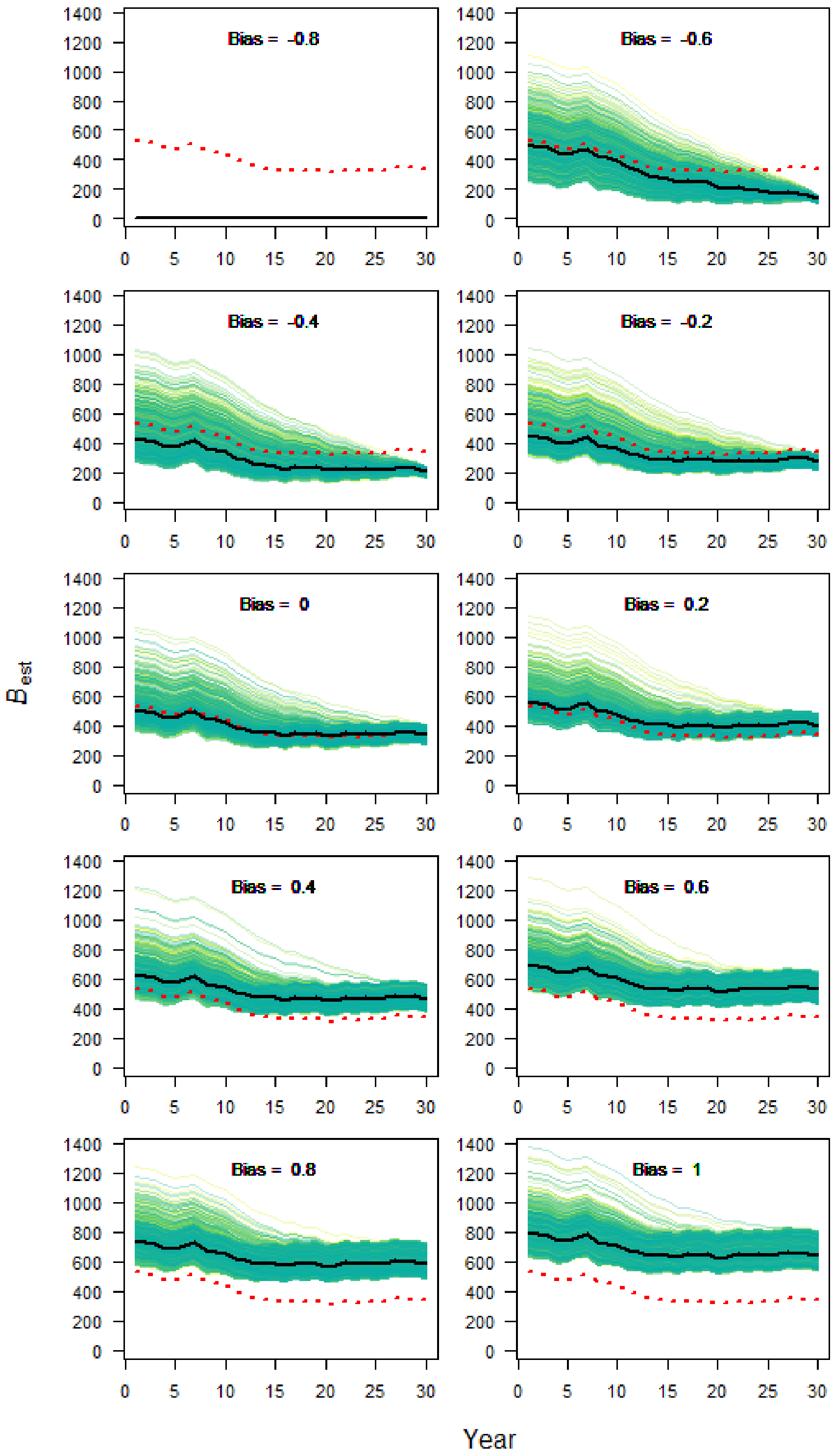


Figure 6-50. Effect of B_y bias on trajectories of estimated biomass. The solid thick black lines are the median of the 1000 simulations and the dashed red lines are the true biomass.

6.6.3 APPLICATION TO SELECTED STOCKS

Tiger Flathead (Neoplatycephalus richardsoni)

The catch history and natural mortality come from the most recent stock assessment (Klaer 2011). Biomass in 2009 is assumed known and we tested two biomass estimates, one from the stock assessment and the other one derived from catch data using the cross sampling method (see previous chapter). The biomass used is the "summary biomass" from the full stock assessment, which includes both sexes, spawning biomass, and biomass of juveniles above the size at recruitment. From catch time-series and natural mortality, the chase-catch method produces an initial estimate of virgin biomass $B_{0,\text{prior}}$.

The inputs and assumptions are listed in Table 6-21. Two estimates of B_{2009} were compared, one from full stock assessment and one from cross-sampling described in the previous chapter. The scale ω linking F_{MSY} to M is from Zhou et al. (2012).

The results were compared with full stock assessment output, assuming the latter is correct (Table 6-22, Figure 6-52). The full retained stochastic trajectories of biomass over the fishing history are shown in Figure 6-52 and the distribution of retained B_0 in Figure 6-53. The CSSRA produced a slightly lower B_0, higher r, MSY, and depletion $B_{2009}/B_{0,\text{post}}$ (Table 6-22). The differences indicate that the stock was estimated to be more productive (a larger r) than predicted by the full stock assessment.

Table 6-21. Input parameters for Tiger Flathead.

Parameter	Distribution	Value
B_{2009}		23070 (stock assessment) 21798 (cross-sampling)
$B_{0,\text{prior}}$, median		35956 (from CC)
$B_{0,\text{prior}}$, distribution	Uniform lognormal	log(0.5 $B_{0,\text{prior}}$), log(1.5 $B_{0,\text{prior}}$)
M		0.27
ω (for Scorpaeniforms)		0.694
r	Uniform lognormal	log(0.5*2*ωM), log(1.5*2*ωM)
$B_{\text{MSY}}/B_{0,\text{post}}$	Uniform	0.1, 0.9

Table 6-22. CSSRA results for Tiger Flathead. CSSRA 1 used B_{2009} from stock assessment and CSSRA 2 used B_{2009} from cross-sampling.

Parameter	Stock assessment	CSSRA 1			CSSRA 2		
		2.5%	median	97.5%	2.5%	median	97.5%
$B_{0,post}$	43159	29421	37921	52429	29954	39121	52590
r_{post}	0.24	0.23	0.39	0.55	0.22	0.40	0.56
n	2	0.18	1.56	15.97	0.18	1.57	15.37
MSY (Hybrid)		2734	3537	4682	2692	3647	4910
MSY (Shaefer)	2564	2763	3686	5081	2710	3804	5267
$B_{2009}/B_{0,post}$	0.534	0.39	0.58	0.73	0.40	0.60	0.74

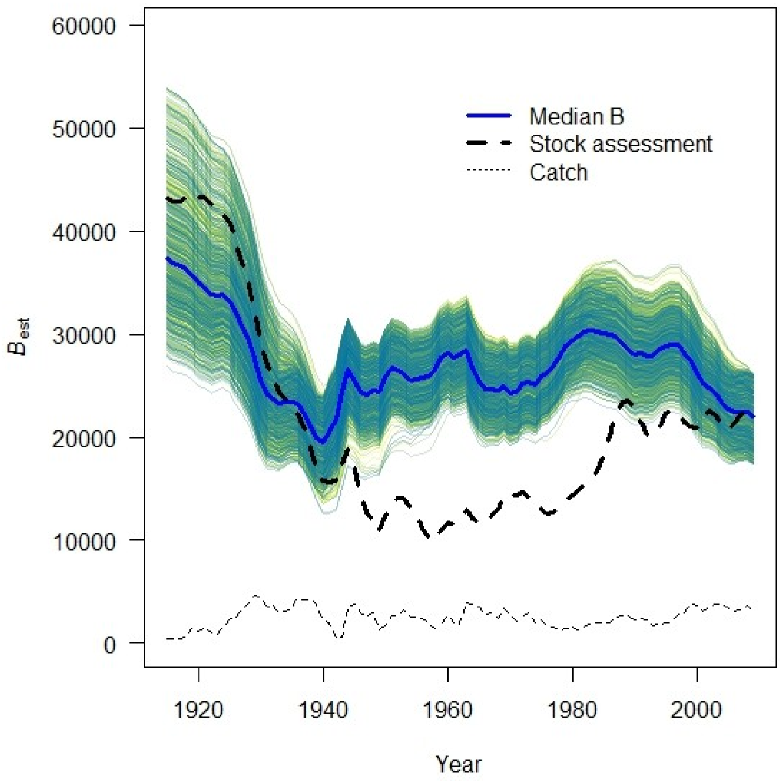


Figure 6-51. Tiger Flathead biomass trajectories from 1915 to 2009. The median trajectory is compared with summary biomass from full stock assessment. The CSSRA method assumes that the biomass in 2009 is known, and is the same as that from the full stock assessment. The scalar ω = 0.694 for Scorpeaniforms is used.

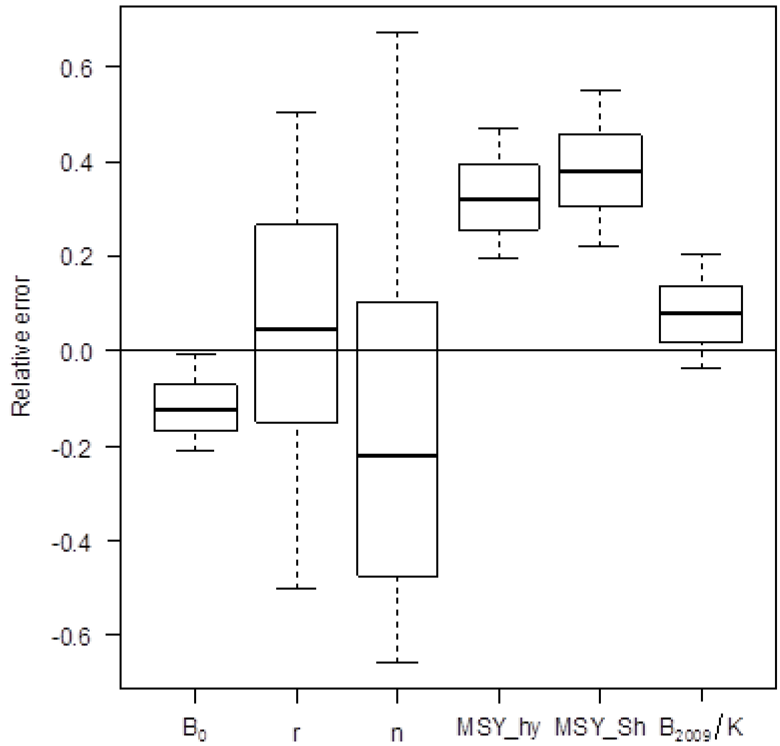


Figure 6-52. Tiger Flathead relative error for key parameters based on hybrid Graham-Shaefer and Pella-Tomlinson-Fletcher models (MSY_hy) and using *B_{2009}* from stock assessment. As a comparison, MSY_Sh is from Shaefer's model.

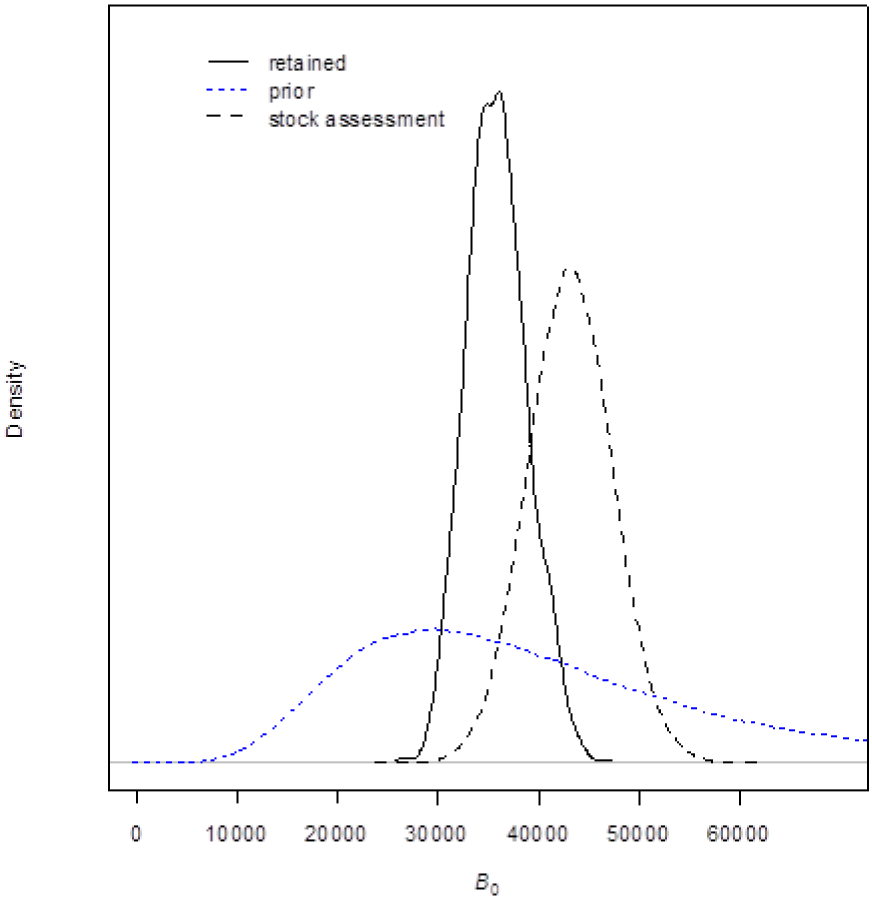


Figure 6-53. B_0 distribution for Tiger Flathead from full stock assessment and CSSRA method.

Jackass Morwong (*Nemadactylus macropterus*): Eastern and Western Stocks

The source of input data are the same as for Flathead, that is, the catch history and natural mortality from the most recent stock assessment, and the scalar ω from Zhou et al. (2012). We also tested two estimates of B_{2009}, one from the full stock assessment and one from the cross-sampling method (Table 6-23). The full retained stochastic trajectories of biomass over the fishing history are shown in (Figure 6-52). The results were compared with full stock assessment output, assuming the latter is correct (Table 6-22, Figure 6-52). In general, the results are not too far off. The CSSRA produced a slightly lower B_0, higher r, MSY, and depletion than the full stock assessment (Figure 6-53), indicating that the stock was more productive (a larger r) than predicted by the full stock assessment. Using B_{2009} from cross-sampling method increases the difference because the final biomass is larger than for the full stock assessment.

Table 6-23. Input parameters for Jackass morwong.

Parameter	Distribution	Value
B_{2009}		10551 (full stock assessment) 12744 (cross sampling)
$B_{0,prior}$, median		22262 (chase-catch method)
$B_{0,prior}$, distribution	Uniform lognormal	log(0.5 $B_{0,prior}$), log(1.5 $B_{0,prior}$)
M		0.15
ω		0.92
r	Uniform lognormal	log(0.5*2*ωM), log(1.5*2*ωM)
$B_{MSY}/B_{0,post}$	Uniform	0.1, 0.9

Table 6-24. CSSRA results for Jackass Morwong. CSSRA 1 used B_{2009} from stock assessment and CSSRA 2 used B_{2009} from cross-sampling.

		CSSRA 1			CSSRA 2		
Parameter	Stock assessment	2.5%	median	97.5%	2.5%	median	97.5%
$B_{0,post}$	30128	17086	27168	33103	16647	20215	32500
r_{post}	0.24	0.17	0.24	0.41	0.19	0.37	0.41
n	2	0.17	1.68	26.05	0.15	0.76	9.21
MSY (hybrid)		1410	1576	1713	1454	1685	1853
MSY (Shaefer)	1482	1413	1636	1988	1458	1756	2079
$B_{2009}/B_{0,post}$	0.35	0.28	0.40	0.70	0.36	0.70	0.87

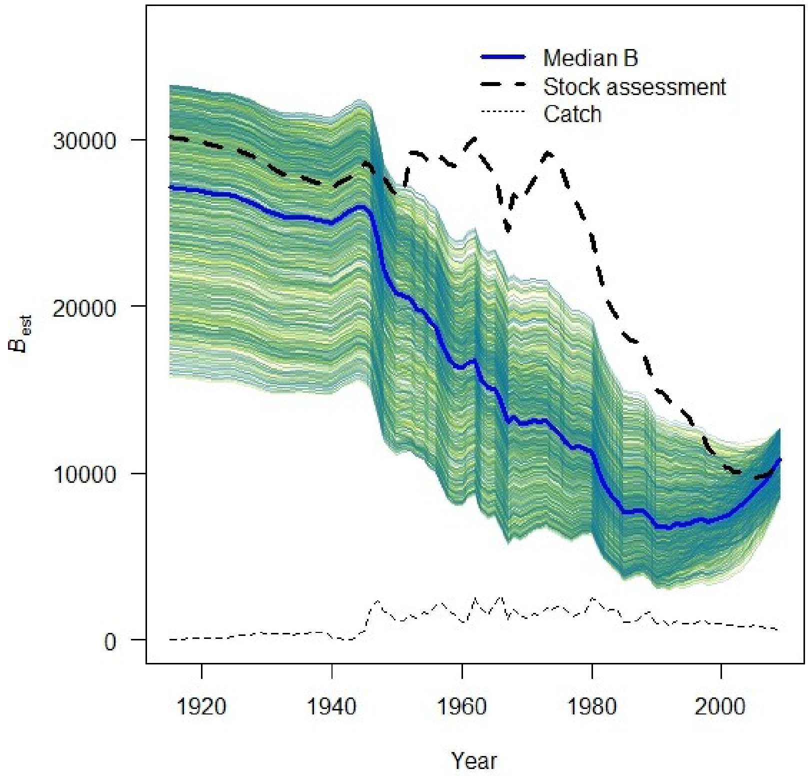


Figure 6-54. Retained simulations of Jackass Morwong biomass trajectories from 1915 to 2009. The median trajectory is compared with the summary biomass from the full stock assessment. The CSSRA method assumes that the biomass in 2009 is known, and is the same as that from the full stock assessment.

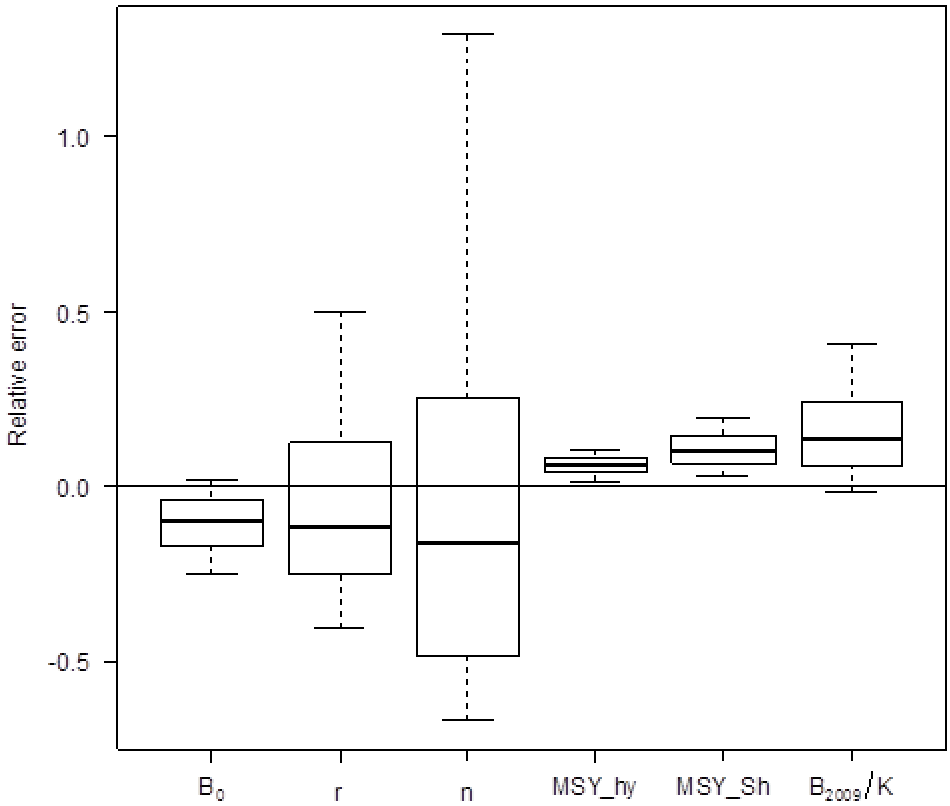


Figure 6-55. Relative bias of key parameters from CSSRA for Jackass Morwong using B_{2009} from stock assessment. The posterior MSY is based on the hybrid Graham-Shaefer and Pella-Tomlinson-Fletcher models.

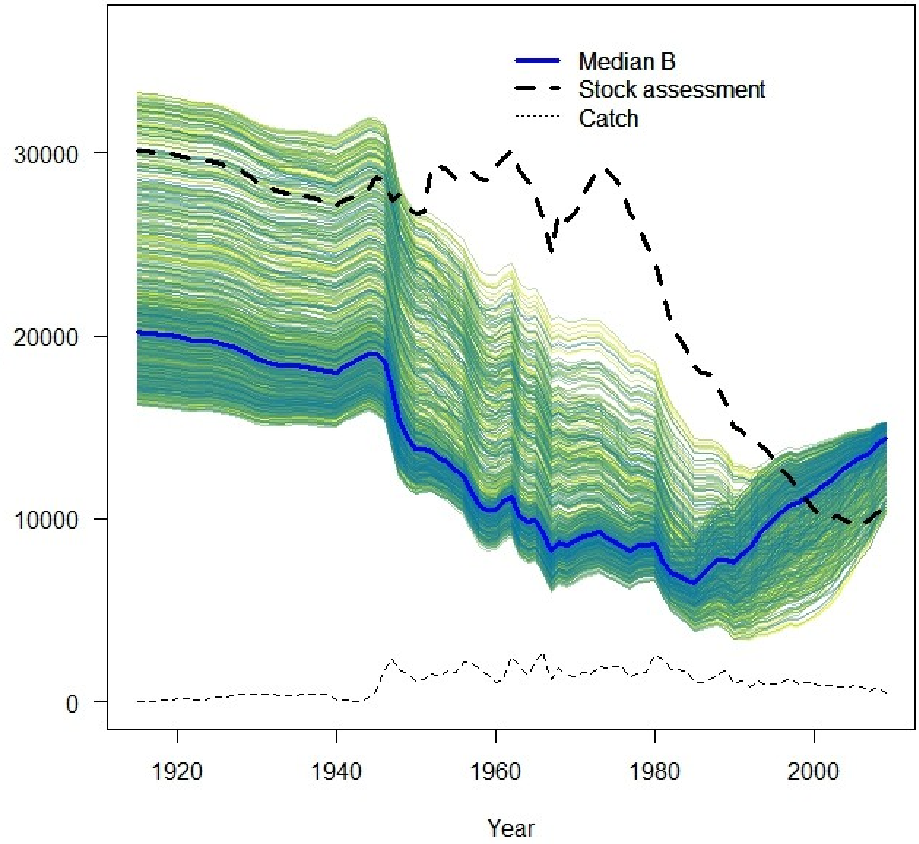


Figure 6-56. Retained simulations of Jackass Morwong biomass trajectories from 1915 to 2009. The median trajectory is compared with summary biomass from full stock assessment. The CSSRA method assumes that the biomass in 2009 is known, which is derived from cross-sampling method with fish density and distribution area.

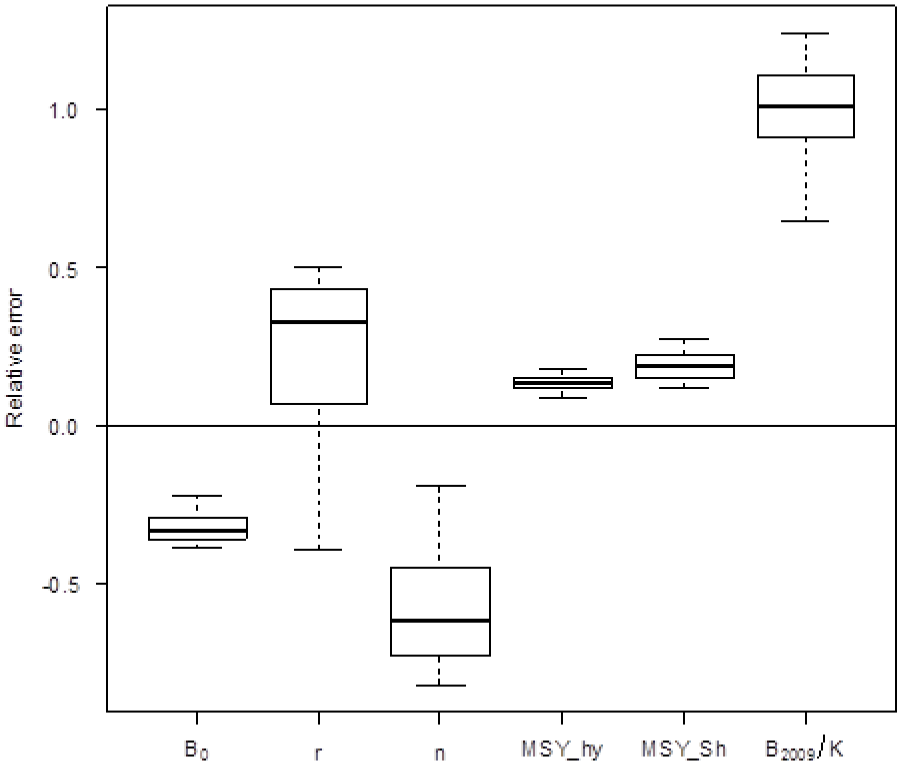


Figure 6-57. Relative bias of key parameters from CSSRA for Jackass Morwong using B_{2009} = 12,744 t derived from cross-sampling method, with fish density and distribution area. The posterior MSY is based on the hybrid Graham-Shaefer and Pella-Tomlinson-Fletcher models and.

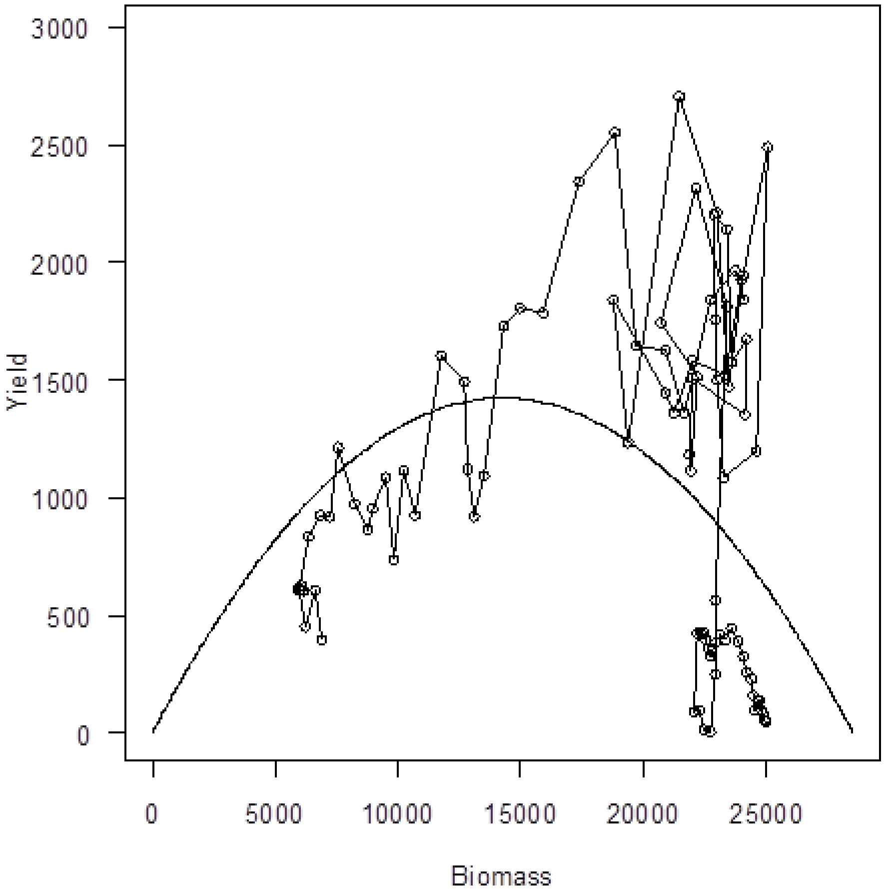


Figure 6-58. Morwong biomass dynamics model based on "true biomass" from full stock assessment. The circles with line are "true catch".

6.6.4 DISCUSSION

In this chapter, we describe the deterministic method (chase-catch, CC) and the conditional stochastic stock reduction analysis (CSSRA) to derive biomass-based reference points including MSY. The primary data required are complete catch history and an estimate of recent biomass. They can be considered as methods for data-poor or data-limited situations because they do not need information about age composition, fish effort, catch rate, fishery-independent survey, sex composition, individual growth, reproduction patterns, etc. We conducted extensive simulations to evaluate the sensitivity and performance of these methods, and applied them to real stocks and compared with results from other methods.

The results show that the CC method can estimate the virgin biomass, and hence other biological reference points, such as MSY, B_{MSY}, F_{MSY}, etc., if the assumptions can be satisfied: accurate catch history, known natural mortality rate and its relationship with F_{MSY}, and known biomass, or fishing mortality rate, or depletion status in one recent year. Although biases in these assumed parameters (i.e., B_y, M, and F_{MSY} ~ M relationship) will cause bias in estimated B_0 and the resulting BRP, the relative errors are generally smaller than the errors in the input predictors. Importantly, the estimate of MSY is more stable than the bias in r and B_0 due to these biases acting in the opposite direction. This is perhaps why previous studies have focused on estimating MSY alone (e.g., Martell and Froese 2012).

Several recent papers studied stochastic stock reduction analysis (Walters et al. 2006, Dick and MacCall 2011, Wetzel and Punt 2011, Martell and Froese 2012). In this study we have attempted to improve the method and have carried out systematic simulations to evaluate performance and sensitivity of the method.

Our results (unsurprisingly) reveal that an increase in prior variability results in high variance in the posterior for retained key parameters. Besides, this change also causes bias to some extent in addition to imprecision when the prior has a skewed distribution. Bias in priors, including assumed virgin biomass B_0, population growth rate r, and biomass in recent year B_y, results in corresponding bias in the posterior for key parameters. Yet, all the resulting biases are smaller than the bias in the input parameters and are typically within the range of 0.5 times the true value. Such a level of bias may be tolerable for data poor species. Bias for the estimated MSY appears to be smaller than that for the virgin biomass and population growth rate.

The results also reflect uncertainty about the type of priors, their distributions and parameter values, as all these affect the posterior estimates to some degree. Is there a better approach free of more or less arbitrary determined priors? This question is explored in the next chapter.

6.7 Application of Posterior-focused Catch-BRP to Australian stocks

6.7.1 TIGER FLATHEAD (*NEOPLATYCEPHALUS RICHARDSONI*)

The data used are the same as in the CSSRA section. That is, catch history comes from the full stock assessment, and the biomass in 2009 is assumed known, and is the same as in the full stock assessment. These are the only information needed for the catch-BRP method and natural mortality as well as its relationship with F_{MSY} is not required. The priors for r and K are uniform and large: r ~ dunif(0, 10), and K ~ dunif[max(C), 800,000]. We assumed some values here (i.e., 10, max(C), and 800,000) simply for the purpose of reducing the computation time because values outside the range will certainly not be retained. This means that the priors are essentially free of statistical distribution constraints. Any iterations that results in $B_t < K$, $B_t > C_t$, and $|(B_y - B_{2009})/B_{2009}| < 0.2$ are retained.

Simulations did not retain extremely large values for r and K. For the retained iterations, it is apparent that $K > \exp(12)$ is unlikely (Figure 6-59 and Figure 6-62). The log-log plot in panel C is not ideal. However, the results from such a wide range of priors are not far from full stock assessment, and in particular, the relative bias of MSY is less than 5%.

The results are improved after the data at the two ends of panel B and C in Figure 6-59 are excluded using the mid-point approach (Figure 6-60). The posterior key parameters are similar to those estimated in the full stock assessment (Table 6-25, Figure 6-61).

Table 6-25. Catch-BRP results for Tiger Flathead and compared to other methods. B_{2009} from stock assessment is assumed.

		CSSRA 1			Catch-BRP		
Parameter	Stock assessment	2.5%	median	97.5%	2.5%	median	97.5%
$B_{0,post}$	43159	29421	37921	52429	42382	48130	55422
r_{post}	0.24	0.23	0.39	0.55	0.18	0.23	0.26
n	2	0.18	1.56	15.97			
MSY (Hybrid)		2734	3537	4682			
MSY (Shaefer)	2564	2763	3686	5081	2501	2711	3011
$B_{2009}/B_{0,post}$	0.534	0.39	0.58	0.73	0.38	0.49	0.57

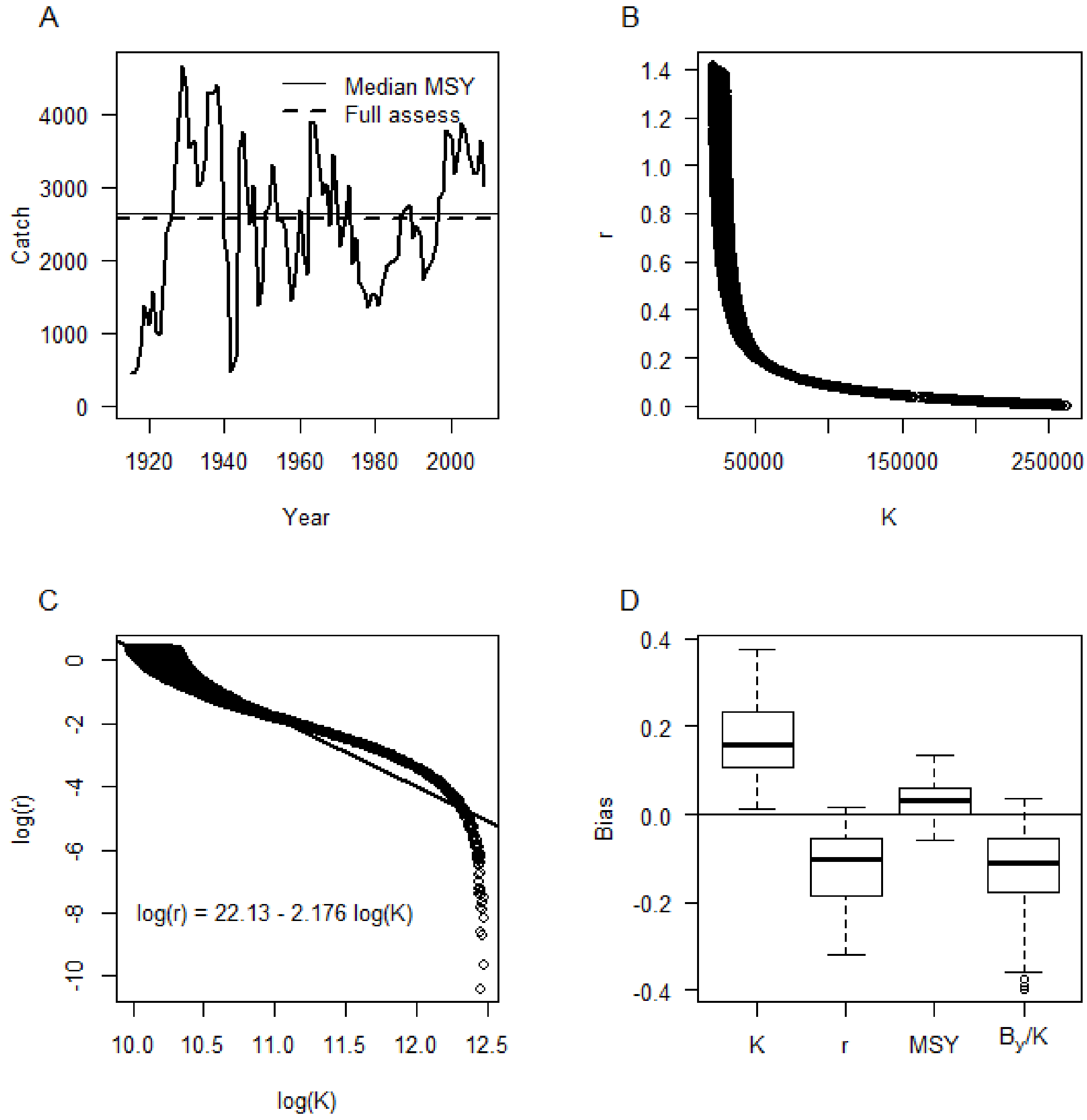


Figure 6-59. Result of Tiger Flathead using all retaining iterations from priors *r* ~ dunif(0, 10), and *K* ~ dunif(0, 800,000).

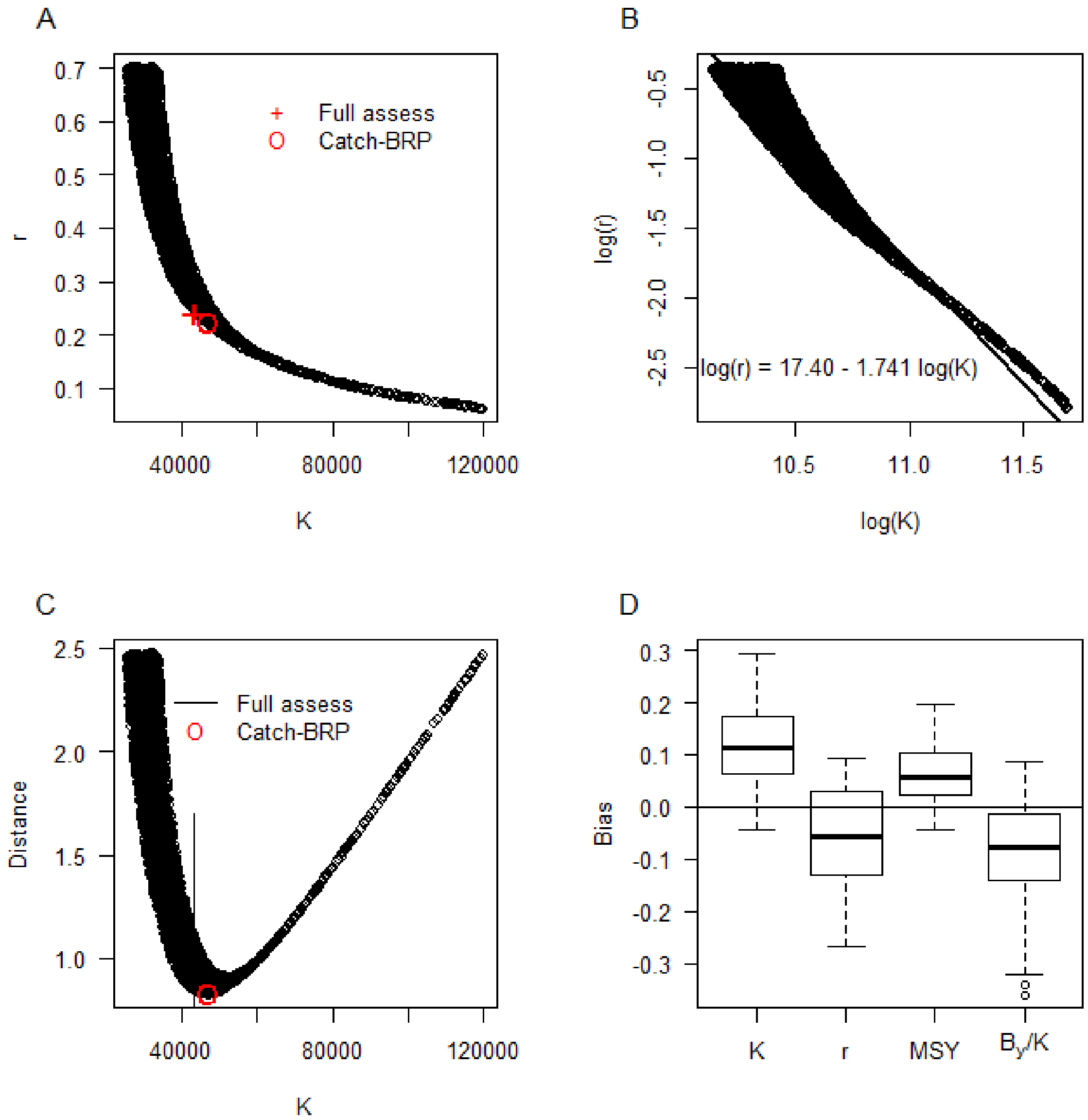


Figure 6-60. Results of Tiger Flathead after removing data at the ends of the r ~ K curves using mid-point method. The red circle is where standardized distance to the origin is minimum.

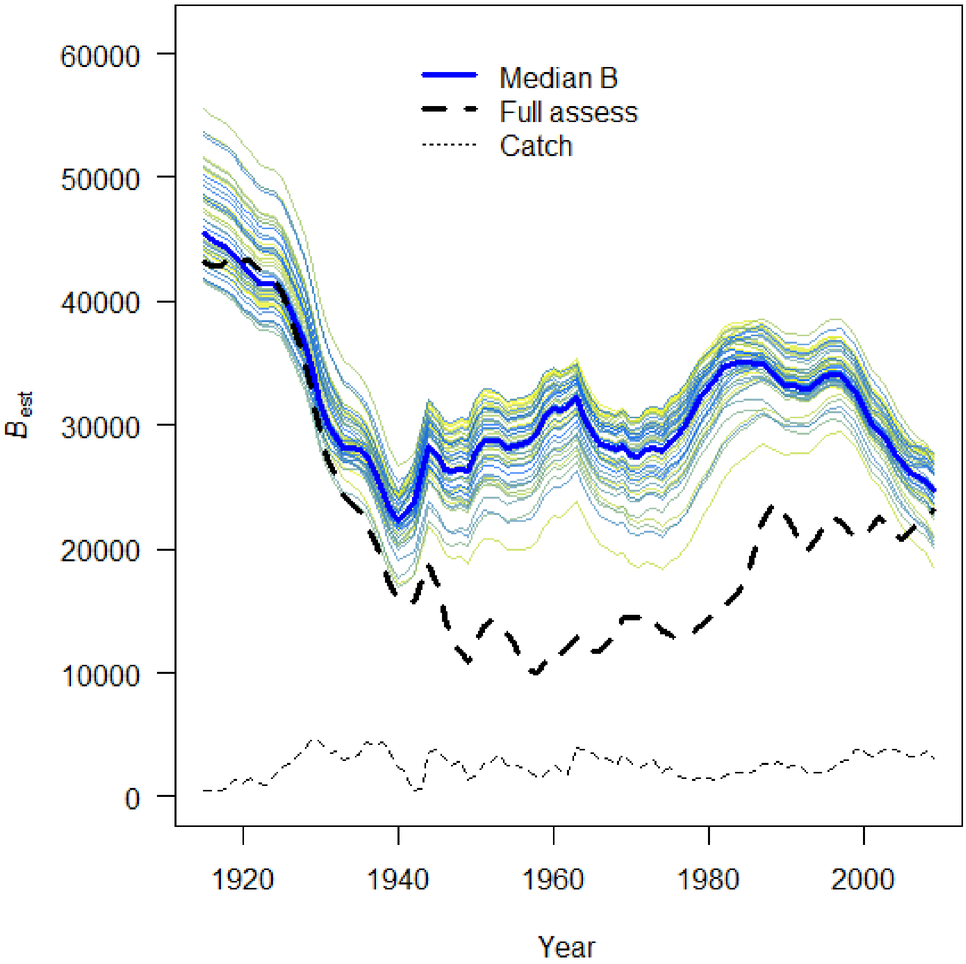


Figure 6-61. Catch-BRP result of Tiger Flathead biomass trajectories from 1915 to 2009. The median trajectory is compared with summary biomass from full stock assessment, where the biomass in 2009 is assumed same.

6.7.2 JACKASS MORWONG

Only two types of input data were used: the catch history and assumed biomass at the end of the time series, where we used the same values from the full stock assessment so the results can be compared. Natural mortality, growth rate, the scale parameter between F_{MSY} and M, etc., are not needed. The priors for r and K are sufficiently large to encompass all possible values: r ~ dunif(0, 3), and K ~ dunif[max(C), 70,000]. Any iterations that result in $B_t < K$, $B_t > C_t$, and $|(B_y - B_{2009})/B_{2009}| < 0.2$ are retained.

Apparently, it is unlikely that $r > 0.7$ and $K > \exp(11.0)$ (Figure 6-62). The log-log plot in panel C is not ideal. However and surprisingly, the result from such a wide range of priors are not far from full stock assessment, and in particular, the biases of K, MSY, and depletion B_{2009}/K were less than 5%.

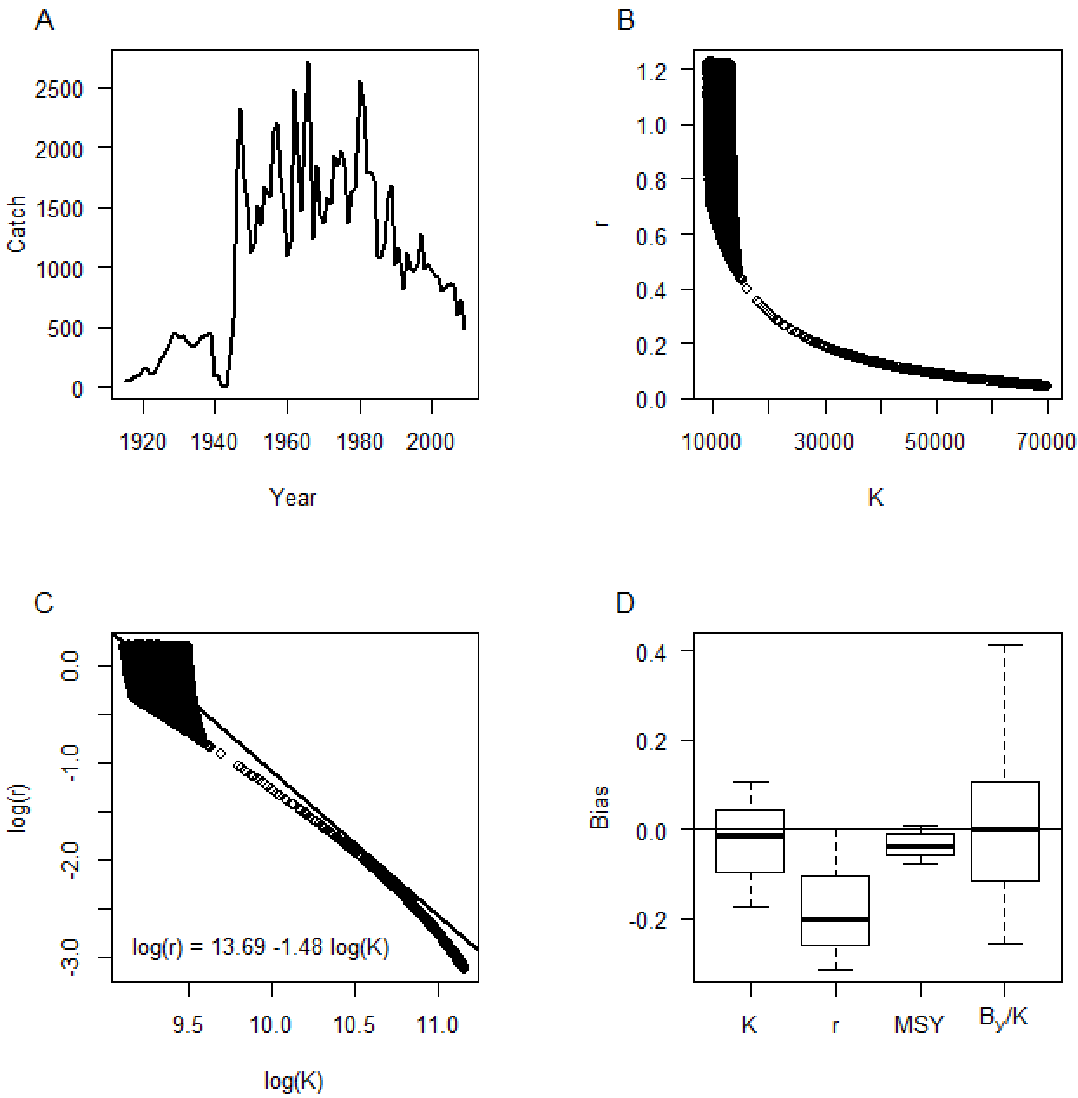


Figure 6-62. Result of Jackass Morwong using all retaining iterations from priors r ~ dunif(0, 3), and K ~ dunif(max(C), 70,000).

We may refine the retained iterations by gradually removing the data points at the two ends of panels B and C in Figure 6-62 until a sufficiently good linear regression line is obtained (Figure 6-63). Using the mid-point method and comparing to the full stock assessment result, this refinement does not improve much over Figure 6-62, except for MSY and *r* (Table 6-26). The relative biases for *K*, *r*, MSY, and depletion are -0.12, -0.08, -0.01, and 0.18, respectively. Overestimation of B_{2009}/K is due to an underestimation of *K* (Figure 6-64).

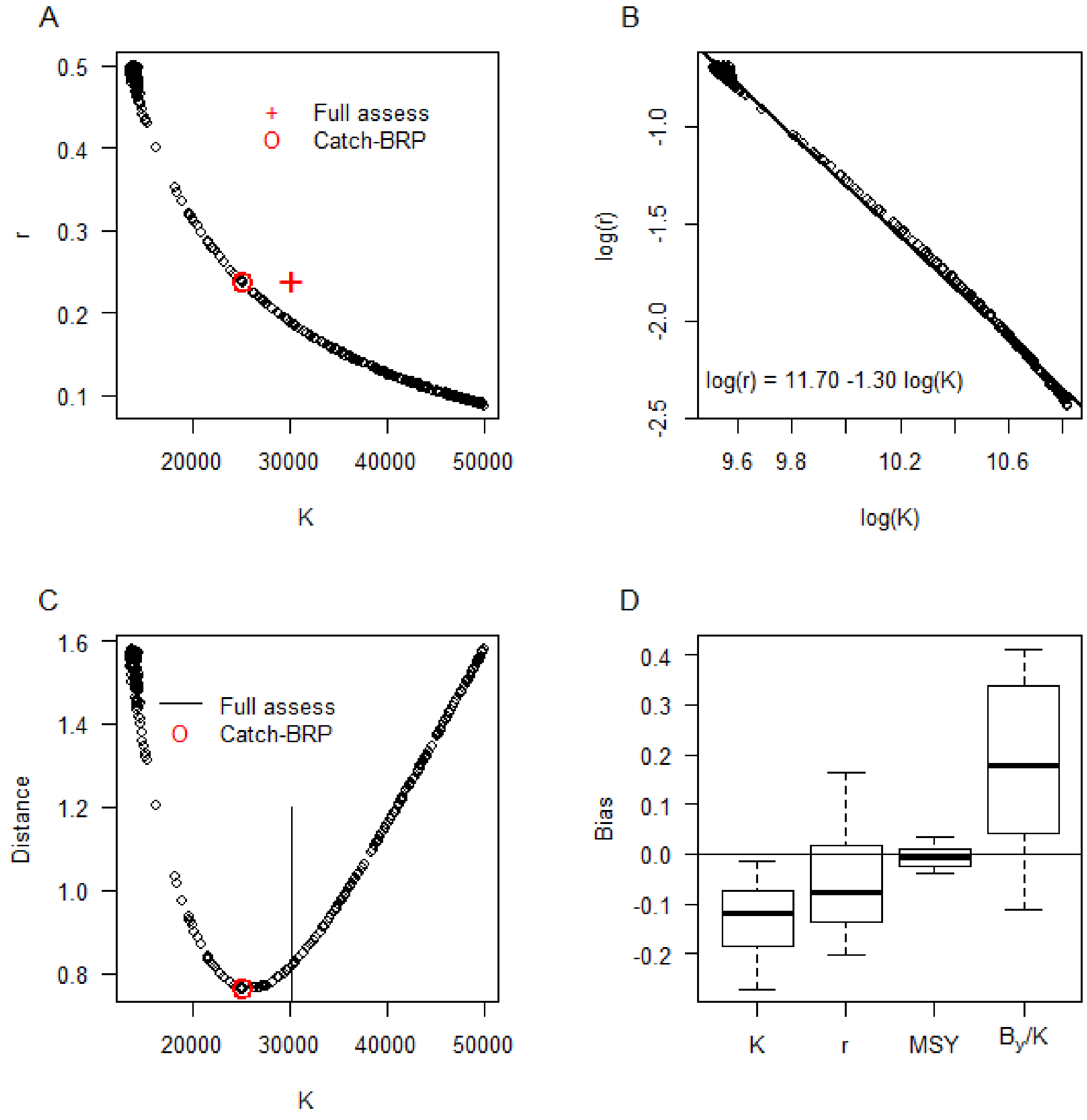


Figure 6-63. Results of Jackass Morwong after removing data at the ends of the *r* ~ *K* curves. The red circle is where the standardized distance to the origin is at the minimum.

Table 6-26. Catch-BRP results for Jackass Morwong and compared with other methods. B_{2009} from stock assessment is assumed.

Parameter	Stock assessment	CSSRA 1			Catch-BRP		
		2.5%	median	97.5%	2.5%	median	97.5%
$B_{0,post}$	30128	17086	27168	33103	21992	26577	29689
r_{post}	0.24	0.17	0.24	0.41	0.19	0.22	0.28
n	2	0.17	1.68	26.05			
MSY (hybrid)		1410	1576	1713			
MSY (Shaefer)	1482	1413	1636	1988	1424	1472	1535
$B_{2009}/B_{0,post}$	0.35	0.28	0.40	0.70	0.33	0.41	0.49

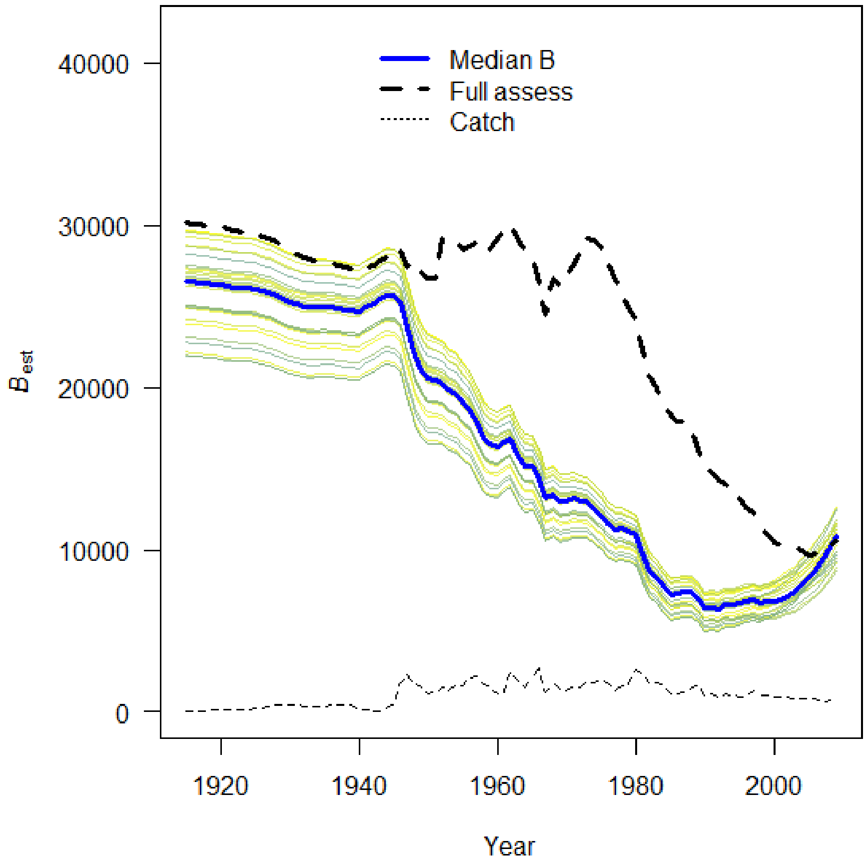


Figure 6-64. Retained simulations of Jackass Morwong biomass trajectories from 1915 to 2009. The median trajectory is compared with summary biomass from full stock assessment.

6.7.3 JOHN DORY

The catch history was provided by N. Klaer (CSIRO), and includes discards. We used the biomass in 2009 from cross-sampling method and area expansion because it was not available from other sources. The priors for r and K are very large: r ~ dunif(0, 3), and K ~ dunif[max(C), 60,000]. Any iterations that results in $B_t < K$, $B_t > C_t$, and $|(B_y - B_{2009})/B_{2009}| < 0.2$ are retained.

Simulations did not retain r greater than about 2 and K greater than about 7,000 (Figure 6-65). For the retained iterations, it is apparent that values of log(K) smaller than 7.9 and greater than 8.5 are unlikely (Figure 6-62). After excluding the data at the two ends of the curves and using the mid-point method, we obtained improved results (Figure 6-66, Table 6-27). The posterior key parameters are slightly larger than those derived from fitting a biomass dynamics model to catch rate data (result provided by N. Klaer).

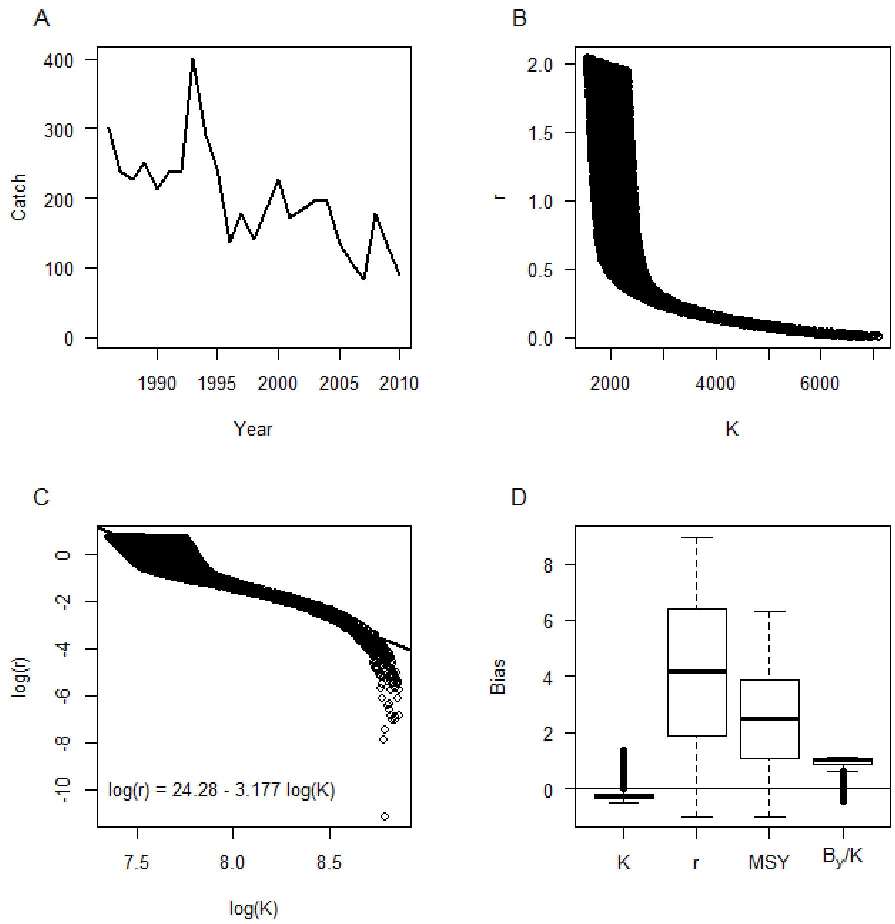


Figure 6-65. Result of John Dory using all retaining iterations from priors r ~ dunif(0, 3), and K ~ dunif(max(C), 70,000).

Table 6-27. Catch-BRP results for John Dory and comparison with fitting biomass dynamics model to catch rate data. $_{B2009}$ from stock assessment is assumed.

		Catch-BRP		
Parameter	Biomass dynamics model	2.5%	median	97.5%
$B_{0,post}$	3022	2881	3300	3724
r_{post}	0.205	0.17	0.21	0.24
MSY (Shaefer)	155	148	172	193
$B_{2009}/B_{0,post}$	0.47	0.47	0.58	0.67

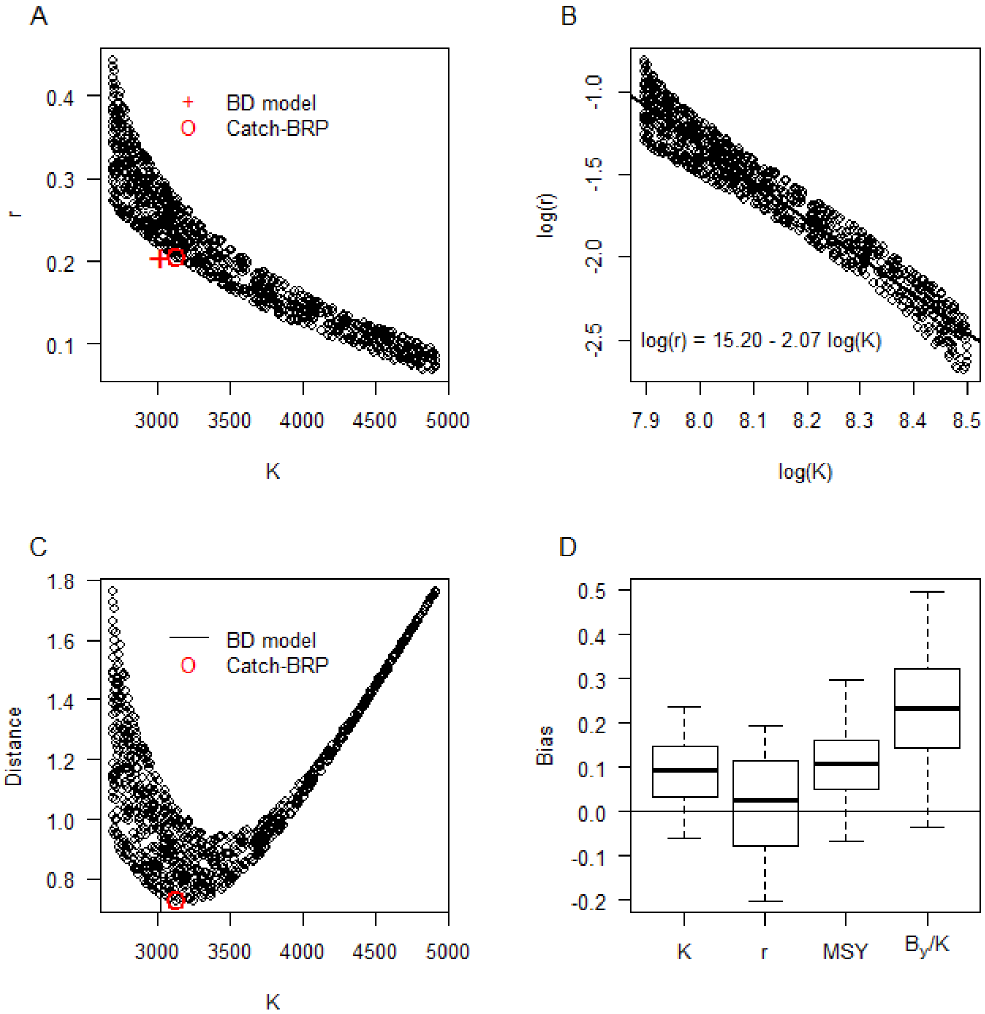


Figure 6-66. Results of John Dory after removing data at the ends of the r ~ K curves. The red circle is the where standardized distance to the origin is minimum.

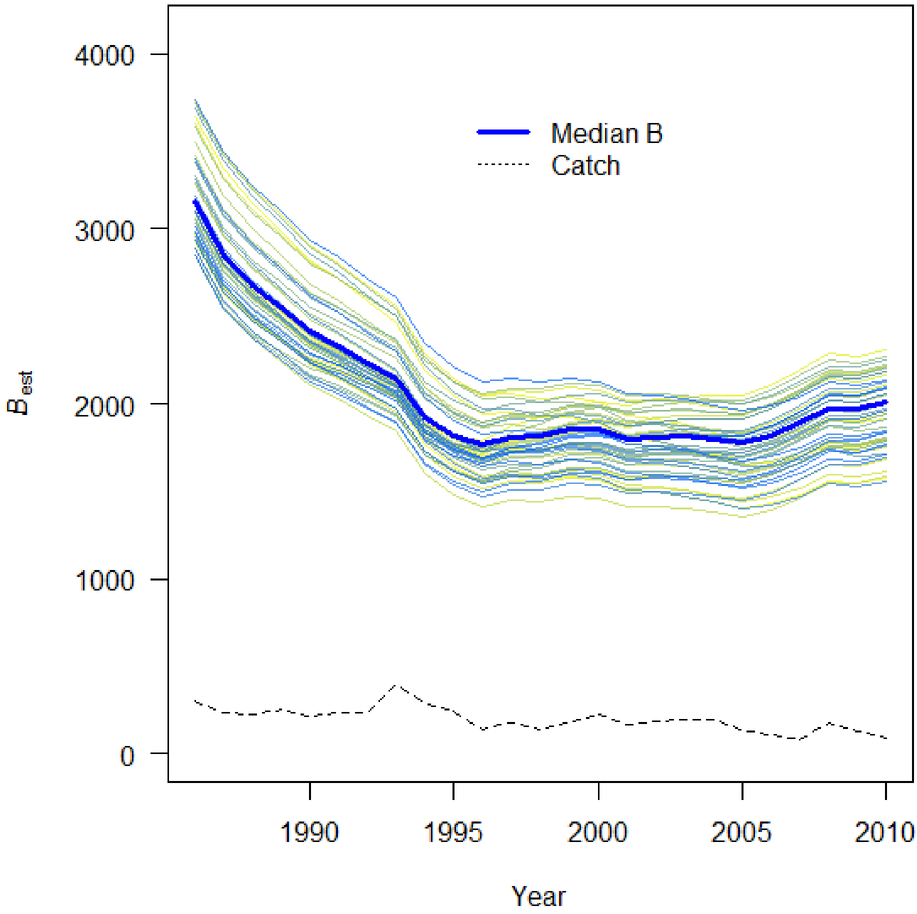


Figure 6-67. Retained simulations of John Dory biomass trajectories from 1986 to 2010.

6.7.4 EASTERN GEMFISH

We used catch data and B_{2009} from the full stock assessment (Tuck 2011) for illustration, because biomass estimated from cross-sampling method and area expansion includes both Eastern and Western stocks. The priors for r and K are very large: r ~ dunif(0, 5), and K ~ dunif[max(C), max(C)*100]. Any iterations that result in $B_t < K$, $B_t > C_t$, and $|(B_y – B_{2009})/B_{2009}| < 0.2$ are retained.

Interestingly, very few simulations were retained from 10,000 random iterations. Figure 6-68 compared all retained iterations with the result from fitting a Shaefer production model to the catch rate data (result provided by N. Klaer).

Since it is unlikely that log(*K*) > 11.0, we obtained improved results after excluding these extreme data points and using the mid-point method (Figure 6-66, Table 6-27). However, very few data remained for inference. One reason for this is that the initial biomass in year 1968 may be much smaller than the carrying capacity *K* (Figure 6-70). The biomass dynamics model used in the Catch-BRP method cannot accept biomass in any year larger than K.

Table 6-28. Catch-BRP results for Eastern Gemfish and comparison with fitting biomass dynamics model to catch rates. B_{2009} from stock assessment of 4177 t is assumed.

		Catch-BRP		
Parameter	Biomass dynamics model	2.5%	median	97.5%
$B_{0,est}$	3700	47092	51526	51696
r_{est}	0.208	0.19	0.19	0.23
MSY (Shaefer)	1925	2419	2430	2714
B_{2009}/B_0	0.11	0.09	0.09	0.10

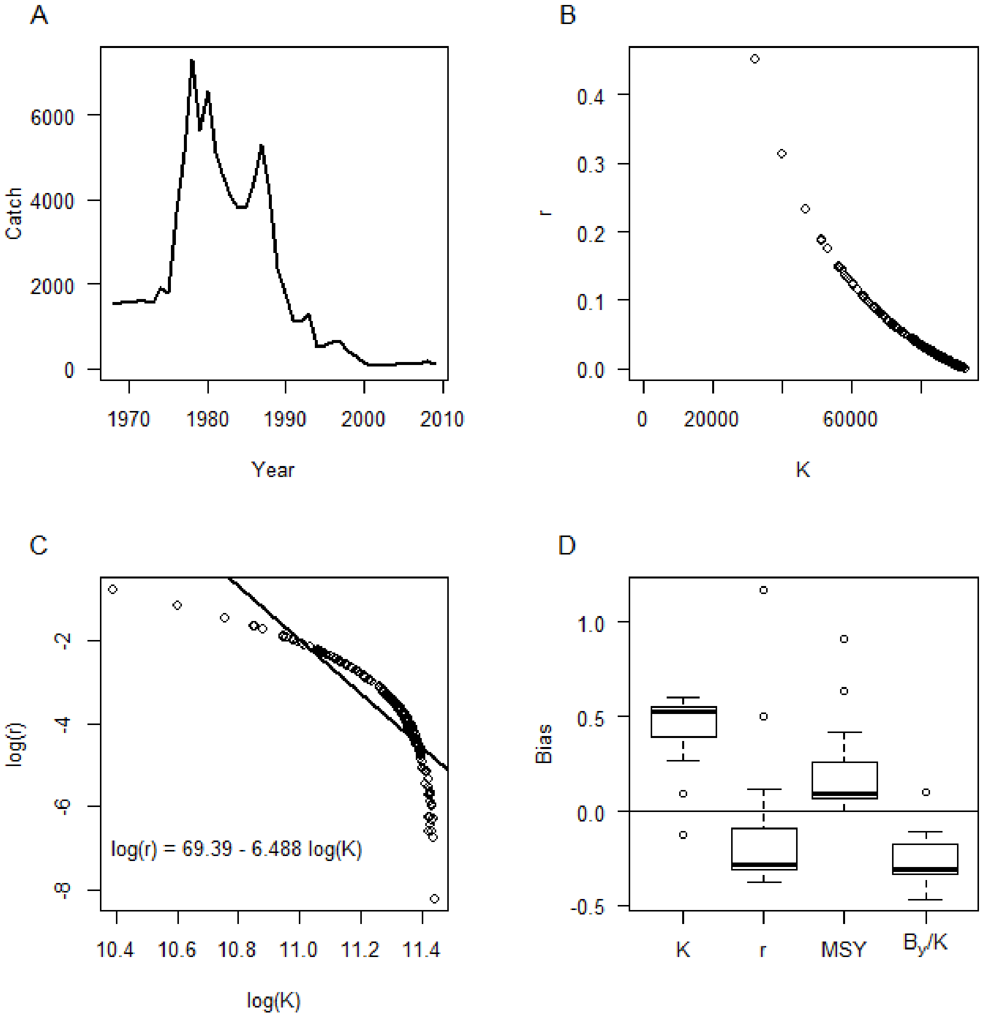


Figure 6-68. Result of Eastern Gemfish using all retaining iterations from priors *r* ~ dunif(0, 5), and *K* ~ dunif[max(C), max(C)*100].

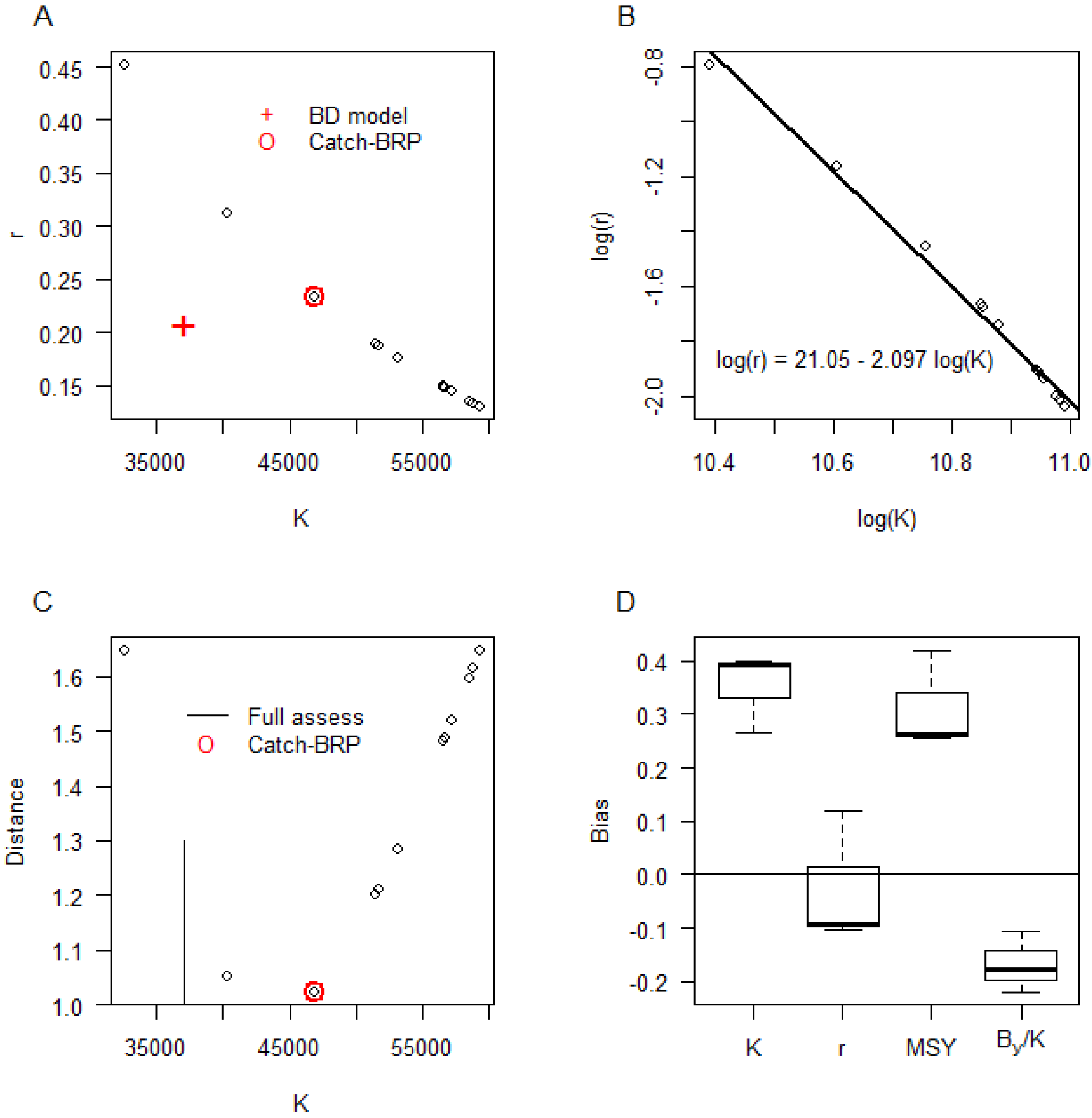


Figure 6-69. Results of Eastern Gemfish after removing data at the ends of the *r* ~ *K* curves. The red circle is the where standardized distance to the origin is at a minimum.

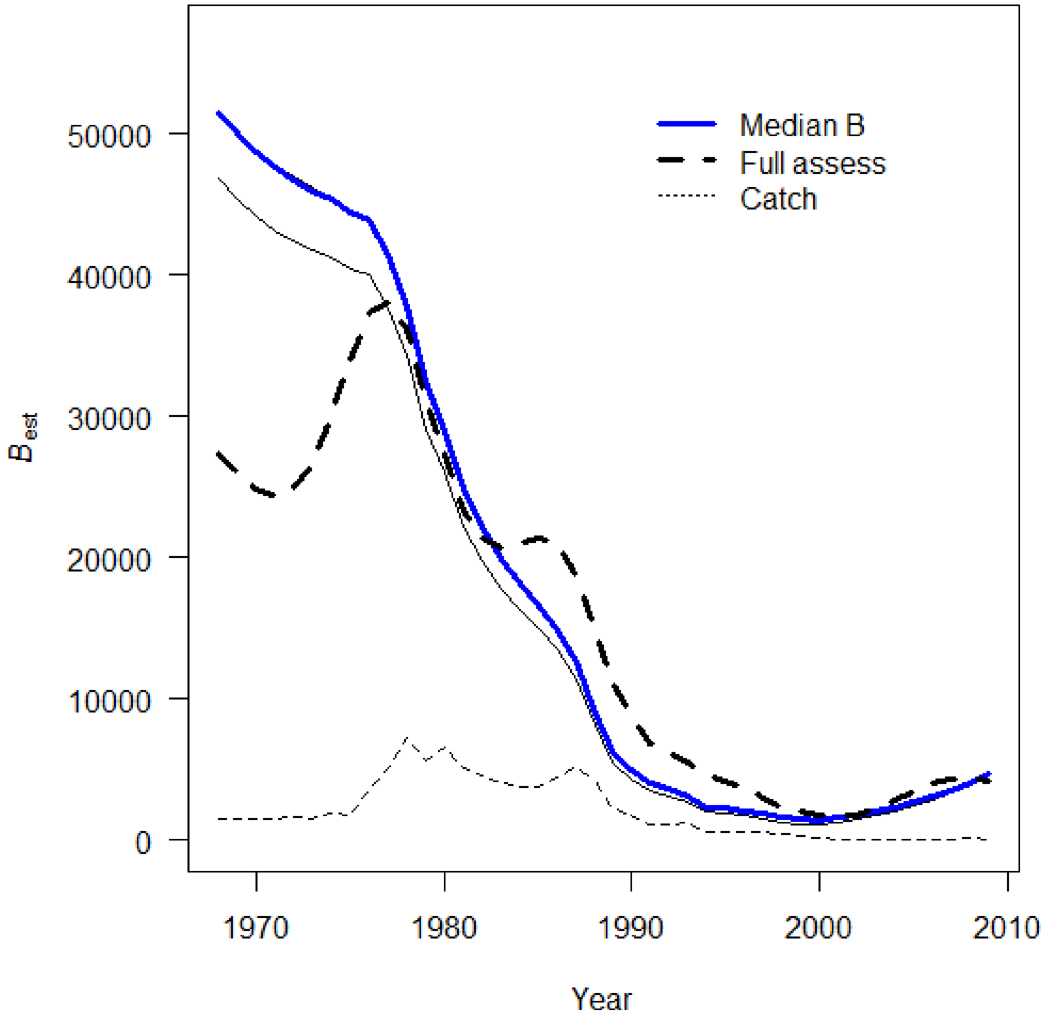


Figure 6-70. Retained simulations of Eastern Gemfish biomass trajectories from 1966 to 2009.

6.7.5 DISCUSSION

The method described in this section (referred to as Posterior-focused Catch-BRP for convenience) demonstrates a promising way to further improve CSSRA. The central advantage is the avoidance of choosing priors and the priors' impact on the posteriors. The main challenge is to accurately determine the viable range in the *r-k* curves, even though the results are robust to some extent to the variation of the range chosen. However, determining the viable range in the posterior r-k curve is less troublesome than choosing the priors. We use visual identification and find mid-point methods, but it would be possible to develop a more rigorous mathematical or statistical method for such purpose.

As we described above, the log(r) ~ log(K) plot forms a straight line. When the population is at equilibrium, the slope of the line is -1. The degree of departure from -1 may be used as a quantity to signal the rate of biomass changes over the timeframe of the catch history being used for analysis. Combined with the length of the history, it may be another measure of stock depletion. This could be an interesting topic for further research.

The methods described in the report, including CC, CSSRA, and Catch-BRP, require a complete and accurate catch history. If data in early years are missing or unreliable, or significant discards are not included, obviously the results will be affected. Furthermore, if the catch is very small compared to the stock size, there may not be sufficient signal to detect the reduction so the methods cannot be applied. We tried to apply the methods to Ruby Snapper in the Western Deepwater Trawl Fishery without success because the catch recorded in the logbook did not include data for Western Australia and was sporadic and very low.

6.8 SRA MSE testing results

One hundred 30-year simulations were conducted for each scenario, with differences between simulations due to observation error in the generated data, and process error in the population dynamics (future recruitment deviations). Summary statistics were combined over all simulations to provide a set of performance measures for assessing scenarios. In the figures showing the future trajectories of relative biomass and catch (Figures 7-71 to 7-74), the RBC shown in the middle right-hand plot is that calculated by the SRA assessment. The TAC shown in the bottom left plot can differ from the RBC by the subtraction of expected discards, and by the constraints that the TAC cannot change more than 50% from year to year, and remains the same if the change from one year to the next is less than 10%. The catch shown in the bottom right plot can differ from the TAC if the TAC is greater than the remaining vulnerable biomass.

For all scenarios, the SRA assessment is not performed for the first two years of the simulation, and instead the TAC from the final historic year is used as the RBC. This is because, in order to simulate what happens in practice, the RBC for each year is calculated from data 'collected' two years previously. Thus, as the historic data input to the simulations ends in 2008, the first two assessments determine the RBC in 2009 and 2010, using data from 2007 and 2008, respectively. As the SRA is fitting to recruited biomass in 2009, this cannot be used until 2011.

For the flathead below-target scenario (Figure 7-71), where the 2009 estimated recruited biomass used in the SRA was considerably higher (232%) than the true value (Table 6-8), the SRA overestimates stock status and current biomass. Thus the catch is set too high, and the stock remains at a low level. The RBC is slightly different each year, but as it is less than 10% different from the previous year's TAC , the TAC remains unchanged until the RBC does become greater than 10% higher than the previous year's TAC at around year 2024. At this point the TAC increases, causing the step in the future catch trajectory, and depleting the stock further. In some simulations towards the end of the projection, the TAC can no longer be taken, and the actual catch is much less than the TAC.

As the estimated 2009 recruited biomass used in the SRA is closer to the true value for the above-target scenario (Table 6-8), the final relative biomass level is correspondingly closer to the target relative biomass for this scenario (Figure 7-72).

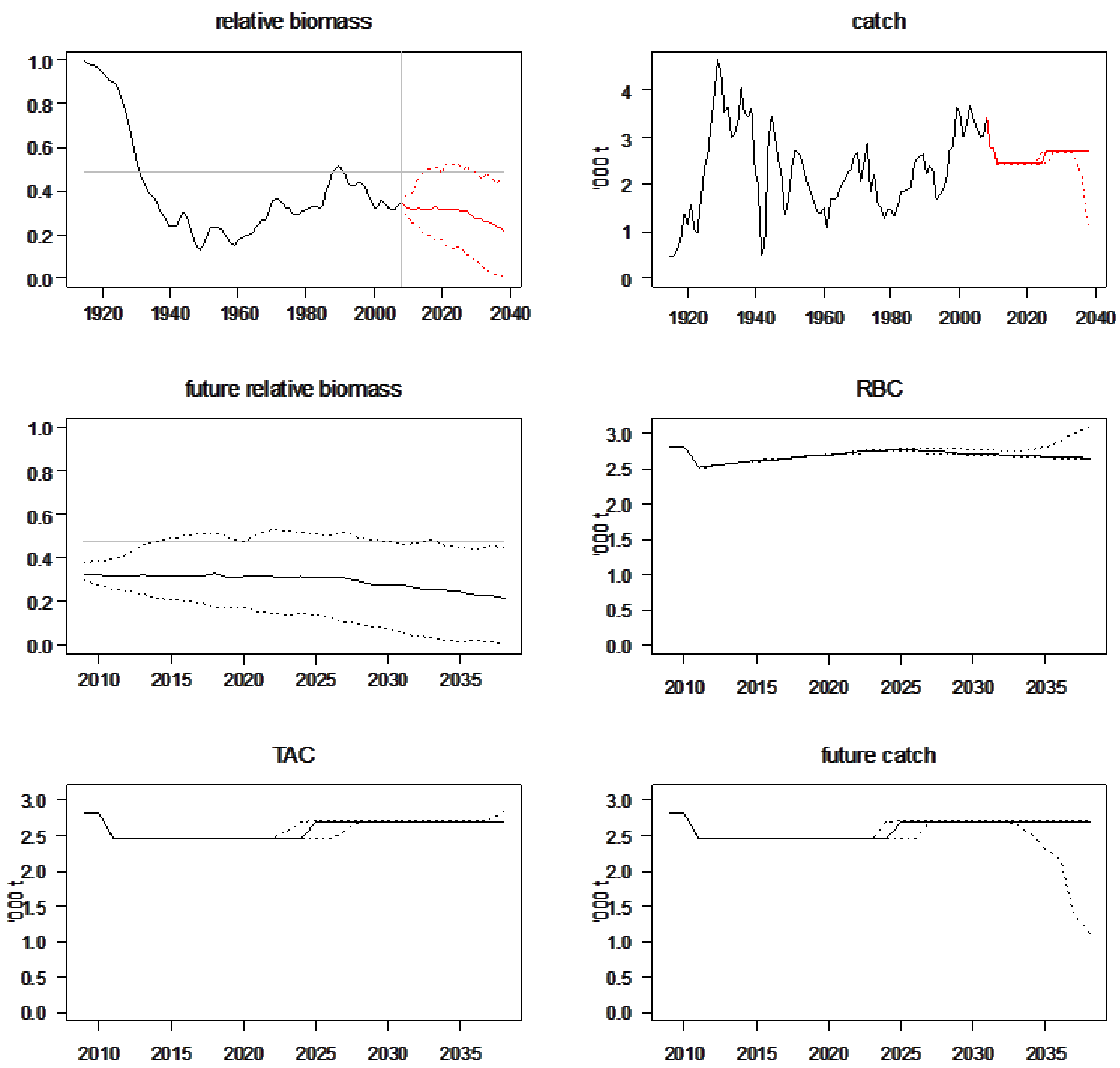


Figure 6-71. The operating model trajectory of relative biomass and RBC, TAC and catch over time for the Flathead below-target scenario. The solid line is the median, and the dotted lines are the 2.5 and 97.5 percentiles. The horizontal gray line indicates the biomass target (*B_{48}*) and the vertical gray line indicates the start of future projections. The top two plots show both the historic and projected relative biomass and catch series, and the remaining plots show only the future projections.

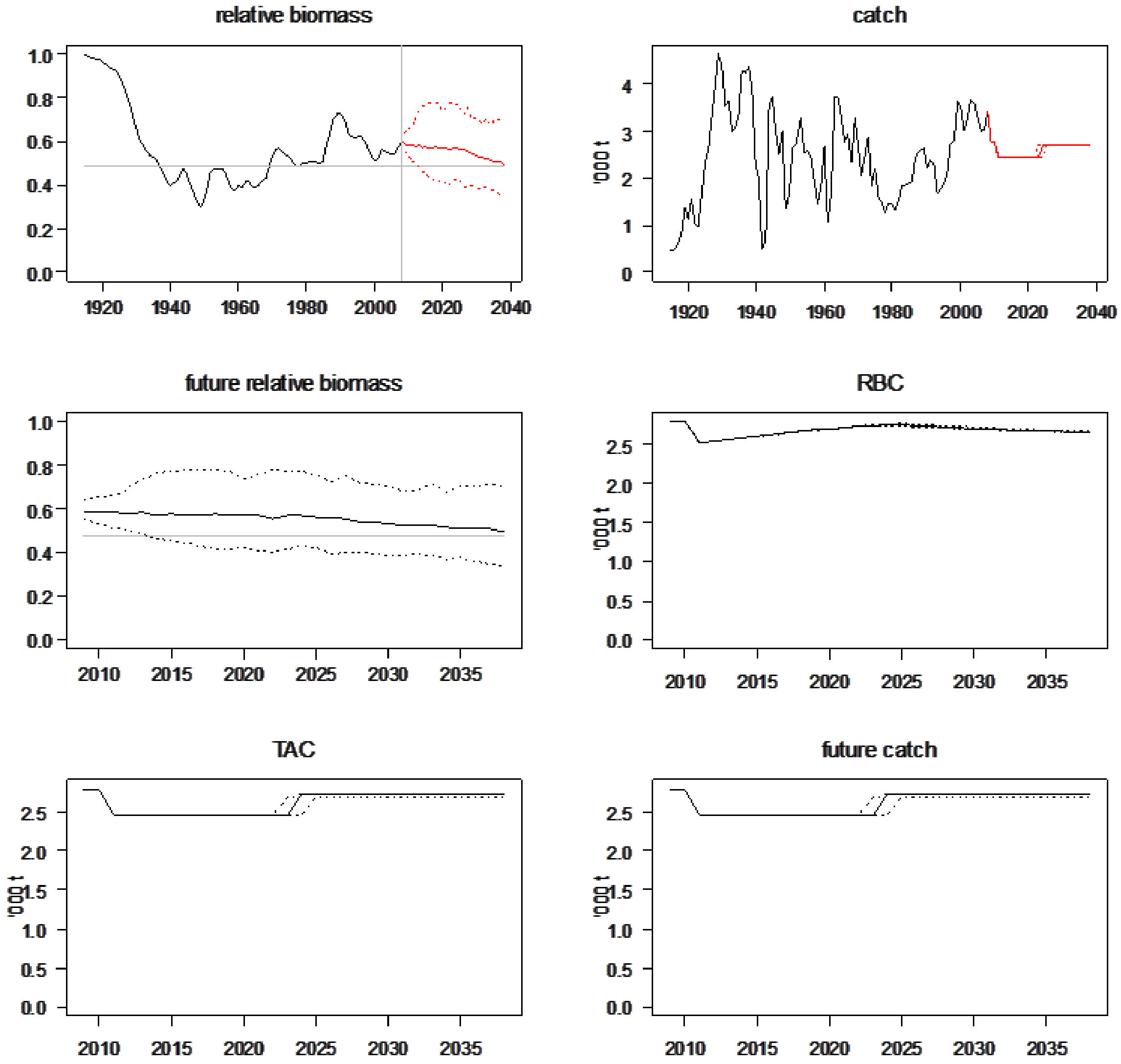


Figure 6-72. The operating model trajectory of relative biomass and RBC, TAC and catch over time for the Flathead above-target scenario. The figure description is as for Figure 6-71.

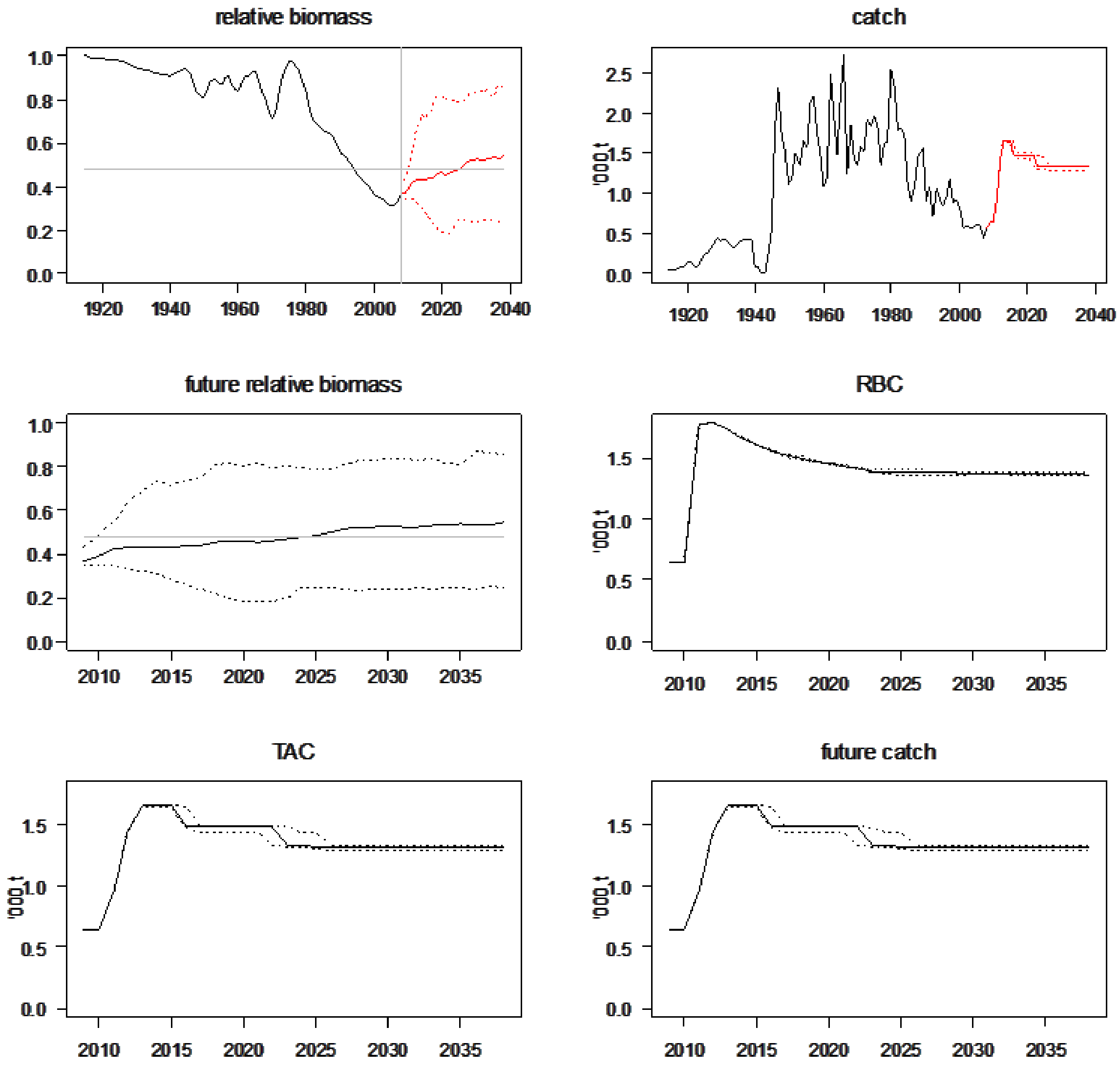


Figure 6-73. The operating model trajectory of relative biomass and RBC, TAC and catch over time for the Morwong below-target scenario. The figure description is as for Figure 6-71.

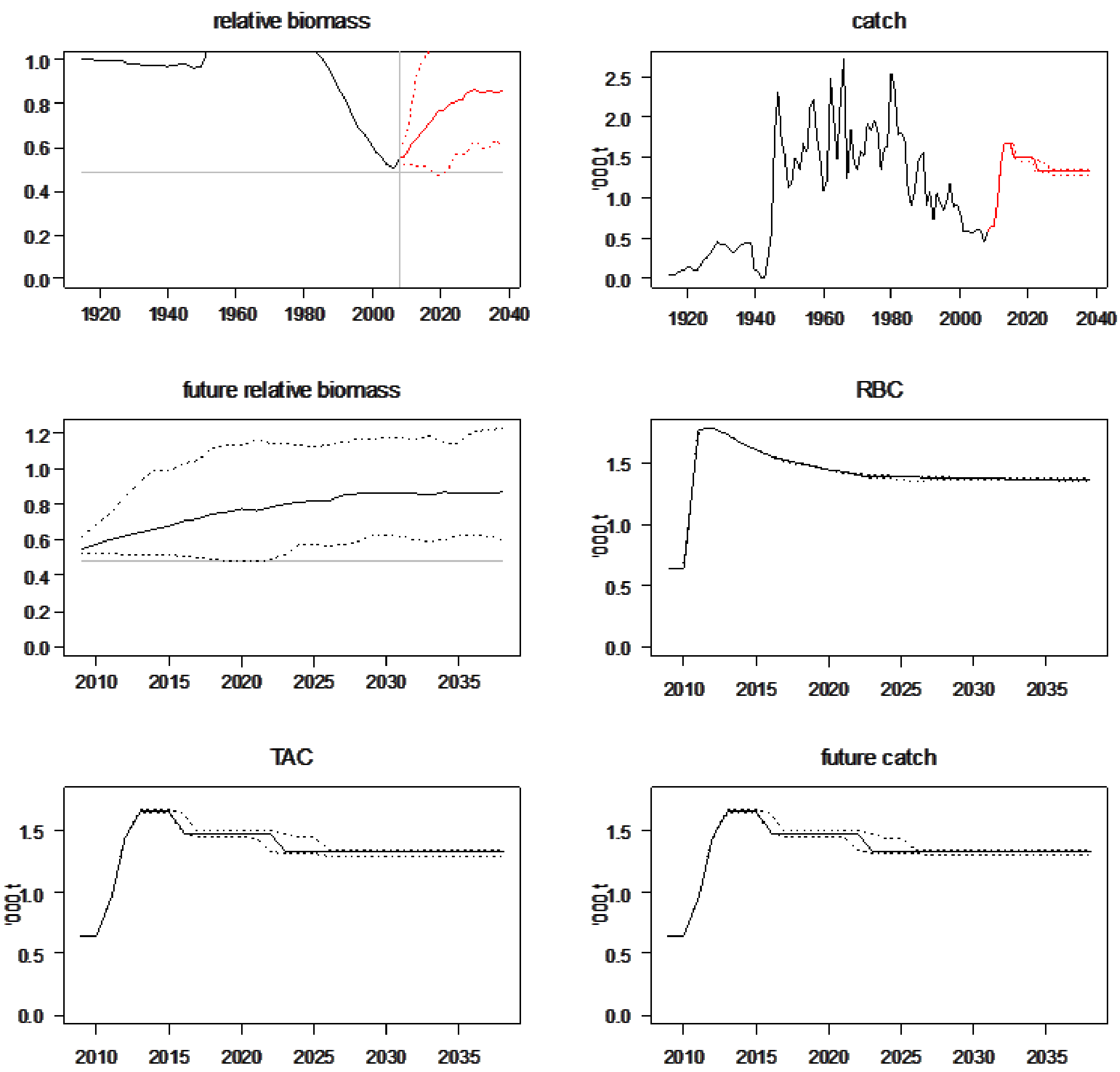


Figure 6-74. The operating model trajectory of relative biomass and RBC, TAC and catch over time for the Morwong above-target scenario. The figure description is as for Figure 6-71.

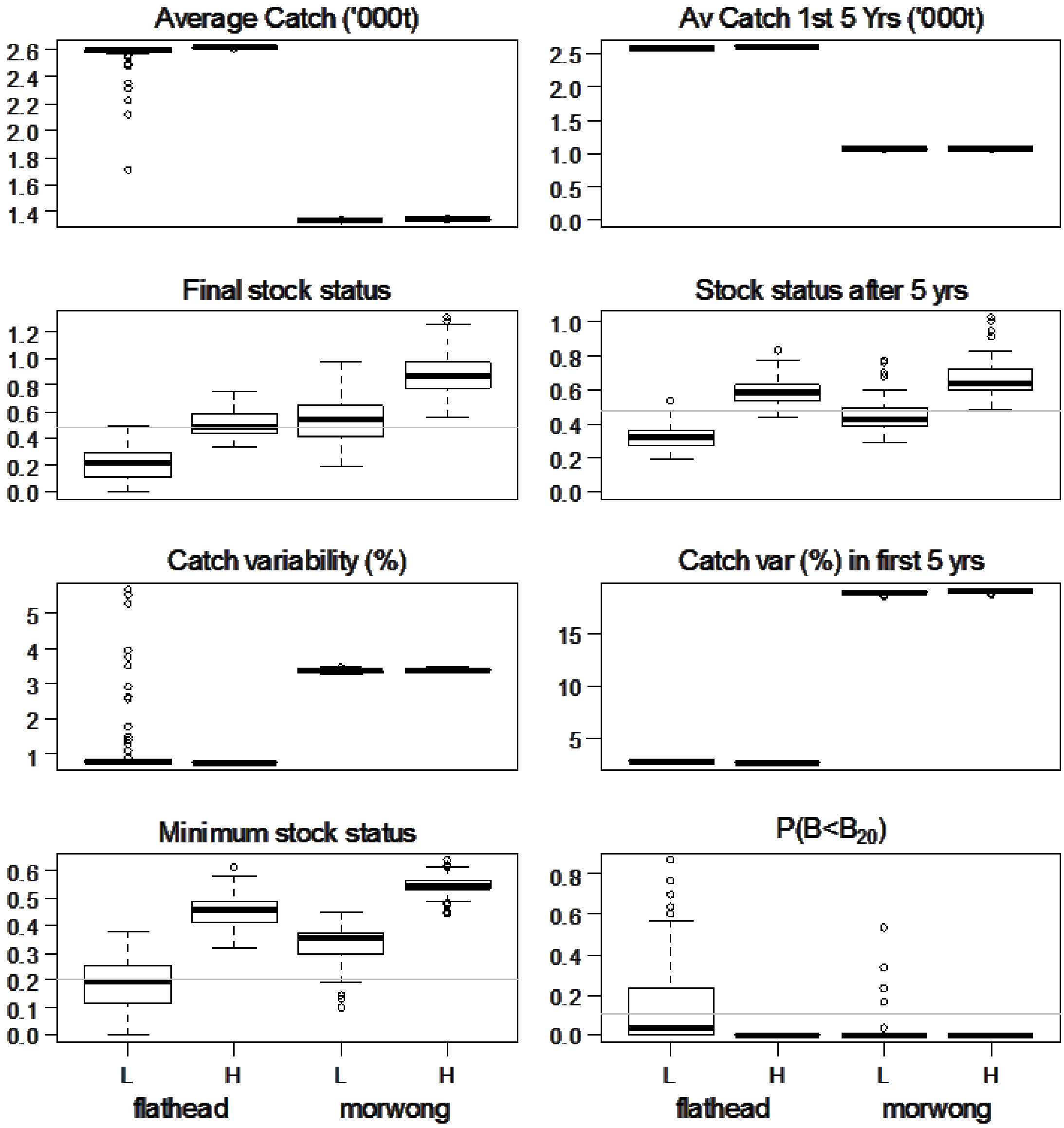


Figure 6-75. Box plots of performance statistics for the four scenarios. The top plots show the average catch over the 30 year projection period (left), and in the first five years (right). The plots in the second row show the 'true' stock status in the final and fifth years of the projection. The gray horizontal line is the target stock status. The third row shows the catch variability (average percentage difference in catch from year to year) over the 30 year projection period (left), and in the first five years (right). The bottom left plot shows the minimum 'true' stock status (lowest *SSB*/*SSB*$_0$ ratio in any year) over the projection period. The gray horizontal line is the limit stock status. The bottom right plot shows the probability of the 'true' stock status being below the 20% limit reference point during the projection.

With the starting "true" biomass close to B_{Lim} while the estimated biomass was near the target, the Flathead below-target scenario does not meet the first risk criterion of the CHSP in the long-term, as the median minimum relative biomass over the 30 year projection is slightly below the limit level (Figure 6-75, Minimum stock status), although the median probability of the true spawning biomass falling below the limit reference point is lower than 10% [Figure 6-75, P($B<B_{20}$)]. Only the above-target scenario meets the target biomass criterion of the CHSP in the long-term (Figure 5, Final stock status).

For the Morwong below-target scenario (Figure 6-73) the 2009 estimated recruited biomass used in the SRA is slightly higher (126%) than the true 2009 biomass (Table 5-8), so the SRA is able to return the stock to the target level even though the catch may have been set too high. In the Morwong above-target scenario, the starting "true" biomass was 4.3 times of the estimated biomass and catch was set too low. Consequently, biomass increases rapidly to about 80% B_0 in 30 years. However, this level of bias is much lower than the initial bias in the estimated biomass.

Both of the Morwong scenarios meet the risk criteria of the CHSP, but only the below-target scenario meets the target biomass criterion (Figure 6-75).

6.8.1 DISCUSSION

SRA is a simple procedure that provide a means to estimate B_0 and relevant biological reference points using catch history alone when catch at age or CPUE data are not available. As implemented here, the method contains no time-varying biological processes and cannot detect changing stock productivity over time. More sophisticated assessment methods have the ability to estimate, in particular, annual recruitment deviations. For standard SRA, a fixed stock-recruitment relationship is assumed, and all annual recruitments are assumed to be at average values using that relationship. This means that if the full catch history is known and time-invariant assumptions can be made about fishery selectivity and stock biological characteristics, the full biomass series is determined if the biomass or F in any year is also known (with an additional constraint on the maximum F allowed in any year). Extension of the SRA procedure for data-poor stocks simply says that if a recent F or biomass value is known or can be reasonably estimated, the full stock biomass series can also be determined using the catch history. Probably the most significant assumption that makes this possible is that recruitment deviations from the average relationship are zero. On the other hand, for the purpose of obtaining B_0, an accurate full stock biomass series is not essential.

Clearly the estimate of absolute stock biomass or F in recent times will affect the result, and essentially scale the entire biomass series. That estimate effectively provides the answer for how depleted the stock is, compared to the unfished level, and whether overfishing is currently occurring. It follows then, that the behaviour of the CCSRA method and HCR combination to determine RBC values should critically depend on how well the recent biomass/F estimate matches that of the true population. The SRA method tested here does lead to the required biomass target if the initial biomass guess is close to the true value. If the initial guess is greater than the true value, the stock stabilises below the target, and vice versa.

7 Benefits

Several novel methods have been developed in this project, using both biological analysis for limit reference points and economic analysis for target reference points. These methods are generic in nature. Hence they can be applied to any fisheries that have similar limited data. The immediate sectors to benefit will be the Commonwealth managed fisheries that use the Harvest Strategy Policy. Applying the methods developed in this project, reference points and associated indicators can be quantified for a range of stocks where this was not considered feasible at the beginning of the project. The outcomes will be valuable to fishery managers, including AFMA and its MACs and RAGs, who are required to develop harvest strategies. The State and recreational fisheries can also benefit from this project should they adopt the methodology.

The success of the project and the development of effective reference points and associated measures in data poor fisheries will lead to improved profits for the fishing industry. This will be due to a combination of increased productivity leading to lower costs, improved management practices, and increases in efficiency. The associated higher stocks will lead to enhanced resource sustainability, be more resilient to environmental fluctuations and have potentially lower variability in annual catches.

This project has achieved more than we expected in the original proposal. For example, in the beginning of the project we were not sure if it was possible to develop reference points and associated performance measures by using catch only data, which are commonly available for many fisheries. Here we have developed the innovative cross-sampling method that can estimate fishing gear efficiency, abundance, fishing mortality, as well as true biological reference points (rather than proxies), including B_{MSY}, B_{LIM}, MSY, depletion level, etc.

In the economic component, we have estimated costs structures in data-limited fisheries and derived “rules of thumb” that link fishery characteristics to ratios of $\mathrm{B_{MEY}}$ to $\mathrm{B_{MSY}}$. The method enables reasonable estimates of most cost components to be made given information on the vessel sizes, fishing gears, fishing effort, and the type of management. Based on knowledge of these variables, it is possible to estimate the likely ratio of E_{MEY} to E_{MSY} for a particular fishery.

8 Further Development

In this report, we apply new methods to several selected species, mainly to test their performance and as case studies. Most of the methods are ready to be applied to other fisheries and stocks. We recommend that relevant fishery managers (AFMA and its RAGs and MACs.) critically review these approaches and assess whether they could be adopted in the annual management process. Besides the utility for data-poor and data-limited situations, the methods can also be used as a comparison for stocks that have been assessed by other more data intensive methods.

Some methods will benefit from further fine tuning and development. For example, in the cross-sampling method, gear affected area can be more rigorously defined and tested for non-sweeping gear types such as line and hook, trap, and gillnet. When estimating biomass using catch data, an improved species distribution map and the relationship between abundance and grid cell size will increase the accuracy of the method. Computing limitation in fitting GAM model can be solved by using alterative operating system or different software. More rigorous techniques can be developed to determine the optimal scope of the posterior key parameters in the Posterior-focused Catch-BRP method. Hence research in these areas will be valuable for data poor species assessment.

The relationship between E_{MEY} and E_{MSY} (and B_{MEY} and B_{MSY}) has been developed primarily for single species fisheries, although the results appeared relevant for key species in multispecies fisheries (based on comparison with bioeconomic modelling results for several fisheries). For many minor species, the ratio is likely to depend on other factors, such as the contribution of the species to the overall revenue. Work is being undertaken in a separate project (FRDC project 2011/200) to progress this work in a multispecies framework with particular focus on the byproduct species.

Clearly, the project outputs have management application for many data-poor fisheries. The outputs from this project will guide fishery management agencies in their development of policies and management rules. The final report will be made available to the relevant management agencies and industry, and findings will be communicated to various stakeholders further through seminars, meetings, publications and conferences. The methods developed in the report, with endowment from relevant management bodies, can be readily applied to similar fisheries and species.

The large proportion of the data used in the project comes from existing database, such as AFMA logbook, Bioregional mapping, fishbase, and published literature. The economic analysis uses some confidential data, which are maintained by ABARES and will continue to be maintained by the same agency. Hence, there is no data storage, maintenance, or security issue after the completion of the project.

9 Planned outcomes

The planned outcomes in the project application were:

The project will develop improved proxy measures for maximum economic yield for fisheries where reasonable stock information is available but economic information is limited. Further, the planned outputs will include methods that identify biological, economic or fishery related indicators that correlate with target or limit reference points for selected representative data-poor stocks. Standard options will be developed to cope with data poor situations where there are either unreliable or no catch rate data, and where there are no reliable fisheries data. Minimum data requirements for the estimation of limit and reference points will be identified.

The economic component has developed improved proxy measures that provide greater options than jus the default $1.2B_{MSY}$. The results suggest that for many fisheries, it is likely that an appropriate target reference point would be higher than this (in the range 1.3 to 1.4 B_{MSY}). This work will have direct implications for the review of the Commonwealth Harvest Strategy that is currently underway. The results of the cost modelling also have implications for setting target reference points in data-rich fisheries where bioeconomic models are available. The results of the analysis relating to depreciation rates was adopted relatively early in the Northern Prawn Fishery modelling work, and has been used in the last two years' assessments. There has been considerable interest in the results from overseas agencies who have been confronted by similar issues.[14]

In the biological component, we have developed both F-based and B-based reference points for data poor fisheries, as well as their associated indicators. These measures can be considered as actual quantities derived from alternative and novel approaches, rather than proxies that may have different meaning from traditional stock assessment. Therefore, they can be easily understood by fishery biologists, managers, and the industry. In the current Commonwealth TIER management system, catch rate data are necessary for the lowest TIER 4 approach. Our methods only require catch data, which means they can be applied to fisheries where catch rate data are not available or reliable. For the F-based reference points, our approach only requires limited life-history

[14] A paper on the methods and results was presented at an international conference in July 2012, and several requests for copies of the paper have already been received.

parameters, particularly the natural mortality rate. Hence, it can be applied to fisheries where reliable fisheries data are not available.

Some of the outcomes from the project have been published in scientific journals. Additional papers will be prepared for publication after the completion of the project. We have presented and will continue to present the result in national and international conferences. In addition to a final report, we intend to provide the results and outcomes to relevant fishery managers and industries in other forms, such as seminars and meetings.

10 Conclusion

This project aimed to: (1) identify biological reference points with associated performance measures and proxies for data-poor fisheries, and to test harvest strategies and quantitatively define limit and / or target reference points in line with the requirements of the Commonwealth Harvest Strategy Policy. (2) Identify cost-effective methods of incorporating economic indicators into biological reference points that could be determined. (3) Develop case studies that demonstrate how these methods could be implemented in other Australian fisheries.

The project has successfully identified methods to determine and use biological reference points (BRP) with associated performance measures for data-poor fisheries. To facilitate the understanding, acceptance, and implementation in management, we have devoted our effort to identifying the reference points and associated performance measures specified in the Commonwealth Fisheries Harvest Strategy: $B_{TARG} \geq B_{MEY}$; $B_{LIM} \geq 0.5\ B_{MSY}$; and $F_{LIM} \leq F_{MSY}$. Another advantage of using these reference points (rather than identifying new and uncommon proxies) is to reduce the need of further testing of their performance in harvest strategy and management. However the level of uncertainty in some of these reference points may require further analysis.

For fishing mortality-based reference points, we have derived F_{MSY} (as well as F_{proxy}, $F_{0.5r}$) through a meta-analysis on 245 fish species worldwide and linked F_{BRP} to M and other life-history parameters (LHP). We used Bayesian hierarchical errors-in-variables models to investigate the relationships and included the effect of taxonomic class and order. We compared various models and found that natural mortality is the most important LHP affecting F_{BRP}. Other covariates, such as von Bertalanffy growth coefficient, asymptotic length, maximum age, and habitat types add little to the relationship, partially due to correlation and large measurement and process errors. The best model results in F_{MSY} = 0.87 M (SD 0.05) for teleosts and F_{MSY} = 0.41 M (SD 0.09) for chondrichthyans.

For biomass-based and catch-based reference points, we developed and applied the cross-sampling method to estimate biomass from catch data alone. From estimated annual biomass, fishing mortality rate can be readily obtained. Further, the estimated biomass can be fed into chase-catch (CC) and conditional stochastic stock reduction analysis (CSSRA) to derive various BRPs, including B_0, MSY, B_{MSY}, B_{LIM}, F_{MSY}, and depletion status.

Finally, the CSSRA method is improved by Posterior-focused Catch-BRP where the difficulties in choosing priors on key inputs are avoided. The success of this project enables us to estimate BRP and associated measures from limited data: catch history and a few life-history parameters. In this sense, the project has exceeded its original objectives.

For high value fisheries, bioeconomic analysis with “real” data is still preferred for assessing target reference points, but for many fisheries with a relatively low overall value, the cost of specific economic data collection and full bioeconomic model development may outweigh the benefits of the improved information. In such cases, the approach developed in this report provides a good alternative to establish economic reference points. The econometric methods applied to estimate cost structures for different fleet types could also be repeated in the future, as the economic information that is collected for higher value fisheries is updated, leading to revised economic targets.

11 References

ABARES. 2010a. Australian Commodity Statistics 2010. Canberra: ABARES. p. 233.

ABARES. 2010b. Australian Fisheries Statistics 2009. Canberra: ABARES.

Armstrong, C. W., and Sumaila, U. R. 2001. Optimal Allocation of TAC and the Implications of Implementing an ITQ Management System for the North-east Artic Cod. Land Economics, 77: 350-359.

Arnason, R. 1990. Minimum Information Management in Fisheries. Canadian Journal of Economics, 23: 630-653.

Arreguin-Sanchez, F. 1996. Catchability: a key parameter for fish stock assessment. Reviews in Fish Biology and Fisheries 6: 221-242.

Asche, F., Eggert, H., Gudmundsson, E., Hoff, A., and Pascoe, S. 2008b. Fisher's behaviour with individual vessel quotas - Over-capacity and potential rent: Five case studies. Marine Policy, 32: 920-927.

Bentley, N., and Stokes, K. 2009a. Contrasting Paradigms for Fisheries Management Decision Making: How Well Do They Serve Data-Poor Fisheries? Marine and Coastal Fisheries 1: 391-401.

Bentley, N., and Stokes, K. 2009b. Moving Fisheries from Data-Poor to Data-Sufficient: Evaluating the Costs of Management versus the Benefits of Management. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 1: 378-390.

Boncoeur, J., Coglan, L., Gallic, B. L., and Pascoe, S. 2000. On the relevance of rates of return measures of economic performance to small boats. Fisheries Research 49: 105-115.

Borgström, R., Plahte, E. 1992. Gillnet selectivity and a model for capture probabilities for a stunted brown trout (Salmo trutta) population. Canadian Journal of Fisheries and Aquatic Sciences 49: 1546–1554.

Brandt, S. and Ding, N. 2008. Impact of property rights on labor contracts in commercial fisheries. Ocean & Coastal Management 51: 740-748.

REFERENCES

Bromley, D. W. 2009. Abdicating responsibility: the Deceits of Fisheries policy. Fisheries 34: 280-291.

Caddy, J. F. 2004. Current usage of fisheries indicators and reference points, and their potential application to management of fisheries for marine invertebrates. Canadian Journal of Fisheries and Aquatic Sciences 61: 1307-1324.

Caddy, J. F., and Mahon, R. 1995. Reference points for fisheries management. 83 pp.

Caddy, J.F. 1995. Mahon R. Reference points for fisheries management. FAO Fisheries Technical Paper 347. Rome: FAO. p. 83.

Caddy, J.F. 2004. Current usage of fisheries indicators and reference points, and their potential application to management of fisheries for marine invertebrates. Canadian Journal of Fisheries and Aquatic Sciences 61: 1307-24.

Cadrin, S.X. and M.A. Pastoors. 2008. Precautionary harvest policies and the uncertainty paradox. Fisheries Research 94**:** 367-372.

Cappo, M., Speare, P. and D'eath, G. 2004. Comparison of baited remote underwater video stations (BRUVS) and prawn (shrimp) trawls for assessments of fish biodiversity in inter-reefal areas of the Great Barrier Reef Marine Park. Journal of Experimental Marine Biology and Ecology 302: 123-152.

Caton, A., McLoughlin, K. 2000. Fisheries Status Reports 1999. Canberra: Bureau of Rural Sciences.

Chae, D. R., and Pascoe, S. 2005. Use of simple bioeconomic models to estimate optimal effort levels in the Korean coastal flounder fisheries. Aquatic Living Resources 18: 93-101.

Christensen, V. 2010. MEY = MSY. Fish and Fisheries 11: 105-110.

Clark, C. W. 1973. The Economics of Overexploitation. Science 181: 630-634.

Clark, C. W. 1990. Mathematical Bioeconomics: The Optimal Management of Renewable Resources, John Wiley and Sons, USA.

Clark, F, Brook, B.W., Delean, S. Akcakaya, H.R., Bradshaw, C.J.A. 2010. The theta-logistic is unreliable for modelling most census data. Methods in Ecology and Evolution 1: 253–262.

Cope, J.M. and Punt, A.E. 2009. Length-based reference points for data-limited situations: Applications and restrictions. *Marine and Coastal Fisheries: Dynamics, Management, and* Ecosystem Science 1: 169-186.

REFERENCES

Cortés, E. 1998. Demographic analysis as an aid in shark stock assessment and management. Fisheries Research 39: 199-208.

DAFF (Australian Government Department of Agriculture, Fisheries and Forestry). 2007. Commonwealth Fisheries Harvest Strategy: policy and Guidelines, DAFF, Canberra. 55p.

Dichmont, C.M., Deng, A.R., Punt, A.E., Venables, W. and M. Haddon. 2006. Management strategies for short-lived species: The case of Australia's Northern Prawn Fishery 2: Choosing appropriate management strategies using input controls. Fisheries Research 82: 221-234.

Dichmont, C. M., Deng, A., Punt, A. E., Ellis, N., Venables, W. N., Kompas, T., Ye, Y., et al. 2008. Beyond biological performance measures in management strategy evaluation: Bringing in economics and the effects of trawling on the benthos. Fisheries Research 94: 238-250.

Dichmont, C. M., and Brown, I. W. 2010. A Case Study in Successful Management of a Data-Poor Fishery Using Simple Decision Rules: the Queensland Spanner Crab Fishery. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science: 1-13.

Dichmont, C. M., Pascoe, S., Kompas, T., and Punt, A. E. 2010b. On implementing maximum economic yield in commercial fisheries. Proceedings of the National Academy of Science 107: 16-21.

Dick, E.J., and MacCall, A.D. 2011. Depletion-Based Stock Reduction Analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. Fisheries Research 110: 331-341.

Dick, E.K. and A.D. MacCall. 2010. Estimates of sustainable yield for 50 data-poor stocks in the Pacific Coast Groundfish Fishery Management Plan. *NOAA Technical Memorandum NMFS-SWFSC*-460, 208p

Dickson, W. 1993. Estimation of the capture efficiency of trawl gear. II: Testing a theoretical model. Fisheries Research 16: 255-272.

Doole, G. J. 2005. Optimal Management of the New Zealand Longfin Eel (Anguilla dieffenbachia). Australian Journal of Agricultural and Resource Economics 49: 395-411.

Dowling, N. A., Smith, D. C., Knuckey, I., Smith, A. D. M., Domaschenz, P., Patterson, H. M., and Whitelaw, W. 2008. Developing harvest strategies for low-value and data-poor fisheries: Case studies from three Australian fisheries. Fisheries Research 94: 380-390.

Dupont, D. P. 1990. Rent dissipation in restricted access fisheries. Journal of Environmental Economics and Management 19: 26-44.

REFERENCES

EconSearch. 2010a. Economic Indicators for the South Australian Lakes and Coorong Fishery 2008/09. Report prepared for Primary Industries and Resources South Australia. Marryatville: EconSearch.

EconSearch. 2010b. Economic Indicators for the South Australian Abalone Fishery 2008/09. Report prepared for Primary Industries and Resources South Australia. Marryatville: EconSearch.

EconSearch. 2010c. Economic Indicators for the South Australian Blue Crab Fishery 2008/08. Report prepared for Primary Industries and Resources South Australia. Marryatville: EconSearch.

EconSearch. 2010d.Economic Indicators for the South Australian Marine Scalefish Fishery 2008/08. Report prepared for Primary Industries and Resources South Australia. Marryatville: EconSearch.

Eggert, H., and Tveteras, R. 2007. Potential rent and overcapacity in the Swedish Baltic Sea trawl fishery for cod (Gadus morhua). ICES Journal of Marine Science 64: 439-445.

Ellis, D. M. and DeMartini, E. E. 1995. Evaluation of a video camera technique for indexing the abundances of juvenile pink snapper, *Pristipomoides filamentosus*, and other Hawaiian insular shelf fishes. Fishery Bulletin 93: 67-77.

FAO. 1996. Precautionary approach to fisheries. *FAO Fisheries Technical Paper* 350(2) Rome, FAO, 210p.

Fay, G., Punt, A.E., Smith, A.D.M. 2009. Operating model specifications. In: Wayte, S.E. (Ed.), Evaluation of New Harvest Strategies for SESSF Species. CSIRO Marine and Atmospheric Research, Hobart and Australian Fisheries Management Authority, Canberra, pp. 125–133.

Felthoven, R. G., and Morrison Paul, C. J. 2004. Multi-output, nonfrontier primal measures of capacity and capacity utilization. American Journal of Agricultural Economics 86: 619-633.

Fletcher, R.I. 1978. On the restructuring of the Pella–Tomlinson system. Fish. Bull. 76 (3), 515–521.

Francis, R. I. C. C. 1992. Use of risk analysis to assess fishery management strategies: a case study using Orange Roughy (*Hoplostethus atlanticus*) on the Chatham Rise, New Zealand. Canadian Journal of Fisheries and Aquatic Sciences 49, 922-930.

Fulton, E. A., Smith, A. D. M., and Smith, D. C. 2007. Alternative Management Strategies for Southeast Australian Commonwealth Fisheries: Stage 2: Quantitative Management Strategy

Evaluation. Report to the Australian Fisheries Management Authority and the Fisheries Research and Development Corporation. 400 pp.

Garcia, S., Sparre, P., and Csirke, J. 1989. Estimating surplus production and maximum sustainable yield from biomass data when catch and effort time series are not available. Fisheries Research, 8: 13-23.

Garcia, S.M. 1994. The precautionary principle: its implications in capture fisheries management. Ocean & Coastal Management 22: 99-125.

George, D. Vieira, S. and New R., 2012, Australian fisheries surveys report 2011, results for selected fisheries 2008–09 to 2010–2011, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra, February.

Gordon, H. S. 1954. The economic theory of a common-property resource: The fishery Journal of Political Economy 62: 124–142

Grafton, R. Q., Kompas, T., and Hilborn, R. W. 2007. Economics of Overexploitation Revisited. Science 318: 1601.

Grafton, R. Q., Kompas, T., Chu, L., and Che, N. 2010. Maximum economic yield. Australian Journal of Agricultural and Resource Economics 54: 273-280.

Grafton, R.Q., Kompas, T., Hilborn, R.W. 2007. Economics of Overexploitation Revisited. Science 318: 1601.

Guyader, O., Daures, F., and Fifas, S. 2004. A bioeconomic analysis of the impact of decommissioning programs: application to a limited-entry French scallop fishery. Marine Resource Economics 19: 225-242.

Haddon, M. 2007. Tier 4 Analyses 1994 – 2006 pp 498 – 545 *in* Tuck, G.N.(*ed*) *Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery 2006 – 2007 Volume 2: 2007.* Australian Fisheries Management Authority, Canberra, and CSIRO Marine and Atmospheric Research, Hobart. 584p.

Haddon, M. 2009. Tier 4 Analyses 1994 – 2007 pp 255-304 *in* Tuck, G.N.(*ed*) *Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery 2008 Volume 2.* Australian Fisheries Management Authority, Canberra, and CSIRO Marine and Atmospheric Research, Hobart. 331p.

REFERENCES

Haddon, M., Ziegler, P., Lyle, J. and P. Burch. 2005. Using a spatially structured model to assess the Tasmanian fishery for banded morwong (*Cheilodactylus spectabilis*) pp 737-756. In *Assessment and Management of New and Developed Fisheries in Data-Limited Situations*. Lowell Wakefield Symposia; Alaskan Sea-Grant Program. 948 p.

Heap, A.D., Harris, P.T., Last, P., Lyne, V., Hinde, A., Woods, M. 2005. Draft Benthic Marine Bioregionalisation of Australia's Exclusive Economic Zone. Geoscience Australia Report to the National Oceans Office. Geoscience Australia, Canberra.

Hoff, A., and Frost, H. 2007. Optimal vessel quotas and capacity of a Danish trawler fleet segment: A dual approach. Marine Resource Economics 22: 1-14.

Hoff, A., Andersen, J., Christensen, A., and Mosegaard, H. 2012. Modelling the economic consequences of Marine Protected Areas using the BEMCOM model. Journal of Bioeconomics: 1-19.

Hulten, C. R., and Wykoff, F. C. 1996. Issues in the measurement of economic depreciation introductory remarks. Economic Inquiry 34: 10-23.

Huppert, D. D., and Squires, D. 1987. Potential economic beneflts and optimum fleet size in the Pacific Coast trawl fleet. Marine Resource Economics 3: 297-318.

Johannes, R. E. 1998. The case for data-less marine resource management: examples from tropical nearshore finfisheries. Trends in Ecology & Evolution 13: 243-246.

Jorgenson, D. W. 1996. Empirical studies of depreciation. Economic Inquiry 34: 24-42.

Kallayil, J.K., Jørgensen, T., Engas, A., Ferno, A. 2003. Baiting gill nets—how is fish behaviour affected? Fisheries Research 61: 125–133.

Kar, T. K., and Chakraborty, K. 2011. A bioeconomic assessment of the Bangladesh shrimp fishery. World Journal of Modelling and Simulation 7: 58-69.

Kelly, C. J., and Codling, E. A. 2006. `Cheap and dirty' fisheries science and management in the North Atlantic. Fisheries Research 79: 233-238.

Kimura, D.K., and Tagart, J.V. 1982. Stock reduction analysis, another solution to the catch equations. Canadian Journal of Fisheries and Aquatic Sciences 39: 1467–1472.

Kimura, D.K., Balsiger, J.W., and Ito, D.H. 1984. Generalized stock reduction analysis. Can. J. Fish. Aquat. Sci. 41: 1325–1333.

Klaer, N.L. 2006. Changes in the Structure of Demersal Fish Communities of the South East Australian Continental Shelf from 1915 to 1961. PhD Thesis, University of Canberra.

Klaer, N.L., Wayte, S.E., and Fay, G. 2012. An evaluation of the performance of a harvest strategy that uses an average-length-based assessment method. Fisheries Research 134-136:42-51.

Klaer, N., 2011. Tiger flathead (*Neoplaycephalus richardsoni*) stock assessment based on data up to 2009. In: Tuck, G.N. (Ed.), Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery: 2010, vol. 1. Australian Fisheries Management Authority and CSIRO Marine and Atmospheric Research, Hobart, pp. 238–247.

Kompas, T. 2005. Fisheries management: economic efficiency and the concept of 'maximum economic yield'. Australian Commodities 12: 152-160.

Kompas, T., Dichmont, C. M., Punt, A. E., Deng, A., Che, T., Bishop, J., Gooday, P., et al. 2010a. Maximizing profits and conserving stocks in the Australian Northern Prawn Fishery. Australian Journal of Agricultural and Resource Economics, 54: 281-299.

Kompas, T., Dichmont, C. M., Punt, A. E., Deng, A., Che, T. N., Bishop, J., Gooday, P., et al. 2010b. Maximizing profits and conserving stocks in the Australian Northern Prawn Fishery. Australian Journal of Agricultural and Resource Economics 54: 281-299.

Kompas, T., Grafton, R. Q., and Che, T. N. 2010c. Bioeconomic losses from overharvesting tuna. Conservation Letters 3: 177-183.

Kompas, T., Grafton, R. Q., Che, N., and Gooday, P. 2009. Development of methods and information to support the assessment of economic performance in Commonwealth fisheries.

Little, R. and Rowling, K. 2011. Update of the Eastern Gemfish (*Rexea solandri*) stock assessment. In: Tuck, G.N. (Ed.), Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery: 2010, vol. 1. Australian Fisheries Management Authority and CSIRO Marine and Atmospheric Research, Hobart, pp. 97–127.

Little, L.R., Wayte, S.E., Tuck, G.N., Smith, A.D.M., Klaer, N., Haddon, M., Punt, A.E., Thomson, R., Day, J. and M. Fuller. 2011. Development and evaluation of a cpue-based harvest control rule for the southern and eastern scalefish and shark fishery of Australia. ICES Journal of Marine Science 68: 1699-1705.

Little, L.R., Wayte, S.E., Tuck, G.N., Thomson, R., Smith, A.D.M., Klaer, N., Punt, A.E. and M. Haddon. 2009. Testing an alternative Tier 4 control rule and CPUE reference points for the SESSF. Pp 98-112 *in* Wayte, S.E. (*ed*) *Evaluation of new harvest strategies for SESSF species.* Australian Fisheries Management Authority, Canberra, and CSIRO Marine and Atmospheric Research, Hobart. 2006/815. 137pp.

Lleonart, J., Maynou, F., Recasens, L., and Franquesa, R. 2003. A bioeconomic model for Mediterranean fisheries, the hake off Catalonia (western Mediterranean) as a case study. Scientia Marina 67: 337-351.

Løkkeborg, S., Bjordal, A., and Ferno, A. 1989. Responses of cod (*Gadus morhua*) and haddock (*Melanogrammus aeglefinus*) to baited hooks in the natural environment. Canadian Journal of Fisheries and Aquatic Sciences 46: 1478–1483.

Løkkeborg, S., Olla, B.L., Pearson, W.H., and Davis, M.W. 1995. Behavioural responses of sablefish, *Anoplopoma fimbria*, to bait odour. Journal of Fish Biology 46: 142–155.

MacCall, A.D. 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES Journal of Marine Science 66: 2267–2271.

Mace, P.M. 1994. Relationships between Common Biological Reference Points Used as Thresholds and Targets of Fisheries Management Strategies. Canadian Journal of Fisheries and Aquatic Sciences 51: 110-122.

Martell, S., and Froese Rainer. 2012. A simple method for estimating MSY from catch andresilience. Fish and Fisheries. DOI: 10.1111/j.1467-2979.2012.00485.x

Martinet, V., Thébaud, O., and Doyen, L. 2007. Defining viable recovery paths toward sustainable fisheries. Ecological Economics 64: 411-422.

McAllister, M.K., Babcock, E.A., Pikitch, E.K., Prager, M.H., 2000. Application of a non-equilibrium generalized production model to South and North Atlantic swordfish: combining Bayesian and demographic methods for parameter estimation. Col. Vol. Sci. Pap. ICCAT 51: 1523–1550.

McConnell, K. E., and Price, M. 2006. The lay system in commercial fisheries: Origin and implications. Journal of Environmental Economics and Management 51: 295-307.

Milton, D., S. Zhou, G. Fry, and Q. Dell. 2007. Risk assessment and mitigation for sea snakes caught in the Northern Prawn Fishery. Final Report on FRDC Project 2005/051. CSIRO Cleveland. pp. 130.

Munro, G. R. 2010. From drain to gain in capture fishery rents: a synthesis study. ICES Document 538. 49 pp.

Norman-López, A., and Pascoe, S. 2011. Net economic effects of achieving maximum economic yield in fisheries. Marine Policy 35: 489–495.

Olson, J. 2011. Understanding and contextualizing social impacts from the privatization of fisheries: An overview. Ocean & Coastal Management 54: 353-363.

O'Neill, M. F., Campbell, A. B., Brown, I. W., and Johnstone, R. 2010. Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (*Ranina ranina*) fishery. ICES Journal of Marine Science 67: 1538-1552.

Pascoe, S., and Mardle, S. 2001. Optimal fleet size in the English Channel: a multi-objective programming approach. European Review of Agricultural Economics 28: 161-185.

Pascoe, S., Vieira, S., Dichmont, C. M., and Punt, A. E. 2011. Optimal vessel size and output in the Australian northern prawn fishery: a restricted profit function approach. Australian Journal of Agricultural and Resource Economics 55: 107-125.

Pascoe, S., Vieira, S., Dichmont, C.M., Punt, A.E. 2011. Optimal vessel size and output in the Australian northern prawn fishery: a restricted profit function approach. Australian Journal of Agricultural and Resource Economics 55: 107-25.

Pauly, D. 1979. Theory and management of tropical multispecies stocks: A review, with emphasis on the Southeast Asian demersal fisheries. ICLARM Studies and Reviews No. 1, 35 p. International Centre for Living Aquatic Resources Management, Manila.

Pelletier, D., Mahevas, S., Drouineau, H., Vermard, Y., Thebaud, O., Guyader, O., and Poussin, B. 2009. Evaluation of the bioeconomic sustainability of multi-species multi-fleet fisheries under a wide range of policy options using ISIS-Fish. Ecological Modelling 220: 1013-1033.

Perks, C., Vieira, S. 2010. Australian fisheries surveys report 2010. Results for selected fisheries, 2007-08 and 2008-09. Preliminary estimates for 2009-10. ABARES report prepared for the Fisheries Resources Research Fund. Canberra: ABARES. p. 67.

REFERENCES

Pezzuto, P.R., Alvarez-Perez, J.A., and Wahrlich, R. 2008. The use of the swept area method for assessing the seabob shrimp *Xiphopenaeus kroyeri* (Heller, 1862) biomass and removal rates based on artisanal fishery derived data in southern Brazil: using depletion models to reduce uncertainty. Latin American Journal of Aquatic Research 36: 245-257.

PIRSA. 2007. South Australian Fisheries Resources — Current Status and Recent Trends 2006. South Australian Fisheries Management Series Paper number 49. Adelaide: Primary Industries and Resources South Australia.

Pope, J.G., MacDonald, D.S., Daan, N., Reynolds, J.D. and Jennings, S. 2000. Gauging the impact of fishing mortality on non-target species. ICES Journal of Marine Science 57: 689–696.

Prchalová, M, Kubecka, J., Ríha, M., Mrkvicka, T., Vasek, M., Juza, T., Kratochvíl, M., Peterk, J., Drastíka, V., and Krízek, J. 2009. Size selectivity of standardized multimesh gillnets in sampling coarse European species. Fisheries Research 96: 51–57.

Punt, A. E., Deng, R. A., Dichmont, C. M., Kompas, T., Venables, W. N., Zhou, S., Pascoe, S., et al. 2010. Integrating size-structured assessment and bioeconomic management advice in Australia's northern prawn fishery. ICES Journal of Marine Science 67: 1785-1801.

Punt, A. E., Deng, R., Pascoe, S., Dichmont, C. M., Zhou, S., Plagányi, É. E., Hutton, T., et al. 2011. Calculating optimal effort and catch trajectories for multiple species modelled using a mix of size-structured, delay-difference and biomass dynamics models. Fisheries Research 109: 201-211.

Schaefer, M. B. 1954. Some aspects of the dynamics of populations important to the management of commercial marine fisheries. Bulletin of the Inter-American Tropical Tuna Commission 1: 25-56.

Schaefer, M. B. 1957. A study of the dynamics of fishery for yellowfin tuna in the Eastern tropical Pacific Ocean. Bulletin of the Inter-American Tropical Tuna Commission 2: 247-285.

Scott, A. 1955. The Fishery: The Objectives of Sole Ownership. The Journal of Political Economy, 63: 116-124.

Sigler, M.F. 2000. Abundance estimation and capture of sablefish (*Anoplopoma fimbria*) by longline gear. Canadian Journal of Fisheries and Aquatic Science 57: 1270–1283.

Smith, A.D.M., Smith, D.C., Tuck, G.N., Klaer, N., Punt, A.E., Knuckey, I., Prince, J., Morison, A., Kloser, R., Haddon, M., Wayte, S., Day, J., Fay, G., Pribac, F., Fuller, M., Taylor, B., and L.R. Little. 2008.

REFERENCES

Experience in implementing harvest strategies in Australia's south-eastern fisheries. Fisheries Research 94: 373-379.

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. 2009. Reconciling Approaches to the Assessment and Management of Data-Poor Species and Fisheries with Australia's Harvest Strategy Policy. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science: 244-254.

Somerton, D., Ianelli, J., Walsh, S., Smith, S., Godø, O. R., and Ramm, D. 1999. Incorporating experimentally derived estimates of survey trawl efficiency into the stock assessment process: a discussion. ICES Journal of Marine Science 56: 299–302.

Szakiel, S., Che, N., Gooday, P., and Elliston, L. 2006. Measuring Capacity in Commonwealth Fisheries. ICES Document 06.1. 28 pp.

Tingley, D., and Pascoe, S. 2005. Factors Affecting Capacity Utilisation in English Channel Fisheries. Journal of Agricultural Economics 56: 287-305.

Tingley, D., Pascoe, S., and Mardle, S. 2003. Estimating capacity utilisation in multi-purpose, multi-métier fisheries. Fisheries Research 63: 121-134.

Townsend, R. E. 1985. On "Capital-stuffing" in Regulated Fisheries. Land Economics, 61: 195-197.

Tuck, G.N. (ed.) 2011. Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery 2010. Part 2. Australian Fisheries Management Authority and CSIRO Marine and Atmospheric Research, Hobart. 419 p.

Ulrich, C., Andersen, B. S., Sparre, P. J., and Nielsen, J. R. 2007. TEMAS: fleet-based bio-economic simulation software to evaluate management strategies accounting for fleet behaviour. ICES Journal of Marine Science 64: 647-651.

Ulrich, C., Pascoe, S., Sparre, P. J., De Wilde, J. W., and Marchal, P. 2002. Influence of trends in fishing power on bioeconomics in the North Sea flatfish fishery regulated by catches or by effort quotas. Canadian Journal of Fisheries and Aquatic Sciences 59: 829-843.

Upston, J. and Klaer, N. 2011. Integrated Scientific Monitoring Program for the Southern and Eastern Scalefish and Shark Fishery – Discard estimation: 2010. CSIRO report to the Australian Fisheries Management Authority.

Vieira, S., Perks, C., Mazur, K., Curtotti, R., and Li, M. 2010. Impact of the structural adjustment package on the profitability of Commonwealth fisheries. ABARE research report 10.01, Canberra, February.

Walters, C.J., Martell, S.J.D., Korman, J., 2006. A stochastic approach to stock reduction analysis. Canadian Journal of Fisheries and Aquatic Sciences 63: 212–223.

Wayte, S.E. and Klaer, N.L. 2010. An effective harvest strategy using improved catch-curves. Fisheries Research 106: 310–320.

Wayte, S., 2011. Jackass Morwong (*Nemadactylus macropterus*) stock assessment based on data up to 2009. In: Tuck, G.N. (Ed.), Stock Assessment for the Southern and Eastern Scalefish and Shark Fishery: 2010, vol. 1. Australian Fisheries Management Authority and CSIRO Marine and Atmospheric Research, Hobart, pp. 135–187.

Wetzel, C.R. and Punt, A.E. 2011. Model performance for the determination of appropriate harvest levels in the case of data-poor stocks. Fisheries Research 110: 342–355.

Whitmarsh, D., James, C., Pickering, H., and Neiland, A. 2000. The profitability of marine commercial fisheries: a review of economic information needs with particular reference to the UK. Marine Policy 24: 257-263.

Wood, S.N. 2006. Generalized Additive Models: An Introduction with R. CRC/Chapman & Hall.

Woodhams, J., Stobutzki, I., Vieira, S., Curtotti, R., and Begg, G.A. (eds). 2011. Fishery Status Reports 2010: status of fish stocks and fisheries managed by the Australian Government, ABARES, Canberra.

World Bank and FAO. 2009. The Sunken Billions: the economic justification for fisheries reform. 104 pp.

Zhou, S., A.D.M. Smith, M. Fuller. 2011a. Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. Fisheries Research 112: 168-178.

Zhou, S., A.E. Punt, R. Deng, M. Kienzle, and W. Rochester. 2011b. Bayesian fishable biomass dynamics models incorporating fished area and relative fish density. Canadian Journal of Fisheries and Aquatic Sciences 68: 1603-1614.

Zhou, S., D.J. Vance, C.M. Dichmont, C.Y. Burridge, and P.J. Toscas. 2008. Estimating prawn abundance and catchability from catch-effort data: Comparison of fixed and random effects models using maximum likelihood and hierarchical Bayesian methods. Marine and Freshwater Research 59: 1-9.

Zhou, S., Yin, S., Thorson, J.T., Smith, A.D.M., Fuller, M. 2012. Linking fishing mortality reference points to life history traits: an empirical study. Canadian Journal of Fisheries and Aquatic Science 69: 1292–1301.

12 Appendix 1: list of project team

James Larcombe, ABARES

Malcolm Haddon, CSRIRO Hobart

Natalie Dowling, CSRIRO Hobart

Neil Klaer, CSRIRO Hobart

Olivier Thebaud, CSRIRO Brisbane

Sean Pascoe, CSRIRO Brisbane

Sally Wayte, CSIRO Hobart

Shijie Zhou, CSRIRO Brisbane

Simon Vieira, ABARES

Tony Smith, CSRIRO Hobart

13 Appendix 2. The rejected catch-rate gradient method

13.1 Model specification

The full specification of the original Tier 4 HCR in the SESSF (Haddon, 2007) contains three components 1) the catch rates and their regression, 2) the calculation of average catches and discards, and 3) the calculation of the TAC from the catches and regression.

In 2007, for the Tier 4 analyses, it was agreed that the best option was to conduct a linear regression on the standardized catch-rates, the yearly indices of which are the proportional differences in catch rate between years. To standardize the catch-rate data, the CPUE, conditioned on positive catches of the species of interest, was statistically modelled with a normal GLM on log-transformed CPUE data:

$$\mathrm{Ln}\left(CPUE_i\right) = \alpha_0 + \alpha_1 x_{i,1} + \alpha_2 x_{i,2} + \sum_{j=3}^{N} \alpha_j x_{ij} + \varepsilon_i \qquad (0.1)$$

where Ln($CPUE_i$) is the natural logarithm of the catch rate (usually kg/h, but sometimes kg/shot) for the *i*-th shot, x_{ij} are the values of the explanatory variables *j* for the *i*-th shot and the α_j are the coefficients for the *N* factors *j* to be estimated (α_0 is the intercept, α_1 is the coefficient for the first factor, *etc*.). For the lognormal model the expected back-transformed year effect involves a bias-correction to account for the log-normality; this then focuses on the mean of the distribution rather than the median:

$$CPUE_t = e^{\left(\gamma_t + \sigma_t^2/2\right)} \qquad (0.2)$$

where γ_t is the Year coefficient for year *t* and σ_t is the standard deviation of the log transformed data (obtained from the analysis).

The linear regression of catch-rates against year is simply:

$$CPUE_i = Intercept + Gradient.Year_i \qquad (0.3)$$

where *i* indexed the most recent four years.

C_{cur} is the average total catch combined with any discards across the same four most recent years as the regression catch-rates.

$$C_{cur} = \frac{\sum_{yr=1}^{4} C_{yr}}{4} + D_{cur} \tag{0.4}$$

The estimated discards were changing rapidly at the time the harvest strategies were being introduced. The expected level of discards was estimated as a weighted average from the previous four years with earlier years being given less weight:

$$D_i = \left(1.0D_{i-1} + 0.5D_{i-2} + 0.25D_{i-3} + 0.125D_{i-4}\right)/1.875 \tag{0.5}$$

Because the $CPUE_i$ are proportional changes through time this has the additional advantage that the α in:

$$TAC = \left(1 + \alpha.Gradient\right)C_{cur} \tag{0.6}$$

can be set at 1.0 for all species rather than having to have a specific value for each species.

The age-structured operating model, described in Section 14.2, was used to examine the performance of the original Tier 4 HCR. First the characteristics of a simulated population were determined (Figure). The unfished stock had a constant catch applied for sufficient years so as to deplete it from unfished. In the example given this treatment depleted the simulated stock to about 26.3% unfished spawning biomass levels.

Following the initial depletion the simulated fishery was exposed to 35 years of constant catches at 2,300 t, which is approximately the maximum sustainable yield. After that there followed a further 35 years during which the HCR was applied to the fishery along with recruitment variability and variation applied to the estimated catch-rates (Figure).

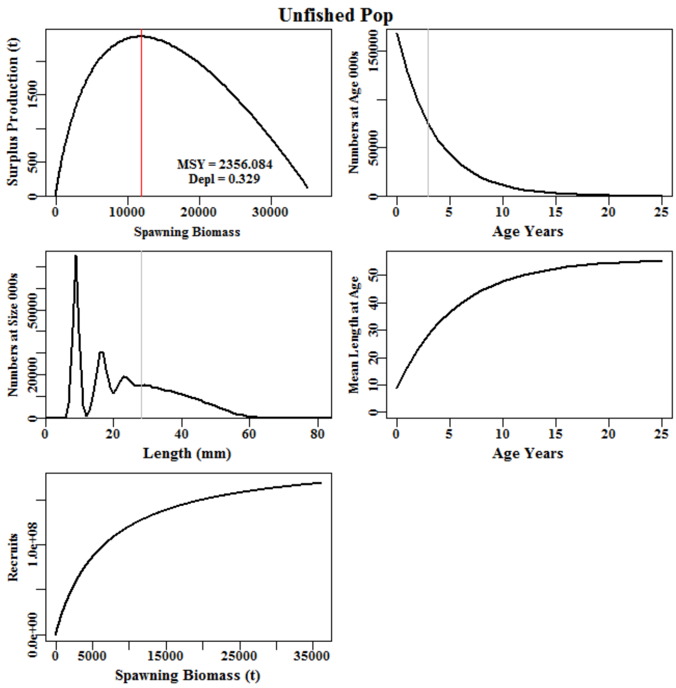


Figure 14-1. Characterization of the properties of the unfished simulated fish population obtained from the operating model that was used to test the original Tier 4 HCR.

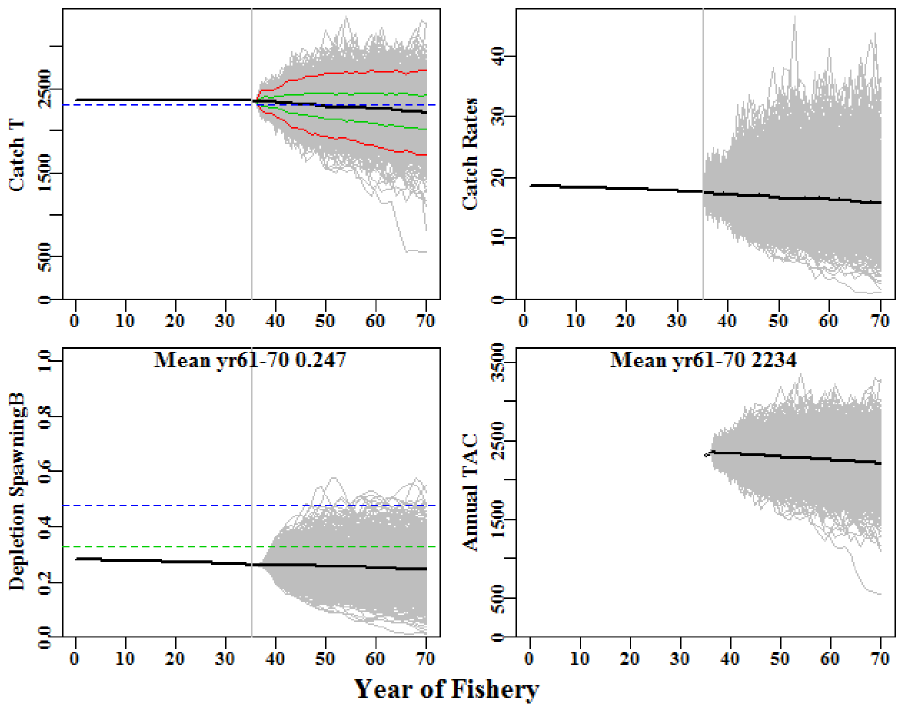


Figure 14-2. The simulated fishery after 35 years of the Tier 4 HCR; 1000 iterations. In the top left graph the green lines are the inner 50% quantiles while the red lines are the inner 90% quantiles. In the bottom left graph the blue line is the SESSF target of 48%B0 and the green line is the depletion that gives rise to the MSY.

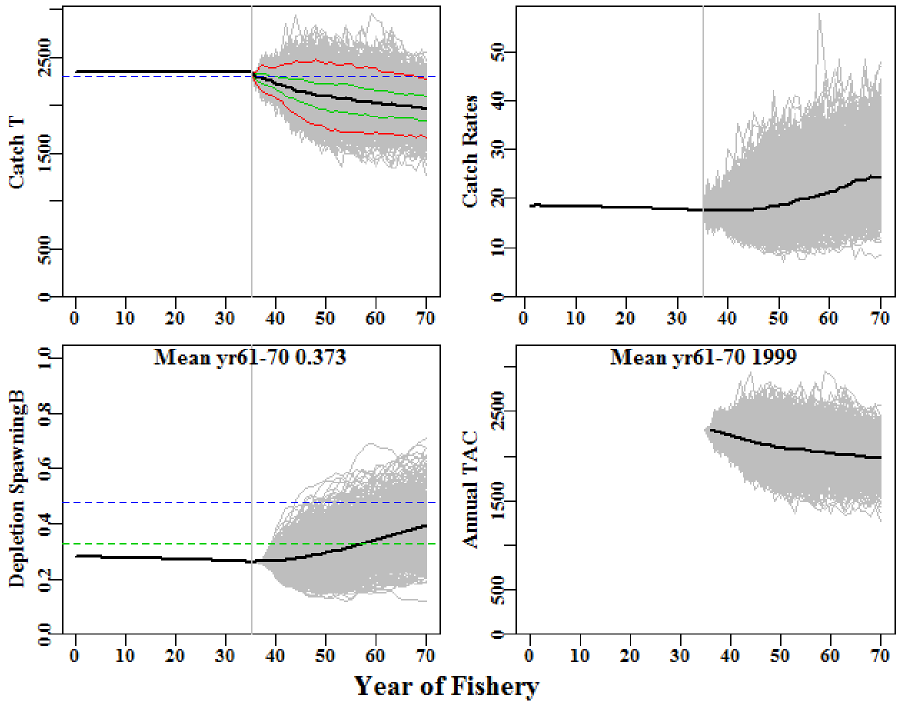


Figure 14-3. 1000 iterations of the simulated fishery after 35 years of the Tier 4 HCR with only 90-100% of the TAC being taken each year (Figure). In the top left graph the green solid lines are the inner 50% quantiles while the red lines are the inner 90% quantiles. In the bottom left graph the blue line is the SESSF target of 48%B0 and the green dashed line is the depletion that gives rise to the MSY.

The notion that this HCR tends to lead to a status quo appears justified. However, this assumes that the TAC is always taken exactly. In fact, in many years, the TAC is not taken in many species because the available quota is spread among numerous operators and each tends to retain some quota right to the end of the year to prevent them having problems reconciling their catches against their quota. It is often the case that between 100 and 90% of the TAC is taken (Figure). Because the original Tier 4 HCR calculated the TAC based on actual catches such a failure to take the TAC, purely for operational reasons rather than availability, was expected to lead to a gradual ratchet down of the TAC (Figure).

Clearly the effect of the catch ratchet was detrimental to the fishery. While it certainly led to the stock becoming larger and catch rates rising, such a fall in catches would continue until only a tiny fishery remained. This HCR needed to be changed.

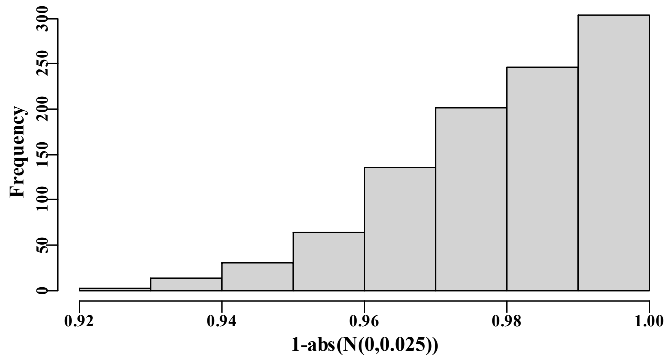


Figure 14-4. The distribution of deviations from the TAC included in the simulations depicted in Figure. This is the complement of a truncated normal distribution with mean = 0.0, and standard deviation = 0.025.

13.2 Operating model

13.2.1 INITIATION OF AGE-STRUCTURED MODEL

At equilibrium, in an un-exploited population, the age-structure is assumed to be the result of natural mortality acting alone upon constant average unfished levels of recruitment. This would be the stable age distribution, which in year 1 of the time series is defined as:

$$N_{a,1} = \begin{cases} N_{0,1}e^{-M} & a = 0 \\ N_{a-1,1}e^{-M} & 1 \le a < a_x \\ N_{a_x-1,1}e^{-M} / \left(1 - e^{-M}\right) & a = a_x \end{cases} \tag{0.7}$$

where $N_{a,1}$ is the numbers of age a, in year 1, a_x is the maximum age modelled (the plus-group), and M is the instantaneous rate of natural mortality. In a pre-exploitation population there is no fishing mortality. The final component of Eq. (0.7), where $a = a_{max}$, is referred to as the plus group because it is the series which combines ages a_x and all older ages that are not modelled explicitly. This requires the inclusion of the $(1 - e^{-M})$ divisor to force the equation to be the sum of an exponential series.

13.2.2 DEFINING THE SPAWNING STOCK RECRUITMENT RELATIONSHIP

The biomass A_0 can be defined as the mature stock biomass that would develop given a constant recruitment level of one i.e. in Eq. (0.7), $N_{0,1}e^{-M} = 1$. Thus, at a biomass of A_0, distributed across a stable age distribution, the resulting average recruitment level would be $R_0 = 1$. A_0 acts as a scaling factor in the recruitment equations by providing the link between R_0 and B_0

$$A_0 = \sum_{a=1}^{a_x} n_{a,1} m_a w_a \tag{0.8}$$

where m_i is the proportion mature at age a, $n_{a,1}$ is the virgin number of animals per recruit of age a in year 1, and w_a is the weight of an animal of age a. The average unfished recruitment level, R_0, is directly related to the virgin mature, or recruited, biomass, B_0

$$R_0 = B_0 / A_0 \tag{0.9}$$

By determining A_0, from a constant recruitment level of one, the recruitment levels from realistic B_0 levels can be obtained by applying Eq. (0.9). Once R_0 has been determined the unfished number at age distribution can be obtained by substituting R_0 into the first term of Eq. (0.7).The spawning stock – recruitment relationship can be described by the Beverton – Holt relationship:

$$R_{y+1} = \frac{aB_y^S}{b + B_y^S} e^{\varepsilon - \sigma_R^2/2} \tag{0.10}$$

A re-parameterization of the Beverton-Holt parameters in terms of steepness, h, and B_0 is possible:

$$a = \frac{4hR_0}{5h-1} \qquad \text{and} \qquad b = \frac{B_0(1-h)}{5h-1} \tag{0.11}$$

Using this re-parameterization the Beverton-Holt relationship can be used to determine the number of recruits produced in year y from the spawning biomass in year y-1:

$$N_{0,y} = \frac{4hR_0 B_{y-1}^{Sp}}{\left(1-h\right)B_0 + \left(5h-1\right)B_{y-1}^{Sp}} e^{\varepsilon - \sigma_R^2/2}, \qquad \varepsilon = N\left(0, \sigma_R^2\right) \tag{0.12}$$

The expected residual error distribution around the expected is log-normal; the $-\sigma_R^2/2$ is the log-normal bias correction term. In the simulations, if the σ_R term is set as a very small number the recruitment will be effectively deterministic.

13.2.3 STOCK DYNAMICS

To describe the dynamics subsequent to population initiation (i.e. the generation of $N_{a,y}$, the number at age a in year y, for years other than 0), requires the inclusion of the stock recruitment relationship and the impact of fishing mortality. Not all age classes are necessarily fully selected, thus the fishing mortality term must be multiplied by the selectivity associated with the fishing gear for age a, s_a, described by a logistic curve:

$$s_a = \frac{1}{\left(1 + e^{-\left(\frac{a - a50}{\delta}\right)}\right)} \qquad (0.13)$$

where *a50* is the age at which 50% of individuals are selected by the fishing gear, and δ is a parameter that determines the width or steepness of the selectivity ogive. A term is also needed for the recruitment in each year, equation (0.12), and this is assumed to be a function of the spawning biomass of the stock at the end of the previous year *y*, B_y^{Sp} . The spawning biomass for a year *y* is:

$$B_y^{Sp} = \sum_{a=0}^{a_x} m_a w_a N_{a,y} \qquad (0.14)$$

If this is applied to the unfished stable age distribution this would provide an estimate fo the unfished spawning biomass-per-recruit. When using difference equations (rather than continuous differential equations) the dynamics of the fishery, in terms of the order in which growth, natural, and fishing mortality occur, are important when defining how the numbers at age change. If the transition of numbers at age in year *y* into numbers at age in year *y*+1 is made in a number of steps this simplifies the calculation of internally consistent estimates of exploitable biomass, catch rates, and harvest rates. If it is assumed that the dynamics of a population entails that fish first grow from year *y*-1 to year *y*, then undergo half of natural mortality before they are fished and only then undergo the final half of natural mortality this would imply two steps to define the transition from one year to the next. The first step entails recruitment, growth from each age class to the next, and the application of the effect of half of natural mortality:

$$N_{a,y*} = \begin{cases} N_{0,y} & a = 0 \\ N_{a-1,y-1} e^{-M/2} & 1 \le a < a_x - 1 \\ \left(N_{a_x - 1,y-1} + N_{a_x,y-1}\right) e^{-M/2} & a = a_x \end{cases} \qquad (0.15)$$

where $N_{0,y}$ is defined by Equ (0.12), ages 1 to a_x-1 are modelled by adding 1.0 to the previous year's ages 0 to a_x – 2 and imposing the survivorship from half the natural mortality, and the plus group (a_x) is modelled by adding 1.0 to the previous year's age a_x - 1 and adding those to the numbers in the previous year's age a_x and then applying the survivorship from half the natural mortality. Equation (0.15) thus leads to the mid-year exploitable biomass (mid-year being the reason for the $e^{-M/2}$) in year y being defined as:

$$B_y^E = \sum_{a=0}^{a_x} w_a s_a N_{a,y*} \tag{0.16}$$

The dynamics within any year are completed by the application of the survivorship following fishing mortality across all ages (expressed as an annual harvest rate), followed by the survivorship following the remainder of natural mortality. Natural mortality is not applied directly to the new recruits until they grow into the next year:

$$N_{a,y} = \begin{cases} N_{0,y*} & a = 0 \\ N_{a,y*}\left(1 - s_a \hat{H}_y\right) e^{(-M/2)} & 1 \le a \le a_x \end{cases} \tag{0.17}$$

In equation (0.17), the $N_{a,y}$ refer the numbers in age a at the end of year y (i.e. after all the dynamics have occurred). The predicted harvest rate, $\hat{H}_y$, given an observed or recommended catch level in year y, $\tilde{C}_y$, is estimated as

$$\hat{H}_y = \frac{\tilde{C}_y}{B_y^E} \tag{0.18}$$

where B_y^E is defined in equation (0.16).

The catch at age, in numbers, is therefore defined by:

$$C_{a,y}^N = N_{a,y*} s_a \hat{H}_y \tag{0.19}$$

and the total catch by mass is the sum of the separate catches at age multiplied by their respective average weights for all ages:

$$C_y = \sum_{a=0}^{a_x} w_a C_{a,y}^N \tag{0.20}$$

Predicted catch rates also derive from the exploitable biomass although this would also have some observation error associated with the catchability coefficient, *q*, in any real fishery:

$$I_y = qB_y^E e^{\varepsilon_y - \sigma_q^2/2} \tag{0.21}$$

14 Appendix 3: Linking fishing mortality reference points to life history traits: an empirical study[15]

SHIJIE ZHOU*1, SHAOWU YIN2, JAMES T. THORSON3, ANTHONY D.M. SMITH4, MICHAEL FULLER4

[1]CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, PO Box 2583, Brisbane, Qld 4001, Australia

[2]School of Life Sciences, Nanjing Normal University, 1 Wenyuan Road, Nanjing,

Jiangsu 210046, P R China

[3]School of Aquatic & Fishery Sciences, Box 355020, University of Washington,
Seattle, WA 98195-5020

[4]CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, Castray Esplanade, Hobart, Tas 7001, Australia

*Corresponding author: Tel.: +61 7 3833 5968, Fax: +61 7 3833 5525. Email: shijie.zhou@csiro.au

14.1 Abstract

The rule of thumb that fishing mortality to achieve maximum sustainable yield (F_{msy}) equals natural mortality (M) has been both criticised and supported by theoretical arguments. However, the relationship has been rarely investigated using empirical data. We carried out a meta-analysis on 245 fish species worldwide and linked three types of reference points (F_{BRP}: F_{msy}, F_{proxy}, and $F_{0.5r}$) to M and other life-history parameters (LHP). We used Bayesian hierarchical errors-in-variables models to investigate the relationships and included the effect of taxonomic class and order. We compared various models and found that natural mortality is the most important LHP affecting F_{BRP}. Other

[15] Published in Canadian Journal of Fisheries and Aquatic Science 69: 1292–1301 (2012).

covariates, such as von Bertalanffy growth coefficient, asymptotic length, maximum age, and habitat types add little to the relationship, partially due to correlation and large measurement and process errors. The best model results in F_{msy} = 0.87 M (SD 0.05) for teleosts and F_{msy} = 0.41 M (SD 0.09) for chondrichthyans. F_{proxy} based on per-recruit analysis is about 15% smaller than F_{msy}. Results could be used to estimate F_{BRP} from LHP in data-poor situations.

Key words: stock assessment, per-recruit, life table, demographic analysis, measurement error, bycatch, non-target

14.2 Introduction

Biological reference points (BRPs) are used both as targets and limits in stock status assessment, harvest control rules and tactical fisheries management. Generally, BRPs may be based either on fishing mortality (F_{BRP}) or biomass (B_{BRP}). There are also two general approaches to calculating F_{BRP} and B_{BRP}. F_{msy} and B_{msy} are calculated from population dynamics models (e.g., stock-recruitment or biomass dynamic models) and include estimated compensatory effects (e.g. recruitment compensation). Alternatively, $F_{0.1}$, $F_{x\%}$, $B_{0.1}$, $B_{x\%}$ are based on per-recruit analysis (e.g. yield-per-recruit or spawner-per-recruit). The per-recruit approach requires fishery selectivity and individual growth and mortality parameters, and does not use data to estimate recruitment processes or density-dependent mechanisms, although the numeric target for each per-recruit proxy (e.g., $F_{35\%}$ vs. $F_{25\%}$) implies an assumed value for steepness (see Quinn and Deriso 1999 for more details). Data required for deriving these BRPs vary widely and MSY-based BRPs may be preferred over per-recruit BRPs when data are available to estimate recruitment compensation, recognizing that the precision of MSY-based reference points depends on the specific model and the quality of the data.

Estimating BRPs for fishery management can be difficult. Reliable estimation requires parameters derived from quantitative stock assessments (e.g., selectivity at age), and often requires time series data and considerable biological information. Unfortunately, most commercial species worldwide do not have sufficient data to use quantitative stock assessment methods. This is particularly the case for small fisheries with low economic value, new fisheries in exploratory or developmental phases, species fished opportunistically due to sporadic availability, by-product species, etc. Furthermore, the goals of maintaining biodiversity and ecosystem structure in fishery management require that all species impacted by fishing be sustainable in the long term. The ecosystem approach to fishery management calls for sustainability evaluation for both target and non-target species (FAO

2003). However, it would be impossible to develop BRPs using formal stock assessment methods for hundreds of non-target bycatch species that have little data.

One possible approach to identifying F_{BRP} for data-poor stocks is to identify a relationship between F_{BRP} and commonly available estimates of life history traits. There has been a long history of interest in using life history traits as a surrogate for optimal fishing mortality. Early studies included Alverson and Pereyra (1969), who suggested using natural mortality as a proxy for sustainable fishing mortality, and Gulland (1970, 1971), who used natural mortality and pristine biomass to derive an estimate for maximum sustainable yield. These early works resulted in the well-known approximation $F_{msy} = M$.

Since the 1970s, numerous theoretical studies (Table 1) have tried to prove, improve, or disprove this relationship between F_{BRP} and M. Francis (1974) showed that optimal fishing mortality $F_{msy} = M$ held if recruitment was constant using Schaeffer surplus production model, but that density-dependent recruitment would affect this relationship. Deriso (1982) included the von Bertalanffy growth coefficient (κ) and reproductive parameters using a delay-difference model, and found that F_{msy} could be equal to, less than, or greater than M depending on other variables. Deriso (1987) explored the impact of life history parameters, and concluded that $F_{0.1}/M$ ranged from 0.88 to 1.25 over a wide range of M/κ (i.e., ratio between natural mortality and growth parameter). Through simulation with a range of life history parameter values typical of demersal fish and a range of realistic spawner-recruit relationships, Clark (1991) showed that yield will be at least 75% of maximum sustainable yield so long as the spawning biomass was maintained in the range of about 20-60% of the unfished level, regardless of the form of the spawner-recruit relationship. A relative spawning biomass in this range can be achieved by choosing a fishing mortality rate that will reduce the spawning biomass per recruit (SPR) to about 35% of the unfished level. This is the level of fishing mortality that maximizes the minimum yield among all of the spawner-recruit relationships. Clark (1993) revised the recommendation of 35% SPR to 40% due to serial correlation in recruitment, and even higher for species with low levels of resiliency (Clark 2002). Similarly, Thompson (1992) found that F_{msy} could be greater or less than M depending on the power parameter in a stock-recruitment relationship, while Thompson (1993) concluded that setting a maximum fishing mortality rate at 80% of the natural mortality rate would in general prevent overfishing.

Other studies have used age-structured and multispecies models to explore the relationship between F_{BRP} and M. Mace (1994) used age-structured population models and assumed forms for recruitment compensation, and showed that $F_{0.1}$, F_{max}, $F_{20\%}$, and $F_{35\%}$ all increased with both M and κ. For each M-k combination, $F_{0.1}$, $F_{35\%}$, and $F = M$ were of similar magnitude. Using a fully age-structured model, Kirkwood et al. (1994) showed that when recruitment was constant and independent of mature stock size, the yield as a proportion of unexploited biomass was directly proportional to the natural mortality rate. When recruitment was allowed to vary deterministically with mature stock size, this proportional relationship held approximately, at least for biologically feasible parameter combinations. Collie and Gislason (2001) tested a suite of F_{BRP} types for their robustness to observed changes in natural mortality and growth rates in a multispecies context, and found that F_{BRP} was much more sensitive to the changes in natural mortality rates than to growth variation. Siddeek (2003) developed a general formulation of the F_{msy} to M relationship, and found that F_{msy} exceeded M for most cases. Using life-history invariants, Beddington and Kirkwood (2005) estimated F_{msy} from growth parameters, length at first capture, and recruitment steepness, and concluded that F_{msy}/M increased with higher levels of steepness, but that $F_{msy} < M$ for most stocks.

By contrast to these theoretical and simulation modelling studies, few studies have empirically investigated the relationship between F_{BRP} and LHP. Such a relationship from data-rich stocks would be extremely valuable for data-poor stocks. Patterson (1992) related change in stock biomass to exploitation rate using data from 28 stocks of 11 small pelagic species. He concluded that fishing at exploitation rate $F/Z = 0.4$ would keep biomass from declining. This is equivalent to $F = 2/3M$. Mertz and Myers (1998) compiled data for a broad range of taxa and found that the long-term ratio of biomass-averaged fishing mortality to the biomass-averaged total mortality (F/Z) around 0.8 for piscivore ground fish and near 0.5 for prey species, which means $F = 4\ M$ and $F = M$, respectively.

In this paper, we compiled F_{BRP} data for more than 200 species and stocks worldwide that have been assessed with different methods. We conducted a meta-analysis and linked fishing mortality based reference points to natural mortality and other commonly available life-history parameters by taking errors in variables into account. Our goals were (1) to estimate the ratio of F_{BRP} to M; (2) to estimate the differences between F_{msy}, F_{proxy}, and $F_{0.5r}$; (3) to explore the impact of other life history parameters on F_{BRP}; and (4) to explore differences in productivity (e.g., F_{BRP}/M) by taxonomic class and order. The results aim to provide management guidance for data-poor and bycatch species (Smith et al. 2009; Zhou et al. 2009a) that do not have sufficient data for quantitative stock assessment.

14.3 Materials and Methods

14.3.1 DATA

We collected F_{BRP} data from a variety of sources, including published research papers, reports, and unpublished documents. Fishing mortality has often been expressed in two ways: the instantaneous fishing mortally rate (F) and exploitation rate (E). The majority of data we collected were based on F_{BRP}. For the literature that reported exploitation rates, we converted E_{BRP} into F_{BRP} by incorporating natural mortality (Quinn and Deriso 1999). When available, we recorded life-history parameters from the same paper, report, or document as used to provide the F_{BRP}. When LHP were not listed in the original material, we collected these data from fishbase (www.fishbase.org). Considering potential large uncertainty in fishbase, we avoided using data flagged as "questionable". Data from fishbase may not be deemed to be accurate by local practitioners, but represents a data source that is generally available for data-poor assessments. We therefore believe that sourcing data from fishbase allows model estimates of error-in-variables that will be immediately applicable for future data-poor assessments. A total of 245 species with 333 F_{BRP} were included in the analysis (Table 2).

14.3.2 FISHING MORTALITY-BASED BIOLOGICAL REFERENCE POINTS (F_{BRP})

We distinguish between three broad categories of F_{BRP} when compiling and analysing these data. Within each category, definitions and methods used to derive the reference points may differ, but we do not distinguish them further. For example, F_{msy} can be defined from an age-structured model or a biomass dynamics model. This broad grouping is to increase the sample size in each category while allowing the models to capture the uncertainty.

F_{msy} from formal stock assessments: This category includes age-structured stock assessment models fit to time-series data for estimating fishing mortality rate that will result in maximum sustainable yield. It also includes biomass-dynamic (a.k.a. surplus production) models fitted to survey or annual catch-effort data. The resulting estimate of F_{msy} accounts for compensatory processes (recruitment compensation for age-structured models, or aggregate compensation for surplus production models), and is currently the standard for single-species stock assessment F_{BRP}. It should be noted that the values of F_{msy} depend on the methodologies, assumptions, and data being used to estimate them and thus represent a summary of current stock assessment estimates of F_{msy} with any inaccuracies or biases this may imply.

F_{proxy} from per-recruit methods: This category includes BRPs derived from yield-per-recruit (e.g., $F_{0.1}$) and spawner-per-recruit ($F_{x\%}$) analyses. Per-recruit analysis incorporates information about individual growth and fishery selectivity parameters and is generally less data-intensive than assessment estimates of F_{msy}. When multiple proxies were available, we chose to use $F_{0.1}$ (i.e. the fishing mortality where marginal yield-per-recruit is 10% of its level for an unexploited population).

$F_{0.5r}$ from demographic analyses of intrinsic growth rate: Population growth rate r for a given population can be derived from life history tables and or Leslie matrices (e.g., Smith et al. 1998; Cortes 2002). The resulting estimate r has often been interpreted as the intrinsic growth rate in the fisheries literature (Smith et al. 1998; Cortes 2002, 2006), although this is only true where the demographic parameters are estimated while the population is severely depleted (Gedamke et al 2007). Resulting estimates of r can then be transformed to an estimate of F_{msy}, given an assumed form for the surplus production relationship. We adopt the convention that $F_{msy} = F_{0.5r} = r/2$, as implied by the Schaeffer surplus production model (Quinn and Deriso 1999).

Within the three categories, F_{msy} is our primary interest because it takes density-dependent processes into account and hence incorporates information regarding long term sustainability of a stock. The second category, F_{proxy}, implies an assumed value for recruitment compensation. It is interesting to compare it with F_{msy} because F_{proxy} is widely used in fishery management. The third category of F_{BRP} based on population growth rate is typically used in conservation but rarely used in fishery management. However, it is often the only method available for long-lived species such as sharks so it is also informative to include $F_{0.5r}$ as a comparison, noting the potential bias pointed out by Gedamke et al (2007).

14.3.3 PARAMETER ESTIMATION USING BAYESIAN HIERARCHICAL ERROR-IN-VARIABLE MODELS (BHEIV)

The LHPs that we investigated were natural mortality rate (M), von Bertalanffy growth coefficient (κ), asymptotic length (L_{∞}), maximum age (A_{max}), and habitat type (H). These data were sourced primarily from fishbase, so that model inference would be appropriate when applied to data-poor species where fishbase often represents the only available source of life history information. Species are categorized into five habitat types: bathypelagic (depth about 1000-4000 m), benthopelagic (about 100 m off the bottom of the ocean), demersal (close to the bottom of the ocean), pelagic (near the surface), and reef fish. We group data at class (Teleosts and Chondrichthyes) and order levels to capture major life-history variability and to avoid over-parameterization at species or stock levels. Along with three F_{BRP} categories (Type), we consider these groups (a matrix composed of taxonomic levels and the type of methods) as multiple populations. The amount of data and their quality vary substantially among these populations (Table 2) but populations share certain similarities in their life-history traits and BRPs. Hence, we take the advantage of Bayesian hierarchical modelling to derive robust estimates from such a multilevel structure.

Because natural mortality rate M, growth coefficient κ, asymptotic length L_∞, and maximum age A_{max}, cannot be accurately measured, ignoring errors in these variables would result in biased estimates of their effects on F_{BRP}. To obtain unbiased estimates, we specifically incorporated measurement errors in these variables by using an error-in-variable (EIV, also called measurement-error) model (Fuller 1987; Quinn and Deriso 1999). Let us assume that y_i is the real unobserved values of the observed explanatory variable x_i for species i. The EIV model is then

$$y_i = x_i e^{\varepsilon_{\mathbf{x},i}}, \qquad (1)$$

where $\varepsilon_{\mathbf{x},i} \sim normal(0, \sigma^2_{\varepsilon,\mathbf{x}})$. Assuming lognormal distribution for y_i avoids generating negative values and is generally appropriate for life history parameters such as natural mortality rate (Hilborn and Mangel 1997). Hence, the general model can be expressed as

$$\begin{aligned} F_{BRP,t,c,o,i} &= \beta_{t,c,o,y}\mathbf{y}_i + e_{t,c,o,i} \\ &= \beta_{t,c,o,x}\mathbf{x}_i \exp(\varepsilon_{\mathbf{x},t,c,o,i}) + e_{t,c,o,i} \end{aligned} \qquad (2)$$

where $\mathbf{x}_i$ is a matrix of covariates (composed of one or more of M, κ, L_∞, A_{max}, and H depending on the model evaluated), $\beta_{t,c,o,x}$ is the parameter for variable x for method type t, class c, and order o. This model has an additive error structure where $e_{\bullet,i}$ is an independent normal random variable with mean 0 and variance $\sigma^2_{e_\bullet}$. The symbol • indicates that the heterogeneity may vary between types, classes, or orders depending on model specification. We also tested a multiplicative error structure but focused on models of additive error structure because the plot of F_{BRP} with M does not show clear evidence of increasing variability as M increases. The results from the additive error model indicate a more significant contribution from each LHP than models of multiplicative error structure. We used the classical stepwise model building as a preliminary step to evaluate relative important of various covariates in Eqn (2), but only reported the result of BHEIV models.

We assumed $\beta_{\bullet,\mathbf{x}} \sim normal(\mu_{\beta_\mathbf{x}}, \sigma^2_{\beta_\mathbf{x}})$, where μ_{β_x} is the prior mean for parameter $\beta_\mathbf{x}$, and $\sigma^2_{\beta_\mathbf{x}}$ is the variance. As natural mortality is the key predictor, we treated β_M, and $\sigma^2_{\beta_M}$ as hyper-parameters across populations and assumed $\mu_{\beta_M} \sim normal(\bar{\mu}_{\beta_M}, \sigma^2_{\bar{\mu}_{\beta M}})$ and $\sigma^2_{\beta_M} \sim gamma(r = 0.01,\ \ \mu = 0.01)$ (Gelman 2006; Zhou et al. 2009b). We tested gamma and half-Cauchy distributions for $\sigma^2_{\bar{\mu}_{\beta M}}$ but reported $\sigma^2_{\bar{\mu}_{\beta M}} \sim gamma(r = 0.01, \mu = 0.01)$ as the results were similar. Further, we used a normal distribution with a large variance for the hyper-mean, $\bar{\mu}_{\beta_M} \sim normal(0.5,\ 1000)$. For the measurement error variance, we specified $\sigma^2_{\varepsilon,\mathbf{x}} \sim gamma(r = 0.01,\ \ \mu = 0.01)$. These specifications provide relatively non-informative priors and hyper-priors, as *gamma*(0.01, 0.01) represents a mean 1 and variance 100. We tested a range of models (Table 3) with alternative priors and used deviation information criteria DIC (Spiegelhalter et al. 2003) as primary criteria for model comparison.

We applied the Gibbs sample implemented using the WinBUGS program to sample parameter vectors from the above posterior distribution. Three Markov chains were constructed based on dispersed initial values and the results of the first 10,000 cycles of each chain were discarded. The results of an additional 30,000 cycles from the three chains were saved for further analysis. We visually examined the chains for each parameter in the model as well as analysed the saved samples by using the CODA package (Best et al. 1996) to ensure that there was no evidence for non-convergence in the MCMC sampling chain.

14.4 Results

We investigated a range of models, ranked by the preliminary stepwise regression and confirmed by BHEIV models. These models included various LHPs with normally distributed and log-normally distributed error structures, and heterogeneity among populations for both measurement error $\varepsilon_{\bullet,i}$ and process error $e_{\bullet,i}$ in Eqn (2). Most of these models converged quickly, in less than 2000 cycles of the MCMC algorithm. There was no evidence of non-convergence for any model after sufficient cycles. Comparison of the top seven low DIC models is presented in Table 3. The best model with the lowest DIC has natural mortality *M* and growth coefficient κ as predictors with a homoscedastic error between populations (Model 1 in Table 3). The posterior mean and standard deviation of parameters are provided in Table 4 and their distributions are shown in Figure 1.

APPENDIX 3

Although including growth coefficient κ leads to a reduction in DIC, the parameter β_κ itself is very small: the 95% credible interval encompasses zero, meaning it is biologically insignificant (Table 4).

Clearly, the relationship between F_{BRP} and M differs between chondrichthyans and teleosts, and between the three types of reference points. For example, the overall F_{msy}:M ratio (where M is a median as in Eq. 1) for chondrichthyans is 0.411, which is about half of the teleost F_{msy}:M value (0.866). The coefficient of variation (cv) for the posterior mean F_{msy}:M ratio is 0.21 and 0.06 for chondrichthyes and teleosts, respectively (Table 4). Their overall predictive cv is 0.55. Most analyses for chondrichthyans are based on the demographic method, which results in a much lower $F_{0.5r}$:M than F_{msy}:M (0.253 vs. 0.411). Within teleosts, F_{proxy}:M is smaller than F_{msy}:M by about 14%.

Models at order level (Models 3-7 in Table 3) have higher DIC than the two models with lowest DIC at class level. However, we present results for Model 6 (which includes M and κ similar to DIC-selected Model 1) to illustrate the effect of taxonomic order on the ratio of F_{BRP}:M (Table 5, Figure 2). Within chondrichthyans, Carcharhiniforms has a lower F_{msy}:M ratio than the combined chondrichthyans. However, this is not necessary true for F_{proxy}:M and $F_{0.5r}$:M ratios. This indicates that the results of a lower β_M from stock assessment method for carcharhiniforms may be artificial, because the sample size is very small, i.e., only one species in the two non-carcharhiniforms Orders. Within teleosts, scorpaeniformes has the lowest β_M than other orders (Figure 2). Scorpaeniformes include many groundfish species and they tend to have a lower productivity (for example, expressed as maximum reproductive rate at low population sizes) than other species (Myers et al 1999). Again, the parameter β_κ is very small at order level and its 95% credible interval encompasses zero.

The results of the errors-in-variables model (Eqn 1) indicated that the values of input covariates from the literature and fishbase contained high uncertainty. For the natural mortality M the log-scale median measurement-error variance $\sigma^2_{\varepsilon,M}$ is 0.23, representing a cv[M] = $\sqrt{\exp(0.23)-1}$ = 0.51. In comparison, the hierarchical Model 2 resulted in σ^2_e = 0.0012, corresponding to cv[F_{msy}] = 0.15. When measurement error is taken into account, the mean natural mortality for each stock is higher than the reported value which is assumed to be median-unbiased. Thus, the mean natural mortality will be exp($\sigma^2_{\varepsilon,M}$ /2) = 1.12 higher than the reported value. This is equivalent to increasing β_M in Tables 3 and 4, which are calculated from the observed median M as in Eqn 2. For example, the mean-unbiased F_{msy}:M ratio becomes 0.970 for teleosts (compared to 0.866), and 0.460 for chondrichthyans (compared to 0.411).

14.5 Discussion

This paper appears to be the first research to undertake a comprehensive empirical analysis linking various biological reference points to fish life-history traits. Through a meta-analysis on more than 200 species we estimated effects between several fishing mortality-based BRPs and LHPs for different taxonomic groups.

14.5.1 EFFECT OF LIFE HISTORY TRAITS ON F_{BRP}

Our results show that data collected from stock assessments worldwide generally support previous theoretical research regarding F_{BRP} and LHPs. Specifically, we find that natural mortality is the most important factor affecting F_{BRP}. Other life-history parameters, such as maximum age, growth coefficient, maximum length, and habitat type contribute limited additional improvement to the relationship. Although DIC selects the von Bertalanffy growth coefficient κ in addition to natural mortality M, its 95% credible interval overlaps zero and hence has little interpretable impact on F_{BRP}. One of the possible explanations is that natural mortality M is often incorporated into models that are used to estimate F_{BRP} thus causing a strong correlation between M and F_{BRP}. Furthermore, natural mortality is rarely estimated in assessment models but often calculated from an assumed relationship between M with κ and L_∞. This means that it is in fact κ and/or L_∞ that are the reliable predictors (Zhou et al. in preparation). These von Bertalanffy growth parameters are often available, even for many data-poor species. Because natural mortality correlates with many other life history parameters (Charnov 1993; Jennings et al. 1998; Goodwin et al. 2006), including growth rate, and life history parameters may involve considerable measurement errors, our result implies that using M alone as the predictor is generally sufficient to determine the F-based biological reference points. This result suggests that it may be redundant and overuse of information to include multiple life history parameters in qualitative and semi-qualitative assessment of species vulnerability (e.g. Stobutzki et al. 2001; Wesley et al. 2010).

14.5.2 COMPARISON OF F_{MSY}:M RATIO BETWEEN TAXONOMIC GROUPS

Our study reveals significant differences between chondrichthyans and teleosts. Most chondrichthyans are long-lived species with low natural mortality and low fecundity. Their life-history traits already make them more vulnerable to fishing (Stevens et al. 2000). On top of this vulnerability, our analyses demonstrate that the ratio of F_{msy}:M is much smaller for chondrichthyans than for teleosts (i.e., 0.41 vs. 0.87). Furthermore, the order Carcharhiniformes contains the largest sample size and has a mean F_{msy}:M ratio of 0.34. Because large species of chondrichthyans have lower growth rates and lower potential population increases (Frisk et al. 2001), the results support the assertion that assuming $F_{msy} > 0.5M$ for sharks and rays must be carefully justified (Walters and Martell 2002).

We estimate that the F_{msy}:M ratio is less than 1 for teleosts when observed M is assumed to be a median from a log-norm distribution and when all species are analysed together (mean 0.87, 95% CI between 0.77 and 0.97). Closer examination reveals some difference among orders. For example, Gadiformes, Perciformes, and Pleuronectiformes have F_{msy}:M ratio close to 1, while this ratio is less than 0.7 for Scorpaeniformes. This latter order has the largest sample size, which may have lowered the overall estimate to 0.87. The result at order level reinforces that the "rule of the thumb" approximation $F_{msy} = M$ is by and large acceptable for many teleosts (Alverson and Pereyra 1969; Gulland 1970, 1971). On the other hand, the result at class level (i.e., combining all teleosts) also supports the argument that F_{msy} should be lower than M for most species (Thompson 1993; Beddington and Kirkwood 2005).

Few studies have established a link between F_{BRP} and LHP for chondrichthyans. This is understandable, since there have been few quantitative stock assessments using time-series data for this Class of fishes. Furthermore, assessments of chondrichthyans often acknowledge uncertainty about basic demographic parameters and instead report results for a wide range of demographic values (Punt 2000; Cortes 2006).

14.5.3 BAYESIAN HIERARCHICAL ERROR-IN-VARIABLES MODEL

Bayesian hierarchical models have several advantages over classical data analysis methods. BHM can explicitly model all variability sources, can be applied to small sample sizes as they borrow information from all studies, and are well-suited for meta-analysis. The hierarchical Bayesian estimates of between-group divergence are less variable than maximum likelihood estimates because they are based on the data from all populations (Lockwood et al. 2001). These improved between-group variance estimates improve the estimation of the optimal degree of shrinkage, which is less affected by sampling variability at each population. BHM has the tendency to shrink population parameters toward the population mean, where parameters with more precise data are pooled less toward the population mean than more variable data. Shrinkage of the model as a whole makes use of the fact that the multilevel estimates of the individual parameters, if treated as point estimates, understate the between-group variance (Gelman and Pardoe 2006).

The challenge of building a credible relationship between BRPs and LHPs hinges on obtaining reliable life-history parameters. We emphasize the errors-in-variables models because it is clear that the dependent variables such as *M* cannot be accurately measured and the estimates are biased when measurement errors are not taken into account (Fuller 1987). The difficulty of estimating LHP is well recognized by fisheries scientists (Quinn and Deriso 1999). The uncertainty in LHP may arise from two major sources: (1) natural variation among stocks of the same species due to variability in stock structure, location, time, and other environmental factors, and (2) true measurement error due to our inability to accurately measure LHP for specific stock at specific time and location. For example, our estimation of large measurement error in natural mortality is consistent with other studies and observations (Quiroza et al. 2010). MacCall (2009) also reported the large standard error (0.56 and 0.50) in estimating *M* based on the Pauly (1980) and Hoenig (1983) methods, which values are very close to our results. The data in fishbase show that large differences exist in the estimated *M* for the same species. Different methods may result in very different estimates of *M* for the same species (Zhou et al. 2011). For these reasons, it is essential to take errors in variables into account when one studies the relationship between BRP and LHP.

The posterior measurement-error variance for natural mortality, $\sigma^2_{\varepsilon,M}$ is substantial. This indicates a skewed distribution of *M*. If one is interested in the mean value, which is affected by potential outliers, then applying a factor of 1.12 to obtain expected *M* increases the posterior β_M, pushing F_{msy}:*M* ratio closer to 1 for combined teleosts. However, this is not a normal way for specifying *M* in fishery stock assessments.

14.5.4 COMPARISON BETWEEN TYPES OF REFERENCE POINTS

F_{msy} is our focus in this study because it is based on analysis of time series data, results from population dynamics across many generations, and takes compensatory processes into account. It is also widely used in stock assessment and harvest control rules. We include F_{proxy} and $F_{0.5r}$ mainly for the purpose of comparison with F_{msy}. F_{proxy} is based on per-recruit analysis and does not directly take compensatory processes into account. Overall, F_{proxy} (primarily composed of $F_{0.1}$) is a more conservative reference point than F_{msy} for teleosts (about 15% lower than F_{msy}). Other studies have also found that more species had F_{msy} greater than their $F_{0.1}$ (Deriso 1987). In contrast, per-recruit analysis has rarely been applied in chondrichthyans. The small sample size for F_{proxy} (total 4 species) in chondrichthyans produces a greater F_{proxy} than F_{msy} with a large variance.

A large number of studies on chondrichthyan population vulnerability are based on demographic analyses of intrinsic growth rate derived from life history tables or Leslie matrices. Our analyses show surprisingly high precision in the posterior $F_{0.5r}$ but the mean value is smaller than F_{msy} for chondrichthyans. This method however has two major potential problems. Firstly, life history tables and Leslie matrices generally assume no density dependence. They provide an instantaneous rate of population growth for a specified set of life history traits that correspond to a specific population size (Gedamke et al 2007). Many investigators use these models to compute rates of population growth and claim this is the maximum (intrinsic) population growth rate. However, demographic modelling cannot estimate intrinsic *r* without additional information. The estimate *r* in much of the literature is typically population growth rate under special conditions. Secondly, $F_{msy} = r/2$ is only true when the population dynamics can be expressed by the symmetric Schaeffer surplus production model. On the first of these issues, it is interesting to note that estimates of *r* for chondrichthyans seem to be biased low by a factor of nearly 0.5. This would be consistent with these estimates being derived from populations that are on average at about half carrying capacity, rather than from highly depleted populations.

Our results, in particular the relationships between F_{msy} from stock-assessment and natural mortality *M*, will have wide applicability in management of data-poor species. Furthermore, ecosystem-based fishery management is being developed worldwide to conform to increasingly strict environmental and fishery legislation. Combining these issues, fishery scientists and managers are looking for innovative methods that can be utilized for the evaluation of fishing impact on non-target species that have very limited information. The results of this study will be useful in helping to meet the broad objectives of ecosystem-based fisheries management.

14.6 Acknowledgements

We thank A. Punt and E. Plaganyi-Lloyd, A. McCall and an anonymous reviewer for their review and comments on drafts of this manuscript. This work was funded by Fisheries Research and Development Corporation, Project No: 2010/044, as well as CSIRO Wealth from Ocean Flagship and the Division of Marine and Atmospheric Research. The China Scholarship Council provided financial support for S. Yin.

14.7 References

Alverson, D.L., Pereyra, W.T. 1969. Demersal fish exploitations in the northeastern Pacific Ocean—an evaluation of exploratory fishing methods and analytical approaches to stock size and yield forecasts. J. Fish. Res. Board Can. 26: 1985-2001.

Beddington, J.R. and Kirkwood, G.P. 2005. The estimation of potential yield and stock status using life-history parameters. Phil. Trans. Royal Soc. London B. Biol. Sci. 360: 163-170.

Best, N., Cowles, M.K., and Vines, K. 1996. CODA Convergence Diagnosis and Output Analysis Software for Gibbs Sampling Output. (MRC Biostatistics unit, Cambrdge, UK.)

Charnov, E.L. 1993. Life History Invariants. Oxford University Press, Oxford.

Clark, W.G. 1991. Groundfish exploitation rates based on life history parameters. Can. J. Fish. Aquat. Sci. 48: 734-750.

Clark, W. G. 1993. The effect of recruitment variability on the choice of a target level of spawning biomass per recruit. In Kruse, G., Marasco, R.J., Pautzke, C., and Quinn II, T,J. editors. *Proceedings of the international symposium on management strategies for exploited fish populations*. University of Alaska, Alaska Sea Grant College Program Report 93-02, Fairbanks, Pages 233–246.

Clark, W. G. 2002. F35% revisited ten years later. North Am. J. Fish. Manag. 22: 251–257.

Collie, J.S. and Gislason, H. 2001. Biological reference points for fish stocks in a multispecies context. Can. J. Fish. Aquat. Sci. 58: 2167-2176.

Cortes, E. 2002. Incorporating uncertainty into demographic modelling: application to shark populations and their conservation. Cons. Biol. 16: 1048-1062.

Cortes, E. 2006. Assessment of small coastal sharks, Atlantic sharpnose, bonnethead, blacknose and finetooth sharks using surplus production methods. SEDAR13-AW-01. http://www.sefsc.noaa.gov/sedar/download/SEDAR13_AW_01.pdf?id=DOCUMENT.

Deriso, R. B. 1982. Relationship of fishing mortality to natural mortality and growth at the level of maximum sustainable yield. Can. J. Fish. Aquat. Sci. 39: 1054-1058.

Deriso, R.B. 1987. Optimal $F_{0.1}$ criteria and their relationship to maximum sustainable yield. Can. J. Fish. Aquat. Sci. 44: 339-348.

FAO (Food and Agriculture Organization of the United Nations), 2003. The ecosystem approach to fisheries. FAO Technical Guidelines for Responsible Fisheries, No. 4, Suppl. 2. Rome, FAO. 112 pp.

Francis, R.C. 1974. Relationship of fishing mortality to natural mortality at the level of maximum sustainable yield under the logistic stock production model. J. Fish. Res. Board Can. 31: 1539-1542.

Frisk, M.G., Miller, T.J. and Fogarty, M.J. 2001. Estimation and analysis of biological parameters in elasmobranch fishers: a comparative life history study. Can. J. Fish. Aquat. Sci. 58: 956-981.

Fuller, W.A. 1987. Measurement Error Models. John Wiley and Sons Inc., New York.

Gedamke, T., Hoenig, J.M., Musick, J.A., and Dupaul, W.D. 2007. Using demographic models to determine intrinsic rate of increase and sustainable fishing for elasmobranchs: pitfalls, advances, and applications. North Amer. J. Fish. Manag. 27:605–618.

Gelman, A. 2006. Prior distributions for variance parameters in hierarchical models. Bayesian Analy. 1: 515-534.

Gelman, A. and Pardoe, I. 2006. Bayesian measures of explained variance and pooling in multilevel (hierarchical) models. Technometrics 48: 241-251.

Goodwin, N.B., Grant, A., Perry, A.L., Dulvy, N.K. and Reynolds, J.D. 2006. Life history correlates of density dependent recruitment in marine fishes. Can. J. Fish. Aquat. Sci. 63: 494-509.

Gulland, J.A. 1970. The Fish Resources of the Ocean. FAO Fisheries Technical Paper. No 97.

Gulland, J.A. 1971. Science and fishery management. J. Cons. Int. Explor. Mer 33 471-477.

Hilborn, R., Mangel, M. 1997. The Ecological Detective: Confronting Models with Data. Princeton University Press, Princeton.

Hoenig, J. M. 1983. Empirical use of longevity data to estimate mortality rates. Fish. Bull. 82: 898–903.

Jennings, S. Reynolds, J.D. and Mills, S.C. 1998. Life history correlates of responses to fisheries exploitations. Proc. Roy. Soc. Lond. B Biol. Sci. 265: 333-339.

Kirkwood, G.P., Beddington, J.R. and Rossouw, J.R. 1994. Harvesting species of different lifespans. In: Edwards P.J., May R., Webb N.R.(eds) Large-scale ecology and conservation biology. Blackwell Scientific, Oxford. pp. 199–227.

Lockwood, J.R., Roeder, K, and Devlin, B. 2001. A Bayesian hierarchical model for Allele frequencies. Genetic Epidm. 20: 17-33.

MacCall, A.D. 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J. Mar. Sci. 66, 2267–2271.

Mace, P.M. 1994. Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. Can. J. Fish. Aquat. Sci. 51: 110-122.

Mertz, G. and Myers, R.A. 1998. A simplified formulation for fish production. Can. J. Fish. Aquat. Sci. 55: 478-484.

Myers, R.A., Bowen, K.G., and Barrowman, N.J. 1999. Maximum reproductive rate of fish at low population sizes. Can. J. Fish. Aquat. Sci. 56: 2404-2419.

Patterson, K. 1992. Fisheries for small pelagic species: an empirical approach to management targets. Rev. Fish Biol. Fish. 2: 321-338.

Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. J. Cons. Int. l'Expl. Mer, 39: 175–192.

Punt, A. E. 2000. Extinction of marine renewable resources: a demographic analysis. Popul. Ecol. 42: 19-27.

Quinn, T. J., and Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Quiroza, J.C., Wiffa, R., and Canecob, B. 2010. Incorporating uncertainty into estimation of natural mortality for two species of Rajidae fished in Chile. Fish. Res. 102: 297-304.

Siddeek, M.S.M. 2003. Determination of biological reference points for Bristol Bay red king crab. Fish. Res. 65: 421-451.

Smith, S. E., Au, D.W. and Show, C. 1998. Intrinsic rebound potentials of 26 species of Pacific sharks. Mar. Freshwater Res. 49: 663-678.

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. 2009. Reconciling approaches to the assessment and management of data-poor species and fisheries with Australia's harvest strategy policy. Mar. Coast. Fish. Dyn. Manag. Ecosys. Sci. 1 244-259.

Spiegelhalter, D., Thomas, A., Best, N., Lunn, D. 2003. WinBUGS User Manual, V.1.4. (MRC Biostatistics Unit, Cambridge, U.K.)

Stevens, J.D., Bonfil, R., Dulvy, N.K, and Walker, P.A. 2000. The effects of fishing on sharks, rays, and chimaeras (chondrichthyans), and the implications for marine ecosystems. ICES J. Mar. Sci. 57: 476-494.

Stobutzki, I.C., Miller, M.J., Brewer, D.T. 2001. Sustainability of fishery bycatch: a process for dealing with highly diverse and numerous bycatch. Environ. Conserv. 28, 167–181.

Thompson, G.G., 1992. Management advice form a simple dynamic pool model. Fish. Bull. 90: 552-560.

Thompson, G.G., 1993. A proposal for a threshold stock size and maximum fishing mortality rate. Can. J. Fish. Aquat. Sci. 120: 303–320.

Walters, C., Martell, S.J.D. 2002. Stock assessment needs for sustainable fisheries management. Bull. Mar. Sci. 70: 629–638.

Wesley, P.S., Spencer, P., Link, J., Cope, J., Field, J., Kobayashi, D., Lawson, P., Gedamke, T., Cortes, E., Ormseth, O., Bigelow, K., and Overholtz, W. 2010. Using productivity and susceptibility indices to assess the vulnerability of United States fish stocks to overfishing. Fish. Bull. 108: 305-322.

Zhou, S., Griffiths, S.P., and Miller, M. 2009a. Sustainability assessments for fishing effects (SAFE) on highly diverse and data-limited fish bycatch in a tropical Australian trawl fishery. Mar. Freshwater Res. 60: 563-570.

Zhou, S, Punt, A.E., Deng, R., Dichmont, C.M., Ye, Y., and Bishop, J. 2009b. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Mar. Freshwater Res. 60: 1298-1308.

Zhou, S., Smith, A.D.M., Fuller, M. 2011. Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. Fish. Res. 112: 168-178.

APPENDIX 3

Table 1. Examples of theoretical studies on biological reference points with life-history traits.

Reference	Formula	Note
Francis (1974)	$F_{msy} = M$	If recruitment was constant
Deriso (1982)	$F_{msy} = (\alpha - M)/2$	α: parameter of logistic spawner-recruit model
Deriso (1987)	$F_{0.1} = 0.88 \sim 1.25M$	For a wide range of M/κ
Clark (1991)	$F_{mmy} \approx F_{0.1} \approx M$	In most cases. F_{mmy} is the maximum of the minimum yields at each level of spawning biomass per recruit
Thompson (1992)	F_{msy} > or < M	Depending on the power parameter in a power function of stock-recruitment relationship
Thompson (1993)	$F \leq 0.8\,M$	Would prevent stock from overfishing
Mace (1994)	$F_{0.1} \approx F_{35\%} \approx M$	For each M-κ combination.
Kirkwood et al. (1994)	$F_{msy} \propto M$	For given length at first exploitation l_c and M/κ
Siddeek (2003)	$F_{msy} = \left[\frac{W(F_{msy})R(F_{msy})\left(1-\exp[-Z_{msy}(\lambda - t_r)]\right)}{XW(0)R(0)\left(1-\exp[-Z_{msy}(\lambda - t_r)]\right)}\right]M$	Based on general growth and mortality assumptions
Beddington and Kirkwood (2005)	$F_{max} = a(L_c, h)\kappa$	$a(L_c, h)$ is a constant depending on the length at first exploitation and steepness

APPENDIX 3

Table 2. Number of species and data points included in the analysis. Type is the methods used to derive the three types of reference points.

	Chondrichthyes		Teleost	
Type	Species	Data points	Species	Data points
F_{msy}	10	12	73	88
F_{proxy}	4	4	99	131
$F_{0.5r}$	52	87	7	11
Total	66	103	179	230

Table 3. Comparison Bayesian hierarchical error-in-variable models using deviation information criteria. Type is the type of methods, i.e., F_{msy}, F_{proxy}, and $F_{0.5r}$, M is natural mortality, κ and L_∞ are von Bertalanffy growth parameters, A_{max} is maximum age, and H habitat.

Model	Variables	ΔDIC
1	Class, Type, M, κ	0
2	Class, Type, M	63.4
3	Class, Order, Type, M, κ, A_{max}, H	260.3
4	Class, Order, Type, M, κ, L_∞, A_{max}, H	261.8
5	Class, Order, Type, M, κ, H	278.6
6	Class, Order, Type, M, κ	316.0
7	Class, Order, Type, M	322.7

APPENDIX 3

Table 4. Posterior mean and standard deviation of Bayesian hierarchical errors-in-variables model $F_{BRP,i} = \beta_{t,c,M}\, M_i\ \exp(\varepsilon_M) + \beta_{\kappa}\, \kappa_i + e_i$ (t = type of method, c = class), and n is sample size.

Parameter	Class	Type	Mean	SD	n
$\beta_{1,1,M}$	Chondrichthyes	F_{msy}	0.411	0.088	12
$\beta_{2,1,M}$	Chondrichthyes	F_{proxy}	0.825	0.215	4
$\beta_{3,1,M}$	Chondrichthyes	$F_{0.5r}$	0.253	0.026	87
$\beta_{1,2,M}$	Teleost	F_{msy}	0.866	0.053	88
$\beta_{2,2,M}$	Teleost	F_{proxy}	0.730	0.036	131
$\beta_{3,2,,M}$	Teleost	$F_{0.5r}$	0.920	0.147	11
β_{κ}			0.017	0.009	333

Table 5. Posterior mean and standard deviation of Bayesian hierarchical errors-in-variables model $F_{BRP,i} = \beta_{t,c,o,M} M_i \exp(\varepsilon_M) + \beta_{\kappa} \kappa_i + e_i$ (t = type of method, c = class, o = order), and n is sample size.

Parameter	Class	Type	Order	Mean	SD	n
$\beta_{1,1,1,M}$	Chond	F_{msy}	Carcharhiniformes	0.335	0.095	10
$\beta_{1,1,2,M}$	Chond	F_{msy}	Lamniformes	0.463	0.365	1
$\beta_{1,1,3,M}$	Chond	F_{msy}	Other chondrichthyes	0.967	0.561	1
$\beta_{2,1,1,M}$	Chond	F_{proxy}	Carcharhiniformes	0.876	0.323	2
$\beta_{2,1,,2,M}$	Chond	F_{proxy}	Lamniformes	0.640	0.365	1
$\beta_{2,1,3,M}$	Chond	F_{proxy}	Other chondrichthyes	0.801	0.415	1
$\beta_{3,1,1,M}$	Chond	$F_{0.5r}$	Carcharhiniformes	0.266	0.038	55
$\beta_{3,1,2,M}$	Chond	$F_{0.5r}$	Lamniformes	0.280	0.101	11
$\beta_{3,1,3,M}$	Chond	$F_{0.5r}$	Other chondrichthyes	0.269	0.086	21
$\beta_{1,2,4,M}$	Teleost	F_{msy}	Clupeiformes	0.880	0.200	2
$\beta_{1,2,5,M}$	Teleost	F_{msy}	Gadiformes	1.014	0.136	11
$\beta_{1,2,6,M}$	Teleost	F_{msy}	Perciformes	0.922	0.092	23
$\beta_{1,2,7,M}$	Teleost	F_{msy}	Pleuronectiformes	1.160	0.154	12
$\beta_{1,2,8,M}$	Teleost	F_{msy}	Scorpaeniformes	0.694	0.095	35
$\beta_{1,2,9,M}$	Teleost	F_{msy}	Other teleost	0.896	0.162	5
$\beta_{2,2,4,M}$	Teleost	F_{proxy}	Clupeiformes	0.634	0.100	10
$\beta_{2,2,5,M}$	Teleost	F_{proxy}	Gadiformes	0.718	0.074	21
$\beta_{2,2,6,M}$	Teleost	F_{proxy}	Perciformes	0.742	0.043	66
$\beta_{2,2,7,M}$	Teleost	F_{proxy}	Pleuronectiformes	0.715	0.087	19
$\beta_{2,2,8,M}$	Teleost	F_{proxy}	Scorpaeniformes	0.667	0.132	3
$\beta_{2,2,9,M}$	Teleost	F_{proxy}	Other teleost	0.683	0.090	12
$\beta_{3,2,4,M}$	Teleost	$F_{0.5r}$	Clupeiformes	0.843	0.290	1
$\beta_{3,2,5,M}$	Teleost	$F_{0.5r}$	Gadiformes	1.013	0.200	8
$\beta_{3,2,6,M}$	Teleost	$F_{0.5r}$	Perciformes	0.752	0.323	1
$\beta_{3,2,7,M}$	Teleost	$F_{0.5r}$	Pleuronectiformes	0.966	0.324	1
β_{κ}				-3.4×10^{-6}	7.2×10^{-5}	333

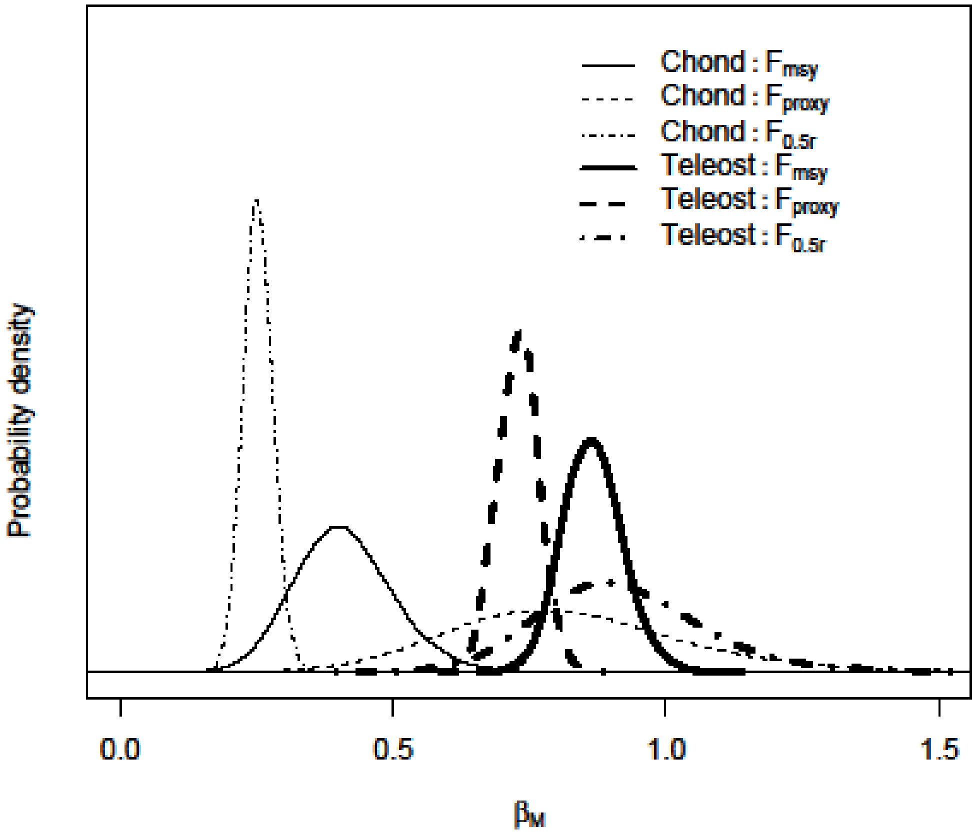


Figure 1. Posterior distributions for coefficient of natural mortality $\beta_{\bullet,M}$ by Class (chondrichthyans and teleosts) and Type (F_{msy}, F_{proxy}, and $F_{0.5\mathrm{r}}$).

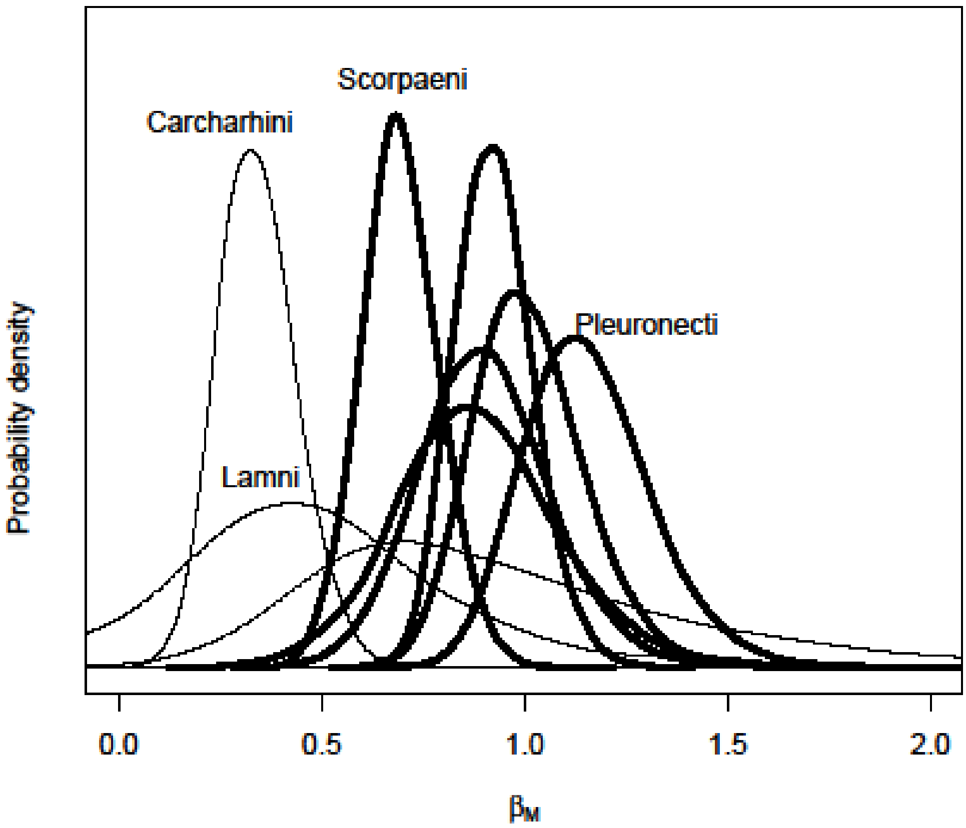


Figure 2. Posterior distributions for coefficient of natural mortality $\beta_{\cdot,M}$ by Class (chondrichthyans and teleosts), and Order (Carcharhiniformes, Lamniformes, Other chondrichthyes; Clupeiformes, Gadiformes, Perciformes, Pleuronectiformes, Scorpaeniformes, Other teleost) for stock assessment method (Type F_{msy}). The thin lines are chondrichthyans and the thick lines are teleosts. Four Orders are indicated while there is only one species in the Order of Lamniformes and other chondrichthyes.

15 Appendix 4: Measuring economic depreciation in fisheries

Sean Pascoe, CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, Sean.Pascoe@csiro.au

Simon Vieira, ABARES, Simon.vieira@daff.gov.au

Olivier Thebaud, CSIRO – CMAR and Wealth from Oceans Flagship, Olivier.Thebaud@csiro.au

15.1 Abstract[16]

Australia has a policy of achieving maximum economic yield (MEY) in Commonwealth fisheries, with many States also interested in the MEY target. Bioeconomic models are being developed for estimating MEY for several fisheries, supported by economic surveys of the fisheries. While most cost components can be derived directly from the survey information, capital values are incorporated into the models usually through the opportunity cost of capital and depreciation – both imputed values. Information on the former can be derived from capital markets. Depreciation measures, however, are often distorted by accounting practices and taxation regulations rather than actual capital consumption. In this paper, we estimate the actual rate of economic depreciation in Australian fisheries, and find it is substantially lower than values usually used in most bioeconomic analyses.

[16] Submitted to Marine Resource Economics

15.2 Introduction

Increasingly in Australian fisheries and elsewhere, there is a move to include economic considerations into fisheries management. In Australia, the Commonwealth Government has introduced an explicit policy of pursuing maximum economic yield (MEY) as its primary objective for fisheries management (DAFF, 2007), and some States have also identified MEY as a management target (DEEDI, 2009).

The move to MEY, and dynamic MEY in particular (Grafton *et. al.*, 2010), as a management target requires the development of appropriate bioeconomic models and the use of appropriate economic data (Dichmont *et. al.*, 2010). Most economic data can be collected from industry, and economic surveys are common features in many fisheries internationally (Lam *et. al.*, 2011). While most fisheries inputs are bought through competitive markets (e.g. labor and fuel), these cash costs can be assumed to be reasonably representative of the opportunity cost (and hence economics cost) of the inputs. However, not all costs are cash costs, notably the value of owner operator labor, the opportunity cost of capital and depreciation. In fleets where there is a mixture of owner-operators and employed skippers, the share paid to skippers can be used as a reasonable proxy for the opportunity cost of owner-operator labor (on the assumption that the next best use of their time is skippering someone else's boat). The opportunity cost of capital is, to a large extent, defined by capital markets so an independent value can be derived.[i] Depreciation in vessel accounts, however, is largely defined by taxation regulations, with incentives in some instances created to encourage investment by allowing high deprecation rates.

The concept of economic depreciation is based on the actual capital consumption during the production process. This can only be measured through changes in capital values over time. Capital consumption (economic depreciation) can be offset by repairs and maintenance (Eggert and Ulmestrand, 1999), which are generally treated as either fixed or variable costs in their own right (Dichmont *et. al.*, 2010). Hence, the rate of depreciation is to a large extent endogenous, as more intensive use increases the cost of its maintenance, and the net impact on capital depends on set of incentives for maintaining the asset (Koulovatianos and Mirman, 2007).

Earlier theoretical analyses showed that the depreciation rate plays complex roles in determining optimal investment levels (Charles, 1983) as well as optimal participation rates in international fisheries (Charles, 1986). An increase in depreciation rate results in lower optimal fish stock levels through its impact on costs. However, it may also have other effects through its impact on the rate of investment, and these may vary depending on the unit capital costs. Theoretical model have found that depreciation and opportunity cost of capital are key determinants of optimal capital stock and investment strategies in a fishery when capital is malleable (McKelvey, 1983). Others suggest that the depreciation rate and discount rate play identical roles in determining optimal capacity (Charles, 1985).

Despite the apparent importance of depreciation as a cost, it has received little attention in the literature, and many modeling approaches seem to apply depreciation rates in an ad hoc manner. The aim of this paper is to determine an appropriate rate of depreciation to use in bioeconomic modeling, at least in the Australian context when deriving estimates of MEY. We derive the depreciation rate from economic survey information collected from a wide range of Australian fisheries.

15.3 Depreciation in the literature

A review of bioeconomic models suggests that only cursory attention is paid to depreciation rates. In many cases they are assumed zero, while in others they range from 1 per cent to 30 per cent (Table 1). In some cases, a justification was given in terms of an annualized cost of capital based on the expected life of the vessel, but in many cases, no justification for the rate was given, and instead an assumed rate was imposed. A greater number of papers than those indicated in Table 1 did not report a depreciation rate *per se*, but included depreciation as a given (fixed) cost. Similarly, a large number of papers reported depreciation as a component of fixed costs but did not specify how it was calculated (or how much of the fixed cost it comprised). That is, it was treated as a given.

Many of the studies with zero discount rate were theoretical in nature, and assumed a zero rate on the basis that capital investment was irreversible (Clark *et. al.*, 1979; Sumaila, 1995) or assumed a zero rate to simplify the analysis (Munro and Sumaila, 2002). Others developed more applied models, but also applied a zero rate assuming capital was a sunk cost (Castro *et. al.*, 2001; Gasalla *et. al.*, 2010). As a general rule, papers with depreciation rates between 1 and 10 per cent were based on an assumed rate; higher rates were based in straight-line annualization of capital costs assuming a given life of a vessel and zero scrap value.

APPENDIX 4

Table 1. Rates used in bioeconomic models and other fisheries economic analyses

Rate	citation	Rate	citation
0	(Sumaila, 1995)	0.05-0.1	(Lee *et. al.*, 1997)
0	(Gasalla *et. al.*, 2010)	0.06-0.2	(Ponce-MarbÃ¡n *et. al.*, 2006)
0	(Clark *et. al.*, 1979)	0.08	(Eggert and Tveteras, 2007)
0	(Castro *et. al.*, 2001)	0.1	(Drynan and Sandiford, 1985)
0	(Munro and Sumaila, 2002)	0.1	(Martinez and Seijo, 2001)
0.0001	(Ganguly and Chaudhuri, 1995)	0.1	(Smith and Crowder, 2011)
0.01	(Pradhan and Chaudhuri, 1999)	0.1	(Huo *et. al.*, 2012)
0.01	(Kar, 2004)	0.1	(Najmudeen and Sathiadhas, 2008)
0.03	(Maynou *et. al.*, 2011)	0.1-0.2	(Ceregato and Petrere Jr, 2003)
0.03-0.04	(Macher *et. al.*, 2008)	0.12	(Breen *et. al.*, 2008)
0.04	(Clarke *et. al.*, 1992)	0.15	(Charles, 1983)
0.04	(De Ionno *et. al.*, 2006)	0.15	(Clark and Lamberson, 1982)
0.05	(Warren *et. al.*, 1982)	0.15	(Charles and Munro, 1985)
0.05	(Stage, 2006)	0.16	(Duy *et. al.*, 2012)
0.05	(Kjaersgaard and Frost, 2008)	0.175	(Henderson and Tugwell, 1979)
0.05	(Wespestad and Terry, 1984)	0.2-0.3	(Sanders and Beinssen, 1996)
0.05	(Vestergaard *et. al.*, 2011)		

15.4 Methods and data

Depreciation represents the rate of change in capital stock as a result of its use. Hence, to estimate depreciation rates, we need to estimate how the stock of capital used in fishing changes over time. The rate of economic depreciation, therefore, represents the rate of net loss of capital value, as indicated by changes in the resale value of the capital asset over time (also adjusting for general price changes) (Hulten and Wykoff, 1996).

Estimating capital values in fisheries is complex as vessels are constantly repaired and upgraded (through refits), and vessels have widely varying configurations in terms of specifications and on-board equipment. Capital value is expected to decrease over time due to depreciation, but at a lower rate than standard accounting depreciation as ongoing repairs and maintenance (which are also included as costs) is likely to help maintain the value of the capital asset. Estimating capital values is also made difficult by relatively few market transactions for second-hand vessels. In most economic analyses, capital values are based on the owner's estimated market value of the vessel in each time period.

Given that reasonable estimates of capital values can be obtained, the level of capital invested in the vessel (including the engine, electronics and gear) is expected to vary with the length of the vessel and the type of fishery. Several different modeling approaches exist to estimate the rate of economic depreciation (Jorgenson, 1996). In this study, a multiplicative model was chosen of the form:

$$K = e^{\beta_0} p_K^{\beta_{pk}} L^{\beta_L} \left(\prod e^{\beta_D D} \right) e^{-\beta_A A} \tag{1}$$

where *K* is the capital value, p_k is the price index for capital, *L* is the length of the boat, *D* are the set of fishery and other characteristics dummies and *A* is the age of the boat in each time period. The estimated coefficient β_A represents the rate of economic depreciation.

The functional form of the model is given by

$$\ln K = \beta_0 + \beta_{pk} \ln p_k + \beta_L \ln L + \sum \beta_D D + \beta_A A \tag{2}$$

15.4.1 DATA

Information on costs of fishing in Australia is currently collected for a limited number of fisheries at the Commonwealth (e.g. ABARES) and State level (e.g. SA). ABARES (formerly ABARE) has been conducting economic surveys of Commonwealth fisheries since the early 1980s and has maintained a regular survey program for selected fisheries since 1992. The current program involves surveying major Commonwealth fisheries every two years with each survey collecting data for the previous two financial years. The aggregated financial and economic performance results generated from each survey are made publicly available through the annual Australian Fisheries Surveys Report series (Perks and Vieira, 2010) for the most recent report). Similar information is collected by the consulting firm *Econsearch* as part of their economic surveys of South Australian commercial fisheries. EconSearch has been undertaking these surveys since 1999 (EconSearch, 2010a, b, c, d). Each fishery is generally surveyed every three to four years and only data from the preceding financial year are collected. Survey definitions and terms have been kept consistent with those used by ABARES where possible (EconSearch, 2010a, b, c, d),. This means that the two datasets are reasonably consistent with each other and can be combined relatively easily.

Data from the two surveys over the period 1998 to 2010 were pooled. In total, 1961 observations were available across 14 different fishing methods (Table 2). Ideally, the models would have been run as panel data models to capture any vessel-specific characteristic not captured by the general characteristics considered. However, vessel identifiers had been removed for the south Australian data and it was not possible to track individual vessels over time in the data. As a result, all observations are considered to be independently distributed.

Capital costs were kept in nominal terms for the analysis, as a capital price index (Figure 1) was included in the model. Data on input prices in fisheries is generally unavailable, and where input price data has been used, it has either had to be derived based on a range of assumptions (e.g. (Pascoe *et. al.*, 2011)) or been provided by the industry (e.g. (Punt *et. al.*, 2010)). However, there is an a priori expectation that prices of inputs such as fuel, capital and freight in fisheries should be similar to input prices in agriculture. Agricultural price paid indexes are annually produced and published by ABARES (ABARES, 2010), with a separate index for each major input category.

Table 2 – Summary of vessels in the data set

Gear type	Number of obs.	Capital Average	St. Dev.	Length Average	St. Dev.	Age Average	St. Dev.
Automatic Longline	20	508,000	606,887	18.17	2.65	23.40	10.22
Danish Seine	67	249,403	111,119	16.84	1.33	26.04	5.75
Demersal Longline	16	103,750	82,412	11.41	2.30	33.94	11.71
Dive	41	231,393	171,474	7.14	0.70	6.41	4.66
Dropline	167	106,393	139,621	8.09	3.22	14.54	10.26
Fish Trawl	161	435,460	278,319	19.84	3.86	25.28	7.80
Gillnet	170	209,230	167,835	11.61	5.85	18.35	9.16
Mixed Gear	58	110,806	122,051	8.91	2.80	14.26	9.10
Pelagic Longline	327	826,894	447,358	20.24	4.75	12.93	9.55
Pots	309	375,423	201,084	11.98	2.92	14.09	10.22
Purse Seine	34	2,066,110	1,470,460	24.25	3.66	16.50	13.16
Squid Jigging	7	323,571	139,245	18.42	4.32	18.14	10.95
Trawl Prawns Temperate	59	1,377,145	709,305	21.10	0.91	13.41	9.42
Trawl Prawns Tropical	509	1,099,984	453,210	22.24	2.67	18.12	7.08
Trawl Roughy	16	1,369,750	534,106	36.25	6.08	27.69	14.30
All gears	1961	657,757	594,169	17.04	6.67	16.93	9.97

While it is expected that price changes in the fisheries sector should follow similar trends to that in agriculture, it is possible that they may change at different rates. The estimated coefficients relating to the price indexes in the model can be used to adjust these price indexes to make them more relevant to the fishing industry.

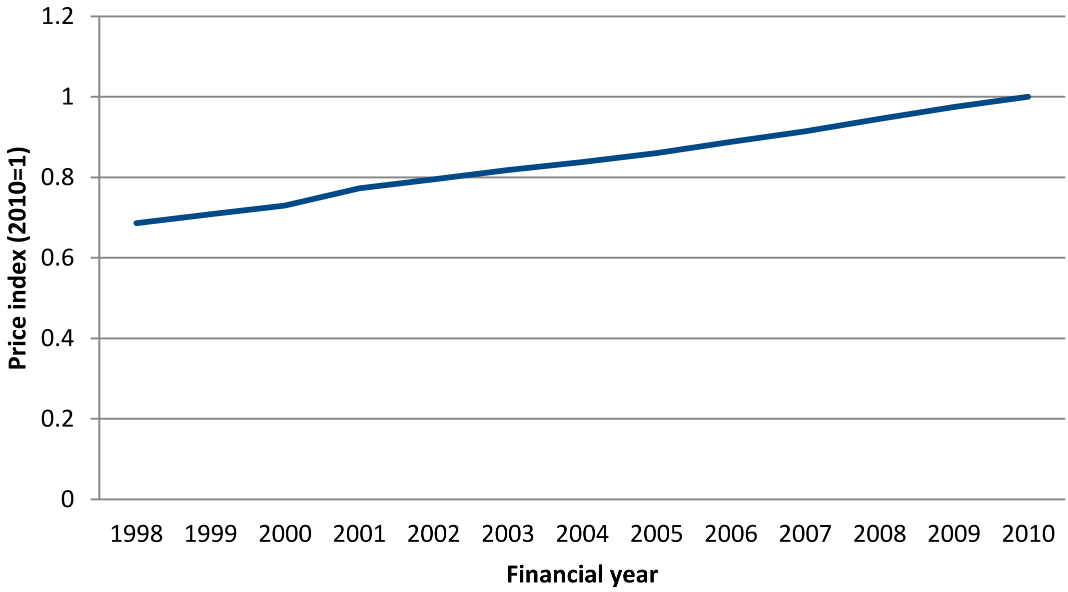


Figure 1. Capital price index (Derived from ABARES' *Australian Commodity Statistics 2010* Table 92 (ABARES, 2010))

Data to characterize individual vessels related to the technical characteristics of the vessels, including their size and whether they were equipped with on-board freezing capacity, the vessel age, the type of fishery in which the vessels operate, defined in terms of the main gear combinations used and target species, and whether access to the fishery is based on input or output controls.

15.5 Modelling results

The results of the model are given in Table 3. Commonwealth (fish) trawl vessels were used as the base in the model. The model was able to explain around 75 per cent of the variation in the data, and most of the coefficients were significantly different from zero. The coefficient on the price index for capital is not statistically different from one (1) as would be expected. However, as the price index is for agricultural capital, then some divergence from the a value of one is reasonable if the cost of building fishing vessels has generally increased at a faster rate than capital costs in agriculture in general.

Capital costs also appear to increase at an increasing rate as vessel size increases. Again, this is not unexpected, as length is a one dimensional measurement whereas vessels are three dimensional objects. Larger boats would also be able to use more crew, increasing the need for accommodation on board but also allowing proportionally more gear to be held on board. More and larger engines are also required to run the larger vessels and the larger vessels are also likely to use proportionally more electronics than their smaller counterparts. While it would be expected that larger vessels would have a freezer, this is captured separately in the model, as a factor that increases capital costs.

The effort control dummy suggests that – length for length – vessels operating in effort control fisheries have higher capital costs than those in ITQ fisheries. Incentives exist for “capital stuffing” in input controlled fisheries (Townsend, 1985) whereas ITQs create incentives to reduce costs, including capital costs (Asche *et. al.*, 2008)

The coefficient on the vessel age variable represents the rate of economic depreciation. From the model, this is estimated to be around 2.3 per cent per annum.

15.6 Discussion and conclusions

The estimated economic depreciation rate for the Australian fisheries was low relative to what has been used in many bioeconomic analyses internationally (Table 1). Other attempts at similar analyses have suggested a similar low rate of economic depreciation of around 3%, with a higher rate in first year (Daurés *et. al.*, 2006; Le Floc'h *et. al.*, 2008).

An interesting associated result from the analysis presented in this paper is the relatively higher capital costs encountered in fisheries in which access is regulated through input controls. As noted above, this provides further evidence for capital stuffing in input regulated fisheries (Townsend, 1985), and/or cost minimization in output controlled fisheries (Asche *et. al.*, 2008).

Table 3 – Estimated model for Capital costs

Coefficients	Estimate	Std. Error	t value	
Constant	9.584	0.187	51.376	***
Price index for capital	1.050	0.129	8.146	***
Length	1.325	0.059	22.378	***
Gear type dummy variables				
Danish seine	-0.216	0.085	-2.530	*
gillnets	-0.320	0.073	-4.370	***
Longline demersal	-0.400	0.142	-2.828	**
Longline pelagic	-0.729	0.420	-1.737	.
Longline automatic	-0.457	0.449	-1.018	
Trawl deep water	-0.129	0.439	-0.293	
Trawl prawns tropical	-0.416	0.419	-0.993	
Trawl prawns temperate	0.488	0.115	4.256	***
Dropline	-1.109	0.086	-12.882	***
Dive	0.254	0.121	2.091	*
Pots	0.302	0.064	4.680	***
Jigging (squid)	-0.653	0.235	-2.774	**
Multiple Gear	-1.174	0.101	-11.593	***
Purse seine	1.020	0.113	9.054	***
Freezer dummy	0.750	0.417	1.797	.
Effort control dummy	0.405	0.070	5.812	***
Vessel age	-0.023	0.002	-14.968	***
$\bar{R}^2$	0.749			
$F_{19,1941}$	309.5			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

From the fisheries economics literature, there is a tendency to either ignore capital costs (such as in the studies with a zero depreciation rate in Table 1) or overestimate them substantially. This has obvious implications for estimates of economic performance of management, and will also results in distortions in estimates of MEY where these are the objective of the study. The significant non-zero rate also suggests that, on average, capital is quasi-malleable in practice. Hence, the assumption of non-malleability in fisheries analyses is not valid. This has several implications for both modeling and management of fisheries. If capital was perfectly malleable, then “bang-bang” management solutions are appropriate (e.g. complete moratoriums can be applied if the stock falls below the optimal level) (Clark *et. al.*, 1979). With capital non-malleability, “optimal” capital levels are higher and stocks lower than in cases (with overcapitalization being optimal) where vessels depreciate. Conversely, with quasi-malleability, optimal capital levels are lower and stocks higher and a stable long run equilibrium position can be determined (i.e. maximum economic yield) (Clark *et. al.*, 1979).

The need for more empirical research on capital dynamics and their drivers in marine fisheries has increasingly been acknowledged (Munro, 2010; Nøstbakken et al., 2011). This requires the development of better methods for valuing capital stocks based on the available data, even if the limitations of available information on capital asset values also point to a need to improve the data collected on these in the future. Our empirical analysis provides a best estimate of capital depreciation schedules for Australian commercial fishing vessels, based on the data collected on the Australian fleets over the last decade. Determining whether this can be transposed to fleets elsewhere would require the replication of similar analysis on data sets relating to fisheries in other parts of the world. We contend that both this type of empirical analyses, and the collection of more systematic information on the capital costs of fishing fleets will play a key role in future efforts to guide fisheries towards maximum economic yield.

15.7 Acknowledgements

This study was undertaken as part of FRDC project 2010-044. Funding was also provided by the CSIRO Wealth from Oceans Flagship and the Australian Bureau of Agricultural and Resource Economics and Science (ABARES).

15.8 References

ABARES, 2010, Australian Commodity Statistics 2010, 233, ABARES, Canberra.

Asche, F., H. Eggert, E. Gudmundsson, A. Hoff, and S. Pascoe, 2008, Fisher's behaviour with individual vessel quotas-Over-capacity and potential rent Five case studies, Marine Policy, 32(6), pp 920-927.

APPENDIX 4

Asche, Frank, 2001, Fishermen's discount rates in ITQ systems, Environmental and Resource Economics, 19, pp 403-410.

Breen, P. A., D. J. Gilbert, and K. Chant, 2008, Bioeconomic Modelling of the New Zealand Fishery for Red Rock Lobsters (Jasus edwardsii), In Spiny Lobsters, 376-385, Blackwell Science Ltd.

Castro, L. A. B., M. Petrere Jr, and A. E. Comune, 2001, A bio-economic appraisal of pair trawl fisheries off southeastern Brazil, Brazilian Journal of Oceanography, 49(1-2), pp 39-48.

Ceregato, S. A., and M. Petrere Jr, 2003, Financial comparisons of the artisanal fisheries in Urubupungã Complex in the middle Paranã River (Brazil), Brazilian Journal of Biology, 63(4), pp 673-682.

Charles, A. T., and G. R. Munro, 1985, Irreversible investment and optimal fisheries management: a stochastic analysis, Marine Resource Economics, 1(3), pp 247-64.

Charles, Anthony T., 1983, Optimal Fisheries Investment: Comparative Dynamics for a Deterministic Seasonal Fishery, Canadian Journal of Fisheries and Aquatic Sciences, 40(12), pp 2069-2079.

Charles, Anthony T., 1985, Nonlinear costs and optimal fleet capacity in deterministic and stochastic fisheries, Mathematical Biosciences, 73(2), pp 271-299.

Charles, Anthony T., 1986, Coastal state fishery development: Foreign fleets and optimal investment dynamics, Journal of Development Economics, 24(2), pp 331-358.

Clark, C. W., and R. Lamberson, 1982, An economic history and analysis of pelagic whaling, Marine Policy, 6(2), pp 103-120.

Clark, Colin W., Frank H. Clarke, and Gordon R. Munro, 1979, The Optimal Exploitation of Renewable Resource Stocks: Problems of Irreversible Investment, Econometrica, 47(1), pp 25-47.

Clarke, R. P., S. S. Yoshimoto, and S. G. Pooley, 1992, A bioeconomic analysis of the Northwestern Hawaiian Islands lobster fishery, Marine Resource Economics, 7(3), pp 115-140.

Curtis, John A., 2002, Estimates of Fishermen's personal discount rate, Applied Economics Letters, 9, pp 775-778.

DAFF, 2007, Commonwealth fisheries harvest strategy: policy and guidelines, Department of Agriculture Fisheries and Forestry, Canberra.

Daurés, F., J. Bihel, O. Guyader, P. Le Floc'h, N. Roudaut, C. Brigaudeau, O. Thébaud, and M. Jézéquel, 2006, Estimating capital value and depreciation of fishing fleets: Application to French fisheries, In Thirteenth

Biennial Conference of the International Institute of Fisheries Economics and Trade (IIFET), University of Portsmouth UK, Portsmouth, UK.

De Ionno, Paul N., Graeme L. Wines, Paul L. Jones, and Robert O. Collins, 2006, A bioeconomic evaluation of a commercial scale recirculating finfish growout system â€" An Australian perspective, Aquaculture, 259(1-4), pp 315-327.

DEEDI, 2009, Queensland Fisheries Strategy, 2009–14, The State of Queensland Department of Employment, Economic Development and Innovation, Brisbane.

Dichmont, C. M., S. Pascoe, T. Kompas, A. E. Punt, and R. Deng, 2010, On implementing maximum economic yield in commercial fisheries, Proceedings of the National Academy of Sciences, 107(1), pp 16-21.

Drynan, R. G., and F. Sandiford, 1985, Incorporating economic objectives in goal programs for fishery management, Marine Resource Economics, 2(2), pp 175-195.

Duy, Nguyen Ngoc, Ola Flaaten, Nguyen Thi Kim Anh, and Quach Thi Khanh Ngoc, 2012, Open-access fishing rent and efficiency"The case of gillnet vessels in Nha Trang, Vietnam, Fisheries Research, (0).

EconSearch, 2010a, Economic Indicators for the South Australian Abalone Fishery 2008/09, In Report prepared for Primary Industries and Resources South Australia, EconSearch, Marryatville.

EconSearch, 2010b, Economic Indicators for the South Australian Blue Crab Fishery 2008/08, In Report prepared for Primary Industries and Resources South Australia, EconSearch, Marryatville.

EconSearch, 2010c, Economic Indicators for the South Australian Lakes and Coorong Fishery 2008/09, In Report prepared for Primary Industries and Resources South Australia, EconSearch, Marryatville.

EconSearch, 2010d, Economic Indicators for the South Australian Marine Scalefish Fishery 2008/08, In Report prepared for Primary Industries and Resources South Australia, EconSearch, Marryatville.

Eggert, H., and R. Tveteras, 2007, Potential rent and overcapacity in the Swedish Baltic Sea trawl fishery for cod (Gadus morhua), ICES Journal of Marine Science: Journal du Conseil, 64(3), pp 439-445.

Eggert, H., and M. Ulmestrand, 1999, A Bioeconomic analysis of the Swedish fishery for Norway lobster (Nephrops norvegicus), Marine Resource Economics, 14(3), pp 225-244.

Ganguly, S., and K. S. Chaudhuri, 1995, Regulation of a single-species fishery by taxation, Ecological Modelling, 82(1), pp 51-60.

APPENDIX 4

Gasalla, Maria A., Amanda R. Rodrigues, Luis F. A. Duarte, and U. Rashid Sumaila, 2010, A comparative multi-fleet analysis of socio-economic indicators for fishery management in SE Brazil, Progress In Oceanography, 87(1-4), pp 304-319.

Grafton, R. Quentin, Tom Kompas, Long Chu, and Nhu Che, 2010, Maximum economic yield, Australian Journal of Agricultural And Resource Economics, 54(3), pp 273-280.

Henderson, J. V., and M. Tugwell, 1979, Exploitation of the lobster fishery: Some empirical results, Journal of Environmental Economics and Management, 6(4), pp 287-296.

Hulten, Charles R., and Frank C. Wykoff, 1996, Issues in the measurement of economic depreciation introductory remarks, Economic Inquiry, 34(1), pp 10-23.

Huo, Hai-Feng, Hui-Min Jiang, and Xin-You Meng, 2012, A Dynamic Model for Fishery Resource with Reserve Area and Taxation, Journal of Applied Mathematics, 2012(Article ID 794719), pp 15 pages,.

Jorgenson, Dale W., 1996, Empirical studies of depreciation, Economic Inquiry, 34(1), pp 24-42.

Kar, Tapan Kumar, 2004, Management of a fishery based on continuous fishing effort, Nonlinear Analysis: Real World Applications, 5(4), pp 629-644.

Kjaersgaard, Jens, and Hans Frost, 2008, Effort allocation and marine protected areas: is the North Sea Plaice Box a management compromise?, ICES Journal of Marine Science: Journal du Conseil, 65(7), pp 1203-1215.

Koulovatianos, Christos, and Leonard J. Mirman, 2007, The effects of market structure on industry growth: Rivalrous non-excludable capital, Journal of Economic Theory, 133(1), pp 199-218.

Lam, Vicky W. Y., Ussif Rashid Sumaila, Andrew Dyck, Daniel Pauly, and Reg Watson, 2011, Construction and first applications of a global cost of fishing database, ICES Journal of Marine Science: Journal du Conseil, 68(9), pp 1996-2004.

Le Floc'h, P., Daurés F., C. Brigaudeau, and J. Bihel, 2008, A comparison of economic performance in the fisheries sector: A short- and long-term perspective, Marine Policy, 32(3), pp 421-431.

Lee, C. S., P. S. Leung, and M. S. Su, 1997, Bioeconomic evaluation of different fry production systems for milkfish (Chanos chanos), Aquaculture, 155(1â€“4), pp 367-376.

Macher, Claire, Olivier Guyader, Catherine Talidec, and Michel Bertignac, 2008, A costâ€“benefit analysis of improving trawl selectivity in the case of discards: The Nephrops norvegicus fishery in the Bay of Biscay, Fisheries Research, 92(1), pp 76-89.

Martinez, J. Antonio, and J. Carlos Seijo, 2001, Economics of risk and uncertainty of alternative water exchange and aeration rates in semi-intensive shrimp culture systems, Aquaculture Economics & Management, 5(3-4), pp 129-145.

Maynou, Francesc, Laura Recasens, and Antoni Lombarte, 2011, Fishing tactics dynamics of a Mediterranean small-scale coastal fishery, Aquatic Living Resources, 24(02), pp 149-159.

McKelvey, Robert, 1983, The fishery in a fluctuating environment: Coexistence of specialist and generalist fishing vessels in a multipurpose fleet, Journal of Environmental Economics and Management, 10(4), pp 287-309.

Munro, Gordon, and Ussif R. Sumaila, 2002, The impact of subsidies upon fisheries management and sustainability: the case of the North Atlantic, Fish and Fisheries, 3(4), pp 233-250.

Najmudeen, T. M., and R. Sathiadhas, 2008, Economic impact of juvenile fishing in a tropical multi-gear multi-species fishery, Fisheries Research, 92(2), pp 322-332.

Pascoe, Sean, Simon Vieira, Catherine M. Dichmont, and André E. Punt, 2011, Optimal vessel size and output in the Australian northern prawn fishery: a restricted profit function approach, Australian Journal of Agricultural and Resource Economics, 55(1), pp 107-125.

Perks, C., and S. Vieira, 2010, Australian fisheries surveys report 2010, Results for selected fisheries, 2007-08 and 2008-09, Preliminary estimates for 2009-10, In ABARES report prepared for the Fisheries Resources Research Fund, 67, ABARES, Canberra.

Ponce-MarbÃ¡n, Donny, Juan M. HernÃ¡ndez, and Eucario Gasca-Leyva, 2006, Simulating the economic viability of Nile tilapia and Australian redclaw crayfish polyculture in Yucatan, Mexico, Aquaculture, 261(1), pp 151-159.

Pradhan, T., and K. S. Chaudhuri, 1999, A dynamic reaction model of a two-species fishery with taxation as a control instrument: a capital theoretic analysis, Ecological Modelling, 121(1), pp 1-16.

Punt, André E., Roy A. Deng, Catherine M. Dichmont, Tom Kompas, William N. Venables, Shijie Zhou, Sean Pascoe, Trevor Hutton, Rob Kenyon, Tonya van der Velde, and Marco Kienzle, 2010, Integrating size-structured assessment and bioeconomic management advice in Australia's northern prawn fishery, ICES Journal of Marine Science, 67(8), pp 1785-1801.

Sanders, M. J., and K. H. H. Beinssen, 1996, Bio-economic modelling of a fishery under individual transferable quota management: A case study of the fishery for blacklip abalone Haliotis rubra in the Western Zone of Victoria (Australia), Fisheries Research, 27(4), pp 179-201.

Smith, Martin D., and Larry B. Crowder, 2011, Valuing Ecosystem Services with Fishery Rents: A Lumped-Parameter Approach to Hypoxia in the Neuse River Estuary, Sustainability, 3(11), pp 2229-2267.

Stage, J., 2006, Optimal harvesting in an age-class model with age-specific mortalities: an example from Namibian linefishing, Natural Resource Modeling, 19(4), pp 609-631.

Sumaila, U. R., 1995, Irreversible capital investment in a two-stage bimatrix fishery game model, Marine Resource Economics, 10, pp 263-284.

Townsend, Ralph E., 1985, On "Capital-stuffing" in Regulated Fisheries, Land Economics, 61(2), pp 195-97.

Vestergaard, Niels, Kristiana A. Stoyanova, and Claas Wagner, 2011, Cost-benefit analysis of the Greenland offshore shrimp fishery, Food Economics - Acta Agriculturae Scandinavica, Section C, 8(1), pp 35-47.

Warren, John P., Wade L. Griffin, and William E. Grant, 1982, Regional fish stock management: A model for North-West Africa, Marine Policy, 6(2), pp 121-130.

Wespestad, V. G., and J. M. Terry, 1984, Biological and economic yields for eastern Bering Sea walleye pollock under differing fishing regimes, North American Journal of Fisheries Management, 4(2), pp 204-215.

16 Appendix 5: Estimating proxy economic target reference points in data poor fisheries

Sean Pascoe,[1]* Olivier Thebaud[1] and Simon Vieira[2]

CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, Brisbane

Australian Bureau of Agricultural and Resource Economics and Science, Canberra

* Corresponding author: CSIRO Marine and Atmospheric Research, EcoSciences Precinct, PO Box 2583, Brisbane QLD 4001, Sean.Pascoe@csiro.au

16.1 Abstract

Bioeconomic models have been applied to a wide range of fisheries around the world. However, an even greater number of fisheries are relatively data poor, and development of traditional bioeconomic models is not feasible. Work on the biological side has resulted in techniques to estimate reference points such as F_{MSY} (fishing mortality at MSY) in such fisheries. In this paper, we extend this work to move from F_{MSY} to F_{MEY} for single species fisheries. We estimate key economic relationships necessary for the assessment of F_{MEY} based on fisheries characteristics. We show that good estimates of economic target reference points can be achieved with limited data.

Keywords: Maximum economic yield, proxy reference points, data poor methods

Paper presented at the 2012 World Conference on Natural Resource Modeling, University of Queensland, 10-12 July 2012

(submitted to Marine Policy)

16.2 Introduction

The use of biological reference points as indicators to guide fisheries management is well established (Caddy 2004, Caddy and Mahon 1995). While numerous types of biological reference points exist (Mace 1994), the most commonly applied are target and limit reference points, usually expressed in terms of either the biomass of the stock or the level of fishing mortality that achieves given outcomes. Limit reference points indicate levels which are to be avoided, while the target reference point represents the point that management is aiming to achieve (Mace 1994). While maximum sustainable yield (MSY) is the most commonly applied target reference point in fisheries management (Caddy and Mahon 1995), there is increasing interest in maximum economic yield (MEY) as an alternative target. Maximum economic yield represents the level of fishing effort and catch that maximises economic profits in the fishery over time (Dichmont et al. 2010, Grafton et al. 2010). This is usually seen as a level of fishing activity which will maximize the welfare generated by fisheries, although this has been debated in the recent literature (Bromley 2009, Christensen 2010). As it generally involves a lower level of fishing effort, it is more conservative in terms of biomass than MSY, and is often considered to be more environmentally beneficial in terms of bycatch and habitat damage (Dichmont et al. 2008, Grafton et al. 2007).

The Australian Commonwealth Harvest Strategy policy (DAFF 2007) identifies the level of biomass that achieves MEY (B_{MEY}) as the target reference point for Commonwealth managed fisheries. The estimation of MEY requires an understanding of both the key economic and biological parameters relevant to the fishery. Where this has been applied, the approach has relied on the development of detailed bio-economic models of the fishery under consideration (cite NPF references). However, due to the costs of systematic data collection for individual fisheries, a range of fisheries exists in which some or all of these parameters may be missing. This raises the issue of how to develop a set of reference points in the context of data poor fisheries, which has been increasingly recognized as an important issue for fisheries management around the world (cite references on the data poor work). Where economic information is missing, the Policy suggests a default value of 1.2 times the biomass that achieves MSY (B_{MSY}) as a proxy for the target reference point (DAFF 2007).[17] However, estimation of B_{MSY} also requires information about the biology of the stock, and assumes that each stock in a multi species fishery can be targeted separately (i.e. there are no technical interactions).

[17] This recognises that the biomass at MEY is greater than that at MSY, but the 1.2 is a relatively arbitrary scaling factor.

Further, the default proxy measure does not take into account the effects of prices and costs, as well as the discount rate if a dynamic MEY is the target.

To ensure sustainable exploitation of these data-poor fisheries, there is a need to develop innovative methods for incorporating economic considerations into harvest strategies without the possibility of developing full bio-economic models, and to quantitatively define proxies for limit and target reference points. This aim of this paper is to present a means of deriving a less arbitrary scaling factor than the default 1.2, in contexts where reasonable biological information is available but economic information is limited. Further, although the ability to estimate B_{MSY} may be limited in most fisheries, a range of simple methods exist to estimate fishing mortality at MSY (F_{MSY}), even with very limited catch and effort data, based on assumptions about some of the biological characteristics of the species (Garcia et al. 1989, Zhou et al. 2012)). Given this, we also derive proxy target reference points of F_{MEY} based on F_{MSY} as an addition to the B_{MEY}/B_{MSY} ratio.

From bioeconomic theory, we show that the relationships B_{MEY}/B_{MSY} and F_{MEY}/F_{MSY} largely depend on the ratio of costs to revenue at MSY. A stochastic simulation is developed using a simple bioeconomic model, and the results used to develop a regression tree to determine simple “rules of thumb” that can be used to indicate appropriate reference points given these costs shares. Individual vessel data covering a wide range of fisheries are used to derive further “rules of thumb” to indicate what the cost share at MSY may be given the characteristics of the fishery.

16.2.1 ESTIMATING MEY IN DATA POOR FISHERIES – A BRIEF REVIEW

Maximum Economic Yield (MEY) in a fishery can be defined as the point at which the sustainable fishing effort level and catches in the fishery entail maximum profits, or the greatest difference between total revenues and total costs of fishing (Grafton et al. 2007, Kompas 2005). The main determinants of MEY in a comparative statics analysis (i.e. without taking into account the adjustment delays which may be required to achieve any catch/effort combination, and the instability which often characterizes real fisheries) are illustrated in Figure 6-1. The point will change with input and output prices, as will the associated level of profits, and identifying MEY in any given fishery requires an assessment procedure allowing to track these changes (Kompas et al. 2009b). The dynamic nature of the MEY objective, as well as its instability due to changes in the key economic drivers of a fishery such as input and output prices, should be fully accounted for in such assessment procedures (Dichmont et al. 2010, Grafton et al. 2010).

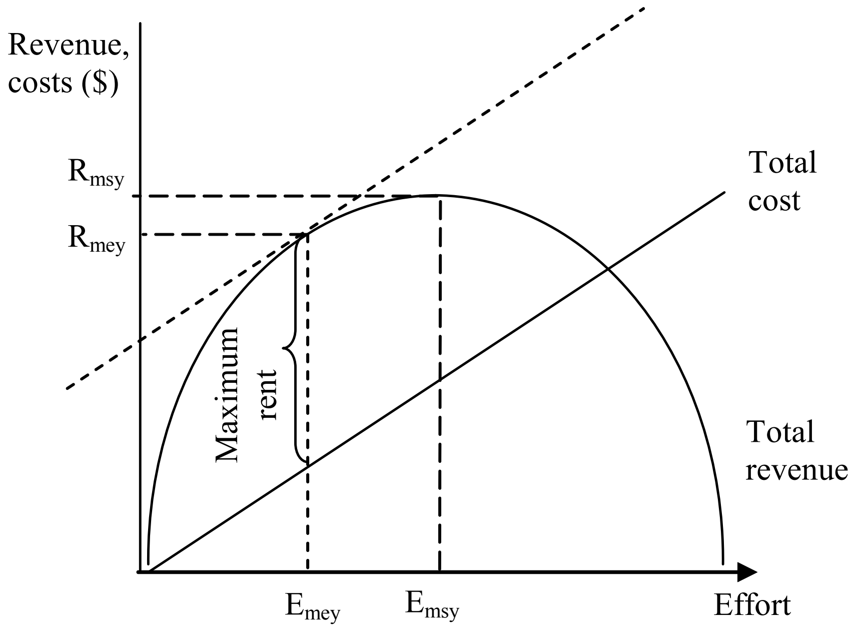


Figure 1 – Main determinants of Maximum Economic Yield (MEY) in fisheries

While the concept has long been identified by fisheries economists as a target that should drive fisheries management (Clark 1973, Gordon 1954, Scott 1955), its identification had largely remained a theoretical exercise until recent years, as it had not been formally adopted as a policy objective internationally. With its inclusion in the Australian Commonwealth fisheries policy,[18] and growing debates on its relevance as an operational management objective in other parts of the world (Bromley 2009, Christensen 2010, Dichmont et al. 2008, Norman-López and Pascoe 2011), the problem of estimating MEY in real fisheries has attracted growing attention. First attempts at identifying MEY as an actual management target have highlighted the empirical difficulties which need to be addressed in doing so, and relate in particular to the alternative treatments of prices and costs, which may result in differing estimates of MEY and associated adjustment trajectories (Dichmont et al. 2010).

It has been possible to overcome these difficulties in the context of data rich fisheries, to which the analysis was first applied. However, it is increasingly proposed that MEY also be applied as a

[18] Ministerial Direction to the AFMA under Section 91 of the Fisheries Administration Act 1991 issued by the Australian Government Minister for Fisheries, Forestry, and Conservation in December 2005.

management objective in a broader set of fisheries, including some which are less well monitored and researched. This requires identification of possible approaches to applying this objective in data poor contexts.

16.2.2 EMPIRICAL APPROACHES

Empirical analysis of MEY in fisheries has largely focused on the development of bioeconomic models. These have been developed for a wide variety of fisheries and for fisheries in most regions of the world (Armstrong and Sumaila 2001, Doole 2005, Kar and Chakraborty 2011, Kompas et al. 2010a, Ulrich et al. 2002). Such models require, at a minimum, some underlying stock dynamics models as well as information on costs of different fishing activities and prices of the main species. Models range in type from static equilibrium based models assuming a single homogenous fleet (Chae and Pascoe 2005, Kompas et al. 2010b) to complete ecosystem based approaches (Fulton et al. 2007) or multi-species and multi-fleet models (Pelletier et al. 2009, Punt et al. 2011, Ulrich et al. 2007). These models are case specific, such that general rules cannot readily be derived that could be applied in data poor contexts. While the models themselves could be adapted to other fisheries, these would require sufficient appropriate data to populate the model parameters. For management purposes, the reliability of these models is intrinsically linked to the data on which they were based, and acceptance of these models by industry and managers is also greatly influenced by data quality (and quantity) (Dichmont et al. 2010).

Non-model based approaches to estimate optimal fleet size in fisheries have largely focused on the estimation of fishing capacity and capacity utilisation (Felthoven and Morrison Paul 2004, Hoff and Frost 2007, Szakiel et al. 2006, Tingley and Pascoe 2005, Tingley et al. 2003). These can be derived using vessel level catch and effort data, but require assumptions as to what catch levels may be appropriate at MEY. At best, they can identify how much excess capacity may exist in the fishery, but do not provide an indication as to what may be an optimal level of either effort or catch .

Several attempts at developing indicators of economic performance exist that can be used to assess whether or not fisheries are improving or deteriorating. These include information on licence values (Arnason 1990), although most approaches require more detailed cost and earnings information (Whitmarsh et al. 2000). As with the capacity measures, these indicators alone do not provide information on where an optimal level of fishing effort or catch may be.

Harvest Control Rules (HCR) (Smith et al. 2009) have been applied across a broad range of fisheries, including data poor fisheries. One such approach is based on the definition of trigger levels associated with the biological status of the resources that also reflect economic performance (Dowling et al. 2008). Several examples of trigger-based management systems exist that have an implicit economic consideration but no explicit economic analysis. These include the data poor and low value spanner crab fishery in Queensland, Australia (Dichmont and Brown 2010, O'Neill et al. 2010), and the banana prawn fishery component of the Northern prawn fishery – a relatively data rich fishery but one in which modelling approaches have proven unreliable. In both cases, appropriate triggers are determined through a co-management arrangement involving industry, scientists and managers. Similar approaches have been proposed for definition of Harvest Control Rules for North Atlantic fisheries management for fisheries in which data are unreliable or unavailable, and complex analytical models cannot be applied (Kelly and Codling 2006).

16.3 Methodology

The aim of this paper is to determine some general "rules of thumb" that may assist managers in identifying appropriate target reference points in data poor fisheries, and in particular refine the existing "1.2B_{MSY}" default target reference point. To this end, a simple bioeconomic model is developed from which the relationship between economic and biological reference points is estimated for varying combinations of biological and economic parameters. The output from the model is summarised using a regression tree approach to determine simple "rules-of-thumb" that could be applied for different fisheries. Finally, simple econometric models of the information required for the "rules of thumb" as a function of fishery characteristics are derived.

16.3.1 A SIMPLE THEORETICAL BIOECONOMIC MODEL

The approach is developed based on a basic bioeconomic model incorporating a logistic biological growth model for a single species fishery (Schaefer 1954, Schaefer 1957) of the form

$$B_{t+1} = B_t + rB_t(1 - B_t/K) - C_t \qquad (1)$$

where B_t is the biomass in time period *t*, *r* is the instantaneous growth rate, *K* is the environmental carrying capacity and C_t is the catch in time period *t*. Catch is assumed to be a linear function of fishing effort and the level of biomass, given by

$$C_t = qE_tB_t \qquad (2)$$

where q is a proportionality constant known as the catchability coefficient and E_t is the level of fishing effort in time t.

At equilibrium, $B_e = B_t = B_{t+1}$ and hence $C_e = rB_e(1 - B_e/K)$ where the right hand side represents the annual growth in the population, also referred to as the surplus production as it is surplus to what is required to keep the population at a stable level of biomass (in the absence of fishing). The maximum equilibrium level of catch (the maximum sustainable yield) is hence given by

$$\frac{dC_e}{dB_e} = r - 2rB_e/K = 0 \tag{3}$$

and hence

$$B_{MSY} = K/2 \tag{4}$$

That is, MSY is achieved when the level of biomass is half the carrying capacity.

Equating catch to the surplus production in the population also allows the sustainable catch to be expressed as a function of fishing effort, given by

$$C = qEK - \frac{q^2K}{r}E^2 \tag{5}$$

From this

$$\frac{dC}{dE} = qK - 2\frac{q^2K}{r}E = 0 \tag{6}$$

And hence

$$E_{MSY} = r/2q \tag{7}$$

The simple model assumes prices are independent of the quantity landed and are hence constant. Similarly, the cost per unit of fishing effort is also assumed constant, such that the average cost equals the marginal cost. Costs in the model are economic costs, and represent full opportunity cost of all inputs in the production process (including unpriced labour and a normal return to capital). Given this, the level of economic profits in the fishery can be given by

APPENDIX 5

$$\pi = pC - cE$$

The level of fishing effort that maximises profits is hence given by

$$\frac{d\pi}{dE} = p\frac{dC}{dE} - c = p\left[qK - 2\frac{q^2K}{r}E\right] - c = 0 \tag{8}$$

From which

$$E_{MEY} = \left(qK - c/p\right)\Big/ 2\frac{q^2K}{r} \tag{9}$$

Given $E_{MSY} = r/2q$, then

$$E_{MEY} = \left(qK - \frac{c}{p}\right)\Big/\frac{qK}{E_{MSY}} \tag{10}$$

and hence

$$\frac{E_{MEY}}{E_{MSY}} = \left(1 - c/pqK\right) \tag{11}$$

Given that fishing mortality is given by $f = qE$, then

$$\frac{f_{MEY}}{f_{MSY}} = \frac{qE_{MEY}}{qE_{MSY}} = \left(1 - c/pqK\right) \tag{12}$$

That is, the ratio of fishing mortality at MEY to fishing mortality at MSY is a function of prices, costs, catchability and the carrying capacity of the stock. This value will always be less than 1 for any value of $c > 0$. By definition, the proportional target reference point expressed in terms of fishing mortality is the same as that expressed in terms of fishing effort.

Similarly, the biomass at MEY is given by

$$B_{MEY} = (K/2)(1 + c/pqK) = B_{MSY}(1 + c/pqK) \tag{13}$$

and hence

$$\frac{B_{MEY}}{B_{MSY}} = (1 + c/pqK) \tag{14}$$

As with the ratio of fishing effort and fishing mortality at MEY and MSY, the ratio of biomass at MEY and MSY is a function of prices, costs, catchability and the carrying capacity of the stock. This value will always be greater than 1 for any value of $c > 0$.

16.3.2 INTRODUCING DYNAMICS

The basic model presented above indicates the optimum level of fishing effort and biomass assuming it can be attained instantaneously. Usually, the process of reaching MEY will involve adjustment delays for stock biomass as well as fishing capacity. In particular, in cases where excess fishing effort is being applied to the stock, adjusting to MEY may involve short term costs in terms of effort reduction (Dichmont et al. 2010, Martinet et al. 2007), and hence the long term benefits need to be balanced against the short term costs. Accounting for this, the functional definition of MEY in the Australian fisheries context is the level of biomass and fishing effort that maximises the net present value of economic profits over time (DAFF 2007). The dynamic version of MEY incorporates a discount rate to allow the trade-off between future benefits and short term costs to be factored into the analysis. Following Clark (Clark 1990), the level of biomass that produces the dynamic MEY (B_{DMEY}) is given by

$$B_{DMEY} = \frac{K}{4}\left[\left(\frac{c}{pqK} + 1 - \frac{d}{r}\right) + \sqrt{\left(\frac{c}{pqK} + 1 - \frac{d}{r}\right)^2 + \frac{8cd}{pqKr}}\right] \tag{15}$$

where *d* is the discount rate. When *d* = 0, the value of B_{DMEY} is equivalent to that given in equation (12).

Where the discount rate is positive, estimating the sustainable level of fishing effort that produces the dynamic MEY (E_{DMEY}) is less straightforward than in the case where the discount rate was zero. Instead, E_{DMEY} needs to be estimated from the value of B_{DMEY}, and the sustainable level of catch at B_{DMEY}. The associated level of catch at MEY is given by $C_{DMEY} = rB_{DMEY}\left(1 - B_{DMEY}/K\right)$ and the level of fishing effort by $E_{DMEY} = C_{DMEY}/qB_{DMEY}$. Consequently, the relationship between E_{DMEY} and E_{MSY} needs to be determined numerically rather than algebraically.

The target reference point, however, needs to be distinguished from the path to achieve it over time. In practice, the pathway to building the biomass to the target level is often subject to a number of constraints (Dichmont et al. 2010, Martinet et al. 2007), which affects the speed of recovery, and, depending on the extent of the constraints, may influence the target reference point also (Dichmont et al. 2010). For data poor fisheries, factoring these considerations into the definition of dynamic target reference points is not possible due to the lack of the detailed dynamic models needed to estimate these reference points taking into account the constraints.

16.3.3 DATA INPUTS INTO THE ANALYSIS

A numerical version of the simple model was developed to assess the relationship between E_{MEY} and E_{MSY}, and to allow the derivation of a simple framework for determining appropriate target reference points in the case where data are limited. Values of the key parameters were varied stochastically and a range of possible relative target reference points (i.e. E_{DMEY}/E_{MSY} and B_{DMEY}/B_{MSY}) were estimated.

The values used in the stochastic analysis and the distributions of the final “acceptable” values are given in Table 1. Ten thousand random values were generated for each of the parameters in Table 1. However, a set of criteria was established to ensure that the set used for the analysis was relatively realistic. First, any set of parameters containing a negative value was discarded (removing some 250 sets). Second, any set of observations that would have result in negative economic profits at MSY was removed. While it is theoretically possible that MSY is not economically feasible, it is rarely observed. This resulted in only 5897 of the 10000 random sets of parameter values being used in the analysis.

APPENDIX 5

Table 1 - Key parameters used in the stochastic analysis

	Values used in stochastic analysis		Distribution of "acceptable" values					
	Mean	Standard deviation	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
r	1.4	0.4	0.065	1.140	1.396	1.400	1.661	3.122
q	0.004	0.001	0.001	0.004	0.004	0.004	0.005	0.008
K	1000	400	138.8	901.0	1126.0	1142.0	1365.0	2639.0
c	15	6	0.021	9.517	13.150	13.320	17.030	33.640
p	10	4	0.575	9.017	11.400	11.510	13.860	25.460
d	0.1	0.04	0.000	0.074	0.101	0.101	0.128	0.251

The choice of the initial mean values of the parameters and their standard deviations was aimed at producing sets of widely varying parameter values that were representative of a wide range of fisheries. The instantaneous growth rate (*r*) ranges from relatively slow growing species (such as shark (Cortés 1998)) to fast growing species (such as prawns). The mean price of all wild caught Australian produce in 2008-09 was $8.10 (Figure Figure 2 - Average prices for Australian fish species 2008-09.2), although prices varied widely between (and within) different types of species groups (ABARES 2010). A mean of $10/kg was chosen as the basis for the model. This is higher than the current average but, with a standard deviation of $4/kg, the distribution largely captured the range of prices observed for Australian wild caught fisheries. Catchability and the carrying capacity are inversely related in terms of scale, as the derivation of the target reference points relies on the value of their product (*qK*). Values of these parameters were chosen along with the mean value for costs in order to give an estimated cost per unit catch at MSY of approximately $7.50/kg (i.e. 75 per cent of the average price). This implies that economic profits are assumed to be at approximately 25 per cent of the revenue at MSY, on average.[19] Cost per unit catch at MSY is given by $c/(0.5qK)$. The model was also run with the discount rate fixed at various levels (0%, 5% and 50%) to test the sensitivity of the relationships to discount rate.

[19] Studies elsewhere suggest that economic profits at MEY may be a substantially higher proportion of revenue than the baseline included in this analysis (Asche et al. 2008a, Dupont 1990, Eggert and Tveteras 2007, Munro 2010). However, empirical analyses of Australian fisheries suggest that a more conservative assumption may be appropriate (Kompas et al. 2010a, Kompas et al. 2009a, Punt et al. 2011).

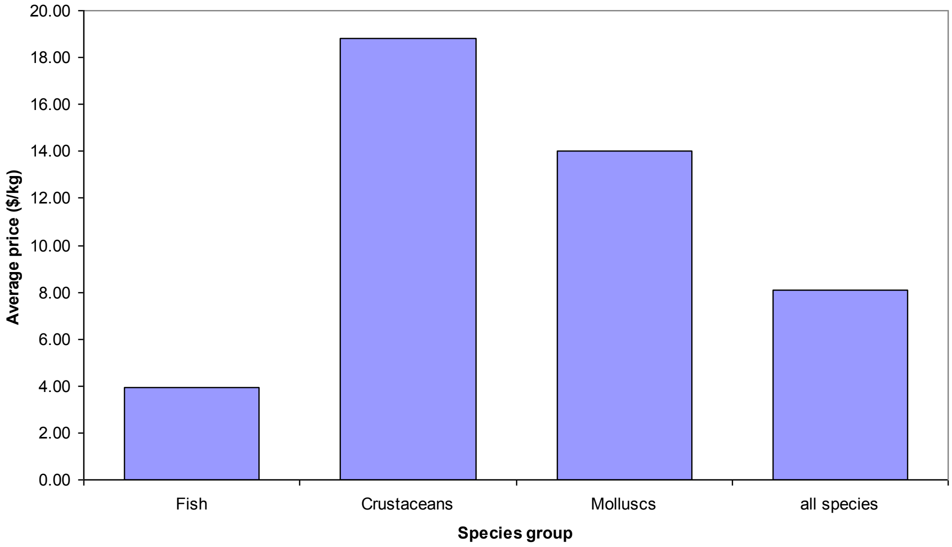


Figure 2 - Average prices for Australian fish species 2008-09. Source: (ABARES 2010)

16.3.4 ESTIMATING COST SHARES

From equations (11) and (14), both B_{DMEY}/B_{MSY} and E_{DMEY}/E_{MSY} are dependent upon the ratio $c/(pqK)$ where $c/(qK)$ effectively represents the cost per unit catch given an unexploited biomass, which is unknown. However, given that the catch per unit of effort at MSY is given by $0.5qK$ (as $B_{MSY} = 0.5K$), then the cost per unit of catch at MSY is equivalent to $c/(0.5qK)$ which is directly proportional to the cost per unit catch given an unexploited biomass.[20] Consequently, at MSY, the cost share of revenue, defined as the cost per unit catch divided by the price, is a feasible proxy measure by which the optimal ratio of biomass and effort can be derived in a comparative statics context. Multiplying both numerator and denominator by the catch at MSY gives the cost share as the ratio of the total fishing cost to the total revenue.

Cost and revenue information is currently available at the individual vessel level for a limited number of fisheries at the Commonwealth (e.g. ABARES) and State level (e.g. SA), although within this set of fisheries a substantial panel of data is being developed. ABARES (formerly ABARE) has been conducting economic surveys of Commonwealth fisheries since the early 1980s and has maintained

[20] The value 0.5qK is equivalent to the catch per unit effort (CPUE) at MSY. Given these relationships, the cost per unit catch at MSY is twice that at the unexploited biomass.

a regular survey program for selected fisheries since 1992. The aggregated financial and economic performance results generated from each survey are made publicly available through the annual Australian Fisheries Surveys Report series (Perks and Vieira 2010).. For South Australian commercial fisheries, EconSearch has been undertaking similar surveys since 1999 (EconSearch 2010a, b, c, d), using consistent definitions as those used by ABARES. Data from the two surveys over the period 1998 to 2010 were pooled, giving a total of 1961 observations across 14 different fishing methods.[21]

Over most of the period of the data, the management target for most fisheries was maximum sustainable yield, although several Commonwealth fisheries were transitioning to a target of MEY from 2008. About 20 per cent of stocks in Commonwealth fisheries were considered overfished in 1999 (Caton and McLoughlin 2000), although this declined to less than 10 per cent in 2010 (Woodhams et al. 2012). For South Australian fisheries, around 20 per cent of stocks were considered over fished during the middle period of the data (2002-2005) (PIRSA 2007). Given this, it can be assumed that most fisheries were at or around MSY for most of the period of the data, and hence the empirical cost shares of revenue are representative of the theoretical shares required for the analysis.

16.4 Results

16.4.1 RELATIONSHIPS BETWEEN TARGET REFERENCE POINTS AND COST SHARES

The distributions of the target reference points for 5 and 10 per cent discount rates are illustrated in Figure 3.In most cases, B_{DMEY}/B_{MSY} >1, while E_{DMEY}/E_{MSY} < 1, with the former ranging between 0.95 and 1.5 and the latter ranging between 0.5 and 1.05 given a 5 per cent discount rate. At higher discount rates, the distribution of B_{DMEY}/B_{DMSY} shifts to the left while E_{DMEY}/E_{MSY} moves to the right.

[21] Ideally, the subsequent analyses would have been run as panel data models to capture any vessel-specific characteristic not captured by the general characteristics considered. However, vessel identifiers had been removed for the South Australian data and it was not possible to track individual vessels over time in the data. As a result, all observations are considered to be independently distributed.

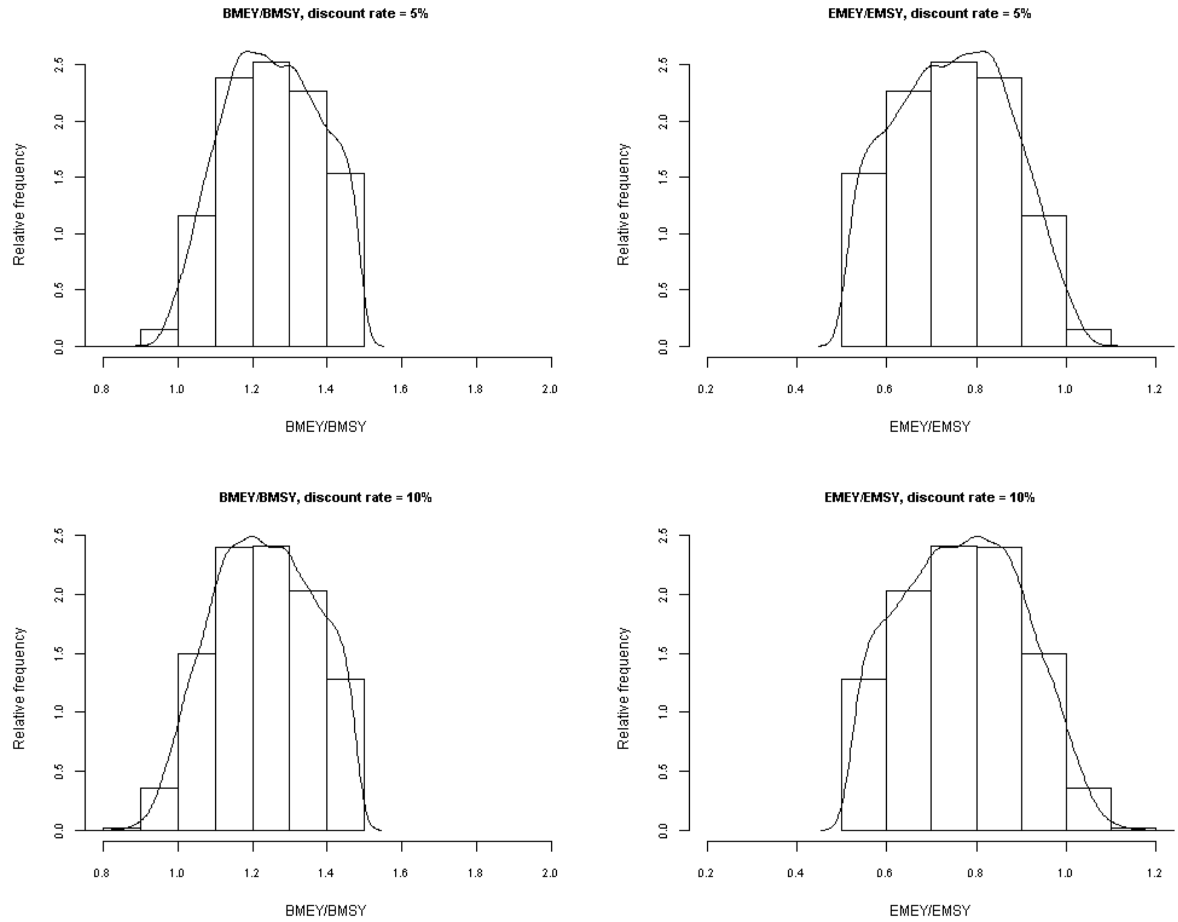


Figure 3 - Distribution of dynamic target reference point ratios

A regression tree analysis was undertaken with cost share and the ratio of the discount rate to the stock growth as the explanatory variables, based on equations 12, 14 and 15. These were undertaken for a given discount rate as this is generally determined exogenously for most fisheries (and public policy) analyses. For all levels of standard discount rates tested (0, 0.05, 0.1 and 0.5), the tree was split only in terms of the cost share component. This is illustrated for the 5 per cent discount rate case in Figure 4. The residual mean deviance of both models was extremely low (0.0004726 for the 5 per cent discount rate model) indicating that the regression tree provided a good representation of the characteristics of the data. The distribution of the error terms (Figure 5) also suggests that the model captures most of the variation in the ratios.

The current proxy value for B_{MEY}/B_{MSY} adopted in Australian fisheries management is 1.2 (DAFF 2007), and the commonly adopted discount rate for MEY estimation is 5 per cent (Punt et al. 2010). From the tree in Figure 6-10, this figure is appropriate for fisheries where the cost share is expected to fall between (roughly) 45 and 55 percent. That is, expected economic profits at MSY are also between 45 and 55 percent of revenue.

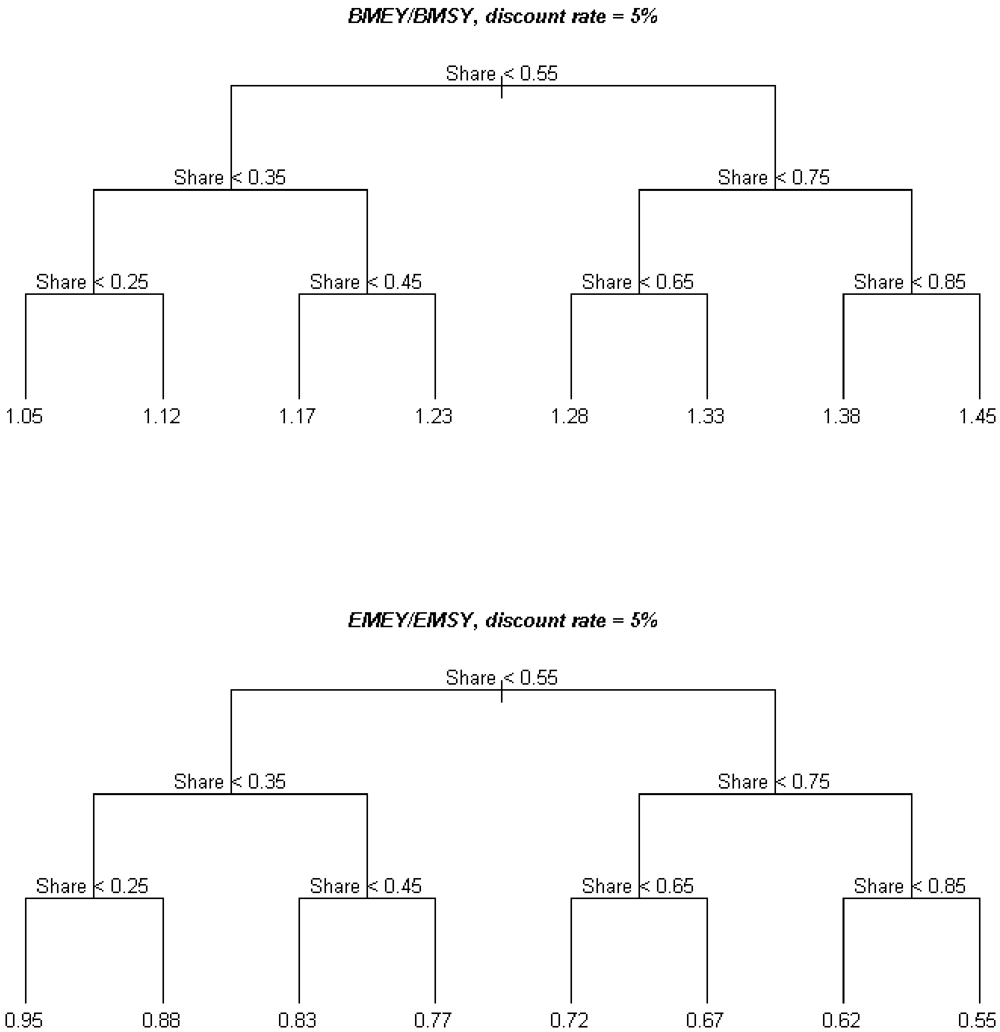


Figure 4 - Regression tree for a 5 per cent discount rate. Branches to the left relate to cases where the inequation is respected.

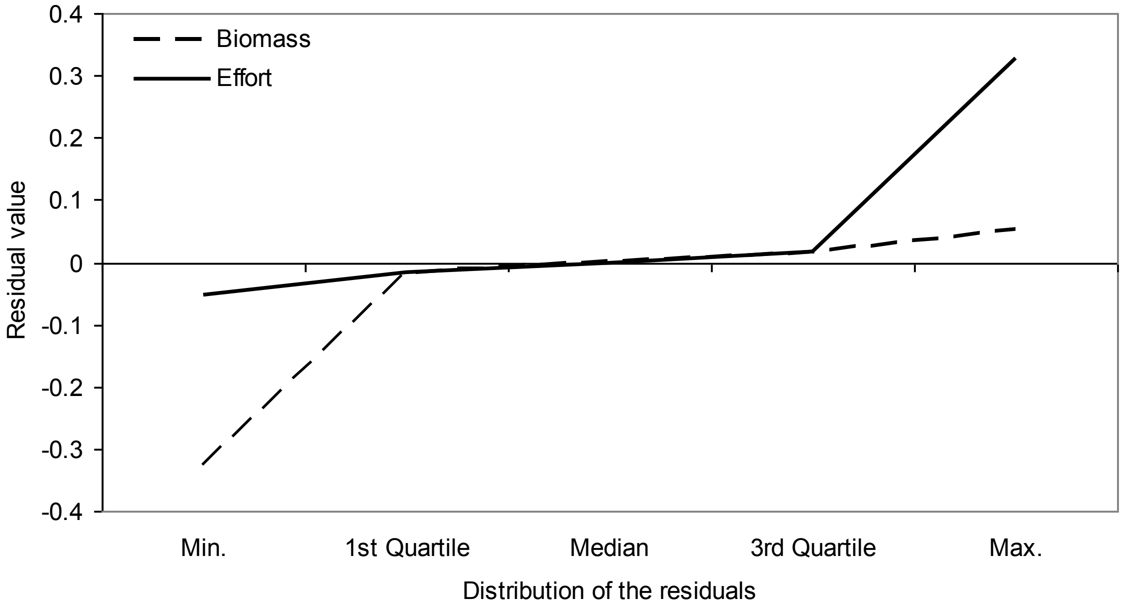


Figure 5 - Distribution of residuals from the regression tree analysis

16.4.2 RELATIONSHIP BETWEEN COST SHARES AND FISHERY CHARACTERISTICS

The theoretically derived model results above require some estimate of the cost share of revenue at MSY in order to derive an appropriate proxy for E_{MEY}/E_{MSY}. While these cost shares are unknown, a reasonable estimate of them may be made based on the economic data used in the previous analysis. The objective of MEY has only been implemented since 2007, and only one fishery (the Northern Prawn Fishery) has had an active policy of moving to MEY (Dichmont et al. 2010), although to date this has not been realised. For the other fisheries, and prior to 2007, the main management objective remains linked to maximising sustainable yields. While these were not necessarily achieved each year and in each fishery (Woodhams et al. 2012), on balance it could be assumed that the observed cost share of revenue was roughly equivalent to the costs shares at or near MSY for most of the period of the data.

The distribution of cost share of revenue in each of the fisheries for which economic data were available is given in Figure 6. Median cost shares for the SA fisheries appeared lower than those of the Commonwealth fisheries, although they were subjective to considerably greater variability.

A priori there is an expectation that cost shares in ITQ fisheries would be lower than those in input control fisheries due to the different incentives faced (Asche et al. 2008a). This is supported to some extent by the data, although there is not a clear significant difference between the cost shares solely on the basis of management type (Figure 7).

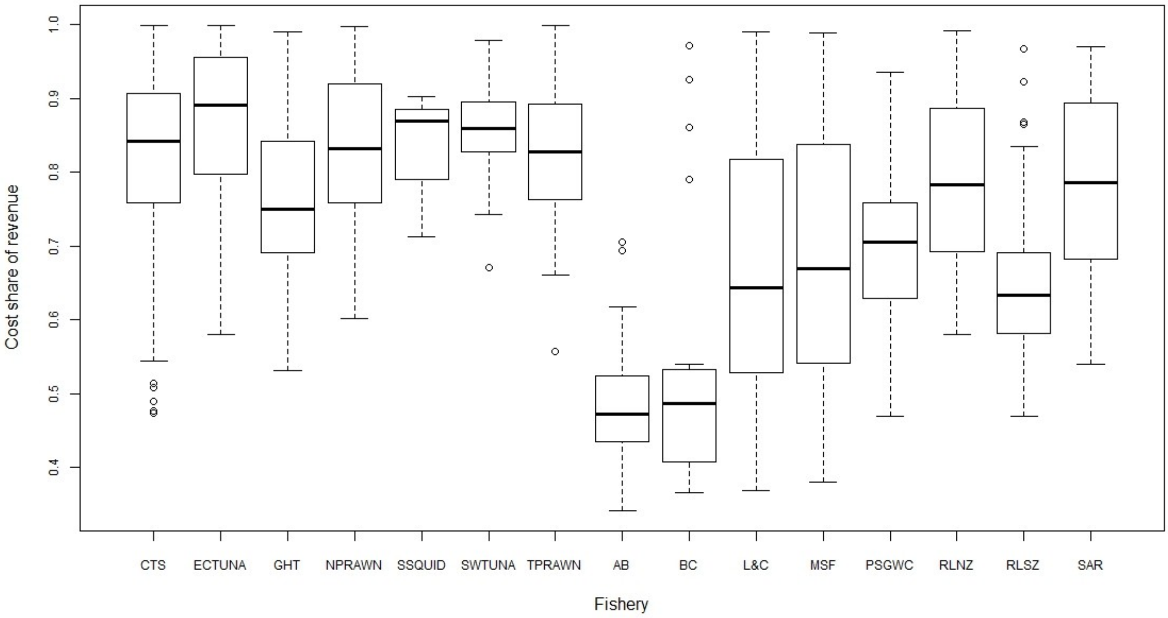


Figure 6: Distribution of cost share of revenue in fisheries with economic survey data

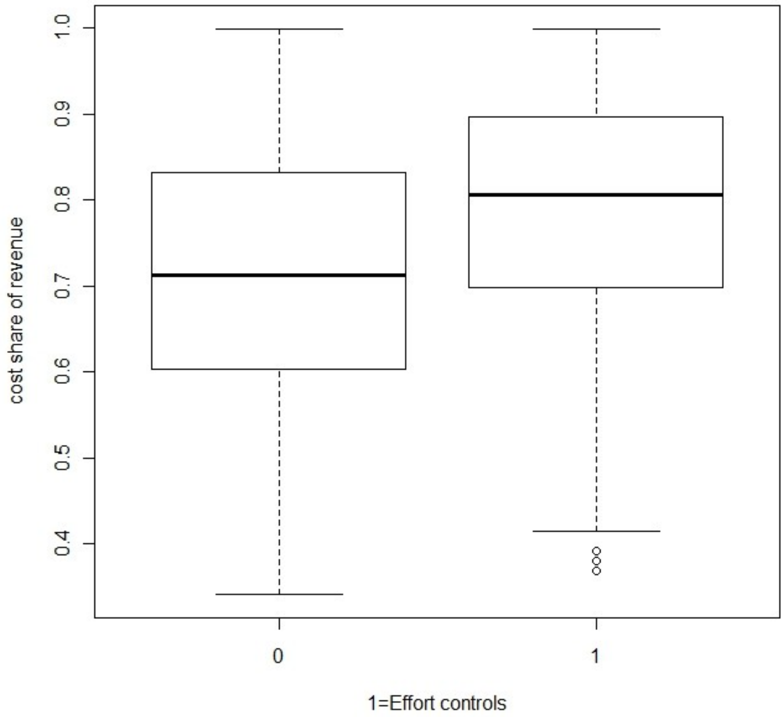


Figure 7: Cost share by management type

The relationship between cost share of revenue and fishery characteristics was examined through simple regression analysis. A priori, it was expected that boat size, fishing method (expressed as dummy variables with trawl as the base), management method (i.e. ITQ or effort controls), and potentially average price would affect the cost share of revenue. A log linear form of the model was assumed.

The results of the initial model are given in Table 2. The explanatory power was relatively low (33%), although this is as expected given the considerable variability between individuals in the data. However, most of the signs on the coefficients were as expected: fisheries with higher prices are likely to have a lower cost share (as revenues are higher, ceteris paribus); larger boats are likely to be higher cost than smaller boats relative to revenue, and cost share differed by main fishing method. The coefficient on the effort control was negative, although this was not significantly different from zero suggesting that effort control fisheries do not have a significantly higher cost share than output control fisheries (consistent with the distribution in Figure 7).

Table 2. Regression results for lnCostShare

	Estimate	Std. Error	t value	
Constant	-0.365	0.059	-6.149	***
lnPrice	-0.045	0.010	-4.450	***
lnLength	0.078	0.018	4.245	***
Method dummy variables				
Dropline	-0.083	0.027	-3.049	***
Trawl prawn	0.029	0.026	1.122	
Gillnet	-0.125	0.023	-5.437	***
Pots	-0.101	0.027	-3.725	***
Dive	-0.369	0.042	-8.824	***
Longline	0.061	0.020	3.067	***
Danish seine	-0.091	0.028	-3.197	***
Purse seine	-0.166	0.043	-3.868	***
Effort control dummy	-0.001	0.017	-0.047	
$\bar{R}^2$	0.338			
F	61.38			***

Note: Significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The coefficients on dropline, gillnets, pots and Danish seine were not significantly different from each other. While Danish seine is a trawl based method, it is very different to other trawl methods so a cost share similar to other static gears is not surprising. For the subsequent analyses, these four gear types were amalgamated into an “other static gear” variable. Prawn trawl was not significantly different than other (fish) trawls.

As the aim of the study is to develop proxy estimates of MEY from limited data, a regression tree analysis was run with cost share as the dependent variable and price, length, and gear types (trawl, dive, long line, purse seine and other static gear) as the explanatory variables. The resultant tree is illustrated in Figure 8, and the distribution of residuals given in Figure 9. The residual mean deviance was 0.014, and in most cases the residuals were less than 0.1. Given individual variability in the fisheries between vessels and between years then this degree of “error” is relatively low, as factors such as individual skipper/crew efficiency and random variations (“luck”) in catch also affect the output and hence cost share of revenue.

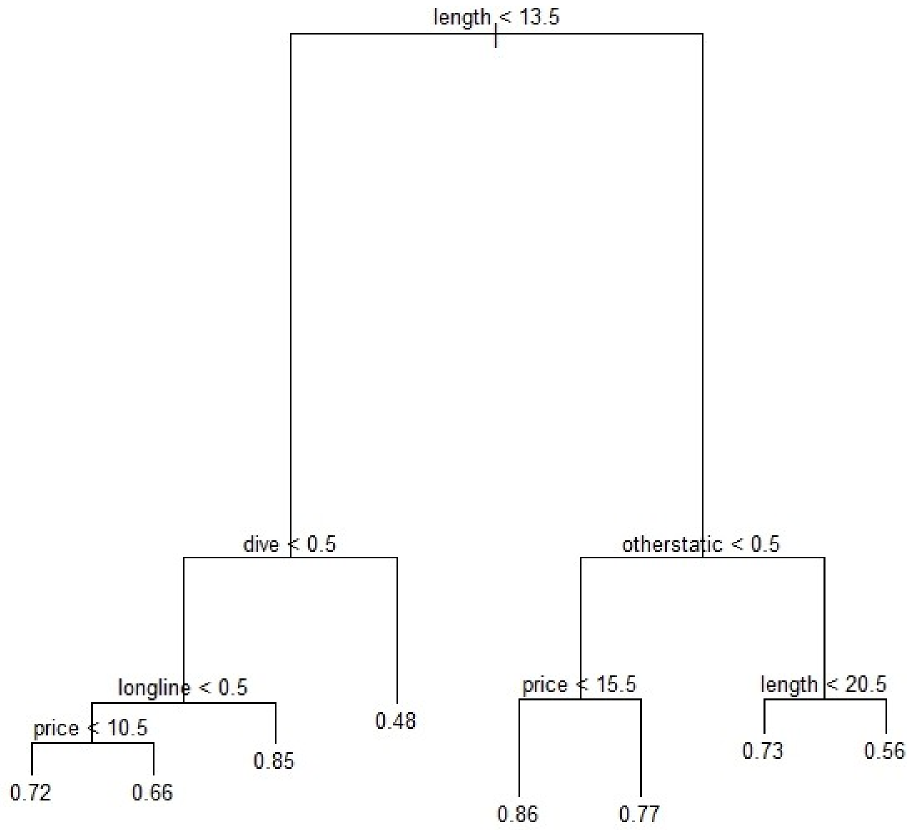


Figure 8: Regression tree describing cost share as a proportion of revenue

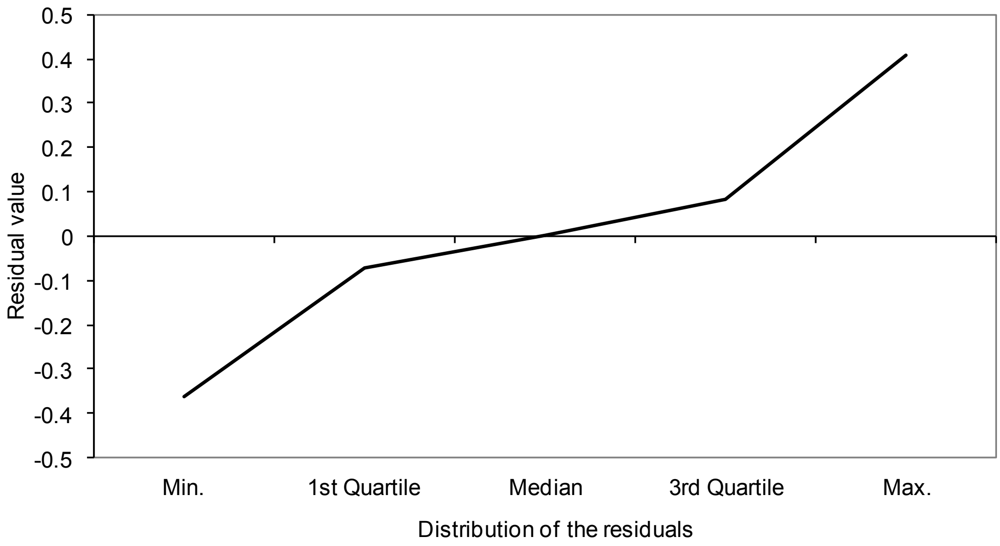


Figure 9. Distribution of cost share residuals

Combining Figures 8 and 4 allows an estimate of the ratio B_{MEY}/B_{MSY} or E_{MEY}/E_{MSY} to be derived based on limited information on the fishery – effectively some indication of the average price, average boat size and the main fishing methods. From Figure 8, larger boats tend to have higher cost shares than smaller boats, although this is not always the case. For example, small longline vessels and small vessels targeting low valued fish species tend to have comparable cost shares to the larger trawl vessels. From the two figures, for example, a trawl vessel targeting relative high valued species (i.e. > $15.50/kg) would have an average cost share of around 0.77 (Figure 8), which would imply a B_{MEY}/B_{MSY} ratio of around 1.38.

16.5 Discussion

In data poor fisheries, it is unlikely that the values of the key biological and economic parameters will be known in any detailed quantitative way. Garcia et al (Garcia et al. 1989) demonstrated that reasonable estimates of B_{MSY} and E_{MSY} can be made with very limited data, based on a few assumptions about the characteristics of the fishery.

Relatively few studies have attempted to quantity the revenue share of economic profits at MSY although several studies have looked at the potential share of profits in the fishery at MEY. Dupont (Dupont 1990) found that in the Canadian Pacific salmon fishery, potential economic profits were about 42 per cent of total revenue. Potential economic profits were estimated to be between 20-30 per cent of revenue for Denmark, Sweden and the UK, and even higher for Iceland and Norway (Asche et al. 2008b, Pascoe and Mardle 2001).

This relationship between economic profits at MEY and economic profits at MSY varies substantially depending on the relative costs and prices of fishing, across fisheries. For some fisheries, economic profits at MSY may be small relative to those at MEY, whereas in other fisheries the difference in economic profits may be large. Assuming that economic profit at MSY is around half that at MEY such that the ratio of economic profits to revenue at MSY ranges between 10-20 per cent, then more appropriate “default” proxy values for B_{MEY} may be 1.3-1.4 times B_{MSY}. Similarly, it might be expected that optimal effort levels are most likely to fall between 55 and 65 per cent of those at MSY.

MEY has been assessed for the Northern Prawn fishery (Punt et al. 2011). This is a relatively high cost per unit effort fishery, and with a low catch is also a relatively high cost per unit catch fishery. Based on the most recent published economic survey estimates, total costs were roughly 84 per cent of revenue for the fishery as a whole in 2008-09 (Vieira et al. 2010). Estimates of S_{MEY}/S_{MSY} for the three primary species in the fishery were 1.15, 1.255 and 1.38, with the stocks of two of the latter species believed to be close to, but above, MSY in 2009 (the reference year for the analysis) (Punt et al. 2011). From the regression tree, a proxy value of 1.396 would have been selected for this fishery (i.e. 0.773< cost share < 0.877) as appropriate for the fishery, reasonably consistent with at least one of the key target species and not substantially greater than the bioeconomic model estimates for the other two species.[22]

Estimates of the ratio B_{MEY}/B_{MSY} have also been undertaken for several species in the South East Trawl fishery, with values ranging from 1.06 for flathead (taken primarily by Danish seiners) to 1.53 or orange roughy (taken primarily by large trawlers), with an average of 1.26 for the set of species considered (Kompas et al. 2009b). Published economic survey results for the fishery as a whole suggest that, in 2009-10, economic profits and total costs were roughly 21 per cent and 79 per cent of the total revenue respectively (Perks and Vieira 2010). Based on our cost share regression tree model, the optimal ratio of B_{MEY} to B_{MSY} would again be 1.396, substantially higher than the existing estimates of optimal values for some species and underestimating them for others. However, several of the species are overfished or are subject to overfishing, and hence lower costs per unit of catch would be expected at higher stock levels (such as B_{MSY}). Adjusting for this would result in a lower optimal biomass ratio (or higher effort ratio) using the regression tree model.

The example fisheries above are all multispecies fisheries, which add an extra complexity to the analysis. The models used in this analysis were based on a single species fishery. In multispecies fisheries, the optimal harvest rate of any individual species in a fishery subject to joint production may differ from the optimal harvest rate of the species if it was a single species fishery. Nevertheless, the proxy values for the relative target reference points based on the single species model were closer to that estimated using a multispecies bioeconomic model than the base assumption of $B_{MEY}=1.2B_{MSY}$.

From the more detailed models, the optimal ratio of B_{DMEY}/B_{MSY} varies by species. However, in multispecies fisheries where the species are caught jointly, there will be only one measure of effort that maximises profits across the fishery (E_{MEY}), and one measure of effort that maximises overall sustainable catch (E_{MSY}), so effort based target reference points may be of more value as a fisheries management tool than biomass based measures in multispecies fisheries.

[22] The issue of join production adds a further complication into the definition of MEY. The optimal yield in a multispecies fisheries is rarely the same as the individual optimal yield if it could be perfectly targeted (Anderson 1975).

16.6 Conclusion

For many fisheries, the cost of data collection and analysis to estimate MEY targets accurately may be high relative to the economic benefits that may result from improved definition of target reference points. Potentially zero, negative or at best small improvement over their existing profitability may be realised if the costs of obtaining “better’ information are taken into account. Scientists are working on data poor methods for assessing F_{MSY} and other proxy measures in such fisheries (Zhou et al. 2012). Given this, and the “rules of thumb” developed through the regression tree analysis, it is possible to extend this to proxy measures of F_{MEY} (through the relative effort at MEY compared with MSY), and hence can help improve the economic performance of such fisheries even in the absence of robust data.

16.7 Acknowledgements

This study was undertaken as part of FRDC project 2010-044. Funding was also provided by the CSIRO Wealth from Oceans Flagship and the Australian Bureau of Agricultural and Resource Economics and Science (ABARES).

16.8 References

ABARES. 2010. Australian Fisheries Statistics 2009, ABARES, Canberra.

Anderson, L.G. 1975. Analysis of Open-Access Commercial Exploitation and Maximum Economic Yield in Biologically and Technologically Interdependent Fisheries. Journal of the Fisheries Research Board of Canada **32**(10): 1825-1842.

Armstrong, C.W., and Sumaila, U.R. 2001. Optimal Allocation of TAC and the Implications of Implementing an ITQ Management System for the North-east Artic Cod. Land Econ. **77**(3): 350-359.

Arnason, R. 1990. Minimum Information Management in Fisheries. Canadian Journal of Economics **23**: 630-653.

Asche, F., Eggert, H., Gudmundsson, E., Hoff, A., and Pascoe, S. 2008a. Fisher's behaviour with individual vessel quotas-Over-capacity and potential rent Five case studies. Marine Policy **32**(6): 920-927.

Asche, F., Eggert, H., Gudmundsson, E., Hoff, A., and Pascoe, S. 2008b. Fisher's behaviour with individual vessel quotas - Over-capacity and potential rent: Five case studies. Marine Policy **32**(6): 920-927.

Bromley, D.W. 2009. Abdicating responsibility: the Deceits of Fisheries policy. Fisheries **34**(6): 280-291.

Caddy, J.F. 2004. Current usage of fisheries indicators and reference points, and their potential application to management of fisheries for marine invertebrates. Can. J. Fish. Aquat. Sci. **61**(8): 1307-1324.

Caddy, J.F., and Mahon, R. 1995. Reference points for fisheries management, FAO, Rome.

Caton, A., and McLoughlin, K. 2000. Fisheries Status Reports 1999, Bureau of Rural Sciences, Canberra.

Chae, D.R., and Pascoe, S. 2005. Use of simple bioeconomic models to estimate optimal effort levels in the Korean coastal flounder fisheries. Aquatic Living Resources **18**(2): 93-101.

Christensen, V. 2010. MEY = MSY. Fish and Fisheries **11**(1): 105-110.

Clark, C.W. 1973. The Economics of Overexploitation. Science **181**(4100): 630-634.

Clark, C.W. 1990. Mathematical Bioeconomics: The Optimal Management of Renewable Resources. John Wiley and Sons, USA.

Cortés, E. 1998. Demographic analysis as an aid in shark stock assessment and management. Fisheries Research **39**(2): 199-208.

DAFF. 2007. Commonwealth fisheries harvest strategy: policy and guidelines, Department of Agriculture Fisheries and Forestry, Canberra.

De'ath, G., and Fabricius, K. E. 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology, **81**: 3178-3192.

Dichmont, C.M., and Brown, I.W. 2010. A Case Study in Successful Management of a Data-Poor Fishery Using Simple Decision Rules: the Queensland Spanner Crab Fishery. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science: 1-13.

Dichmont, C.M., Deng, A., Punt, A.E., Ellis, N., Venables, W.N., Kompas, T., Ye, Y., Zhou, S., and Bishop, J. 2008. Beyond biological performance measures in management strategy evaluation: Bringing in economics and the effects of trawling on the benthos. Fisheries Research **94**(3): 238-250.

Dichmont, C.M., Pascoe, S., Kompas, T., Punt, A.E., and Deng, R. 2010. On implementing maximum economic yield in commercial fisheries. Proceedings of the National Academy of Sciences **107**(1): 16-21.

Doole, G.J. 2005. Optimal Management of the New Zealand Longfin Eel (Anguilla dieffenbachia). Australian Journal of Agricultural and Resource Economics **49**(4): 395-411.

Dowling, N.A., Smith, D.C., Knuckey, I., Smith, A.D.M., Domaschenz, P., Patterson, H.M., and Whitelaw, W. 2008. Developing harvest strategies for low-value and data-poor fisheries: Case studies from three Australian fisheries. Fisheries Research **94**(3): 380-390.

Dupont, D.P. 1990. Rent dissipation in restricted access fisheries. Journal of Environmental Economics and Management **19**(1): 26-44.

EconSearch. 2010a. Economic Indicators for the South Australian Abalone Fishery 2008/09, EconSearch, Marryatville.

EconSearch. 2010b. Economic Indicators for the South Australian Blue Crab Fishery 2008/08, EconSearch, Marryatville.

EconSearch. 2010c. Economic Indicators for the South Australian Lakes and Coorong Fishery 2008/09, EconSearch, Marryatville.

EconSearch. 2010d. Economic Indicators for the South Australian Marine Scalefish Fishery 2008/08, EconSearch, Marryatville.

Eggert, H., and Tveteras, R. 2007. Potential rent and overcapacity in the Swedish Baltic Sea trawl fishery for cod (Gadus morhua). ICES J. Mar. Sci. **64**(3): 439-445.

Felthoven, R.G., and Morrison Paul, C.J. 2004. Multi-output, nonfrontier primal measures of capacity and capacity utilization. American Journal of Agricultural Economics **86**(3): 619-633.

Fulton, E.A., Smith, A.D.M., and Smith, D.C. 2007. Alternative Management Strategies for Southeast Australian Commonwealth Fisheries: Stage 2: Quantitative Management Strategy Evaluation. Report to the Australian Fisheries Management Authority and the Fisheries Research and Development Corporation. , CSIRO Marine and Atmospheric Research, Hobart.

Garcia, S., Sparre, P., and Csirke, J. 1989. Estimating surplus production and maximum sustainable yield from biomass data when catch and effort time series are not available. Fisheries Research **8**(1): 13-23.

Gordon, H.S. 1954. The economic theory of a common-property resource: The fishery Journal of Political Economy **62**: 124–142

Grafton, R.Q., Kompas, T., Chu, L., and Che, N. 2010. Maximum economic yield. Australian Journal of Agricultural And Resource Economics **54**(3): 273-280.

Grafton, R.Q., Kompas, T., and Hilborn, R.W. 2007. Economics of Overexploitation Revisited. Science **318**(5856): 1601.

Hoff, A., and Frost, H. 2007. Optimal vessel quotas and capacity of a Danish trawler fleet segment: A dual approach. Marine Resource Economics **22**(1): 1-14.

Kar, T.K., and Chakraborty, K. 2011. A bioeconomic assessment of the Bangladesh shrimp fishery. World Journal of Modelling and Simulation **7**(1): 58-69.

Kelly, C.J., and Codling, E.A. 2006. `Cheap and dirty' fisheries science and management in the North Atlantic. Fisheries Research **79**(3): 233-238.

Kompas, T. 2005. Fisheries management: economic efficiency and the concept of 'maximum economic yield'. Australian Commodities **12**(1): 152-160.

Kompas, T., Dichmont, C.M., Punt, A.E., Deng, A., Che, T.N., Bishop, J., Gooday, P., Ye, Y., and Zhou, S. 2010a. Maximizing profits and conserving stocks in the Australian Northern Prawn Fishery. Australian Journal of Agricultural And Resource Economics **54**(3): 281-299.

Kompas, T., Grafton, Q., Che, N., and Gooday, P. 2009a. Development of methods and information to support the assessment of economic performance in Commonwealth fisheries., ABARES, Canberra.

Kompas, T., Grafton, R.Q., Che, N., and Gooday, P. 2009b. Development of methods and information to support the assessment of economic performance in Commonwealth fisheries, ABARE, Canberra.

Kompas, T., Grafton, R.Q., and Che, T.N. 2010b. Bioeconomic losses from overharvesting tuna. Conservation Letters **3**(3): 177-183.

Mace, P.M. 1994. Relationships between Common Biological Reference Points Used as Thresholds and Targets of Fisheries Management Strategies. Can. J. Fish. Aquat. Sci. **51**(1): 110-122.

Martinet, V., Thébaud, O., and Doyen, L. 2007. Defining viable recovery paths toward sustainable fisheries. Ecological Economics **64**(2): 411-422.

Munro, G.R. 2010. From drain to gain in capture fishery rents: a synthesis study., Food and Agricultural Organization of the United Nations, Rome.

Norman-López, A., and Pascoe, S. 2011. Net economic effects of achieving maximum economic yield in fisheries Marine Policy **35**(4): 489–495.

O'Neill, M.F., Campbell, A.B., Brown, I.W., and Johnstone, R. 2010. Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (Ranina ranina) fishery. ICES Journal of Marine Science: Journal du Conseil **67**(8): 1538-1552.

Pascoe, S., and Mardle, S. 2001. Optimal fleet size in the English Channel: a multi-objective programming approach. European Review of Agricultural Economics **28**(2): 161-185.

Pelletier, D., Mahevas, S., Drouineau, H., Vermard, Y., Thebaud, O., Guyader, O., and Poussin, B. 2009. Evaluation of the bioeconomic sustainability of multi-species multi-fleet fisheries under a wide range of policy options using ISIS-Fish. Ecological Modelling **220**(7): 1013-1033.

Perks, C., and Vieira, S. 2010. Australian fisheries surveys report 2010, Results for selected fisheries, 2007-08 and 2008-09, Preliminary estimates for 2009-10, ABARES, Canberra.

PIRSA. 2007. South Australian Fisheries Resources — Current Status and Recent Trends 2006, Primary Industries and Resources South Australia, Adelaide.

Punt, A.E., Deng, R., Pascoe, S., Dichmont, C.M., Zhou, S., Plagányi, É.E., Hutton, T., Venables, W.N., Kenyon, R., and van der Velde, T. 2011. Calculating optimal effort and catch trajectories for multiple species modelled using a mix of size-structured, delay-difference and biomass dynamics models. Fisheries Research **109**(1): 201-211.

Punt, A.E., Deng, R.A., Dichmont, C.M., Kompas, T., Venables, W.N., Zhou, S., Pascoe, S., Hutton, T., Kenyon, R., van der Velde, T., and Kienzle, M. 2010. Integrating size-structured assessment and bioeconomic management advice in Australia's northern prawn fishery. ICES Journal of Marine Science **67**(8): 1785-1801.

Schaefer, M.B. 1954. Some aspects of the dynamics of populations important to the management of commercial marine fisheries. Bulletin of the Inter-American Tropical Tuna Commission **1**(1): 25-56.

Schaefer, M.B. 1957. A study of the dynamics of fishery for yellowfin tuna in the Eastern tropical Pacific Ocean. Bulletin of the Inter-American Tropical Tuna Commission **2**: 247-285.

Scott, A. 1955. The Fishery: The Objectives of Sole Ownership. The Journal of Political Economy **63**(2): 116-124.

Smith, D., Punt, A., Dowling, N., Smith, A., Tuck, G., and Knuckey, I. 2009. Reconciling Approaches to the Assessment and Management of Data-Poor Species and Fisheries with Australia's Harvest Strategy Policy. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science: 244-254.

Szakiel, S., Che, N., Gooday, P., and Elliston, L. 2006. Measuring Capacity in Commonwealth Fisheries, ABARES, Canberra.

Tingley, D., and Pascoe, S. 2005. Factors Affecting Capacity Utilisation in English Channel Fisheries. Journal of Agricultural Economics **56**(2): 287-305.

Tingley, D., Pascoe, S., and Mardle, S. 2003. Estimating capacity utilisation in multi-purpose, multi-métier fisheries. Fisheries Research **63**(1): 121-134.

Ulrich, C., Andersen, B.S., Sparre, P.J., and Nielsen, J.R. 2007. TEMAS: fleet-based bio-economic simulation software to evaluate management strategies accounting for fleet behaviour. ICES Journal of Marine Science **64**(4): 647-651.

Ulrich, C., Pascoe, S., Sparre, P.J., De Wilde, J.W., and Marchal, P. 2002. Influence of trends in fishing power on bioeconomics in the North Sea flatfish fishery regulated by catches or by effort quotas. Can. J. Fish. Aquat. Sci. **59**(5): 829-843.

Vieira, S., Perks, C., Mazur, K., Curtotti, R., and Li, M. 2010. Impact of the structural adjustment package on the profitability of Commonwealth fisheries, ABARE, Canberra.

Whitmarsh, D., James, C., Pickering, H., and Neiland, A. 2000. The profitability of marine commercial fisheries: a review of economic information needs with particular reference to the UK. Marine Policy **24**(3): 257-263.

Woodhams, J., Stobutzki, I., Vieira, S., Curtott, R., and Begg, G. 2012. Fisheries Status Report 2010, Department of Agriculture, Fisheries and Food, Canberra.

Zhou, S., Yin, S., Thorson, James T., Smith, Anthony D.M., and Fuller, M. 2012. Linking fishing mortality reference points to life history traits: anÂ empirical study. Can. J. Fish. Aquat. Sci. **69**(8): 1292-1301.

17 Appendix 6. Glossary.

Abundance: The total number of a kind of fish in a population; this is rarely known, and usually estimated from the relative abundance.

Allowable Biological Catch (ABC): A term that refers to the range of estimated allowable catch for a species of species group.

Availability: The fraction of a fish population susceptible to fishing.

Bayesian: A formal statistical approach in which expert or existing knowledge or beliefs are analysed together with data. Bayesian methods make explicit use of probability for quantifying uncertainty.

Bias: A systematic difference between the expected value of a statistical estimate, and the quantity it estimates.

Bioeconomic modelling: Mathematical formulae that simulate the interaction between biological behaviour of fish stocks and human behaviour of users of the resource as it is shaped by economic factors.

Biological reference points (BRP): A biological benchmark against which the abundance of the stock or the fishing mortality rate can be measured in order to determine its status. These reference points can be used as limits or targets.

Biomass (B): The total weight of a group (or stock) of living organisms at a given time.

Biomass limit reference point (B_{LIM}): the point beyond which the risk to the stock is regarded as unacceptably high.

Biomass at maximum economic yield (B_{MEY}): average biomass corresponding to maximum economic yield as estimated from the assessment model.

Biomass at maximum sustainable yield (B_{MSY}): average biomass corresponding to maximum sustainable yield.

Capacity: The potential output from a fishing vessel given its level of capital under normal operating conditions.

APPENDIX 6

Capacity utilisation: The degree to which the vessel capacity is being achieved.

Fishing mortality limit reference point (F_{LIM}): the point above which the removal rate from the stock is regarded as unacceptably high.

Fishing mortality at maximum economic yield (F_{MEY}): fishing mortality rate corresponding to maximum economic yield.

Fishing mortality at maximum sustainable yield (F_{MSY}): fishing mortality rate which corresponding to maximum sustainable yield.

Fixed costs: Costs that are constant irrespective of the actual level of fishing activity or catch. These include administration costs, management fees, and user costs of capital (opportunity cost and economic depreciation). These are a short term concept only as in the longer term owners may vary their fishing scale which may change these costs.

Bycatch: Fish other than the primary target species that are caught incidental to the harvest of the primary species. Bycatch may be retained or discarded.

Capital: The level of investment in the fishing industry by individuals or collectively in the form of fishing vessels, gear and technology.

Carrying Capacity: The maximum population of a species that an area or specific ecosystem can support indefinitely without deterioration of the character and quality of the resource.

Catch per unit (of) effort (CPUE): The quantity of fish caught (in number or in weight) with one standard unit of fishing effort.

Catch rate: Means sometimes the amount of catch per unit time and sometimes the catch per unit effort.

Catchability Coefficient (q): The fraction of a fish stock which is caught by a defined unit of the fishing effort.

Catchability: The extent to which a stock is susceptible to fishing.

Coefficient of variation (CV): The standard error of a statistic, divided by its point estimate. The CV gives an idea of the precision of an estimate, independent of its magnitude.

APPENDIX 6

Data poor: A fishery that lacks sufficient information to conduct a conventional stock assessment, including fisheries with few available data and with low data quality.

Density-dependence: The dependence of a factor influencing population dynamics (such as survival rate or reproductive success) on population density.

Discard: To release or return fish to the sea, dead or alive, whether or not such fish are brought fully on board a fishing vessel.

Discount rate: The rate at which future earnings need to be adjusted (downwards) to give their present value. The discount rate is equivalent in value to the opportunity cost of capital.

Dynamic maximum economic yield: The level of catch and effort that maximises the flow of economic profits over time.

Economic depreciation: The rate at which capital is consumed in the production process, measured as the real change in capital values after regular repairs and maintenance are taken into account.

Economic profit: This is the level of profit over and above what is considered a normal profit. It is estimated as the total amount of profit that could be earned from a fishery owned by an individual after subtracting all input costs (including non-cash costs such as economic depreciation and the opportunity cost of capital, as well as an allowance for unpaid (e.g. owner-operator) labour) from revenue. It is effectively profit in excess to that required to keep the operator active in the fishery.

Exploitation rate: The proportion of a population at the beginning of a given time period that is caught during that time period (usually expressed on a yearly basis).

$F_{0.1}$: The fishing mortality rate which the increase in yield per recruit in weight for an increase in a unit of effort is only 10 percent of the yield per recruit produced by the first unit of effort on the unexploited stock (i.e. the slope of the yield-per-recruit curve for the $F_{0.1}$ rate is only one tenth the slope of the curve at its origin.

Fishing mortality (F): A measurement of the rate of removal from a population by fishing. Fishing mortality can be reported as either annual or instantaneous. Annual mortality is the percentage of fish dying in one year. Instantaneous mortality is that percentage of fish dying at any one time.

Fishing Power: The catch which a particular gear or vessel takes from a given density of fish during a certain time interval.

F_{MSY}: The fishing mortality rate that, if applied constantly, would result in maximum sustainable yield (MSY).

Harvest control rule: Describes how harvest is intended to be controlled by management in relation to the state of some indicator of stock status.

Intrinsic growth rate (r): A value that quantifies how much a population can grow between successive time periods.

Limit reference points: Benchmarks used to indicate when harvests should be constrained substantially so that the stock remains within safe biological limits.

Management strategy: The strategy adopted by the management authority to reach established management goals.

Maximum economic yield (MEY): The level of catch and associated fishing effort and stock biomass that results in the maximum amount of economic profit that could be earned from a fishery. MEY is a static long run concept. See also Dynamic MEY.

Maximum sustainable yield (MSY): The largest average catch or yield that can continuously be taken from a stock under existing environmental conditions.

Meta analysis: A suite of quantitative techniques to statistically analyse combined information across related but independent studies.

Monte Carlo: Monte Carlo simulation is a statistical approach whereby the inputs that are used for a calculation are resampled many times assuming that the inputs follow known statistical distributions.

Natural mortality (M): the rate of deaths of fish from all causes except fishing.

Non-target species: Species not specifically targeted as a component of the catch; may be incidentally captured as part of the targeted catch.

Normal profits: The level of profits that would be expected to be earned given the capital investment if the capital had been invested elsewhere in the fishery. This is the minimum level of profits required to keep the fishing vessel in the fishery (i.e. if earning below normal profits then the fisher may seek to exit the fishery and invest their capital elsewhere).

APPENDIX 6

Normal return to capital: The product of the opportunity cost of capital (a rate) and the total value of capital reflecting the use cost of capital in the fishery. This corresponds to the level of normal profits when all other inputs are valued at their opportunity cost.

Opportunity cost: A measure of the true economic cost of inputs that relates to the value of their use in their next best alternative use. For most inputs, the market price is a reasonable guide to their opportunity cost. Opportunity cost is mostly applied in the case of unpriced inputs (e.g. the use of capital and owner-operator labour).

Opportunity cost of capital: This is the rate of return the owners of the capital could expect to earn if they had invested their capital into another industry with equivalent risk. This is also equivalent in value to the discount rate.

Quasi-fixed costs: A short term concept that relates to input use that has both fixed and variable attributes. In fisheries, repairs and maintenance is the main quasi-fixed cost as some costs are incurred irrespective of effort levels (e.g. a refit every three years), while other costs are directly related to effort levels (e.g. wear and tear on fishing gear).

Reference point: A reference point indicates a particular state of a fishery indicator corresponding to a situation considered as desirable (target reference point) or undesirable (limit reference point).

Resource rent: The return to the resource, and is effectively the unpriced value of the stock input used in the production process. Resource rent is generally captured within economic profits. With a perfectly homogeneous fishing fleet, resource rent and economic profits would be equivalent.

Resource rent charge: A payment to the owners of the resource for use of the resource, usually collected by government on behalf of society (the owners of the resource). This may take the form of a tax or levy.

Schaefer model: The basic form of production model in which the relation between yield and effort takes the form of a symmetric parabola. In the Schaefer model, B_{MSY} is at one-half of the carrying capacity.

Sensitivity analysis: In stock assessment modelling, the process of testing the sensitivity of model results in relation to errors and uncertainties in the input parameters.

Stochastic: Where system components are affected by random variability.

APPENDIX 6

Stock reduction analysis (SRA): a stock assessment method by using historical catch data for a species and an assumed population dynamics model to reconstruct possible trajectories of stock decline over time.

Target biomass (B_{TARG}): the desired condition of the stock.

Target fishing mortality (F_{TARG}): the desired fishing mortality rate for the stock.

Target reference point (TRP): Benchmarks used to guide management objectives for achieving a desirable outcome. In Australian Commonwealth fisheries, the target reference point relates to biomass and fishing mortality rates that result in dynamic maximum economic yield.

Target species: Those species primarily sought by the fishermen in a particular fishery.

Total Allowable Catch (TAC): The annual recommended or specified regulated catch for a species or species group.

Variable costs: Costs that vary depending on the level of fishing activity. In the short term these include costs such as fuel costs, crew costs, freight, food, and ice. In the longer term, all costs are considered variable.

Virgin or unfished biomass (B_0). It is generally calculated as the long-term average biomass value expected in the absence of fishing mortality. In production models, B_0 is also known as carrying capacity K.

Yield per recruit (YPR): The average expected yield in weight from a single recruit.