



THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

**Improving the effectiveness of age-abundance indicators in the
management of fisheries in Queensland, Australia.**

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Master of Philosophy
Post Graduate Diploma in Science
Bachelor of Science

*A thesis submitted for the degree of Doctor of Philosophy at
The University of Queensland in 2015*
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Abstract

The development of fishery indicators is a crucial undertaking as it ultimately provides evidence to stakeholders about the status of fished species such as population size and survival rates. In Queensland, as in many other parts of the world, age-abundance indicators (e.g. fish catch rate and/or age composition data) are traditionally used as the evidence basis because they provide information on species life history traits as well as on changes in fishing pressures and population sizes. Often, however, the accuracy of the information from age-abundance indicators can be limited due to missing or biased data. Consequently, improved statistical methods are required to enhance the accuracy, precision and decision-support value of age-abundance indicators.

This research uses three case studies as the basis for improving the effectiveness of age-abundance indicators in fisheries management: eastern king prawns, stout whiting and spanner crab.

The case study species were chosen to demonstrate different aspects that age-abundance indicators need to adapt to. The case studies contrast different life history characteristics (e.g. varied lifespan), fishery management (e.g. effort versus harvest restrictions) and fishery challenges (e.g. fishing power bias and high operational costs of fishing for eastern king prawns; inconsistent data for stout whiting; need for more comprehensive management methodology for spanner crab). Collectively, the case studies form the scientific detail of the thesis.

The first case study developed new methodology for the calculation of abundance indicators and reference points for eastern king prawns. Bio-economic indicators were standardised for calibrating simulations and identified catch-rate levels that were effective for monitoring profitability and useful in simple within-year effort-control rules. Favourable performance of catch-rate indicators in management was achieved only when a legitimate upper limit was placed on total allowable fishing effort. The findings inform decision makers on the uncertainty and assumptions affecting economic indicators.

For the second case study, a new catch curve methodology was described for estimating annual survival fractions of stout whiting. The method analysed individual fish age-abundance data such as length and age by using Gaussian finite mixtures and was designed to overcome fishery dependent sampling issues, assuming that only fish ages within each length category were sampled randomly and that fish lengths themselves were not. The analysis improved estimates of stout whiting survival in waters along Australia's east coast. The catch curve mixture model applies naturally to monitoring data on fish age-abundance and is applicable to many fisheries.

In the third case study, revised abundance indicators were developed to achieve more responsive spanner crab management. Simulations identified harvest and catch-rate baselines to assist setting quotas that ensured sustainable crab biomass. The management procedure is robust against strong trends in catch rates and adaptable for use in many fisheries.

The following strategies were identified for the case study fisheries to improve the usefulness of age-abundance indicators in determining management decision making reference points:

- Eastern king prawns – the combined approach of setting target fishing effort near the level for maximum economic yield and a secondary in-season lower limit on catch rates.
- Stout whiting – a mean survival fraction calculated over the two most recent years and evaluated against a target fraction corresponding to the years that best represented stable and profitable fishing.
- Spanner crab – precautionary levels of base quota set below average harvests and above average catch rate reference points ensured robust performance of the management procedure.

The general basis of indicator management was not different between species or method of harvest regulation. The analysis procedures adapted allowing application to each species.

The case studies also demonstrate the use of modernised frameworks for generating and using indicators in fisheries management in Queensland. Mitigation of indicator variance

and high risk management strategies rests with setting conservative reference points and decision rules to enable active management. The systems described can help improve and measure sustainable and economic outcomes of other fisheries, both in Australia and globally.

Declaration by author

This thesis is composed of my original work and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

Peer-reviewed papers:

O'Neill, M.F., and Leigh, G.M. 2007. Fishing power increases continue in Queensland's east coast trawl fishery, Australia. *Fisheries Research* 85(1-2): 84-92.

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(8): 1538-1552.

O'Neill, M.F., Leigh, G.M., Wang, Y.-G., Braccini, J.M., and Ives, M.C. 2014. Linking spatial stock dynamics and economics: evaluation of indicators and fishery management for the travelling eastern king prawn (*Melicertus plebejus*). *ICES Journal of Marine Science* 71(2).

Publications included in this thesis

List of research inputs made by co-authors to publications during candidature:

O'Neill and Leigh (2007) – in Appendix I.

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Leigh, G. M.	Statistical advice Edited paper

O'Neill et al (2014) – in Appendix II.

Contributor	Statement of contribution
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Leigh, G. M.	Statistical theory and programming (5%) Wrote and edited paper (5%)
Wang, Y-G.	Statistical advice Edited paper
Braccini, J. M.	Data management and collation (10%) Development of management procedures (33%) Statistical analysis and programming (5%) Edited paper
Ives, M. C.	Data management and collation (5%) Development of management procedures (33%) Edited paper

O'Neill et al (2010) – in appendix V.

Contributor	Statement of contribution
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Campbell, A. C.	Data management and collation (5%) Development of management procedures (33%) Modelling advice (5%) Edited paper
Brown, I. W.	Development of management procedures (33%) Edited paper
Johnstone, R.	Edited paper

Contributions by others to the thesis

This information refers to the unpublished manuscripts included in the thesis.

Dr George Leigh provided advice on the catch curve theory and methodology in Appendices III and IV. This included contribution to the conception and design of the models.

Thesis papers in Appendix III and IV.

Contributor	Statement of contribution
O'Neill, M. F. (Candidate)	Data management and collation (100%) Statistical analysis and programming (100%) Wrote the papers (100%)
Leigh, G. M.	Statistical theory and advice

Statement of parts of the thesis submitted to qualify for the award of another degree

None

Acknowledgements

This PhD research would not have been possible without the support offered by many people. I would like to thank my supervisors, Dr Ron Johnstone, Dr Warwick Nash and Dr You-Gan Wang, for their guidance and advice throughout the duration of my PhD. I also thank the Queensland Government Department of Agriculture, Fisheries and Forestry for their push to commence the PhD, the high level support, the use of facilities and data.

Components of the research were supported and funded by the Queensland Government Department of Agriculture and Fisheries, the New South Wales Department of Primary Industries and the Australian Government's Fisheries Research and Development Corporation (FRDC).

Many thanks go to past and present staff from Queensland Government Department of Agriculture and Fisheries and other research organisations that assisted with initial research designs and methods associated with my PhD and supply of data.

I would like to especially thank my very good friend and work colleague Dr George Leigh for his support, guidance and advice on statistical methodologies. His direction and world class contributions to fisheries and statistical modelling theory in general have established strong foundations for the analyses contained in the PhD publications.

I dedicate this thesis to my loving and beautiful family. I thank my beautiful and ever dynamic wife Erica for her praise, love and support; my parents Arthur and Kath and my Aunty Jean for their life long support of my education; and my children Jemima, Fraser and Matilda who are my source of inspiration.

During my PhD my family was devastated by Mum having a severe stroke. The never ending daily support and love provided by my Dad to my Mum is awe-inspiring. In modern times of overwhelming stress created from work environments and 1st world tasks/problems, all should take time to step back and consider the more important life events that shape our families, environments and others around the world.

Keywords

fisheries, statistics, modelling, management, economics, indicators, prawns, crabs, fish, Queensland

Australian and New Zealand Standard Research Classifications

ANZSRC code: 010401, Applied Statistics, 30%

ANZSRC code: 070402, Aquatic Ecosystem Studies and Stock Assessment, 50%

ANZSRC code: 070403, Fisheries Management, 20%

Fields of Research Classification

FoR code: 0102, Applied Mathematics, 10%

FoR code: 0104, Statistics, 40%

FoR code: 0704, Fisheries Sciences, 50%

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Introduction

Overview

The development and reporting of fishery status indicators is the crucial basis for the provision of accurate information on the status of fished stocks for management agencies, the fishing sectors and the public. It is equally vital for underpinning appropriate management procedures that seek to reach stock sustainability goals. The information reporting process (or “stock assessment process”) typically involves integrating information about the fished species biology, gathering age-abundance data, conducting statistical population analyses and reporting indicator results against reference levels based on objectives to identify appropriate management procedures. This process requires: a) consistent and representative spatial-temporal data collection, b) use of contemporary statistical methodology to address data limitations and to improve time-series validity of age-abundance indicators and c) use of sensible benchmarks to judge indicator signals and set harvest rules based on operational objectives for the fishery. Crucially, all three aspects are necessary to form a robust framework for fisheries management planning and success. Evaluation and discussion of this process is relevant to all fisheries globally, especially for those like Queensland where an appropriate modernised framework is missing for generating and using fishery indicators in management. For Australia, this process has been reviewed and outlined in the national guidelines to develop fishery harvest strategies (Sloan et al., 2014).

For many fisheries globally, age-abundance indicators are traditionally the most used line of evidence to assess the status of fished stocks. Age-abundance indicators generally consist of catch rate and/or age composition data to index changes in population size and rates of survival, which then allow for the assessment of stock status and fishing pressures. The data can be obtained from the fishery (fishery dependent) or sampled through scientific surveys (fishery independent). This data can reveal important species’ life history traits such as age, growth and mortality. A time series of age-abundance indicators, for example, can identify important changes in fishing pressures, population size and success or failure of fishery management (Hilborn and Walters, 1992). Further, time series changes in age-abundance indicators can be used to correlate a wide range of

environmental influences, such as changes in survey catch rates of young lobsters with ocean currents (Caputi et al., 2001). For these reasons, age-abundance indicators are the frequent focus for interpretation in stock assessment.

The limitations of age-abundance indicators have been critiqued globally, where trends in catch rates are often considered not proportional to population abundance and changes in age composition data biased by different fishing gears and locations (Hilborn and Walters, 1992). A broad range of research has been published confronting these issues by using improved analyses and estimation to better represent the uncertainty surrounding model predictions (Maunder and Piner, 2015). These improved statistical techniques represent great advancements but, in some cases, age-abundance data was still shown to contain little contrast or information on the status of the fished population (Walters and Martell, 2004). Hence, the literature has pointed towards new kinds of data or methods such as the spatial mapping of a fishing vessel's satellite location data for measuring absolute densities of abundance (Peel and Good, 2011); fish tagging and genetic mark-recapture experiments for harvest rate monitoring (Walters and Martell, 2004; Buckworth et al., 2012); genetic estimates of effective numbers of spawners (Ovenden et al., 2007); remote sensing of the abundance of fish aggregations using video or sonar technology (Mackie et al., 2009); and large-scale swept area estimates of population size (Dichmont et al., 2000).

To date there has been no routine uptake of these new data indicators due to their own technical limitations, their higher cost of implementation and their unclear use in management. For these reasons, fishery monitoring agencies continue to build on their existing time series of age-abundance indicators. In this context, this thesis takes a focused assessment of age-abundance data in an attempt to overcome data limitations, such as missing or biased spatial-time series data and to improve statistical methodology for standardising fishery dependent age-abundance indicators for applications in management. The need to standardise age-abundance indicators is critical to reduce biases and variability and ensure consistency in management decisions. If not done, over or under estimation of indicators driving management change could incorrectly affect the sustainability, economic and social performance of a fishery.

Accordingly, innovative and case specific statistical applications and simulations were conducted to show how to develop and use appropriate age-abundance indicators in the

management of Queensland's fisheries. Notably, these have highlighted example procedures to reduce and manage indicator variance and bias and to apply quantitative tools in setting decisions on fishing harvest or effort. The results of these applications are presented in five papers using three case study fisheries as presented in appendices I to V. They form the spine and evidentiary basis of the thesis.

The research aimed to explore the following questions:

- What constitutes an appropriate age-abundance indicator?
- What are the risks in using age-abundance indicators?
- What analytical procedures are required to reduce indicator variance and bias?
- What are the important considerations for using age-abundance indicators in fisheries management overall?

To address the research questions, the three case studies were used to characterise the operational and managerial situations for different economically important Queensland fisheries. The species considered in the case studies varied from fast growing and short lived prawns to slower growing and longer lived crabs and fish and encompassed different management approaches of input effort controls versus quota output controls. The case studies allowed the development and testing of improved age-abundance indicators and comparison of results across fisheries. While the case studies are based in Australia, similar fishery characteristics are found globally making the research relevant to fisheries management internationally.

The case studies are categorised as follows:

- Eastern king prawns (fast growing with a lifespan of 1-3 years; managed through input effort controls; indicators developed from fishery dependent logbook catch and effort data); Appendix I and II.
- Stout whiting (moderate growth with a lifespan of 5-9 years; harvest quota managed, large discard mortality; indicators developed from fishery dependent logbook catch and effort data and fish age frequency monitoring); Appendix III and IV.
- Spanner crabs (slow growing with a lifespan of 10-20 years; harvest quota managed with size limit; fishery dependent and independent catch and effort data); Appendix V.

The results from the case studies service the key management components for each species that can integrate under the national harvest strategy guidelines, recognising that periodic adjustment may be needed for future changes and constraints on management and data (Sloan et al., 2014):

- Defined operational objectives for the fishery;
- Indicators of fishery performance related to the objectives;
- A statement defining acceptable levels of risk to meeting the objectives;
- Reference points for performance indicators;
- A monitoring strategy to collect relevant data to assess fishery performance;
- A process for conducting assessment of fishery performance relative to objectives;
- Decision rules that control the intensity of fishing activity and/or catch.

Understanding indicators and their use in fisheries management

Indicators are measurable variables that are designed to identify important changes in the phenomena of interest. They can cover many elements, functions and issues depending on their application and purpose. For fisheries, indicators aim to inform us about changes in stock, environment and fishing conditions over time and space that may have consequences for stock viability and have economic ramifications for industry. Similarly, indicators may provide flags or decision points where strategic decisions are made to manage a stock. For example, low catch rate of prawns may indicate low stock size, prompting further assessment to investigate if this was due to over fishing or changed environmental conditions or both.

Fishery indicators are not only variables that measure the state of the fishery (the stock, commercial/recreational operations and environment) but also the performance of management (Garcia and Staples, 2000). They can track resource (stock), environment, economic and social conditions individually or in an integrated manner. Uses of such indicators include detection of low catch rates (stock), reduced habitat (environment), financial losses (economic) and overly competitive fishing (social). Government and public stakeholders can use such indicators to judge the performance of fisheries management policy and assess fisheries with respect to operational objectives (Fletcher et al., 2002;

Sloan et al., 2014). In some fisheries the policy and operational objectives of different stakeholders can be inconsistent and management performance may be judged by the balance that is achieved rather than the attainment of each specific objective.

Fishery indicators can be developed from fishery dependent or independent data sources. Fish catch rate and age data collected directly from fishers or their markets are fishery dependent sources and subject to their practices at the time of sampling. By comparison, fish catch rate and age data obtained from scientific surveys are fishery independent with data collection structured according to a consistent sampling design. Independent samples are generally more costly and therefore provide relatively limited sample sizes and temporal-spatial coverage, but less subject to the biases and confounding issues that complicate the interpretation of fishery-dependent indices, such as changing fishing gear or locations. Financial limits often prevent or constrain the use of independent sampling (Hilborn and Walters, 1992). Therefore improved analyses are required to make the best use of fishery dependent data.

To interpret indicator results, clear benchmarks are required. These benchmarks are typically discrete values called reference or trigger points believed to represent critical situations (Garcia and Staples, 2000). Developing reference points for a particular fishery is complex. Their setting is reliant on the detailed analyses used to estimate the indicator values and therefore should be designed at the same time. The reference points can then be related directly to the indicator value to help improve and measure the status of a fishery.

Two types of reference points are defined in fisheries management. The most common reference point is known as a limit. A hypothetical example of a limit could be if the average catch rate (indicator: catch-per-standard-unit-effort) of prawns drops below 100 kg per boat night (limit reference point) it indicates the fishery is overfished. The other type of reference point is known as a target, aiming towards a state of fishing and/or resource size that is considered to be desirable. For example, the fishery might produce most profit for industry if average catch rates (indicator) were maintained at 200 kg per boat night (target reference point). This reference point approach is used in the management of a number of fisheries, such as for commercial trawl fisheries (Australian Government, 2007).

The need for monitoring and assessment of important fisheries resources is now embedded in most legislation in the developed world. Governments have strategic responsibilities to ensure sustainable fishery resources; thereby inheriting the burden of developing accurate and timely indicators for ongoing monitoring of fished resources. There are many factors to consider when analysing and developing data for performance indicators and their reference points. For example:

- Is the data collection and data type suitable?
- Are data limitations and biases acknowledged and addressed?
- Are analysis assumptions valid?
- Have the significance and uncertainties of the findings been reported appropriately?

In the stock assessment reporting process these factors need to be considered in order to demonstrate that fishing practices are sustainable, economical and socially acceptable.

Age-abundance indicators

What are they and what do they tell us?

Marine animals generally have complex life dynamics which can make their populations hard and costly to measure. It is often difficult or impossible to conduct large-scale surveys to estimate absolute population numbers. Consequently, age-abundance data are used extensively as surrogate inputs into fishery stock assessment.

The type of age-abundance data can vary between different kinds of fisheries and analyses. In different fisheries either the age or abundance dimension or both may be available to assess. Herein the term "age-abundance" is used interchangeably to describe the data or the indicator calculated from the data, whether it is age or abundance or both.

The "age" dimension typically relates to fish ages derived from laboratory readings of otoliths or other bone structures, or ages derived quantitatively from models for either fish or invertebrate species (Francis and Campana, 2004). This data dimension can also include age covariates such as length, weight, otolith weight and other morphometric measures. The age dimension can inform on different types of population effects: (1) selectivity or vulnerability, with smaller or younger animals usually less susceptible to fishing gear; (2) cumulative mortality, with older or larger animals less abundant; and (3)

recruitment variation, with some age-cohorts being more frequent than others (Walters and Martell, 2004).

The “abundance” dimension usually relates to a relative catch rate measure. It is generally of more importance and informs on the magnitude of change in fished populations (Francis, 2011). Trends over time may reflect changes in the proportion of the population being harvested, changes in the abundance of the fished species or both (Quinn and Deriso, 1999). It is normally assumed that the abundance dimension is related proportionally to the true population size. However, this is questionable if the data represents only a subset of the population (risks discussed below). Stock abundance assessments based only on raw catch and effort data can produce biased predictions owing to efficiency changes in fishing effort through time and between fishing vessels. There is therefore a need for standardised average catches, for example by employing a regression model (Hilborn and Walters, 1992), to reduce the biases or variation in the data by accounting for factors affecting relative abundance and fishing efficiency. This results in a time series of the abundance dimension that is more representative of trends in the population.

The basic guiding concepts and science supporting the use of age-abundance data have been demonstrated in numerous texts such as Hilborn and Walters (1992), Quinn and Deriso (1999) and Walters and Martell (2004). They are built on the dynamic theory that abundance of a species cohort logically declines as it ages due to mortality. Equation (1) outlines the simple mathematical dynamic; which can be expanded to have more realistic and complex spatial-temporal-age-size-weight dynamics (Quinn and Deriso, 1999). Here the equation illustrates that abundance N can change between years t at the mortality rate Z , with the addition of new young recruits R . Inferences from age-abundance data can follow this mathematical logic, where the frequency of younger aged animals can signify the strength of recruitment and the rate of decline in abundance of older fish can measure the level of mortality. Further, changes in abundance N can correlate proportionally with a standardised catch rate index U_t . If the standardised catchability q can be assumed to be constant, then declines in catch rate may indicate reduced abundance and higher mortality (Hilborn and Walters, 1992; Quinn and Deriso, 1999; Haddon, 2001).

$$\begin{aligned} N_t &= N_{t-1} \exp(-Z) + R_t \\ U_t &\propto qN_t \end{aligned} \quad (1)$$

What are the risks of using age-abundance data?

The risks associated with using age-abundance data primarily relate to over or under estimating fish population status and fishing pressures, which may lead to incorrect recommendations for management. These risks can stem from important confounders related to poor fishing and data recording processes, as well as natural biological considerations. Based on my individual workings on fishery logbook and fish age monitoring data, I propose a number of confounders of age-abundance data (Table 1). Examples include fishers improving their fishing methods; fisher behaviour and fisher knowledge leading to bias and overestimated age-abundance (Robins et al., 1998; O'Neill et al., 2003); the aggregation pattern of fish may increase the variance in trying to detect changes in age-abundance and the lack of detailed fishing effort data may remove signals from the age-abundance indicator (Hilborn and Walters, 1992; O'Neill et al., 2011). As a result, complex analyses are required to identify a consistent indicator that is positively correlated with the fished population. For fishery independent surveys, many of these issues can be mitigated with both age and abundance data sampled together using an appropriate spatial and temporally replicated design.

A particular risk associated with the collection of fishery dependent age-abundance data, is when catch rates or age frequencies remain consistent as fish abundance declines. This situation, known as hyperstability (Hilborn and Walters, 1992), can paint an optimistic picture of a fishery (Figure 1). As shown in Figure 1 a very substantial change in stock can occur even when catch rates only change slightly. An alternate risk is when age-abundance declines due to spatial movements of fishing; for example moving fishing effort from distant high fish density locations to close lower density areas thereby underestimating fisheries stock. This situation could occur for financial reasons and spatial adjustments to age-abundance may be required for reporting a consistent index for the whole spatial stock (Walters, 2003).

Hyperstability is the main concerning bias in age-abundance data. Australian examples of hyperstability include the targeted ring netting of schooling ocean beach sea mullet and tailor and offshore spotted mackerel (Leigh and O'Neill, 2004; Begg et al., 2005; Bell et al., 2005). Internationally, hyperstability has been described in a number of species of

schooling fish which have been fished with little indication of stock declines shown in age-abundance indicators (Rose and Kulka, 1999; Harley et al., 2001). Typically this was because of the schooling behaviour of pelagic fish species, where the reported catch rate data remained high and consistent for extended periods even when the abundance was less than predicted. Fish schooling and fishing targeting behaviour caused inaccurate and biased age-abundance data. Even if stock has declined, the schooling behaviour of pelagic fish can still result in commercially economic or recreationally acceptable catches.

In order for age-abundance data to be a reliable index of stock abundance, data collections should be distributed and quantified consistently over a number of areas through time. However, as noted by Hilborn and Walters (1992), any fisher who regularly fished randomly over many sites would soon be out of business as they wouldn't catch many fish. Most commercial fishers know where fish can be found, resulting in non-random fishing, which is typically concentrated on locations with higher numbers of fish. Age-abundance data would be far more accurate if fishers reported daily effort records on each fishing operation's target species, vessels, gear, travel time, search time and efficiency, locations fished, active fishing time and zero catches (Table 1). As an example of the limitation of some commercial logbook data with no records of detailed fishing effort, Figure 2 represents the hypothetical difference between two fishing days of high and low fish abundance with a vessel catching the same number of fish per day but expending different levels of unreported fishing effort. Many variants of this example are possible, which in reality would produce significant variance in the recorded catch rates. In the example without appropriate standardised fishing effort information, trends in age-abundance only indexed changing densities of fish schools when found and caught, not the frequency of schools or stock abundance as would be quantified using the hours of fishing effort. Thus the measure of fishing effort is crucial to ensure catch rates reflect the particular indicator of interest.

Further associated risks include judgements on age-validation and whether sufficient independent and identically distributed random samples of age-abundance have been collected (Sumpton and O'Neill, 2004; Francis, 2011). This is an important consideration particularly when a number of fish lengths are to be converted into a representative age distribution. Other risks or characters relate to parameter estimation, where patterns in age structure may be confounded by changes in fishing mortality, natural mortality and

length/age vulnerabilities. Figure 3 illustrates the difference between logistic (assumes that larger and older animals are fully selected and fished) versus domed (assumes that larger and older animals are less likely to be fished; e.g. too large to be trapped in a net) vulnerability. If domed vulnerability is present, a higher frequency of larger and older spawning fish may be alive and less likely to be exploited. If logistic vulnerability were assumed in analyses, the estimated annual rate of fish survival could be deflated and effect recommendations on sustainable harvests.

Table 1. The confounders of fishery dependent age-abundance data.

Fisher behaviour – capacity to chase fish:

- Efficient at finding fish at local scale.
- Vessels can travel large distances; at sea and from different ports to expand the spatial range of exploitation.
- Improved knowledge and information sharing between vessels that leads to non-random spatial fishing.
- Increased fishing power from using better vessels, gear, techniques and improved knowledge.
- Aggregation of effort at high catch times and areas.
- Seasonality of market demand and price for product.
- Paucity of data from low catch areas.

Fish biology – aggregation patterns:

- The dynamics of schooling and movement.
- Type of concentration profile: the density of animals distributed spatially in time (Hilborn and Walters, 1992).
- Vulnerability to fishing due to environmental drivers.

Commercial logbooks – data reporting templates:

- Limited catch validation via linking catch, disposal and quota reporting systems.
 - No data codes to link fishing trips over multiple days.
 - No daily recording of each fishing operation’s target species, vessels, gear, travel time, search time and efficiency, locations fished, active fishing time, zero catches and catchability.
 - Determinants of effort by fishers not recorded.
 - Determinants of area fished not recorded.
 - Fish age data and validation are generally collected separately and not linked to the catch-abundance data.
-

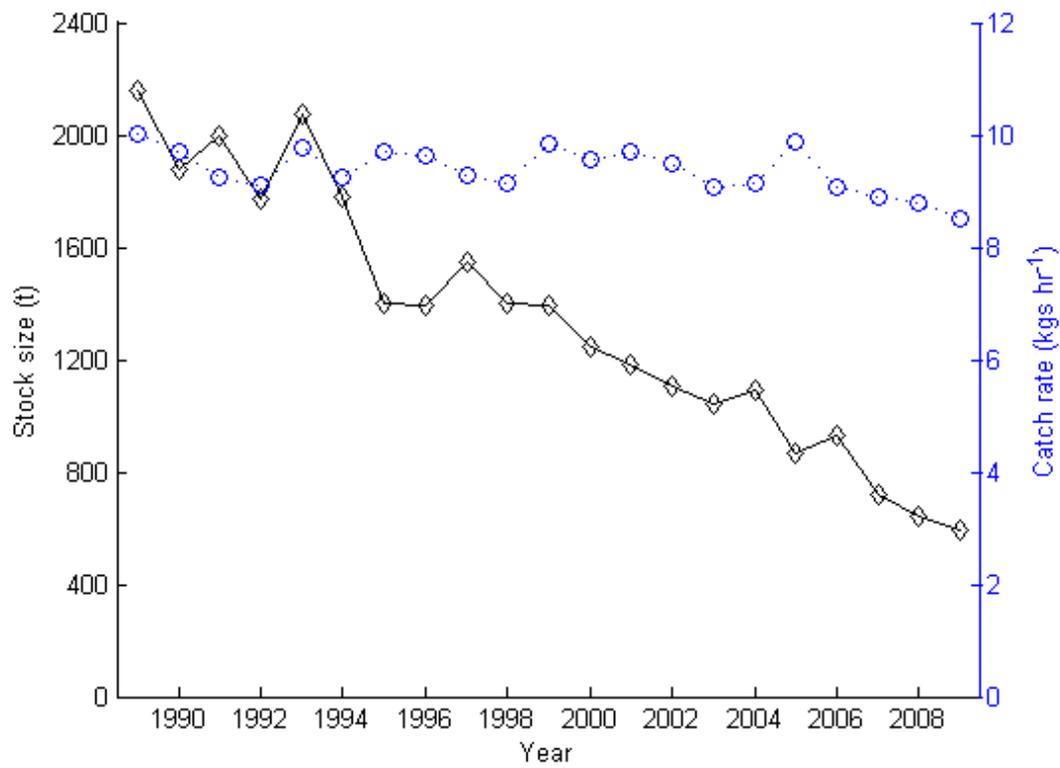


Figure 1. Hypothetical example of a hyperstable relationship between population size (black diamonds) and catch rates (blue circles); as stock size declines catch rates remain steady.

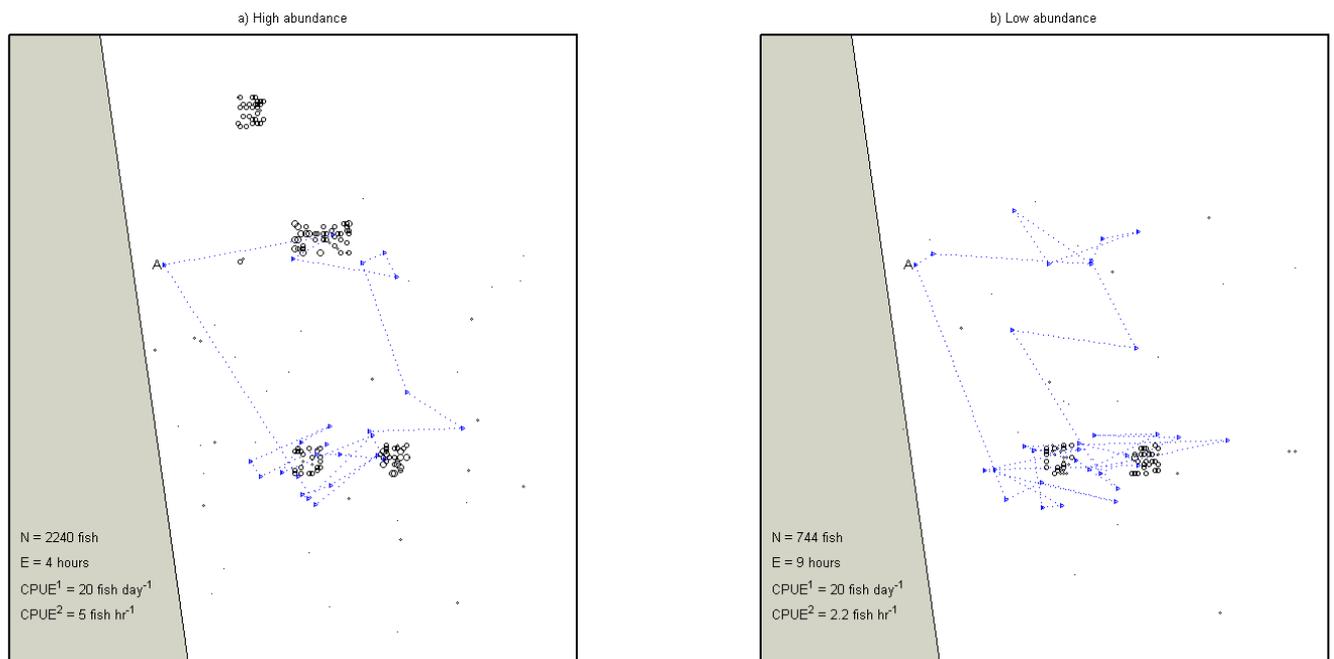


Figure 2 Hypothetical comparison of how limited effort data can cloud catch rate (cpue) differences between a) high and b) low abundance. At high abundance the vessel searched and fished over a four hour day yielding 20 fish at a rate of 5 per hour. At low abundance the vessel had searched and fished over nine hours to yield the same catch at a rate of 2.2 per hour. The daily catch rate ($CPUE^1$), as would be recorded in commercial logbook, indicated no change in abundance (hyperstable). In this hypothetical reality abundance had declined by 2/3 and catch rate per hour ($CPUE^2$) declined by 56% (part-hyperstable). Here the drop in abundance and cpue were not 100% proportional as the fishing pattern was non-random. Legend: N = exploitable population size, E = fishing effort, $CPUE^1$ = daily catch rate, $CPUE^2$ = catch per hour, vessel track = blue lines and symbols, fish = black circles and A = start of fishing track which progressed east and then south, before returning to A.

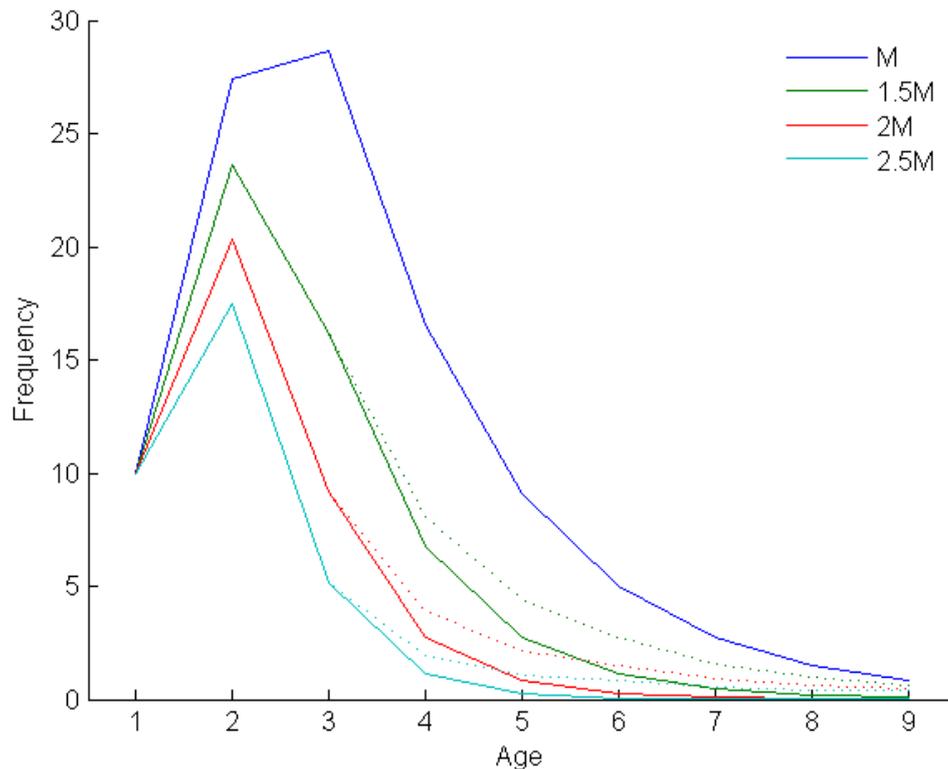


Figure 3. Hypothetical comparison between fish exploitable age structures (maximum age = 9 years and natural mortality $M=0.6 \text{ year}^{-1}$). The curves compare four rates of total mortality assuming logistic vulnerability (solid lines) and the same total mortalities with domed vulnerability (dotted lines), with 95% vulnerability assumed at age group 3.

How can age-abundance data be used in management?

Successful management of a fishery is based on adapting harvest and fishing effort to ensure sustainable, profitable and socially acceptable fishing; with primary focus usually on sustainability. Adaptation is reliant on effective and flexible management procedures. In recent years, dynamic management procedures have been adopted by some Australian and International fisheries (for example: Butterworth and Punt, 1999; Butterworth and Rademeyer, 2005; Australian Government, 2007). These procedures contain indicators that measure the state of the fishery (Seijo and Caddy, 2000) and use them in control rules to alter fishing pressure so as to achieve target goals in a fishery (Rademeyer et al., 2007; Smith et al., 2008). Generally the procedures are designed for commercial fisheries serviced by complex quantitative assessment models (such as maximum economic yield: Grafton et al., 2007; Dichmont et al., 2008). Management procedures can also use simple indicators derived directly from age-abundance data (Bentley et al., 2005; Little et al.,

2011). Irrespective of whether indicators are generated simply or from more intensive methods, the performance of management procedures can be unreliable without critical analysis and consideration of uncertainty, conservative management and data-gathering principles (Dowling et al., 2008; Smith et al., 2008). Examples of published theoretical and applied management procedures using age-abundance indicators include the following:

- (i) Data-based procedures using averaged recent catches of sablefish (*Anoplopoma fimbria*) were smoothed with a research survey index of abundance in Canada to provide a practical means of setting annual catch limits in the absence of an acceptable model based approach (Canada; Cox and Kronlund, 2008).
- (ii) For data-limited estuarine fisheries in New South Wales, Australia, simulations and control charts were used to identify important changes in annual time-series of harvest that detected both recruitment and survival failure; accepting a high rate of false triggers (Scandol and Forrest, 2001; Scandol, 2003).
- (iii) Quota management procedures for the South African west coast rock lobster (*Jasus lalandii*) fishery were first implemented in 1997 and later modified in 2000 and 2003 (Johnston and Butterworth, 2005; Plagányi et al., 2007). Notably, the empirical components used catch rates of lobster from the commercial fishery and a fisheries-independent monitoring survey. The rules altered quota directly from that of the previous year based on a weighted average of fishery and survey catch rates divided by their fixed baselines. Maximum change in annual quota was restricted to 10%. The latest management procedures were simulated to show positive trade-offs between resource recovery and future catch objectives, with the ability to adapt to changes in lobster growth.
- (iv) For Australia's southeastern scalefish and shark fisheries, utilising linear regression of commercial catch rate trends alone to determine quota without benchmarks was found to keep quotas at their current levels and failed to rebuild resources when needed (Smith et al., 2008). The regression method was replaced with a new control rule that compared average catch rates directly against limit and target baselines (Little et al., 2008), with the ability to increase or decrease stock sizes.
- (v) Total harvests of Australia's south east blue eye trevalla (*Hyperoglyphe antarctica*) are assessed using only annual frequencies of fish age, with recommended biological harvests set on the ratio of target fishing mortality

compared to the current estimate of fishing mortality (Fay et al., 2011). Effective implementation required appropriate choice of target reference points, to allow for data uncertainty and assumptions on fish productivity and natural mortality.

These examples, including the case studies herein, provide understanding of how age-abundance data and their attributes can be built into management in order to improve sustainable fishing. This includes examples of appropriate monitoring, analysis of data, setting of reference points and management of data variances. The examples also show that management procedures need to learn from past experiences and evolve in time and need to be focussed on management objectives (e.g. sustainability and/or socio-economic). Herein, specific understandings were learnt from the limitations of using simple nominal catch rates of spanner crab versus the use of standardised catch rates and more precautionary reference points. The benefits of higher fleet profit and higher catch rates of eastern king prawns were demonstrated under more precautionary economic reference points. New catch curve methodology revealed inconsistency in stout whiting age data, which helped direct analyses and the calculation of survival indicators. These results and published experiences demonstrate improved certainty in management procedures in their local contexts but also with potential gain if employed for other fisheries globally.

Using Queensland case studies to improve the use of age-abundance indicators

In many fisheries age-abundance indicators were calculated historically from simple analyses of fishery-dependent nominal data (examples: Hilborn and Walters, 1992; Sparre and Venema, 1992; Flood et al., 2014). These approaches were generally used only for simple stock reporting processes, with no standardisation or adjustments made for the possible confounders (Table 1). Only in the last decade have standardisations been more readily applied (examples: Robins et al., 1998; Campbell, 2004; O'Neill and Leigh, 2006; Carruthers et al., 2011). The adoption of new data analyses and improved indicators in the management of fisheries requires the development of a defined process to utilise the data in a set of management procedures or harvest rules.

The defined process for using indicators in stock assessment requires improved integration of: a) spatial-temporal data, b) use of contemporary statistical methodology to address data limitations and to improve time-series validity of age-abundance indicators and c) use of sensible benchmarks to judge indicator signals and set harvest rules. These three process stages link to the following research questions as previously noted:

- What constitutes an appropriate age-abundance indicator?
- What are the risks in using age-abundance indicators?
- What analytical procedures are required to reduce indicator variance and bias?
- How should age-abundance indicators be used in management overall?

To evaluate these questions a case study approach was used in this thesis as this approach offers the advantage of demonstrating the utility of improved analyses in real stock assessment scenarios. A summary of the case studies is provided below including a detailed presentation of the particular methods and results for each study, as well as a case-specific discussion of the outcomes.

The applications of age-abundance indicators in the case study fisheries are summarised in Table 2. The key data outlined in Table 2 informed the analyses, particularly to account for where, when and how different fishers operated. The fishery dependency of these data carried a number of risks, for example increasing fishing power (catchability), which was

common across the case studies (Table 2). The new analysis procedures developed here in the case studies are adjusted for these risks to improve the validity of data to calculate the age-abundance indicators. The importance of maintaining and improving the representativeness and consistency of the data is an ongoing need, particularly to mitigate the main risks (Table 2) that could undermine the indicator process and result in over or under estimation of stock trends and incorrect recommendations for management. For each study, the process stages have now been established and used to improve fisheries management.

In the following summaries of the respective case studies the major attributes of the fishery and the application of age-abundance data are presented. In addition, each case study seeks to elucidate the specific aspects of utilising this indicator type so as to provide a wider understanding of age-abundance data and its management applications.

Table 2. Application of age-abundance indicators in case study fisheries.

Age-abundance indicators	Case study fisheries		
	Eastern king prawn	Trawl whiting	Spanner crab
Attributes of each fishery	Species lifespan \approx 3 years. Mobile crustacean. Managed by trawl effort control.	Spp. lifespan \approx 9 years. Unreported fishing mortality Main trawl / Danish seine sector managed by harvest quota.	Spp. lifespan \approx 15 years. Capture by entanglement on flat dilly-nets. Managed by harvest quota.
Questions?			
Key indicator	Monthly catch rate.	Annual total mortality. Annual catch rate.	Annual catch rate.
Key data used	Detailed daily fishery catch and effort records. Economic and fishing gear data.	Multivariate fish aging data. Detailed trawl shot-by-shot fishery catch and effort records. Fishing gear data.	Detailed daily fishery catch and effort records. Economic and fishing gear data. Fishery independent survey.
Main risks	Common across studies: Hyperstability, increasing fishing power, aggregation of fishing effort, change in spatial patterns of fishing effort, changing fishing gear, catch rate variance, missing data and data quality.		
New analysis procedures – adjusting for risks above	Catch rate standardisation (REML). Length-spatial stock model.	Catch curve mixture model. Catch rate standardisation (HGLM).	Catch rate standardisation (GLM).
Use in management – stock assessment process established	Monitor total allowable effort and harvest. In-season stock monitoring using catch-rates.	Setting total allowable harvest. Monitor stock and fishing pressures.	Setting total allowable harvest. Monitor stock status.
How have the case studies helped management?	New limit and target reference points to gauge fishery performance.	New estimates of fish survival from age data, which addressed issues of missing and inconsistent data.	Improved catch rate indicators used in a new and more robust management procedure. Limit reference point established to set zero quota.

Eastern king prawn

Work outline and reference:

Manuscripts: O'Neill and Leigh (2007) and O'Neill et al. (2014).

Appendix I: Fishing power increases continue in Queensland's east coast trawl fishery, Australia.

*Appendix II: Linking spatial stock dynamics and economics: evaluation of indicators and fishery management for the travelling eastern king prawn (*Melicertus plebejus*).*

Appendix 1 established methods to standardise the catch rate abundance indicator. It was applied across six trawl sectors operating in Queensland waters. The catch rate standardisation method was employed to analyse updated eastern king prawn data in Appendix 2. Appendix 2 extended to quantify economic indicators for EKP.

The eastern king prawn (EKP, *Melicertus plebejus*) is a major component of otter-trawl fishing along the east coast of Australia with harvests averaging about 3000 t year⁻¹ and landings valued in excess of AUD\$40 million. The EKP is largely spatially separated from other target species and extends across two jurisdictions belonging to the States of New South Wales (NSW) and Queensland (Qld). Separate management regimes operate in each State despite there being a single breeding population, whereby EKP travel large distances from New South Wales and inshore Queensland waters to deep waters (> 90m) off Queensland as individuals grow to spawning size (Braccini et al., 2012).

Reduced economic circumstances of fishers, due to higher costs of fishing and constant or falling prawn prices, have moved management interest in EKP towards profitability (therefore maximum economic yield ~ MEY), rather than maximum sustainable yield (MSY). In order to improve fishing profits, additional management measures were assessed, including further effort control and seasonal closures with options for in-season management based on catch-rate reference points. A length-structured spatial population model (Table 3, Appendix II) and an economic model (Appendix II) were used to assess the fishing pressure, quantify economic performance and update reference points (Table 9, Appendix II) for the EKP fishery.

The Queensland trawl fleet has gradually upgraded characteristics such as engine power and use of propeller nozzles, quad nets, global positioning systems (GPS) and computer mapping software. These changes, together with the ever-changing profile of the fleet, were analysed by linear mixed models (REML) to quantify annual efficiency increases of an average vessel at catching prawns or scallops (Section 2.3, Appendix I). The analyses included daily fishery catch and effort by species and spatial locations, matched with vessel characteristics (treated as fixed effects) and vessel identifier codes (treated as random effects). For eastern king prawn the annual rate of increasing fishing power was estimated near 3% year⁻¹ between 1988 and 2004 (Table 2 and Figure 2, Appendix I). In this case the need to standardise catch rates for increasing fishing power, in order to reduce error of over estimating stock size, was significant. The calculation of monthly fishery dependent abundance indicators illustrates the importance of ongoing monitoring of trawl vessel and fleet characteristics and the need to use this information to standardise catch rate indices.

A newly developed length–spatial stock model was then calibrated to the EKP standardised catch rate abundance indicators, carapace length structures and economic costs of fishing (Appendix II). Model simulations were then conducted to estimate reference points for management. Mean catch rate reference points corresponding to MSY and MEY were calculated (Figure 7, Appendix II). These catch rate reference points established the in-season status and profitability of the fishery month by month in six coastal regions. Retrospectively, the catch rate reference points suggested consistent profitable catch rates of EKP in the last three years of data 2008–2010 across all regions.

A major finding for management is that it is important to limit fishing effort (E) to a level less than E_{MSY} . In the simulations, management rules for closing fishing regions when standardised monthly catch rates fell below thresholds were examined. The catch rate control rules were found to be effective under lower E_{MEY} but much less for higher E_{MSY} (Figure 8, Appendix II). Under simulated E_{MSY} they successfully reduced effort but caused uncertain harvest and often would indicate early closure of fishing regions mid-year. Using a catch rate reference point for MSY, in combination with a lower effort limit of E_{MEY} , was found to be an appropriate trigger point to mitigate catch rate observation error. This trigger point would minimize management mistakes due to data variance.

The new procedures developed in this case study included ongoing monitoring of vessel gear data and methods for estimation of fishing power and standardised catch rates. The spatial monitoring of within year monthly depletion of standardised catch rates was important to gauge the effects of fishing pressure, early season recruitment strength, mid-to-late season spawning abundance and profitability of fishing. The spatial-monthly catch rate abundance indicators were relevant to inform management on fishing effort placed on this short lived mobile species. Incorporation of the catch rate indicators into the new stock model allowed development of catch rate reference points to judge changes in abundance. This was a substantial advance from prior to the study where the confounding level of fishing power increase (Table 1) and reference points for economic considerations was not known. The time-series of standardised catch rates also illustrated the important consideration of variance when interpreting indicators of abundance against reference points.

Stout whiting

Work outline and reference:

Draft manuscript and supplementary analyses:

*Appendix III: Integrating finite mixture and catch curve models for estimation of survival indicators of stout whiting (*Sillago robusta*).*

Appendix IV: Stout whiting catch curve mixture models: supplementary material to Appendix III.

Appendix 3 established methods to estimate rates of fish survival using only age demographic data (model analysis 3). Appendix 4 detailed additional model 1 and 2 analyses, including a standardised catch rate abundance indicator.

Stout whiting (*Sillago robusta*) are fished commercially in the waters of New South Wales and Queensland using Danish seine and otter-trawl methods. There are three fishing sectors and each has different practises, fishing powers and data recording instructions. The Queensland stout whiting sector (T_4) is the primary target fishery with annual harvest monitored and limited under quota (total allowable catch: TAC). The Queensland eastern king prawn (*Melicertus plebejus*) shallow water sector (T_1) catches significant quantities of stout whiting as non-target by-catch, discarded and not reported. The New South Wales fishing sector (T_{NSW}) catches both stout whiting and eastern king prawns, with stout whiting harvests only identified and reported suitably in recent years. Historical records of T_1 and T_{NSW} stout whiting harvest were not complete and fish age data had not been monitored. Consequently an index of stout whiting survival could only be derived from T_4 age-abundance data. Herein fish survival refers to the ratio of abundance between older and younger age groups across cohorts in the same years for fully recruited fish (Table 1, Appendix III).

In this case study a new catch curve analysis was developed to estimate an index of stout whiting survival. The new method is described with application to T_4 fish age-abundance data where the variability in sampling was dependent on fish retained by a small fleet of vessels (maximum 5 per year) and their individual spatial-temporal patterns of fishing. Over recent years inconsistent changes in the time series of data for 1993–2013 between

sampled fish length frequencies and age-length data had become more obvious. The patterns of age structure shifted to older fish from the year 2005, which was not evident in the length of fish harvested (Figure 1, Appendix III). The lengths of fish harvested were generally similar between years. The narrow range of fish lengths sampled each year suggested high sample correlation and small effective sample sizes that may mask signals of changing fish survival. This complex case study fishery provided description of an alternate method of catch curve analysis modified to overcome issues associated with the sample collection of fishery dependent age-abundance data.

Stout whiting survival rates were estimated by joining Gaussian finite mixture, von Bertalanffy growth and catch curve methodology. Model estimates were solved iteratively using the expectation-maximisation algorithm, by estimating differences in fish abundances by age. A standardised catch rate abundance indicator was also quantified through a separate statistical analysis. Overall, three catch curve models were developed in attempt to estimate indices of fish survival from the T_4 data. The three model versions were:

- Model 1 (Table 1, Appendix IV) was first developed to connect the stout whiting standardised catch rate directly with the separate fish-length and age-length data. Its structure was dynamic in an attempt to mitigate confounding between estimated survival rates and variable cohort strengths. The survival results were concluded to be highly variable and overly sensitive to the combined year-to-year variation in catch rates, fish lengths and age data (Figure 3, Appendix IV).
- Model 2 (Table 2, Appendix IV) was then designed without using catch rates, but still used the same fish-length and age-length data. The model still assumed the data were sampled randomly from the exploited population in each year. The model analysis identified inconsistency in the time series between years of sampled fish-length and age-length, with survival results deemed inconsistent in some years (Figure 3, Appendix IV). Samples where fish length frequencies were measured but not aged were highly correlated and contained little information on fish survival compared to the age-length samples (Appendix IV).
- Model 3 (Table 1, Appendix III) was finally designed to analyse only fish that were aged (separate catch rate and fish length data were excluded). The model was now conditional on fish length and assumed that fish ages within each length category

were sampled randomly; it was no longer assumed that fish lengths themselves were sampled randomly (Appendix III).

A number of inferences were of note from the model 3 analysis of stout whiting. First were the low estimates of fish survival 1993–2003. It appeared the 1993–2003 survival rates were down as a result of the high levels of each sectors' catch taken in the years 1994–1999 (Figure 4, Appendix III). The estimates for the years 2003–2006 indicated stronger survival of fish as they recruited and aged (Figure 2, Appendix III). This coincided with reduced T4 harvests and the adoption of by-catch reduction devices by T1 prawn trawl sector. The estimated survival fractions for the years 2007–2012 had stabilised above those from early years (Figure 2, Appendix III). The analysis identified significant changes in fish age-abundance, but was also sensitive to inconsistencies in data. Therefore representative and consistent fishery dependent sampling of age data is important for the methodology. Three different models were designed in order to overcome inconsistencies in stout whiting data. Model 3 corrected the inconsistent results noted in models 1 and 2 by not assuming the fish length data were sampled randomly from the fish population. Together the three models critically evaluated the validity of age-abundance data.

The annual variability of results between years (k) had implications for setting total allowable catches (TAC) for the T4 sector. Direct use of annual estimates of survival may cause the TAC to vary notably from year to year; an undesired behaviour for industry and export markets. Therefore, it is suggested that a mean survival rate (\bar{S}) be calculated over the two most recent years to reduce variance. For the TAC harvest control rule:

$$\text{TAC}_{\text{T4},k+1} = \min(\text{TAC}_{\text{T4},k} \theta_{k+1}, \text{TAC}_{\text{T4},\text{max}} = 1363\text{t}); \theta_{k+1} = \left(\frac{\bar{S}}{S_{\text{target}}} \right)^{1/x},$$

the survival S_{target} reference point should be set at an average survival rate from years that best represented stable and profitable fishing. The use of a cube-root ($x=3$) or square-root ($x=2$) transformation can limit the scale of quota change; for no transformation $x=1$. Thresholds on quota change may also be applied to mitigate year-to-year variance in quota change (like for spanner crab in Appendix V). Gauging the annual standardised catch rate against the 25th and 75th percentiles of the historical time series can provided a further dimension to adjust TAC if required.

This study demonstrates the importance of fully accounting for year-to-year variation in fishery dependent samples. For stout whiting, the new catch curve procedure maximised the information on fish survival using the age data obtained by non-random sampling of fish length. The methodology is relevant to many fisheries with sampling issues associated with non-random patterns of fishing and aggregation of fishing effort associated with the schooling and movement dynamics of fish (Table 1). The data issues were not obvious prior to the study when simple cross-sectional catch curve models were employed. This analysis technique forms a suitable tool to assess rates of fish survival and data consistency before further analysis in detailed age-structure models; which may hide data inconsistencies under stochastic model components. Future focus on improved sampling procedures and control of random sampling from the stout whiting fishery is vital to ensure sound recommendations on sustainable harvests.

Spanner crab

Manuscript: O'Neill et al. (2010),

Appendix V: Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (Ranina ranina) fishery.

The Australian spanner crab fishery operates across the state waters of Queensland and New South Wales. It is the world's largest spanner crab fishery, with annual gross landings between 1500 and 2000 t. In Queensland, the annual spanner crab total allowable catch (TAC) was set historically using a control rule based on linear regression of fishery nominal average annual catch rates. A six-year increasing trend in catch rates (2000–2005) resulted in the control rules recommending a 68% increase in TAC for the fishing years 2006 and 2007, mostly because the control rule method was not robust and nominal catch rates were at risk of being confounded by increasing fishing power. Management acknowledged the need for an alternative more comprehensive stock management methodology based on fishery standardised catch rates and using the fishery independent survey catch rate data. Figure 4 illustrates the fishery regions and the survey locations.

In response to the need for an alternative method, a new management procedure was developed and tested with three precautionary approaches: i) quota increases enacted only when both catch rate indices were above their reference points; ii) quota increases limited to half the full ratio increase as indicated by the catch rate indices compared to their reference points; and iii) quotas reduced by the full ratio decrease when both catch rate indices were below their reference points (Table 1, Appendix V). Simulations were used to identify favourable sustainability, industry and management performance outcomes, using fishery-dependent and fishery-independent standardised catch rate indices together with carefully set reference points. The fishery dependent data were sourced from Queensland daily logbook records of commercial catches. The independent data were from annual surveys of spanner crab abundance conducted across Queensland and New South Wales waters (Brown et al., 2008).

General linear models (GLM) were used to standardise commercial and survey catches of spanner crab. Notably for the commercial data, significant fishing power terms were

identified for each vessel operation, level of skipper experience and number of net lifts fished (Table 4, Appendix V). For the survey, a two-component GLM was used to model the presence or absence of crab in the fishing gear separately to modelling when crab was caught (Table 4, Appendix V). This allowed data regarding the proportion of net-lines not catching crab as well as catch data to be modelled for different survey locations and different lengths of fishing time. The use of these models standardised the spatial and fishing effects needed to reduce indicator variance. Indicator variance was further mitigated by averaging the commercial and survey indices. Ongoing review of the two indices is still required to gauge their correlation and level of agreement in case one is identified as being more reliable. If inconsistencies are identified, the management procedure can still operate using only one indicator.

The management procedure followed a process of developing a baseline TAC and reference point targets for standardized catch rates with range intervals (Tables 1 and 3, Appendix V); no age data were available for spanner crabs. The target catch rates (fishery dependent and independent) and baseline TAC (Q_{base}) were set equal to their annual average between 2000 and 2007 and they were fixed. Upper and lower intervals of $\pm 10\%$ were set on target catch rate reference points to ensure that only significant changes were enacted on TAC. The stock performance indicators were the average fishery and survey standardized catch rates in the most recent biennial TAC period. Standardized catch rates from the fishery and the survey were compared in a decision matrix (Table 1, Appendix V). The spanner crab quota was calculated from the Q_{base} and was made no larger than the maximum tonnage allowed (Q_{max}). New TAC was compared with the tonnage set two years earlier. If the new TAC was within 5% of the previous TAC, then the TAC remained unchanged. TAC was calculated according to the equation:

$$Q_{t+1,t+2} = \min \left[\left\{ \begin{array}{ll} Q_t & , \text{ if } (0.95Q_t \leq \lambda Q_{\text{base}} \leq 1.05Q_t) \\ \lambda Q_{\text{base}} & , \text{ otherwise} \end{array} \right\}, Q_{\text{max}} \right]$$

where Q is the TAC tonnage for biennial setting in years $t+1$ and $t+2$ and λ was the catch rate adjustment factor of TAC (Table 1, Appendix V) which takes into account the comparison of fishery and survey catch rates with their respective reference points.

The performance of the management procedure was dependent on the level of population size present when the reference points were set (Figure 4, Appendix V). Simulations identified that precautionary levels of Q_{base} and catch-rate reference points were required

to ensure robust performance of the management procedure. In choosing reference points, it was important to consider four key aspects: (i) lower-than-perceived stock sizes, (ii) biased fishery catch rates that result in lower biomass, higher TAC and less responsive TAC change, (iii) a Q_{base} of less than the average harvest and (iv) updating catch rate reference points to values that are higher than average. If reference points were set too generously, the rules could incorrectly set high quotas at low population sizes.

The significant risk of using nominal catch rates and simple linear regressions in harvest control rules was not recognised until failure of the management process in 2006. The new procedures developed herein for standardised catch rates and their reference points established a consistent and modernised framework for using abundance indicators to inform changes in spanner crab harvest. This research outcome was positive and addressed concerns of fishing power confounding catch rate data (Table 1). The simulations of the management procedure allowed testing for the effects of different population biomasses, setting of reference points and adjusting for fishing power confounders (Figure 4, Appendix V). As noted above, the lessons of adequate control of indicator variance and use of precautionary reference points form the sound basis of the management procedure given unknown measures of actual spanner crab population size.

Recent TAC analyses conducted in 2015 have emphasised the importance of precautionary reference points to ensure profitable fishing (Campbell et al., 2015). The 2014–2015 average fishery catch rates for legal sized spanner crabs was down 24% below the reference point. In comparison, the average 2014–2015 survey catch rate for both legal and undersized crab was 22% above the survey reference point. The management procedure and analyses developed herein were used to adjust the TAC down to align with the baseline harvest of 1631 t. The TAC adjustment move correctly to ensure sustainability, but an updated review of the catch rate reference points may be required to move the fishery towards more profitable fishing. For this, new data on the economic cost of fishing is needed to be considered in line with recent levels of catch rates, as well as the more recent recommendations on economic reference points for single species fisheries (Pascoe et al., 2014).

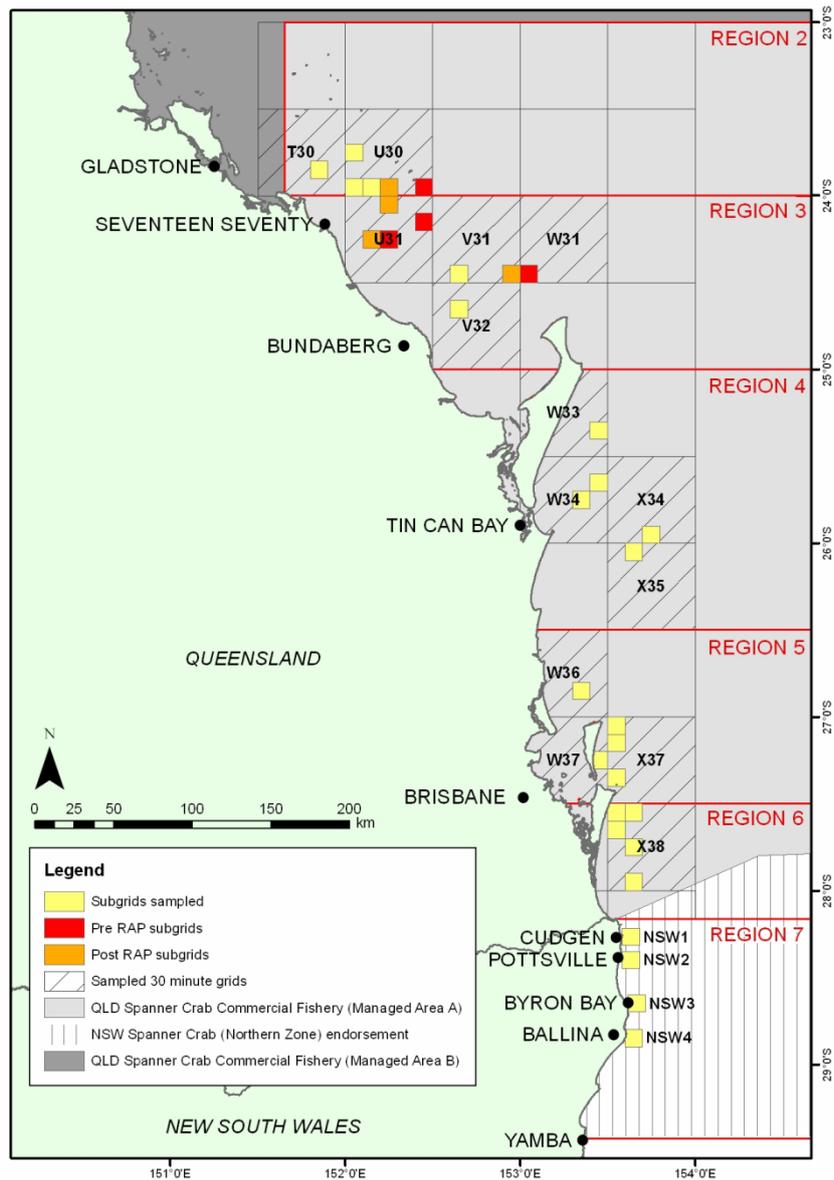


Figure 4. Map of the New South Wales and Queensland spanner crab fishery (map sourced from Campbell et al., 2015), showing the location of Queensland logbook fixed 30' grids within fishery regions and fixed 6' subgrids within grids for the extended monitoring survey.

Discussion

Key findings across case studies

As noted previously, the case studies were selected to contrast the use of age-abundance indicators across fisheries that differed operationally and by species characteristics. The results from the case studies demonstrate that the basis for improving the consistency and representativeness of the chosen fisheries indicators was not different between species life history traits. For all case studies, similar data types and structures can be implemented and analysed; more so for the abundance data as age data cannot be collected for some species like prawns and crabs (Appendix I, II and V). The key requirement in this context was for the data to be collected consistently across a number of areas through time. Unfortunately this cannot be fully controlled through fishery dependent sampling with fishing operations frequently changing their temporal-spatial-gear behaviour. Ideally the data could be improved if these behavioural changes could be captured practically within the current data recording systems. The need to standardise age-abundance is critical to mitigate over or under estimation of indicators that may cause incorrect changes to management.

The statistical methodologies applied in each study significantly improved the validity of their fishery-dependent time series. As demonstrated in all case studies, the analyses identified significant spatial and fishing power adjustments to standardise and improve abundance indicators. It is not always possible to extensively standardise catch rate data in all fisheries because of missing data on fishing operation gears and technologies, but basic statistical accounting for different catching abilities between different vessels and their levels of fishing effort at different times and areas is achievable and essential. For fish age data, the use of the mixture modelling method overcame the problems of inconsistent data, estimated measures of fish survival directly from age-data across years and allowed for the assumptions of random or non-random sampling of fish. These points should be considered as standard components in the assessment of all fishery resources.

For all species the results highlighted the importance of using precautionary reference points to judge the meaning of age-abundance indicators because of possible unaccounted bias and variability. This aspect alone is the key management safe guard to mitigate the risks of over fishing and indicator uncertainty. If this process is employed, then the findings support the effective use of age-abundance indicators in management.

Indicator uncertainty and management

Uncertainty of a fishery's status is always present as populations cannot be easily counted or observed. Accordingly, any measures used as indicators of fishery status can contain significant sources of variance. For managers, a high level of variance can undermine the value of different types of management. Responsibility generally lies with scientists to use contemporary analyses to mitigate variance and clearly explain the meaning of indicator variance in the management process.

So, how have indicator uncertainties and variance arisen? Inevitably, the errors are generated from components such as the variability in the natural fish population dynamics, the spatial and temporal patterns of fishing, the sampling processes, the data collection or sampling procedures, the choice of analyses, assumptions made and the inference beliefs. Normally all of these variance components cannot be simultaneously quantified. The significant variance components need to be identified and mitigated to step forward with positive management outcomes.

For fisheries management, mitigation of variance and high risk management procedures rests with setting conservative reference points and decision rules or having a management rule that ensures the indicator be above reference points with high certainty (e.g. > 75% to 95%) to enable an active management framework. This is to ensure that results from either simple or complex analyses are interpreted cautiously to avoid overfishing and help promote more profitable and successful fishing. For the case study fisheries, the following mitigation strategies were identified for their age-abundance data sources:

- For eastern king prawns, the combined approach of setting target fishing effort near the level for maximum economic yield (conservative lower level < E_{MSY}) and a secondary in-season limit reference point on catch rates.

- For stout whiting, it is recommended to use a mean survival rate calculated over recent years and evaluated against a target rate from years that represent stable and profitable fishing catch rates.
- For spanner crab, precautionary levels of base TAC set below average harvests and above average catch rate reference points were required to ensure robust performance of the management procedure.

Alternatives to using age-abundance data may rely on technological investment into new data sources such as tagging or survey-based indices. They may provide less biased estimates, but management of their variance estimates will still be required using some form of conservative reference points; to recognise the need for precaution arising from uncertainty in the data and analyses (Garcia and Staples, 2000). In addition the use of decision rules is critical to avoid significant risks of overfishing and to form the necessary structure to evaluate age-abundance indicators. Further insights across the case study fisheries suggest that the success of the management framework relies on regulating the open access nature of fishing. If significant levels of fishing effort are available (not appropriately limited or known), then mitigation of variance and high risk management is difficult as demonstrated by the eastern king prawn case study (Appendix II).

Improving age-abundance indicators

Analytically, robust sampling and statistical procedures are required to minimise variance and bias. New methodologies and frameworks have been developed herein to quantify age-abundance indicators from the current fishery dependent and independent data sources (see case study fisheries Appendix I – V). However, if the collection of these data continues into the future, then changes in data or analyses may be needed to further improve the use of the age-abundance fishery indicators.

For prawn catch rate indices, close monitoring of fishing power parameter estimates is required. The parameter estimates were closely examined for eastern king prawns and for the other trawl effort managed sectors, with consistent estimates found over the years analysed (O'Neill and Leigh, 2006). However, as adoption of different fishing gears stabilises over time, their parameter significance and magnitude fade in the statistical analysis of catch rates. This issue has been noted for longer time series analysis of tiger

prawn catch rates in north Queensland (unpublished PhD, N Wang, University of Queensland) and in Australia's Northern Prawn Fishery (Dichmont et al., 2003). When this occurs, trends in fishing effort and fishing power may be underestimated and bias standardised catch rates. To overcome this problem, subsets of the time series when gear adoptions occurred (contrasting when vessels fished with and without different fishing gears) could be specifically analysed. From the subset analysis, gear parameter estimates could then be offset in the full time series analysis (Dichmont et al., 2003).

In addition, further improvements in prawn abundance indicators could be achieved utilising vessel GPS location data to spatially map abundance densities and monitor spatial depletion effects.

For stout whiting, higher effective sample sizes are needed to improve the accuracy of age-abundance indicators through more consistent and representative sampling of catches across time periods, areas and fishing operations. This is of priority, with improved monitoring and laboratory processes also needed to safeguard analysis procedures. Spatial-temporal age-abundance sampling needs to be consistent across the fishery.

For spanner crab, review of catch rate reference points is required each assessment period. They may need to be updated to balance target levels of catch rates against the ever increasing costs of fishing.

Overall, the data analysis procedures demonstrated that the new standardised age-abundance indicators were superior and more representative than the old-style nominal measures. The procedural changes are summarised in Table 3 and show their general gains and limitations. Dealing with fishery dependent confounding issues (Table 1) and variance in age-abundance is the key to minimise type I error (the false-positive: no true change in fish stocks, but calculated age-abundance indicate increases or decreases) or type II error (the false-negative: no change in age-abundance calculated, but true increases or decreases in fish stocks were not detected). Decision tables for changing fisheries management could be utilised to extend the analysis procedures to show the probabilities of different outcomes or hypotheses (Walters and Martell, 2004).

Table 3. Some outcomes of changes (Δ) in age-abundance indicators across case study fisheries.

Aspect	Brief
Δ abundance indicators	Nominal \rightarrow Standardised catch rate; to address fishery dependent confounders (Table 1).
Δ age indicators	Mortality \rightarrow Survival; conditioned for non-random sampling of fish.
Δ management procedures	New modernised frameworks with reference points to set harvests and fishing efforts, and assess the performance of each fishery.
Limitations	Possible statistical confounding of age-abundance signals and its variance; ever present issue for all types of analyses that needs ongoing monitoring and acknowledgment.
	Missing and inconsistent data that require complex change to analyses.
	Use of management procedures and reference points require ongoing cost and review to evolve for changing objectives, data and new ideas.
Gains	Use of quantitative measures to set target reference points and objectives.
	Age-abundance indicators calculated using contemporary methods, published and reviewed, and transparent to engage stakeholders.
	Analyses designed to account for current data variance and sampling uncertainties.
	Management procedures flexible to set variability in quota change.

Recreational fisheries

The case studies herein have demonstrated application of age-abundance indicators in managing commercial fisheries, where frameworks for altering fishing effort or harvest can be defined. But the question persists as to how age-abundance indicators can be used to manage open-access recreational fisheries. The answer is not clear or easy and is influenced by a range of complex social and economic factors. Open access fisheries have the ability to respond to increases in fish abundance with strong effort responses (Walters, 2002). Therefore, based on the insights gained in this PhD study, the success of using an age-abundance indicator may depend on controlling fishing effort via licence systems. Design of such a management framework would need to consider regional scales that address fishing quality for both remote and non-remote areas. Failure to recognise the open access fishing is critical oversight in many fishery management plans (Walters and Cox, 1999). Direct effort control is needed where angling quality or sustainability of fish populations are the main objectives (Walters, 2002). If this is achieved, then age-abundance indicators can be utilised in recreational fisheries with good outcome and decision-support potential.

Considerations for management

Were the age-abundance indicators appropriate?

A mix of statistical and population models were used in this study to analyse available data and construct indicators to explain variances and minimise fishing power bias. For each case study, the following indicators were developed –

- Eastern king prawns: fishery standardised catch rate indicators were used in a population stock analysis to estimate abundance reference points for use in both empirical and model-based management procedures.
- Stout whiting: fishery standardised catch rates and fish age frequencies were used to estimate fish survival indicators for use in empirical management procedures.
- Spanner crab: two standardised catch rate indices from fishery dependent and independent sources were developed for use in empirical management procedures.

The key dimension of the indicators was the standardised catch rates and it was not possible to validate the fishery dependent indices, except to verify trends against independent survey measures. Some minor discrepancies were noted comparing spanner crab indices (Figure 3, Appendix V) and strong correlations have been noted comparing prawn indices (O'Neill and Leigh, 2006). However, critical differences were hard to gauge as survey variances and spatial-temporal replications were limiting. Overall, the standardised catch rate indices appeared appropriate so that it could be assumed they were proportional to exploitable abundance. In this case, most of the drawbacks of using fishery dependent age-abundance data were accounted.

How should the age-abundance indicators be used?

The case studies have demonstrated frameworks for generating and using indicators in a modernised setting for managing fisheries in Queensland. The basis of indicator management was not different between species life history traits: short to longer lived; fast to slower growing. The analysis procedures and data scales adapt accordingly, but highly variable management responses should still be tempered. The key to successful use of indicators in fisheries management lies with a flexible, adaptable and operational

framework. The indicator frameworks should also not be used alone without effective regulation on fishing effort. For quota managed fisheries, harvest settings should not vary greatly above the long term average when faced with uncertainty; as per spanner crab and stout whiting – we don't really know how many fish are in the sea! Quota processes also place significant load on the assessment framework and regulated fishing access is still required to avoid scenarios of over competitive fishing that may cause localised depletion, low catch rates and short seasons. Management by limiting fishing effort was successfully identified in the eastern king prawn fishery. Wider application of such a management process has merit, if the number of licences is limited to ensure profitability and changes in fishing power are accurately accounted for in data analyses. The benefits of spatial time closures also need to be evaluated for managing high fishing power practices.

Concluding remarks

The research used three case study fisheries to demonstrate how to develop and use appropriate age-abundance indicators in the management of Queensland's fisheries. Notably, it has highlighted procedures to reduce and manage indicator variance and bias. It has also highlighted approaches applying quantitative tools in setting decisions on fishing harvest or effort. The analysis and decision rules processes are not demanding and are cost effective to use on age-abundance data. The results highlight the basic principle that when stock status is uncertain, use precautionary reference points to judge age-abundance indicator signals. The systems described can help improve and measure sustainable and economic outcomes of Queensland's fisheries and can be applied to other fisheries globally.

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Appendix I: Fishing power increases continue in Queensland's east coast trawl fishery, Australia.

Fishing power increases continue in Queensland's east coast trawl fishery, Australia

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Received 21 July 2006; received in revised form 6 December 2006; accepted 18 December 2006

Abstract

The Queensland east coast trawl fishery is by far the largest prawn and scallop otter trawl fleet in Australia in terms of number of vessels, with 504 vessels licensed to fish for species including tiger prawns, endeavour prawns, red spot king prawns, eastern king prawns and saucer scallops by the end of 2004. The vessel fleet has gradually upgraded characteristics such as engine power and use of propeller nozzles, quad nets, global positioning systems (GPS) and computer mapping software. These changes, together with the ever-changing profile of the fleet, were analysed by linear mixed models to quantify annual efficiency increases of an average vessel at catching prawns or scallops. The analyses included vessel characteristics (treated as fixed effects) and vessel identifier codes (treated as random effects). For the period from 1989 to 2004 the models estimated overall fishing power increases of 6% in the northern tiger, 6% in the northern endeavour, 12% in the southern tiger, 18% in the red spot king, 46% in the eastern king prawn and 15% in the saucer scallop sector. The results illustrate the importance of ongoing monitoring of vessel and fleet characteristics and the need to use this information to standardise catch rate indices used in stock assessment and management. Crown Copyright © 2007 Published by Elsevier B.V. All rights reserved.

Keywords: Fishing power; Linear mixed models; Prawns; Scallops; Otter trawling

1. Introduction

Harvest landings from the Queensland east coast otter trawl fishery (ECOTF) are in the order of 10–13 kilo-tonnes annually and worth approximately \$100–150 million (AUD) at the wharf. With 504 vessels licensed at the end of 2004, the ECOTF is by far the largest prawn trawl fleet in Australia in terms of the number of vessels. The fishery is complex in nature targeting several species of prawns (mainly *Penaeus* spp., *Melicertus* spp. and *Metapenaeus* spp.) and one main species of scallop (*Amusium balloti*). The ECOTF is characterised by identifiable sectors that are largely based on target species and geographic regions (Fig. 1).

Vessel characteristics change through the adoption of new and better technologies and fishing gear, and individual license holders are free to target any sector they choose. Consequently, interpretation of the catch and effort statistics, and the use

of these statistics for monitoring the status of the fishery and reviewing the suitability of management arrangements are more difficult.

Catch and effort statistics are used as the basis of stock assessments and management in many Australian fisheries (O'Neill and Leigh, 2006). Predictions based on raw data can be biased due to changes in the efficiency of fishing effort through time and between fishing operations or sectors. There is, therefore, a need to standardise catch and effort data to reduce biases and variability. Standardisation, accounting for factors affecting both relative abundance and fishing efficiency, results in time series of catch and effort data that are more representative of trends in population abundance.

Several studies have focussed on standardisation of catch-effort data (Bishop et al., 2000, 2004; Hall and Penn, 1979; O'Neill et al., 2003; Robins et al., 1998; Salthaug and Godø, 2001). Generalised linear regression models (GLM) have been used to estimate changes in relative fishing power and to standardise average catches in the Queensland trawl fishery (O'Neill et al., 2003). They have also been used to quantify the effects of global positioning system (GPS) on average catches in Australia's northern prawn fishery (Robins et al., 1998). Bishop et al. (2000) further developed the analysis of Robins et al. (1998)

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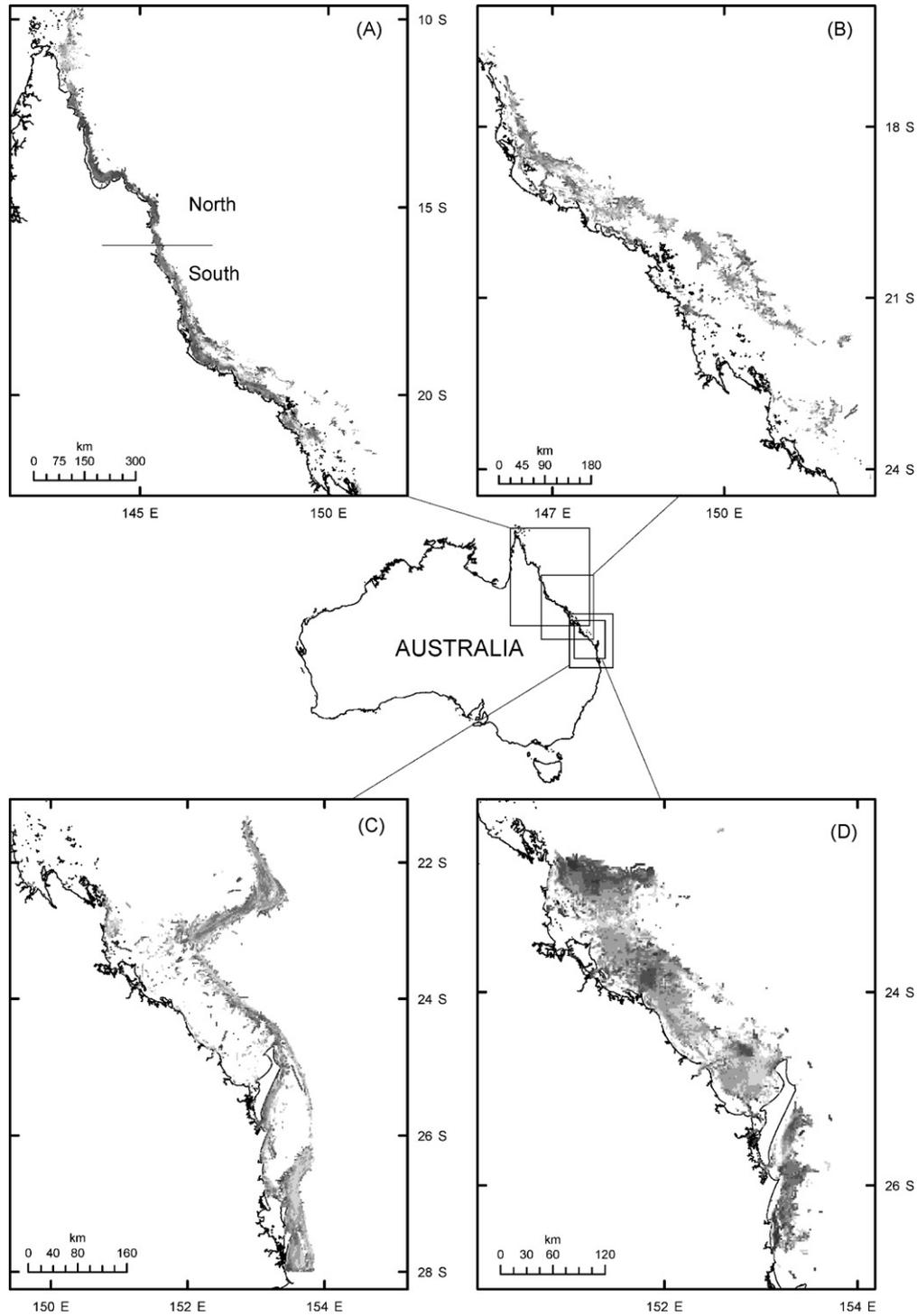


Fig. 1. Spatial distribution of normalised (log transformed) catch rates for: (A) tiger and endeavour prawn, (B) red spot king prawn, (C) eastern king prawn and (D) saucer scallop; the darker shades indicate high catching areas. The horizontal line in (A) at 16° S distinguishes the northern and southern tiger/endeavour prawn trawl sectors.

by using generalised estimating equations (GEE) to account for spatial and temporal correlations in the data. A linear mixed model (LMM) for catches from Australia’s northern prawn fishery ‘produced consistent results when compared with . . . other random vessel models’ (Bishop et al., 2004).

In recent years, the Queensland and Australian governments have addressed Queensland’s trawl fishing power increases by

reducing the total number of nights that vessels are allowed to fish, through the use of penalties for vessel upgrades and surrender provisions on licence and effort trading (Kerrigan et al., 2004). ‘Fishing power’ is the term used to describe the efficiency of an average vessel at catching prawns or scallops. The concept of reducing fishing time (measured in nights) according to potential fishing power increases was implemented by fishery

managers to ensure that effective effort was capped in both the fishery and the Great Barrier Reef Marine Park (O'Neill and Leigh, 2006).

In this paper, linear mixed models are used to quantify fishing power increases from 1988 to 2004. Since previous estimates up to 1999 were published (O'Neill et al., 2003), a further comprehensive survey of fishing operators has been conducted and several more years of catch and effort data have been gathered. Our methods and results further the application of linear mixed models in fisheries research and the calculation of annual fishing powers for use in management.

2. Methods

2.1. Catch data

Analyses were based on compulsory daily logbook data reported by individual vessels from 1988 to 2004 for their catches of tiger prawn (*Penaeus esculentus*), endeavour prawn (*Metapenaeus endeavouri*), red spot king prawn (*Melicertus longistylus*), eastern king prawn (*Melicertus plebejus*) and saucer scallop (*Amusium balloti*). The spatial resolution of catches recorded was 30 × 30 min grids. All data were analysed by vessel codes that identified the combination of vessel hull and owner. Our analysis relates only to prawns recruited to offshore fisheries (i.e. greater than about 20 mm carapace length); this is consistent with stock assessments (O'Neill et al., 2005).

The fishing year for eastern king prawns and saucer scallops was defined to start in November and end in October, to match the cycle of fishing and recruitment to these fisheries (O'Neill et al., 2005). The fishing year for tiger, endeavour and red spot king prawns was defined as a calendar year; this definition suited the life-cycle and seasonal variation in fishing effort for these species (O'Neill and Leigh, 2006). Estimates for the 2004 fishing year were based only on the months up to April; we consider the results indicative for that year as the data covered the peak fishing months. O'Neill and Leigh (2006) describe the data in more detail.

2.2. Vessel and fishing gear data

The analyses considered many different vessel characteristics thought to affect fishing power. Information on when particular fishers adopted new devices and technologies was obtained from two purposely-designed surveys of past and present Queensland ECOTF vessel owner/operators in 2000 and 2004. These data represented, from each trawl sector, a random set of vessels that had fished between 1997 and 2004. The surveys had participation rates of 85 and 84%, respectively, of the operators contacted and collectively covered about 60% of each sector's harvest in the later years (2002–2004). Further details on the survey questionnaire, coverage and sample sizes are given by O'Neill and Leigh (2006) and O'Neill et al. (2003, 2005).

Interviewees provided records of vessel characteristics during personal (face-to-face) interviews. Changes in the following characteristics, and the date of each change, were recorded for each vessel; for the benefit of interviewees, the surveys used

a mix of metric and imperial measurement units, according to prevailing industry usage:

- Engine power (HP), gear box ratio (reduction), average trawl speed (knots), fuel capacity (litres), fuel consumption per night (litres), propeller size (inches) and presence or absence of a propeller nozzle.
- Navigation equipment: presence or absence of global positioning system and plotters, computer mapping software, sonar and colour sounder.
- The use, position, type and size of try-gear; try-gear is a small (1–3 fathom) net used for frequent 10–20 min sampling of trawl grounds.
- The type and use of by-catch reduction devices (BRD) and turtle exclusion devices (TED).
- Trawl net configurations: number of nets (single, double, triple, quad or five nets), total net head rope length (fathoms) combined for all nets, net mesh size (mm), type of ground chain (fixed drop chain, drop chain with sliding rings, drop rope and chain combined, looped chain or other less common configurations), chain size (mm), type of otter board (Bison, flat, Kilfoil, Louvre or other less common types) and size (total board area = board length × width).

2.3. Statistical analyses

Linear mixed models were applied using the method of residual maximum likelihood (REML) assuming normally distributed errors on the log scale (GenStat, 2005; Montgomery, 1997). The response variable was the individual vessel daily catch by species for a spatial area, measured in kilograms of prawns or baskets of saucer scallops. The models included as explanatory variables the fishing year, month, spatial logbook 30 × 30 min grid square, lunar cycle, corresponding catches of other prawn or scallop species and the vessel's gear characteristics. Lunar variation in catches was modelled by a calculated luminance measure ranging between 0 for new moon and 1 for full moon (Courtney et al., 2002). This luminance measure followed a sinusoidal pattern, and was also replicated and advanced 7 days (~1/4 lunar period) to provide an additional degree of freedom for a potential time lag in the response of fisheries to lunar luminance. Together these patterns model a cyclic variation in catches corresponding to new moon, waxing moon, full moon and waning moon phases, and allow the peak catch to occur in any one of these phases. The associated catches of other prawns or scallops were included to adjust for catchability effects when they were caught with the main target prawn or scallop species.

The linear mixed model included both fixed and random model terms. Fixed terms were used for all of the explanatory variables described above. Random terms treat an attribute as a random selection from an overall population. Random terms covered individual vessels in the trawl fleet. Mixed models measure multiple sources of variation in the data, thus providing estimates of variance components associated with random terms in the model. Mixed models have the advantage that the significance of the fixed terms can be assessed considering more than one source of error, improving the accuracy of significance tests.

The model was also able to measure changes in fleet profile not covered by fixed effects, as vessels switched sectors or exited the fishery; these were not modelled by O'Neill et al. (2003).

Definition of the model was as follows:

$$\log_e C = \mathbf{X}\alpha + \mathbf{Z}\gamma + \epsilon \quad (1)$$

where C is the vector of catches; α a vector of fixed terms including β_0 , β_1 , β_2 , β_3 and β_4 , matrix-multiplied by data X (composed of X_1 , X_2 , X_3 and X_4); γ a vector of random vessel terms with design matrix Z indicating which daily catches belong to each vessel and ϵ is a normally distributed error term. Parameter β_0 is a scalar intercept, while β_1 , β_2 , β_3 and β_4 are vector parameters for abundance, catchability, lunar phase and logarithms of corresponding catches of other species, respectively. The abundance vector β_1 consisted of categorical terms for fishing grids, fishing years and months, and their two-way interactions. The catchability vector β_2 included vessel characteristics, navigation equipment, by-catch reduction devices and trawl net configurations, of which some were categorical and others continuous; a log scale was used for the continuous terms. The vector β_3 consisted of a term for lunar luminance and one for luminance advanced seven days. The fishing power components β_2 and γ were the exclusive focus of interpretation to calculate annual changes in fishing power.

The statistical software package GenStat (2005) was used for the analysis and provided asymptotic standard errors for all estimates. Any influential correlations of parameter estimators were assessed and removed if necessary. The importance of individual terms in the linear mixed model was assessed formally using Wald statistics. Wald statistics were calculated by dropping individual fixed terms from the full model. They have asymptotic chi-squared distributions with degrees of freedom equal to those of the fixed model terms (GenStat, 2005). Analysis of residuals from each model, and the importance of having multiplicative errors, supported the use of the normal residual distribution on the log scale (O'Neill and Leigh, 2006).

For the eastern king prawn sector, annual changes in fishing power were calculated for two management sectors: water depths ≤ 50 fathoms (shallow) and waters > 50 fathoms (deep). Net sizes were modelled by their log-residuals to adjust for management bias allowing larger nets in deep waters (O'Neill and Leigh, 2006). The log-residuals were calculated from the simple regression of net size (log transformed) against depth category (shallow or deep). This was to ensure that catch variations with net size were quantified according to vessel differences and were not due to management limitations on net sizes in the different waters. Spatial weightings of 45% for shallow waters and 55% for deep waters were applied to correct for the imbalance of shallow (29%) versus deep water (71%) grid squares in which it was certain whether shallow or deep water fishing nets were used; many predominantly shallow-water squares also contained some deep water and therefore could not be classified with certainty.

2.4. Estimating relative fishing power

Relative fishing power was calculated as a proportional change in average catch rates from fishing year to fishing year

under standard conditions. The expected catch on each day fished by each vessel was calculated as

$$\mathbf{c} = \exp(\mathbf{X}\alpha + \mathbf{Z}\gamma), \quad (2)$$

where \mathbf{c} is the vector of expected catches under standard conditions for each vessel and day fished and \mathbf{X} , α , \mathbf{Z} and γ are as in Eq. (1). Within $\mathbf{X}\alpha$, the terms represented by β_0 , $\mathbf{X}_1\beta_1$, $\mathbf{X}_3\beta_3$ and $\mathbf{X}_4\beta_4$ were held constant to provide standard conditions of abundance, lunar phase and catches of other species, thus enabling prediction of changes in fishing power. Annual fishing power increases due to trawling more on favourable lunar phases were not considered, because changes in the lunar pattern of fishing in each trawl sector were negligible over the period 1988–2004 (O'Neill and Leigh, 2006).

An average catch \bar{c} was defined for each fishing year as the arithmetic mean of elements of \mathbf{c} that were within the year. The fishing power was then defined as

$$\mathbf{f}_y = \frac{\bar{c}}{\bar{c}_{1989}} \quad (3)$$

where \mathbf{f}_y is the vector of proportional change in average catch relative to 1989 and \bar{c} is the vector of annual average catches under standard conditions. The reference fishing year was chosen as 1989 because it was the first fishing year with complete catch records across all sectors, and for consistency with previous work (O'Neill et al., 2003).

Confidence intervals on fishing power estimates from each trawl sector were generated by a Monte Carlo routine of running the model predictions for 1000 realisations of the parameter estimates. The variations in fixed parameters were calculated using the parameter estimates and their covariance matrix to construct a multivariate normal distribution of values. Realisations of the random vessel effects were calculated from normal distributions based on the means and standard deviations for vessels fishing in each fishing year, month and grid square. Calculated 2.5 and 97.5% percentiles on the fishing power distributions represented 95% confidence intervals. As the reference fishing-power year was 1989, the confidence intervals increase in size away from this fishing year. For more information on the Monte Carlo routine see O'Neill et al. (2005).

3. Results

3.1. Analyses and parameter estimates

Table 1 lists the model statistics and parameter estimates for the various gears and technologies for tiger prawns, endeavour prawns, red spot king prawns, eastern king prawns and saucer scallops. The statistics show that the fishing power β_2 parameters (including different vessel characteristics, navigation equipment, by-catch reduction devices and trawl net configurations) were highly significant (***) ($P < 0.001$) after accounting for abundance β_1 (parameterised as location, fishing year, month and their two-way interactions), lunar phase β_3 and catches of other species β_4 . Variance components for the random vessel terms in the different sectors ranged between 0.0509 (equivalent to a coefficient of variation (c.v.) of

Table 1
Summary of analyses, parameter estimates β_2 and standard errors in parentheses from the mixed linear models for each trawl sector

	Northern tiger prawn	Northern endeavour prawn	Southern tiger prawn	Red spot king prawn	Eastern king prawn	Saucer scallop
Summary of analysis						
Number of data (<i>n</i>)	84824	83621	59205	16098	82890	82062
Fishing power β_2 d.f., deviance ratio	15, 13.787	19, 22.484	7, 31.686	12, 9.467	18, 64.556	17, 15.941
Remaining terms d.f., deviance ratio	498, 102.129	498, 78.996	718, 36.043	631, 22.101	562, 44.375	613, 61.974
Residual variance	0.307 (0.002)	0.449 (0.002)	0.336 (0.002)	0.314 (0.003)	0.306 (0.002)	0.397 (0.002)
Variance component	0.0509 (0.0053)	0.0788 (0.0085)	0.0741 (0.0085)	0.0636 (0.0100)	0.1951 (0.0219)	0.0656 (0.0066)
Parameter estimates						
Engine rated power	0.141 (0.024)	0.211 (0.035)	0.135 (0.034)	0.404 (0.080)	n.s.	0.240 (0.029)
Trawl speed	n.s.	0.277 (0.085)	n.s.	-0.480 (0.148)	n.s.	-0.192 (0.064)
Propeller nozzle	0.027 (0.011)	-0.071 (0.013)	n.s.	n.s.	n.s.	n.s.
Sonar	0.073 (0.012)	-0.109 (0.015)	n.s.	n.s.	0.034 (0.013)	n.s.
GPS	0.047 (0.01)	0.023 (0.013)	0.042 (0.014)	n.s.	n.s.	-0.037 (0.012)
Computer mapping	n.s.	0.071 (0.01)	n.s.	0.034 (0.016)	0.028 (0.01)	n.s.
Number of trawl nets						
Single	-	-	-	-	0	-
Twin	0	0	0 (0)	0 (0)	-0.445 (0.058)	0
Triple	-0.238 (0.045)	-0.402 (0.057)	-0.249 (0.039)	-0.329 (0.134)	-0.401 (0.05)	0.248 (0.051)
Quad	-0.127 (0.039)	-0.192 (0.049)	-0.089 (0.031)	-0.217 (0.129)	-0.221 (0.056)	0.301 (0.053)
Five	-	-	0.117 (0.164)	-	0.022 (0.077)	0.564 (0.104)
Net size—combined	n.s.	0.258 (0.104)	0.782 (0.073)	1.213 (0.215)	0.081 (0.005)	0.291 (0.065)
Mesh size	n.s.	0.846 (0.281)	n.s.	n.s.	-1.248 (0.084)	-0.315 (0.112)
Ground gear						
Drop chain	0	0	n.s.	n.s.	0	0 (0)
Sliding rings	0.047 (0.033)	-0.079 (0.039)			0.040 (0.028)	0.006 (0.024)
Looped chain	-0.185 (0.085)	-0.129 (0.104)			0.002 (0.013)	-0.010 (0.021)
Drop rope-chain	0.254 (0.048)	-0.289 (0.06)			-0.056 (0.016)	0.055 (0.035)
Other types	-0.433 (0.328)	0.241 (0.4)			-0.127 (0.016)	-0.078 (0.029)
Chain size	n.s.	-0.229 (0.07)	n.s.	1.028 (0.257)	0.290 (0.052)	0.285 (0.058)
Otter boards						
Standard flat	0	0 (0)		0 (0)	0	0
Bison	-0.028 (0.012)	-0.024 (0.015)		0.183 (0.05)	0.056 (0.041)	-0.088 (0.032)
Louvre/Kilfoil	0.003 (0.01)	-0.044 (0.012)		0.032 (0.04)	-0.012 (0.019)	0.072 (0.015)
Other types	0.067 (0.03)	-0.187 (0.041)		-0.006 (0.115)	0.193 (0.035)	0.026 (0.031)
BRD and TED	-0.024 (0.011)	0.099 (0.013)	n.s.	0.075 (0.025)	0.127 (0.01)	0.046 (0.015)
Net—try gear	0.082 (0.024)	n.s.	0.045 (0.016)	-0.078 (0.026)	-0.051 (0.01)	n.s.

n.s. indicates the parameter was not significant ($P > 0.05$) and was excluded from the analysis. (-) Indicates the gear type was not used in that trawl sector. Response variable and continuous explanatory variables were natural log transformed.

0.0509^{1/2} = 22.6%) and 0.1951 (c.v. 44.2%), thereby accounting for a large part of the variation in vessels' annual catches.

Fishing power estimates are listed in Table 2 and show, for the period from 1989 to 2004, increases of 6% in the northern tiger, 6% in the northern endeavour, 12% in the southern tiger, 18% in the red spot king, 46% in the eastern king prawn and 15% in the saucer scallop sector. These results are described in detail in Section 3.2 below.

Higher engine power was associated with higher catches in all trawl sectors except eastern king prawn (Table 1). Examination of predicted values from the model indicated that vessels with 50 HP extra engine power generally achieved 2–8% larger average catches. The random vessel term (variance component) was largest for the eastern king prawn sector. Slower trawl speeds by (1/2) knot were associated with between 3 and 7% larger average catches of saucer scallops and red spot king prawns, respectively. Vessels installed with sonar were associated with having 7 and 3% better average catches of northern tiger and east-

ern king prawns, respectively. The effect of global positioning systems differed between trawl sectors. For tiger and endeavour prawns, vessels with GPS achieved 2–5% larger average catches, respectively. However, larger catches of red spot king prawns, eastern king prawns and saucer scallops were not correlated with GPS. Vessels fishing for endeavour, red spot king and eastern king prawns with computer mapping software, such as C-plot, made on average 3–7% larger catches. Vessels using quad nets achieved 5–23% better average prawn catches than vessels using triple gear. Generally, larger catches were associated with larger net sizes and (for eastern king prawns and saucer scallops at least) smaller mesh sizes. Drop-chain ground gear was generally used most and was associated with better than average catches. Larger ground chains, typically made from 12 mm versus the smaller 10 mm diameter steel, were associated with 5% better average catches of eastern king prawns and saucer scallops, and 20% better catches of red spot king prawns. Bison and Louvre otter-boards were generally associated with better

Table 2

Mixed linear model calculated proportional change in fishing power from 1988 to 2004 (95% confidence intervals shown in parentheses), for (A) northern tiger prawn, northern endeavour prawn, southern tiger prawn and red spot king prawn and (B) eastern king prawn (all waters, shallow waters and deep waters) and saucer scallop

(A)				
Fishing year	Northern tiger prawn	Northern endeavour prawn	Southern tiger prawn	Red spot king prawn
1988	0.956 (0.944, 0.961)	0.971 (0.954, 0.981)	0.928 (0.911, 0.937)	1.095 (1.044, 1.161)
1989	1	1	1	1
1990	0.949 (0.938, 0.958)	0.950 (0.929, 0.960)	1.074 (1.063, 1.098)	1.097 (1.026, 1.175)
1991	0.967 (0.954, 0.979)	0.983 (0.961, 0.997)	0.996 (0.984, 1.013)	1.045 (0.975, 1.108)
1992	0.963 (0.950, 0.977)	0.988 (0.971, 1.005)	1.012 (0.995, 1.034)	1.029 (0.964, 1.075)
1993	0.982 (0.967, 0.992)	0.992 (0.970, 1.007)	1.039 (1.023, 1.062)	1.144 (1.081, 1.196)
1994	0.967 (0.950, 0.979)	0.987 (0.964, 1.005)	1.054 (1.043, 1.084)	1.108 (1.055, 1.157)
1995	0.984 (0.967, 1.000)	1.013 (0.980, 1.029)	1.088 (1.079, 1.124)	1.047 (0.992, 1.093)
1996	0.975 (0.959, 0.994)	0.942 (0.912, 0.956)	1.101 (1.091, 1.144)	1.029 (0.978, 1.071)
1997	1.013 (0.992, 1.032)	1.014 (0.982, 1.033)	1.068 (1.050, 1.095)	1.045 (0.997, 1.091)
1998	0.997 (0.978, 1.015)	1.022 (0.993, 1.045)	1.046 (1.027, 1.072)	1.107 (1.050, 1.162)
1999	1.018 (0.996, 1.040)	1.065 (1.030, 1.096)	1.143 (1.121, 1.174)	1.074 (1.012, 1.124)
2000	1.041 (1.011, 1.070)	1.112 (1.061, 1.146)	1.098 (1.071, 1.125)	1.162 (1.085, 1.228)
2001	1.046 (1.018, 1.075)	1.094 (1.052, 1.135)	1.035 (1.013, 1.061)	1.089 (1.012, 1.155)
2002	1.059 (1.030, 1.088)	1.125 (1.081, 1.173)	1.089 (1.062, 1.118)	1.137 (1.059, 1.215)
2003	1.079 (1.049, 1.111)	1.132 (1.088, 1.182)	1.078 (1.052, 1.107)	1.168 (1.079, 1.256)
2004	1.060 (1.027, 1.093)	1.064 (1.023, 1.123)	1.118 (1.086, 1.158)	1.177 (1.073, 1.268)

(B)				
	Eastern king prawn: depths combined	Eastern king prawn: depths ≤50 fathoms	Eastern king prawn: depths >50 fathoms	Saucer scallop
1988	1.028 (1.017, 1.053)	0.965 (0.948, 1.006)	1.012 (0.994, 1.028)	0.975 (0.958, 0.994)
1989	1	1	1	1
1990	1.053 (1.036, 1.073)	1.073 (1.047, 1.107)	1.018 (1.003, 1.032)	1.025 (1.012, 1.038)
1991	1.062 (1.054, 1.087)	1.111 (1.096, 1.152)	0.983 (0.970, 0.998)	1.036 (1.018, 1.051)
1992	1.064 (1.053, 1.086)	1.121 (1.100, 1.156)	0.978 (0.966, 0.991)	1.038 (1.021, 1.059)
1993	1.056 (1.043, 1.079)	1.128 (1.103, 1.162)	0.960 (0.947, 0.975)	1.036 (1.014, 1.055)
1994	1.092 (1.081, 1.117)	1.114 (1.091, 1.146)	1.035 (1.026, 1.055)	1.059 (1.039, 1.084)
1995	1.116 (1.103, 1.138)	1.149 (1.123, 1.182)	1.050 (1.039, 1.067)	1.037 (1.015, 1.061)
1996	1.168 (1.158, 1.199)	1.262 (1.247, 1.320)	1.045 (1.030, 1.062)	1.082 (1.059, 1.112)
1997	1.170 (1.158, 1.204)	1.257 (1.242, 1.314)	1.051 (1.033, 1.070)	1.031 (1.007, 1.058)
1998	1.157 (1.139, 1.186)	1.236 (1.215, 1.282)	1.050 (1.027, 1.068)	1.020 (0.995, 1.046)
1999	1.205 (1.183, 1.235)	1.290 (1.261, 1.340)	1.089 (1.063, 1.107)	1.014 (0.992, 1.045)
2000	1.298 (1.271, 1.340)	1.360 (1.328, 1.434)	1.195 (1.162, 1.221)	1.029 (1.003, 1.060)
2001	1.305 (1.275, 1.351)	1.353 (1.318, 1.439)	1.209 (1.173, 1.236)	1.065 (1.035, 1.104)
2002	1.384 (1.350, 1.436)	1.397 (1.351, 1.484)	1.295 (1.256, 1.334)	1.080 (1.041, 1.125)
2003	1.401 (1.364, 1.454)	1.403 (1.358, 1.484)	1.314 (1.273, 1.356)	1.054 (1.017, 1.103)
2004	1.457 (1.423, 1.524)	1.512 (1.467, 1.621)	1.357 (1.313, 1.403)	1.149 (1.102, 1.202)

The proportion change represents the difference from the reference fishing year 1989, which was set at 1. The fishing years represent the months starting from November through to October for eastern king prawns and saucer scallops, and January through to December for tiger, endeavour and red spot king prawns.

average catches across the sectors. Vessels with a turtle excluder device and/or by-catch reduction device tended to have increased catches of endeavour prawns (10%), red spot king prawns (7%), eastern king prawns (13%) and saucer scallops (5%), but 3% smaller catches of northern tiger prawns. Vessels using try nets achieved 5–9% better catches of tiger prawns.

3.2. Estimates of fishing power

Annual increases in average relative fishing power were calculated from the mixed linear model using Eqs. (2) and (3). Changes in fishing power due to vessel upgrades were measured by the fixed effects β_2 . Changes due to evolution of each trawl sector's vessel profile were measured through the random

vessel terms (γ), and are illustrated on Fig. 2 by the difference between the overall fishing power estimate (solid line) and the fishing power estimate from the β_2 fixed effects only (dotted line).

Overall the analyses showed consistent annual increases in fishing power. The prawn sectors were influenced mostly by the changing fleet profile and their vessel power (engine rated power and propeller nozzles) and technology (sonar, global positioning systems and computer mapping) factors. For the saucer scallop sector, net configurations were more important than technology factors. Annual rates of fishing power change are presented in Table 2.

Tiger prawn fishing power in northern waters increased by 8% between 1989 and 2003. The increases were driven by higher

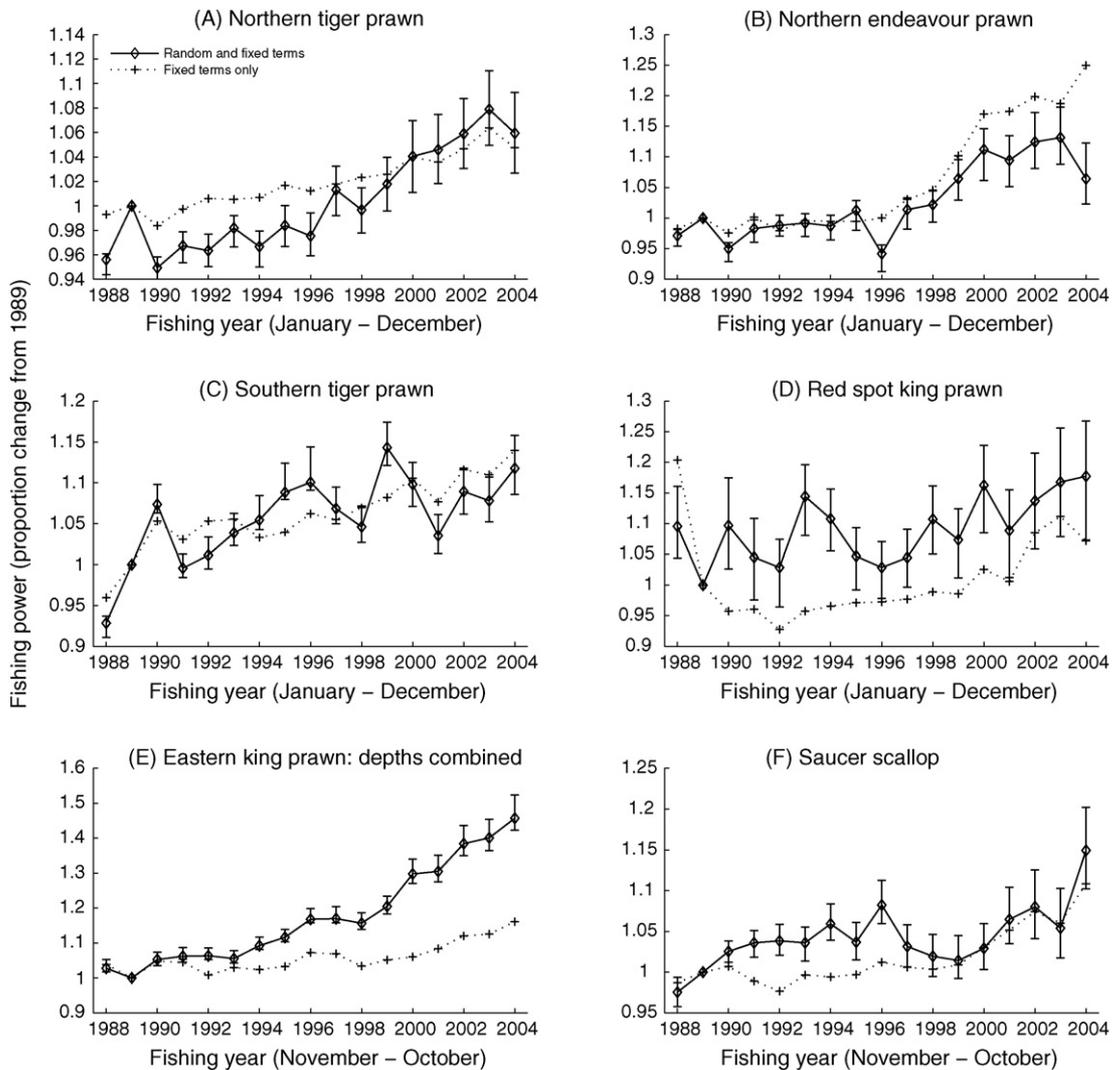


Fig. 2. (A–F) Comparison of fixed and random terms effect on the proportional change in fishing power from 1988 to 2004. The proportional change represents the difference from the reference year 1989, which was set at 1. Error bars illustrate the 95% confidence intervals.

engine power, propeller nozzles, quad net gear, Bison or Louvre/Kilfoil otter-boards, sonar and global positioning systems, together with a trend towards more efficient vessels (i.e. those with high γ -terms). The latter effect is illustrated by the overall fishing power (fixed + random effects; solid line) converging and then overtaking the fishing power corresponding to vessel upgrades (β_2 fixed effects; dotted line). The data for 2004 suggested that fishing power had decreased about 2% due to lower average engine power and less use quad gear. The noticeable 1989 spike in fishing power was due to greater than average effort by efficient vessels.

The increase in northern endeavour prawn fishing power was calculated at 13% between 1989 and 2003. Most of this fishing power increase occurred between 1996 and 2000. Over these 5 years fishing power increased by 17%. The fishing power increases were mostly driven by higher engine rated power, Bison otter-boards and computer mapping systems. The noticeable drops in the 1996 and 2004 fishing power were due to the more efficient vessels fishing fewer nights.

The results show a trend towards less efficient vessels (lower γ -terms) in the northern endeavour prawn sector (Fig. 2B, fall in solid line relative to dotted line), as compared to a trend towards more efficient vessels in the northern tiger prawn sector (Fig. 2A). These sectors are fished by similar vessels in similar waters, but tiger prawns are much more valuable. The analyses indicate that efficient fishing vessels may target tiger prawns in preference to endeavour prawns.

Tiger prawn fishing power in southern waters increased by 12% between 1989 and 2004. Increases in fishing power were associated with improvements in vessels' engine power, and increased use of quad and try trawl nets. Overall there was no trend towards more or less efficient vessels, but random vessel effects (γ -terms) did contribute extra year to year variation in fishing power.

The analysis estimated increases in fishing power at 18% between 1989 and 2004, mainly associated with two major effects within definite time periods: arrival of more efficient boats in this sector in 1990, and a substantial increase in average engine power from 2001 to 2003.

The eastern king prawn sector experienced the largest increase in fishing power. The analysis estimated increases in average annual fishing power of 51% in shallow waters, 36% in deep waters and 46% across all waters between 1989 and 2004. Most of the fishing power increases were measured through the random vessel effects (γ), which absorbed the parameters for engine rated power, trawl speed and propeller nozzle (Table 1). The results illustrate a large effect of change in fleet composition, whereby less efficient vessels have left the trawl sector, while more efficient ones remained. Also, the vessels that fished both northern tiger and eastern king prawns had expended about 15% more effort towards eastern king prawns since 2000. The use of computer mapping, sonar, quad trawl gear and by-catch reduction and turtle excluder devices were also important variables contributing to increased fishing power.

Increases in saucer scallop fishing power were 15% between 1989 and 2004. The random vessel term (γ) absorbed the fishing power effects of propeller nozzle, sonar and computer mapping, but engine rated power ($***P < 0.001$) and quad trawl gear ($***P < 0.001$) were still significant in determining fishing power increases (Table 1). The analysis also indicated that more nights of fishing were expended by the efficient vessels during the high catch years 1990–1996. Catch rates declined after 1996 and the fleet profile changed to less efficient vessels. Since 2000 fishing power increases have been driven by higher engine power and use of quad and try nets.

4. Discussion

Fishing power in the Queensland ECOTF increased substantially between 1988 and 2004. Overall the analyses show that annual changes in prawn trawl fishing power were influenced mostly by changing fleet profiles (vessels changing the number of days they fish in each trawl sector, moving between sectors or in some cases exiting the fishery altogether), upgrades to vessel power (engine power and propeller nozzles) and adoption of new technology (sonar, global positioning systems and computer mapping). Net configurations were more important than technology factors in determining saucer scallop fishing power. The results demonstrate the importance of standardising average catch rates according to changes in average annual fishing power. For example, if 1989 catch rates were standardised to 2004 fishing power they would be between 6 and 51% higher compared to the observed nominal catch rates in 1989 (Table 2). This effect is crucial for stock assessments using catch rates. It is important to note that fishing power estimates do not increase continuously but vary between years. Their influence on estimates of limit reference points such as fishing effort at maximum sustainable yield (E_{MSY}) needs to be recognised, especially in the selection of the past unit of fishing effort to use as the reference for effort creep in future stock assessments.

Our results confirm that major changes have taken place in vessel characteristics, fishing gear, navigation and communication over the last 17 years. The adoption of global positioning systems, computer mapping software and turtle excluder and by-catch reduction devices are nearing 100%. However, several technologies (e.g. new propeller designs) are yet to be adopted

universally by the trawl fleet. Further upgrades in some fleet characteristics, such as engine power and use of trawl quad-nets, can be achieved and are likely to contribute to further increases in fishing power. We also expect new technologies to emerge and be adopted in the future. In addition, each trawl sector's fleet composition will change, affecting its fishing power. Many vessels are currently exiting the fishery in the face of high fuel costs and competition from imported seafood; we expect these vessels to be both less efficient and less powerful than those that remain, contributing to an increase in the fleet's average fishing power.

Global positioning systems, although positively affecting catches in three out of the six sectors, had non-significant ($P > 0.05$) or slight negative effects in the red spot king prawn, eastern king prawn and scallop sectors. This may be due to specific features of these species and their fisheries. Red spot king prawns occur near reefs, allowing visual identification of target areas. Eastern king prawns are much more migratory than tiger/endeavour prawns, occur at much greater depths and are generally fished along narrow depth contours (as illustrated in Queensland waters in Fig. 1C). Skill to find patches of saucer scallop probably does not depend much on use of GPS.

Try gear had a positive effect on tiger and endeavour prawn catches, where its use is widespread (90–100%). However, red spot and eastern king prawn catches were negatively associated with try gear. Usage of try gear is variable and inconsistent for these species, and less common in deep water where eastern king prawns are found. Our finding of positive effects of BRDs and TEDs on catches of target species in four of the six sectors agrees with other studies (Rogers et al., 1997; Broadhurst and Kennelly, 1997; Steele et al., 2002; Courtney and Campbell, 2003). The negative relationship between trawl speed and catch in the red spot king prawn and saucer scallop sectors may show the importance of trawling at a speed that allows the fishing gear to function as designed.

Fishing power analyses can be affected by 'confounding', whereby it is impossible to determine whether a change in catch rate is due to variation in population abundance or changing fishing power. Confounding is a failing not of the analysis technique but of contrast in the data. It can happen, for example, if all vessels in a fleet undergo identical upgrades at the same time. Confounding is a major problem in Australia's Northern Prawn Fishery (NPF), where there are long seasonal closures and vessel ownership is concentrated in large corporations with similar economic motivation (Dichmont et al., 2003).

Confounding is less evident in our study of the Queensland ECOTF, which has comprised 400–900 active vessels, with about as many owners and a wide range of business strategies. Fleet upgrades usually take place over periods of many years. Nevertheless, ongoing independent data are desirable to verify abundance indices. Available data from fishery-independent surveys show good agreement with the standardised catch rates produced by this study (O'Neill and Leigh, 2006; O'Neill and Turnbull, 2006).

Linear mixed models may also find beneficial applications to other fisheries with large data sets that have evolved from many fishing operations or vessels. In our analysis they have been

especially useful in resolving changes in fleet profile that go beyond physical characteristics of the vessels. Broader aspects of their use include testing hypotheses of environment effects such as river flows or rainfall on catches (Tanimoto et al., 2006).

Acknowledgements

The Department of Primary Industries and Fisheries (DPI&F) funded the project, and we gratefully acknowledge their support. The work would not have been possible without the efforts of many people. Special thanks go to: (1) the trawler owners and skippers who provided technical details on their vessels, their fishing gears and technologies, (2) Dr. Anthony Courtney, Mr. Clive Turnbull, Ms. Cassandra Rose, Ms. Joanne Atfield, Mr. Bart Mackenzie, Mr. Chris Barber and Ms. Sarah Kistle who contributed to the survey design, logistics and data collection on vessel fishing gears and technologies and (3) Ms. Kate Yeomans and Mr. Jeff Bibby for providing the prawn and scallop catch data from the DPI&F commercial fishery compulsory daily logbook database (CFISH). Dr. Rick Officer made constructive comments on earlier versions of this manuscript. This work was reviewed by Dr. Ian Poiner (Australian Institute of Marine Science), Dr. Bill Venables (Commonwealth Scientific and Industrial Research Organisation) and Dr. Nick Rawlinson (Australian Maritime College), who all have researched Australia's Northern Prawn Fishery. We also thank the two anonymous journal reviewers for their valuable comments.

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Appendix II: Linking spatial stock dynamics and economics: evaluation of indicators and fishery management for the travelling eastern king prawn (*Melicertus plebejus*)



Linking spatial stock dynamics and economics: evaluation of indicators and fishery management for the travelling eastern king prawn (*Melicertus plebejus*)

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O'Neill, M. F., Leigh, G. M., Wang, Y.-G., Braccini, J. M., and Ives, M. C. Linking spatial stock dynamics and economics: evaluation of indicators and fishery management for the travelling eastern king prawn (*Melicertus plebejus*). – ICES Journal of Marine Science, doi:10.1093/icesjms/fst218.

Received 22 August 2013; accepted 16 November 2013.

Reduced economic circumstances have moved management goals towards higher profit, rather than maximum sustainable yields in several Australian fisheries. The eastern king prawn is one such fishery, for which we have developed new methodology for stock dynamics, calculation of model-based and data-based reference points and management strategy evaluation. The fishery is notable for the northward movement of prawns in eastern Australian waters, from the State jurisdiction of New South Wales to that of Queensland, as they grow to spawning size, so that vessels fishing in the northern deeper waters harvest more large prawns. Bioeconomic fishing data were standardized for calibrating a length-structured spatial operating model. Model simulations identified that reduced boat numbers and fishing effort could improve profitability while retaining viable fishing in each jurisdiction. Simulations also identified catch rate levels that were effective for monitoring in simple within-year effort-control rules. However, favourable performance of catch rate indicators was achieved only when a meaningful upper limit was placed on total allowed fishing effort. The methods and findings will allow improved measures for monitoring fisheries and inform decision makers on the uncertainty and assumptions affecting economic indicators.

Keywords: Australia, catch rate standardization, economic indicators, management strategy evaluation, prawns, spatial stock assessment.

Introduction

In many fisheries globally, challenging economic conditions have moved management agencies towards monitoring indicators for profit alongside traditional indicators for biological sustainability. The Australian eastern king prawn is one such fishery in which economic performance has only in recent years become a concern.

The eastern king prawn (EKP, *Melicertus plebejus* or *Penaeus plebejus*) is a major component of otter trawl fishing along the east coast of Australia. The EKP is largely spatially separated from other target species, exists primarily in subtropical waters and extends across two

jurisdictions belonging to the States of New South Wales (NSW) and Queensland (Figure 1). The otter trawl fishery harvests ~ 3000 t of EKP annually, with a landed value in excess of AUD\$40 million. In addition to EKP, licensed vessels within each jurisdiction are free to direct their fishing effort towards other permitted species.

The jurisdictions currently manage their sectors independently using a range of input controls including limited vessel entry, boat-day/effort-unit allocations, vessel and gear size restrictions, and spatial/seasonal closures. Separate management regimes operate despite strong stock connectivity, whereby EKP travel large distances

from New South Wales and inshore Queensland waters to deep waters (>90 m) off Queensland as individuals grow to spawning size (Montgomery *et al.*, 2007; Lloyd-Jones *et al.*, 2012; Braccini *et al.*, 2012b). In 2010, ~ 600 vessels were licensed to fish EKP and other important Penaeid prawns and saucer scallop. Of these vessels, about 150 did not fish or harvest EKP. Spatially restricted licences were also granted to 24 New South Wales vessels to fish Queensland waters north to Fraser Island (Figure 1).

Even with the trawl fishery input controls, recent years of higher trawling costs and constant or falling product prices have reduced both profit and fishing effort (Figure 2). Over the whole mixed-species fishery, a substantial fraction of the fishing effort capacity may be economically unviable (Ives *et al.*, 2013).

The reduced economic conditions have focused EKP industry and management on developing strategies to maximize economic performance, rather than promoting maximum sustainable yield (MSY) as suggested by an earlier evaluation of this fishery (O'Neill *et al.*, 2005). These economic conditions influenced the Queensland 2010–2011 trawl management review of biological, economic and social objectives (Pascoe *et al.*, 2013; Dichmont *et al.*, 2013). In order to improve fishing profits, additional management measures were discussed, including further effort control and seasonal closures with options for in-season management based on catch rate reference points.

Fishing for EKP has fared better economically than other trawl species, and the EKP stock had experienced record levels of harvest in Queensland waters (Figure 2). This is partly due to the large size of mature EKP providing an export and domestic market niche over smaller prawn species. Also EKP fishing in Queensland occurs close to major markets and to saucer scallop (*Amusium balloti*) grounds that the same vessels can pulse-fish for some of the year. Finally, Queensland vessels may have benefited from recent declines in EKP harvest and fishing effort in New South Wales (Figure 2).

In this paper, in the light of current economic circumstances and record harvests, we apply both a length-structured spatial population model and an economic model to assess the fishing pressure, quantify economic performance and update reference points for the EKP fishery. We also use the models to evaluate stakeholder-suggested management procedures through simulation.

Reference points are key tools for indicating the state of a fishery. They can be based on measures such as catch rates or modelled stock biomasses. But their development is often complex, relying on numerical analyses and accurate data to index population abundance (Hilborn, 2002). Model-based reference points such as MSY and the corresponding fishing effort for MSY (E_{MSY}) have been reported for many prawn fisheries in Australia (Dichmont *et al.*, 2001; O'Neill *et al.*, 2005; O'Neill and Turnbull, 2006). Empirical reference points, which are data-based rather than model-based, have typically been used in prawn fisheries for status reporting and not management (NSW Department of Primary Industries, 2010; Fisheries Queensland, 2013). A notable exception was South Australia's Spencer Gulf Prawn Fishery, where fishery-independent survey catch rates were used to adaptively change spatial and seasonal closures to match resource availability (Dixon and Sloan, 2007). For EKP, empirical catch-rate-limit reference points were implemented for status reporting in Queensland in 1999 (O'Neill *et al.*, 2005) and in New South Wales in 2006 (NSW Department of Primary Industries, 2006), but have not been validated and may be unrelated to sustainable stock levels or economics.

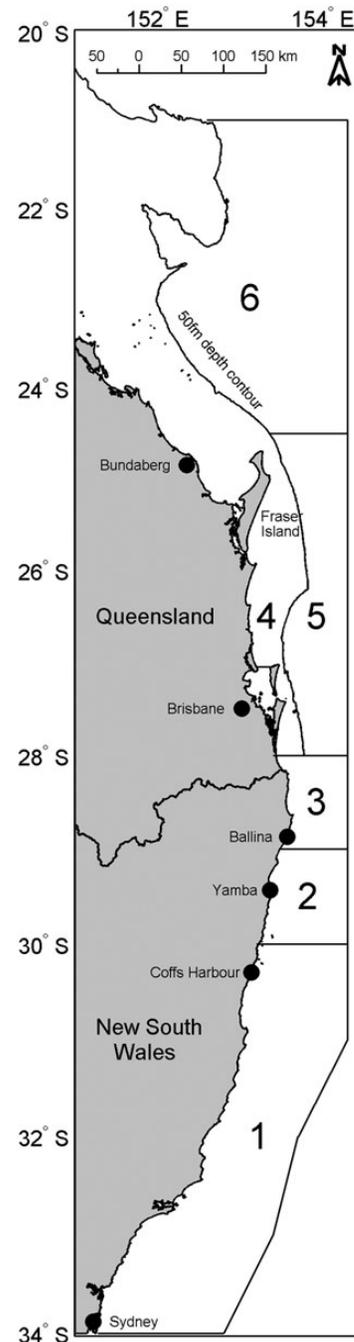


Figure 1. Map of the Australian eastern king prawn fishery zoned by analysis regions 1 to 6. Queensland region 4 covered water depths less than 50 fathom (≈ 90 m) and excluded pre-oceanic-recruits from estuaries, Moreton Bay (adjacent to Brisbane) and Fraser Island north. Queensland regions 5 and 6 covered water depths equal to or greater than 50 fathom. Management and fishing gear were not defined by water depths in New South Wales (regions 1 to 3); region 1 also included minor harvests taken south of Sydney to about 37°S.

A reference-point policy of including vessel-based economics to calculate maximum economic yield (MEY) as a preferred objective to MSY was first introduced into Australian Government fisheries in 2007 (Australian Government, 2007). This was applied to the Northern Prawn Fishery across tropical waters of the Northern Territory and the Gulf of Carpentaria (Punt *et al.*, 2010).

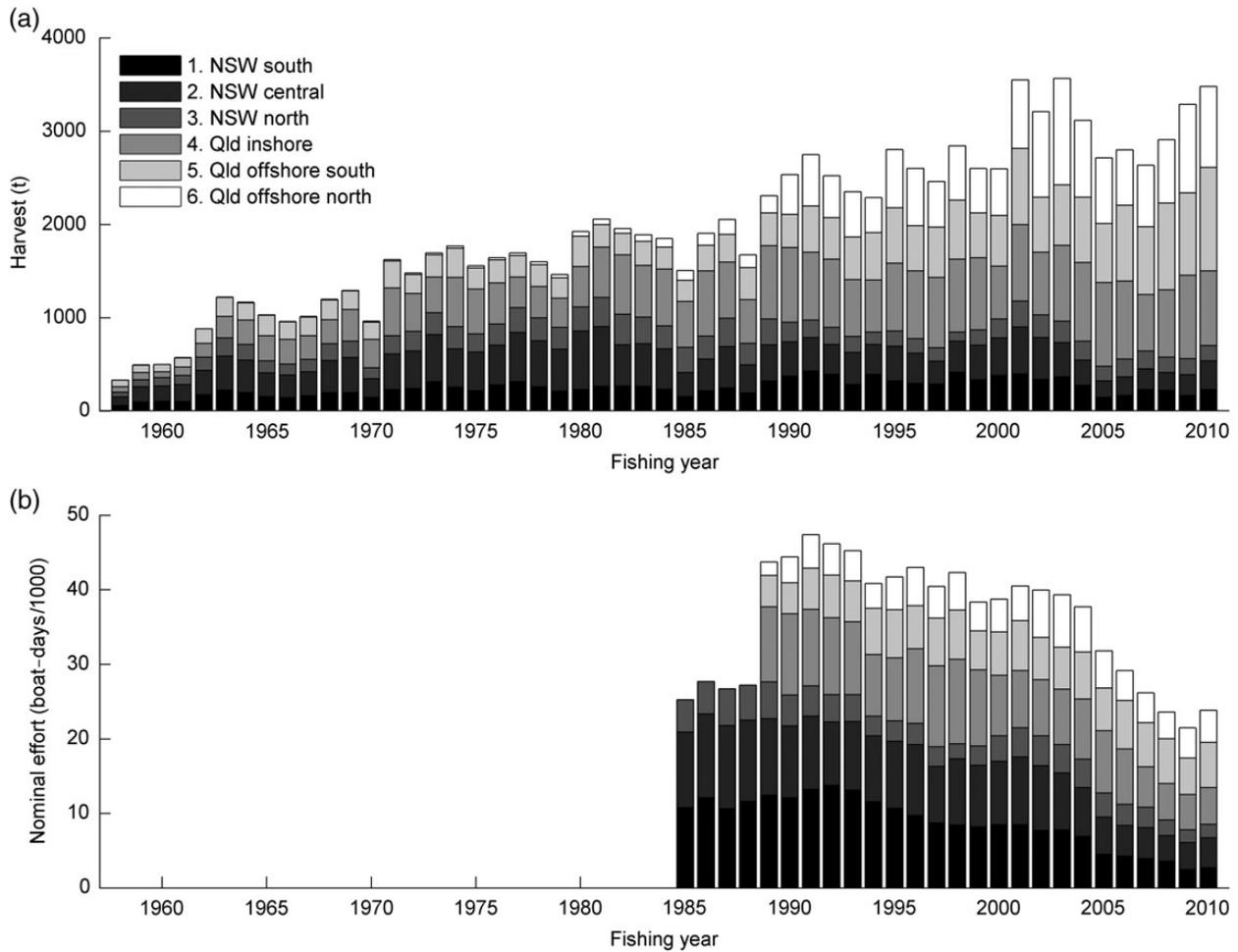


Figure 2. Summary fishery statistics for eastern king prawn (a) harvest, and (b) fishing effort from New South Wales (NSW) and Queensland (Qld) waters. No records on total fishing effort were available before 1985 and 1989 fishing years from NSW and Qld, respectively.

The current study is the first to quantify empirical reference points for the combined New South Wales and Queensland EKP fishery, and the first to quantify economic indicators for the combined fishery. This study also demonstrates the benefits of model testing of indicators and reference points in fisheries science, and highlights important considerations for economic management.

Methods

Commercial harvest data

Data were stratified by six fishing regions across New South Wales (NSW) and Queensland (Qld) State waters (Figure 1). From south to north the regions were defined and labelled as (1) NSW South (waters south of 30°S), (2) NSW Central (between 29°S and 30°S), (3) NSW North (between 28°S and 29°S), (4) Qld Inshore [< 50 fathom, (~ 90 m), water depths, between 21°S and 28°S], (5) Qld Offshore South (≥ 50 fathom water depths, between 24.5°S and 28°S), and (6) Qld Offshore North (≥ 50 fathom water depths, between 21°S and 24.5°S latitude). Juveniles harvested from estuaries, Moreton Bay and Fraser Island north were excluded. Fishing years were defined and labelled from month November (1) to October (12).

Historical harvests of EKP date back to the early 1900s. Harvests were small (< 200 t) until the 1950s, and we assumed year 1958 to be the commencement of significant fishing mortality.

Monthly harvests from 1958–2010 were reconstructed from four data sources: (i) NSW monthly fisher catch returns from 1958–1983, (ii) NSW monthly commercial logbooks from 1984–2010, (iii) Queensland Fish Board annual records from 1958–1980, and (iv) Queensland daily commercial logbooks 1988–2010.

NSW prawn harvest records from 1958–1978 aggregated species and regions. The proportion comprising EKP was separated based on information presented in Annual NSW Fisheries Reports with a base value of 20% given for the years from 1900–1957, and 42% observed in 1979. Hence, EKP was separated assuming a 1% annual increase starting from 21% in 1958 through to 41% in 1978. Regional harvests from 1958–1978 were disaggregated assuming an historical split of 29% for region 1, 47% for region 2, and 24% for region 3 based on the average for these regions between 1979 and 1989. All NSW regional EKP harvests were identifiable from 1979.

Queensland prawn harvests from 1958–1980 also aggregated species, but provided a spatial breakdown by fishing port. We used records from the port of Bundaberg south to the Queensland/NSW state border. The harvests were partitioned into species by removing Moreton Bay harvests ($\approx 38\%$ tonnage) and then assuming an EKP species proportion of 80%. From 1989–2010, Queensland EKP harvests were tallied from compulsory commercial logbooks. Missing records on total annual EKP harvest between 1981 and 1988 were estimated from log-linear regression using 1958–1980 and 1989–2010

annual estimates (adjusted $R^2 = 0.86$). Queensland EKP landings from 1958–1988 were expanded regionally and monthly based on Poisson generalized linear modelling of harvest patterns using 1989–1994 data. A log link was used on catch weight, and dispersion was estimated; the model terms were region \times month + region \times fishing year (adjusted $R^2 = 0.64$). Normal random uncertainty error of 0.26 (standard deviation implied from GLM analysis) was propagated monthly from 1958–1988.

Standardized commercial catch rates

Three catch rate analyses were conducted on New South Wales and Queensland logbook data (Table 1). Analyses 1 and 2 were for Queensland and analysis 3 for NSW. Analyses 1 and 3 were based on whole-fleet compulsory catch reports. Analysis 2 was on Queensland pre-1989 EKP catch rate data from voluntary logbook databases (O'Neill et al., 2005; O'Neill and Leigh, 2006).

The analyses were linear mixed models (REML) with normally distributed errors on the log scale (GenStat, 2011). They included both fixed ($X\beta$) and random ($Z\gamma$) terms, and followed the methods and terminology of O'Neill and Leigh (2007) and Braccini et al. (2012a). Where data ($X_1, X_2, X_3, X_4, X_5, Z_1, Z_2$) were relevant and available, the models were fitted to estimate the following parameter effects:

- scalar model intercept β_0 ,
- abundance β_1 for data X_1 (three-way interaction, fishing year \times month \times region),
- vessel gear β_2 for data X_2 (log engine rated power, propeller nozzle, GPS, net type, log net length \times region interaction, log mesh size, ground gear type, otter board type, BRDs and TEDs, and use of try-gear net.
- lunar phase β_3 for data X_3 (for luminance and luminance shifted 1/4 phase),
- fishing effort β_4 for data X_4 (log hours for Queensland daily catches, log days for NSW monthly catches),

Table 1. Linear mixed models (REML) used to standardize catch rates from New South Wales (NSW) and Queensland (QLD).

Analysis 1	QLD: regions 4–6 and years 1989–2010.
Response:	$\log(\text{kgs boat}^{-1} \text{ day}^{-1})$
Fixed terms:	$\beta_0 + X_1\beta_1 + X_2\beta_2 + X_3\beta_3 + X_4\beta_4$
Random terms:	$Z_1\gamma_1 + Z_2\gamma_2$
Offset:	—
Predictions:	β_1
Analysis 2	QLD: regions 4–6 and years 1969–1988.
Response:	$\log(\text{kgs boat}^{-1} \text{ day}^{-1})$
Fixed terms:	$\beta_0 + X_1\beta_1 + X_3\beta_3 + X_4\beta_4$
Random terms:	$Z_1\gamma_1 + Z_2\gamma_2$
Offset:	Backward linear extrapolation of deep and shallow water EKP log fishing power from β_2 in analysis 1.
Predictions:	β_1
Analysis 3	NSW: regions 1–3 and years 1984–2010.
Response:	$\log(\text{kgs boat}^{-1} \text{ month}^{-1})$
Fixed terms:	$\beta_0 + X_1\beta_1 + X_4\beta_4 + X_5\beta_5$
Random terms:	$Z_1\gamma_1$
Offset:	Combined deep- and shallow-water EKP log fishing power from β_2 analysis 1, and 1984–1988 linearly hind casted.
Predictions:	β_1

- by-catch β_5 for data X_5 (log of NSW school whiting catch + 0.001 kg),
- vessel efficiency random effects γ_1 for vessel identifiers Z_1 , and
- location random effects γ_2 for fishing logbook grid-square identifiers Z_2 .

Analysis 1 was completed with fishing power data X_2 for β_2 . For analyses 2 and 3, the fishing power data X_2 were not available. Therefore the β_2 fishing power effect was not estimated but was inserted as an offset (Table 1). The offset was the estimated log fishing power β_2 for deep and shallow water EKP from analysis 1, with linear trends hind cast for 1969–1988 (fishing power fixed terms only; Braccini et al., 2012a). Because NSW catches were reported monthly, no lunar β_3 or location effects γ_2 could be fitted in analysis 3. Also, the corresponding NSW school whiting (*Sillago robusta* and *S. flindersi*) catch effect was estimated to adjust for logbooks combining monthly effort for EKP and these alternative target species; this targeting/logbook effect was not present in Queensland waters (regions 4 to 6).

Standardized catch rates were predicted from the term β_1 , which provided a relative abundance estimate for each fishing year, month and region. No predictions were formed for missing month or region terms. The GenStat procedure “vpredict” was used to calculate monthly standardized catch rates equivalent to 2010 fleet fishing power in each region. For NSW catch rate analysis 3, predicted catch rates were scaled equivalent to when EKP was the primary target species landed. Queensland EKP analysis 2 standardized monthly catch rates were estimated only where 30 or more fishing days were recorded in a month and region; lower numbers of fishing records exhibited too much variability.

Standardized survey catch rates

Independent surveys of EKP recruitment abundance in region 4 were conducted in the fishing years 2000 and 2007–2010. The surveys monitored juvenile EKP catch rates in Moreton Bay and other prime coastal recruitment waters in Queensland. Between 200 and 300 beam trawl samples were conducted in each sampling year (Courtney et al., 2002; Fisheries Queensland, 2007; Courtney et al., 2012).

Individual beam trawl catches, measured in numbers of prawns, were analysed using a Poisson generalized linear model with log link and estimated dispersion (McCullagh and Nelder, 1989; GenStat, 2011). The explanatory factors were sampling area (two areas within Moreton Bay, plus three ocean areas), month (September to December) and fishing year. Within each sampling area, the trawl swept area changed very little over the fishing years; it was tested statistically, was non-significant and excluded from the model. The mean standardized catch between fishing years was used as a recruitment index.

Size composition data

Two datasets on size structure were used: (i) carapace length frequencies and (ii) commercial size-grade frequencies. Together, these two datasets quantified regional and monthly changes in EKP size.

Carapace-length frequencies were recorded by scientists on board commercial fishing vessels. Each prawn was sexed and measured to 1 mm length classes. From NSW, summaries of monthly length frequencies were provided for a continuous 24-month

period (1991–1992, regions 1 to 3). Length frequencies from Queensland waters were measured sporadically (region 4: November and December 1990, and October 2001; region 5: June and July 1993, and July 2002; region 6: January 2009).

Five vessels operating in Queensland waters provided at-sea EKP size grading data. The grading data were recorded between September 1997 and December 2008 from the deep northern waters of the fishery (region 6). The grading categories classified prawn sizes (number of prawns per pound; heads-on and sexes combined), which were sorted into 5-kg boxes. In total, 136 monthly size-grade frequencies were tallied from 329 612 boxes and 10 947 boat-days of fishing. Size grade had seven categories: (1) $> 30 \text{ lb}^{-1} \approx 1\text{--}27 \text{ mm}$ carapace length, (2) $21\text{--}30 \text{ lb}^{-1} \approx 28\text{--}33 \text{ mm}$,

(3) $16\text{--}20 \text{ lb}^{-1} \approx 34\text{--}37 \text{ mm}$, (4) $10\text{--}15 \text{ lb}^{-1} \approx 38\text{--}43 \text{ mm}$, (5) $8\text{--}10 \text{ lb}^{-1} \approx 44\text{--}47 \text{ mm}$, (6) $6\text{--}8 \text{ lb}^{-1} \approx 48\text{--}53 \text{ mm}$ and (7) $< 6 \text{ lb}^{-1} \approx 54\text{--}75 \text{ mm}$. Soft and broken prawns, classified as an additional category, were infrequent and not analysed. No independent data were available to assess the accuracy of the at-sea commercial EKP size grading, but the same data were acceptable to processors to determine price paid to fishers. Larger prawns fetched a higher price for the same weight. Similar prawn boxes (3 kg) have been validated as a reasonable measure for tiger prawn lengths in the Northern Prawn Fishery (O'Neill *et al.*, 1999).

Economic data

The mean landing prices for EKP by size-grade were sourced from the NSW Sydney fish market and a Queensland processor representative. The price data were re-categorized by carapace length (Figure 3). The average by-product value per boat day by region (Table 2) was calculated using logbook harvests for the scyllarid lobsters, cephalopods and school whiting from New South Wales, and scyllarid lobsters, cephalopods, portunid crabs and saucer scallop from Queensland.

Vessel cost parameters (means and variances), other than fuel, were based on questionnaire responses from 24 vessel owners from the Queensland fishery (Table 2). The average fishing capacity of the vessels in the economic sample was very similar to the whole Queensland 2010 fleet as determined from vessel survey and logbook data (O'Neill and Leigh, 2007; Braccini *et al.*, 2012a). For example, the average vessel length was 17.0 m for the sample vs. 17.5 m for the Queensland fleet. Average costs in NSW were adjusted for the smaller average vessel size there.

Queensland fuel cost (c_F) means and variances were calculated using 2010 regional fuel use data (O'Neill and Leigh, 2007; Braccini *et al.*, 2012a) and average net diesel fuel price paid after subsidies of $\$0.85 \text{ litre}^{-1}$ (ABARES, 2011). Fuel costs (c_F) for New South Wales were based on Queensland inshore vessels (region 4), again adjusted down for the smaller average vessel size in NSW.

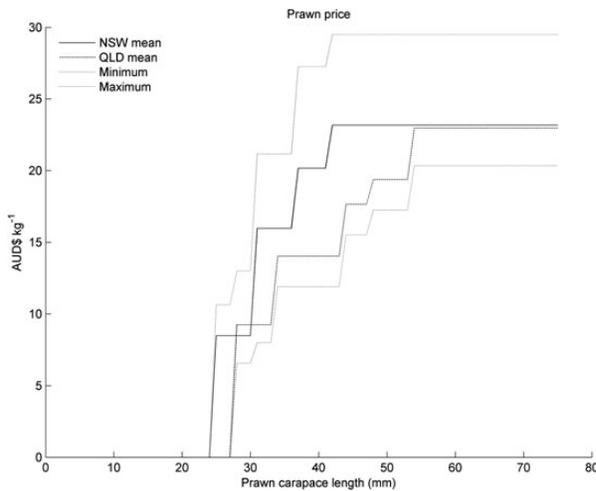


Figure 3. Mean eastern king prawn landing-prices (AUD\$ kg⁻¹) by prawn length and State. The minimum and maximum values indicate monthly variation, with higher prices around December and lower prices around June.

Table 2. Input parameter values and their 95% confidence intervals for the economic model.

Parameters	New South Wales	Queensland
Variable costs:		
Labour (c_L : proportion of catch \$)	0.29 (0.2:0.39)	0.29 (0.2:0.39)
Packaging (c_M : \$ kg ⁻¹)	0.41 (0.28:0.54)	0.41 (0.28:0.54)
Repairs (c_R : \$ boat-day ⁻¹)	288.63 (201.26:415.74)	407.46 (320.82:520.1)
Fuel (c_F : \$ boat-day ⁻¹)	Reg. 1 526.79 (476.8:576.37)	Reg. 4 546.35 (494.58:597.76)
Fuel (c_F : \$ boat-day ⁻¹)	Reg. 2 526.4 (476.99:575.11)	Reg. 5 563.1 (512.04:615.42)
Fuel (c_F : \$ boat-day ⁻¹)	Reg. 3 526.11 (477:576.45)	Reg. 6 760.19 (708.98:812.81)
Incidentals (c_O : \$ boat-day ⁻¹)	44.26 (22.98:65.98)	44.26 (22.98:65.98)
Annual fixed costs:		
Vessel costs (W_j : \$ boat ⁻¹)	28637 (23608:34769)	46170 (39403:53998)
Total investment (K_j : \$ boat ⁻¹)	255330 (191910:338710)	673590 (551810:817980)
Proportion allocated to EKP (ρ)	0.5 (0.4:0.6)	0.67 (0.57:0.76)
Revenue from by-product:		
Catch value (B_j^{by} : \$ boat-day ⁻¹)	Reg. 1 195.91 (182.15:209.65)	Reg. 4 221.89 (86.7:349.14)
	Reg. 2 211.42 (177.06:244.26)	Reg. 5 122.26 (52.08:192.01)
	Reg. 3 112.87 (100.99:124.95)	Reg. 6 62.91 (2.73:122.84)
Annual fishing effort:		
Mean number of days boat-year ⁻¹ (\bar{d})	42 (33:52)	74 (66:83)
Annual economic rates:		
Interest rate (i)	0.05 (0.034:0.072)	0.05 (0.034:0.072)
Opportunity cost (o) = i		
Depreciation rate (d)*	0.02 (0.02:0.037)	0.02 (0.02:0.037)

*Uniform variation was assumed between lower and upper confidence intervals.

Operating model

The population dynamic model had a monthly time step and tracked numbers (N) and biomass (B) of prawns by their sex (s), length (l) and spatial region (r) (Tables 3 and 4), and included the processes of mortality, growth, movement and recruitment in every month (t). The model was run in two phases: (i) historical estimation of the EKP stock from 1958–2010, and (ii) simulations of EKP parameter values and uncertainty to evaluate reference points and management procedures.

Model parameters were estimated by calibrating the model to regional standardized catch rates and size-composition data (Table 5). Primary importance was placed on fitting the standardized catch rates (Francis, 2011). Effective sample sizes for scaling multinomial likelihoods were calculated within the model in order to give realistic weighting to the size composition data. Due to the relatively uninformative (flat) annual trend in EKP catch rates from NSW (regions 1 to 3), a penalty function was included to prevent unrealistically large population estimates and low estimates of harvest rate. Likelihood functions were also used for stock-recruitment steepness (h), natural mortality (M) and annual recruitment variation (η) (Table 6). The estimation process was conducted in Matlab® (MathWorks, 2013), and consisted of a maximum likelihood step followed by Markov Chain Monte Carlo sampling (MCMC). The MCMC used a multivariate vector-jumping Metropolis-Hastings algorithm described by Gelman et al. (2004), with 110 000 samples run to estimate the parameter covariance matrix and customize the vector jumping to ensure acceptance ratios of about

0.2 (Roberts et al., 1997). A further two million samples were run with fixed covariance. Parameter distributions were based on 1000 posterior samples thinned from the last two million simulations. The “coda” package of the software R was used to analyse and confirm MCMC convergence (Plummer et al., 2012).

Economic model and parameters

The economic model calculated net present value (NPV) based on total discounted profit theory (Ross, 1995). The NPV objective function used geometric discounting that summed profits over future model projections:

$$NPV = \sum_{y=1}^{\infty} a^y \pi_y$$

where $a = (1 + i)^{-1}$, i was the annual interest (discount) rate and π_y was the profit during year y . To avoid model projections over many years, the NPV was truncated to a terminal year T and equilibrium was assumed thereafter:

$$NPV = \sum_{y=1}^{T-1} a^y \pi_y + a^{T-1} i^{-1} \pi_T.$$

This NPV function differs from formula (13) of Punt et al. (2010), in that we have consistently discounted annual profits back to the start of the first projection.

Table 3. Equations used for simulating EKP population dynamics (for notation, Table 4).

Monthly population dynamics	Equations
Number of prawns: $N_{l,r,t,s} = \exp(-M) \sum_r T_{r,r',t-1} \sum_s \Xi_{l,l',r',t-1,s} (1 - v_{l',r'} u_{r',t-1}) N_{l',r',t-1,s} + 0.5R_{l,r,t}$	(1)
Recruitment number—Beverton – Holt formulation: $R_{l,r,t} = \frac{E_{y-1}}{\alpha_r + \beta_r E_{y-1}} \exp(\eta_y) \phi_{r,t} \Lambda_{l,r}$ where y indicated the fishing year.	(2)
Spawning index—annual number of eggs: $E_y = \sum_t \sum_r \sum_l N_{l,r,t,s} m_{l,r} f_l \theta_r$	(3)
Recruitment pattern—normalized monthly proportion: $\phi_{r,t} = \exp[\kappa \cos\{2\pi(t - \mu)/12\}] / \sum_{t'=1}^{12} \exp[\kappa \cos\{2\pi(t' - \mu)/12\}]$ where t indicated time-of-year months 1...12.	(4)
Midmonth exploitable biomasses—forms 1 and 2: $B_{r,t}^1 = \sum_l \sum_s N_{l,r,t,s} w_{l,s} v_{l,r} \exp(-M/2)$ $B_{r,t}^2 = \sum_l \sum_s N_{l,r,t,s} w_{l,s} v_{l,r} \exp(-M/2) (1 - u_{r,t}/2)$	(5)
Harvest rate: $u_{r,t} = C_{r,t} / B_{r,t}^1$ where C was a region’s monthly harvest kilograms.	(6)
Prawn vulnerability to fishing: $v_{l,r} = \frac{1}{1 + \exp(\delta(l_r^{50} - l))}$	(7)
Fishery data indicators—catch rates: Fishery (f ; kg boat-day ⁻¹): $c_{r,t}^f = q_r^f(t) B_{r,t} \exp(\epsilon_{r,t}^f)$ Survey (s ; number trawl-shot ⁻¹): $c_{r=4,y}^s = q_4^s \bar{R}_{4,y(1,2)} \exp(-M/2) \exp(\epsilon_{4,y}^s)$ for $r = 4$, fishing months = Oct and Nov	(8)

Table 4. Definitions and values for the population model parameters.

Model parameters	Equations, values and errors	Notes
Assumed		
T	$p_{4 \rightarrow 6} = p_{4 \rightarrow 5} \frac{\exp(\rho)}{1 + \exp(\rho)}$, where ρ was an estimated logit variable.	The values and errors were calculated from published research or data. Transition probability matrix (6×6) for moving EKP between regions $r' \rightarrow r$. The matrix was calculated by aggregating finer scale probabilities to produce an approximate Markov process at the larger region scale (Braccini et al., 2012b). Tag-recapture data was too limited to quantify northern EKP transitions from region 4 to 6. This probability was estimated to be proportional to the region 4 to 5 transition. Twelve matrices were used to vary movement by time-month t .
Ξ	lat = [-32.0, -29.5, -28.5, -26.5, -26.5, -23] $\sigma_{\text{male}} = 2.069$; $\sigma_{\text{female}} = 2.277$	Growth transition matrix allocated a proportion of EKP in carapace length-class l' at time $t - 1$ to grow into a new length l over one time-month t . The transitions varied with prawn sex s , region r and month t , and assumed a normal probability density function (Sadovy et al., 2007; O'Neill et al., 2010; Punt et al., 2010). The growth model was based on the latitudinal and seasonal estimates of EKP (Lloyd-Jones et al., 2012). Their k and θ_1 parameters were rescaled per degree of latitude and month. The parameter "lat" specified the degree latitude for each region and σ were the standard deviations of the monthly growth increment, in millimetre.
Λ	Summary percentiles [2.5 25 50 75 97.5] = 13, 18, 22, 27 and 35 mm.	Proportion of EKP recruitment in length class l (1...75 mm). The proportions were calculated from a lognormal distribution for length at recruitment, based on region 4 monitoring data in fishing years 2000 and 2007–2010. The frequencies were approximately equal for male and female EKP (Courtney et al., 2002).
w	$w_{l,s} = a_s l^{b_s} / 1000$, $a_{\text{male}} = 0.0017$, $b_{\text{male}} = 2.7005$, $a_{\text{female}} = 0.0021$, $b_{\text{female}} = 2.6333$	Average EKP weight (kg) at length l for sex s (Courtney, 1997).
f	$f_l = 10^{(a+l b)}$ $a = 0.0199$; $b = 4.7528$	Fecundity (egg production) at length per female EKP (Courtney, 1997; Montgomery et al., 2007).
m	Summary of maturity schedule: $l_{50} = 38$; $l_{95} = 45$ for $r = 3, 5, 6$ $l_{50} = 40$; $l_{95} = 45$ for $r = 1, 2, 4$	Logistic maturity schedule by carapace length (mm) and region. The schedule was estimated using binomial regression and logit link, $m \sim \text{Constant} + \text{Year} + \text{Month} + \text{Region}/\text{Length}$; adjusted $R^2 = 0.746$. The GenStat model terms Year, Month and Region were factors, while Length was a variate.
θ	$\theta = [0.15, 0.33, 0.6, 0.6, 0.6, 0.75]$	Proportion of EKP spawning by region (Montgomery et al., 2007).
Estimated		
ξ and Y_r	$n = 76$ $\alpha_r = E_0(1 - h)/(4hR_{0,r})$ $\beta_r = (5h - 1)/(4hR_{0,r})$ $R_{0,r} = \exp(Y_r) \times 10^8$ $h = \exp(\xi)/1 + \exp(\xi)$	The values and their variances and covariances were estimated. Five parameters for the Beverton–Holt spawner-recruitment equation 2 (Table 3), that defined α and β (Haddon, 2001). Virgin recruitment (R_0) was estimated on the log scale separately for regions 1 to 4 in 1958. One estimated logit value of steepness (h) was assumed for the EKP stock, according to log-likelihood equation 12 (Table 6). E_0 was the calculated overall virgin egg production.
μ and κ	μ_r for each region 1 to 4. κ_1 for regions 1 to 3 (New South Wales). κ_2 for region 4 (Queensland).	Six parameters for the estimated mode (μ) and concentration (κ) of the monthly (time-months 1...12) recruitment patterns, equation 4 (Table 3); according to a von Mises directional distribution (Mardia and Jupp, 2000).
l^{50} and δ	l_1^{50} for region 1. l_2^{50} for regions 2 to 4. l_3^{50} for regions 5 and 6.	Four parameters for the estimated logistic vulnerability, equation 7 (Table 3). δ governed the initial steepness of the curve and l^{50} was the length at 50% selection by region.
M	Normal prior distribution	One parameter for instantaneous natural mortality month ⁻¹ , according to log-likelihood equation 13 (Table 6). The prior distribution allowed for two to three years longevity (Lloyd-Jones et al., 2012), and values around those used in previous EKP modelling (Lucas, 1974; O'Neill et al., 2005). Ives and Scandol (2007) summarized estimates of EKP M ranging from 0.13–0.35, with values ≥ 0.24 possibly biased upwards (Glaister et al., 1990).
ρ	See variable T	One parameter for calculating EKP movement from region 4 to 6.
ζ	$\boldsymbol{\eta} = \boldsymbol{\zeta} \mathbf{e}$ $\mathbf{e} = \text{zeros}(\text{nparResid}, \text{nparResid} + 1)$; for $i = 1:\text{nparResid}$ $\text{hh} = \text{sqrt}(0.5 * i ./ (i + 1))$; $\mathbf{e}(i, 1:i) = -\text{hh} ./ i$; $\mathbf{e}(i, i + 1) = \text{hh}$; end ; $\mathbf{e} = \mathbf{e} ./ \text{hh}$;	Recruitment parameters to ensure log deviations sum to zero with standard deviation σ , equation 14 (Table 6). $\boldsymbol{\zeta}$ were the 52 estimated parameters known as barycentric or simplex coordinates, distributed $NID(0, \sigma)$ with number $\text{nparResid} = \text{number of recruitment years} - 1$ (Möbius, 1827; Sklyarenko, 2011). \mathbf{e} was the coordinate basis matrix to scale the distance of residuals (vertices of the simplex) from zero (O'Neill et al., 2011).

Continued

Table 4. Continued

Model parameters	Equations, values and errors	Notes
$q_r^f(t)$ and q_4^s	$q_r^f(t) = \exp\left(\log(q_r^f) - s(\cos(t) + \vartheta_r \sin(t))/\sqrt{1 + \vartheta_r^2}\right)$ $t = 2\pi \text{ seqmonth}/12$	Fishery catchability was based on a sinusoidal function to model monthly patterns using the variable 'seqmonth'. As the maximum water temperature was in February, seqmonth = 1 in March and = 12 in February. The equation controlled the amplitude (s) of catchability across regions, but allowed for different peaks (ϑ_r) (7 parameters estimated). The equation was divided by a square root term to ensure the parameters were not periodic. Each region's overall catchability q_r^f was calculated as closed-form mean estimates of standardized catch rates divided by the midmonth biomass form2 (Table 3) (Haddon, 2001). Survey catchability was a single closed-form mean of standardized survey catch rates divided by region 4 recruitment adjusted by $\exp(-M/2)$.

Table 5. Negative log-likelihood functions for calibrating population dynamics.

-LL functions for:	Theory description	Equations
Log standardized catch rates (c^f or c^s): $\frac{n}{2}(\log(2\pi) + 2\log(\hat{\sigma}) + 1)$, or simplified as $n \log(\hat{\sigma})$, where $\hat{\sigma} = \sqrt{\sum (\log(c) - \log(\hat{c}))^2 / n}$ and n was the number of monthly catch rates.	Normal distribution (Haddon, 2001)	(9)
Length (l) and box-grading (g) size-composition data: $-\sum \left(\log(v^{(\tilde{n}-1)/2}) - \left(\frac{1}{2}(\tilde{n}-1) \frac{v}{\hat{v}} \right) \right)$, or simplified as $-\sum \frac{1}{2}(\tilde{n}-1)(\log v - v/\hat{v})$, where \tilde{n} was the total number of size categories (l or g) with proportion-frequency > 0 , $\hat{v} = (\tilde{n}-1)/2 \sum \hat{p} \log(\hat{p}/p)$, $v = \max(2, \hat{v})$ specified sample size bounds, \hat{p} were the observed proportions > 0 and p were predicted.	Effective sample size (v) in multinomial likelihoods (O'Neill et al., 2011)	(10)
Preventing unrealistically large population estimates and low estimates of harvest rate: $0.5 \left(\frac{\tilde{u} - \max(CN_y/R_y)}{\sigma} \right)^2 b$, where \tilde{u} was the minimum annual harvest fraction 0.2, σ was the user defined std for penalty weighting (0.005), CN_y was the annual total number of EKP caught over the regions, R_y the annual recruitment, and b was a logical switch for $\max(CN_y/R_y) < \tilde{u}$. The penalty was applied between 1992 and 2010.	Optimization penalty (Hall and Watson, 2000)	(11)

Annual profit was calculated as the harvest value minus the variable and fixed costs:

$$\pi_y = \sum_r \left(\sum_t \left(\sum_l v_{r,t,l} C_{r,t,l} - \Omega_{r,t}^V \right) + \bar{B}_r^{by} (1 - c_L) E_{r,y} - \left(\Omega_{r,y}^F \frac{E_{r,y}}{\bar{d}_r} \rho \right) \right)$$

where $v_{r,t,l}$ was the average price received by fishers for EKP in region r , time-month t and length class l (Figure 3), $C_{r,t,l}$ was the EKP harvest weight, $\Omega_{r,t}^V$ was the total variable costs, \bar{B}_r^{by} was the average by-product value (\$) taken each boat day, c_L was the share of the catch paid to crew members (a labour cost), $E_{r,y}$ was the total annual boat days fished, $\Omega_{r,y}^F$ the average annual fixed

costs, \bar{d} was the mean number of days fished per boat year and ρ was the fraction of fixed costs allocated to the EKP fishery (Table 2). The division by \bar{d}_r allowed the annual number of vessels to change based on profitability.

Variable costs $\Omega_{r,t}^V$ were calculated by region r and time-month t . This included the proportional labour cost (c_L), cost of packaging and marketing (c_M) per unit weight of catch, cost of repairs and maintenance per boat-day (c_K), fuel cost per boat-day (c_F), and other incidental costs per boat-day (c_O) (Table 2):

$$\Omega_{r,t}^V = \sum_l (c_{L,r} v_{r,t,l} + c_{M,r}) C_{r,t,l} + (c_{K,r} + c_{F,r} + c_{O,r}) E_{r,t}$$

Average annual fixed costs $\Omega_{r,y}^F$ were calculated using regional vessel costs (W_r), and opportunity (o) and depreciation (d) rates on average total investment value per vessel ($K_{r,y}$) (Table 2):

$$\Omega_{r,y}^F = (W_r + (o + d)K_{r,y}).$$

Annual vessel costs (W_r) were not related to fishing effort. They were the sum of costs needed to support a vessel before fishing.

Simulation and management procedures

Model simulations were used to estimate management reference points and evaluate proposed management procedures. The simulations were driven by forward projection methodology similar to Richards *et al.* (1998). To drive the simulations from 2011–2020, 1000 multivariate length-spatial parameter estimates were created from the MCMC covariance matrix. For economics, 1000 random variations on Table 2 were generated based on each variable’s variance. The parameters were used to simulate future uncertainties, including stochastic recruitment.

Equilibrium reference points for MSY and MEY were calculated by optimizing the population and economic models through mean monthly fishing mortality proportional to fishing effort. All

parameter uncertainties as outlined above were included except stochastic recruitment variation. The population dynamics were propagated to equilibrium using the mortality rates and monthly fishing pattern calculated from data from the five years 2006–2010.

Nine management procedures were developed by consultation with fishery managers and stakeholders (Table 7). They utilized one-month trawl closures, a cap on total fishing effort, and within-year catch-rate control rules. Management procedures 1 to 4 represented *status quo* total fishing effort and compared alternative one-month regional EKP closures. Procedure 5 contrasted procedure 4 with reduced total fishing effort at $E_{MEY_{fv}}(\bar{d})$. Procedures 6 to 9 used regional MSY and MEY_v catch rate control rules to manage total fishing efforts of E_{MSY} and $E_{MEY_{fv}}(\bar{d})$.

In addition, the management procedures were replicated in two scenarios: (A) 1–9 under 2010 fishing costs and fishing power, and (B) 10–18 under 3% p.a. increased costs and power. In total, 18 cases were simulated (nine management procedures by two economic scenarios) to assess management performance over ten years. Each case was evaluated using six performance measures grouped into three pairs: (i) industry functioning: average annual harvest and effort; (ii) economics: relative net present value (NPV) and average catch rates; and (iii) 2020 population status: spawning egg production and exploitable biomass. The NPV calculated over all future years was used in order to record a long-term benefit for fishing EKP after 10 years, whereas the other performance measures were averaged over 10 years to provide a shorter-term perspective.

For management procedures 6 to 9 (Table 7), closures for different areas were calculated based on catch rate thresholds:

$$m_r = \text{first month } (c_{r,m}^f < c_{r,m}^{\text{limit}}) + 1,$$

where $c_{r,m}^f$ was the fishery standardized catch rate (kg) for region r and month m , $c_{r,m}^{\text{limit}}$ was the standardized catch rate reference point for either MSY or MEY_v, and +1 month provided industry time to prepare for area shut down. The first two months of the fishing year, November and December, were always open.

Simulated total fishing effort was split across regions and months based on historical patterns. A beta distribution was assumed for

Table 6. Negative log-likelihood functions for parameter bounds and distributions.

-LL functions for:	Equation
Stock recruitment steepness h:	(12)
$0.5 \left(\frac{\text{logit}(h) - \text{logit}(0.5)}{\sigma} \right)^2$, where $\sigma = 0.7$ defined a broad prior distribution.	
Instantaneous natural mortality M month⁻¹:	(13)
$0.5 \left(\frac{M - 0.2}{\sigma} \right)^2$, where $\sigma = 0.05$ defined the prior distribution \cong 28% CV.	
Annual log recruitment deviates η_{ly}:	(14)
$\frac{n}{2} (\log(2\pi) + 2 \log(\sigma) + (\hat{\sigma}/\sigma)^2)$, or simplified as $n(\log \sigma + \frac{1}{2}(\hat{\sigma}/\sigma)^2)$, where $\sigma = \min(\max(\hat{\sigma}, \sigma_{\min}), \sigma_{\max})$, $\sigma_{\min} = 0.1$ and $\sigma_{\max} = 0.4$ specified bounds, $\hat{\sigma} = \sqrt{\sum \eta_{ly}^2/n}$ and n was the number of recruitment years y .	

Table 7. Eastern king prawn management procedures developed by consultation and simulated over ten future years.

Management brief	Management procedures		
	Total effort (max boat-days)	Regions closed	Month closed (month number)
1. <i>Status quo</i> .	Max last five years, $\sum \approx 30\ 000$	Qld (area 4)	Oct (12)
2. Close NSW southern and Qld inshore waters in January.	Max last five years, $\sum \approx 30\ 000$	NSW (area 1) Qld (area 4)	Jan (3)
3. Close Qld waters in January.	Max last five years, $\sum \approx 30\ 000$	Qld waters (areas 4 to 6)	Jan (3)
4. Close all NSW and Qld waters in January.	Max last five years, $\sum \approx 30\ 000$	All waters (areas 1 to 6)	Jan (3)
5. Limit total effort to $E_{MEY_{fv}}$ and close all waters in January.	$E_{MEY_{fv}} \approx 8000$	All waters (areas 1 to 6)	Jan (3)
6. Limit total effort to E_{MSY} and close regional waters on MSY catch rate thresholds.	$E_{MSY} \approx 38\ 000$		Variable m_r to Oct (12)
7. Limit total effort to $E_{MEY_{fv}}$ and close regional waters on MSY catch rate thresholds.	$E_{MEY_{fv}} \approx 8000$		Variable m_r to Oct (12)
8. Limit total effort to E_{MSY} and close regional waters on MEY _v catch rate thresholds.	$E_{MSY} \approx 38\ 000$		Variable m_r to Oct (12)
9. Limit total effort to $E_{MEY_{fv}}$ and close regional waters on MEY _v catch rate thresholds.	$E_{MEY_{fv}} \approx 8000$		Variable m_r to Oct (12)

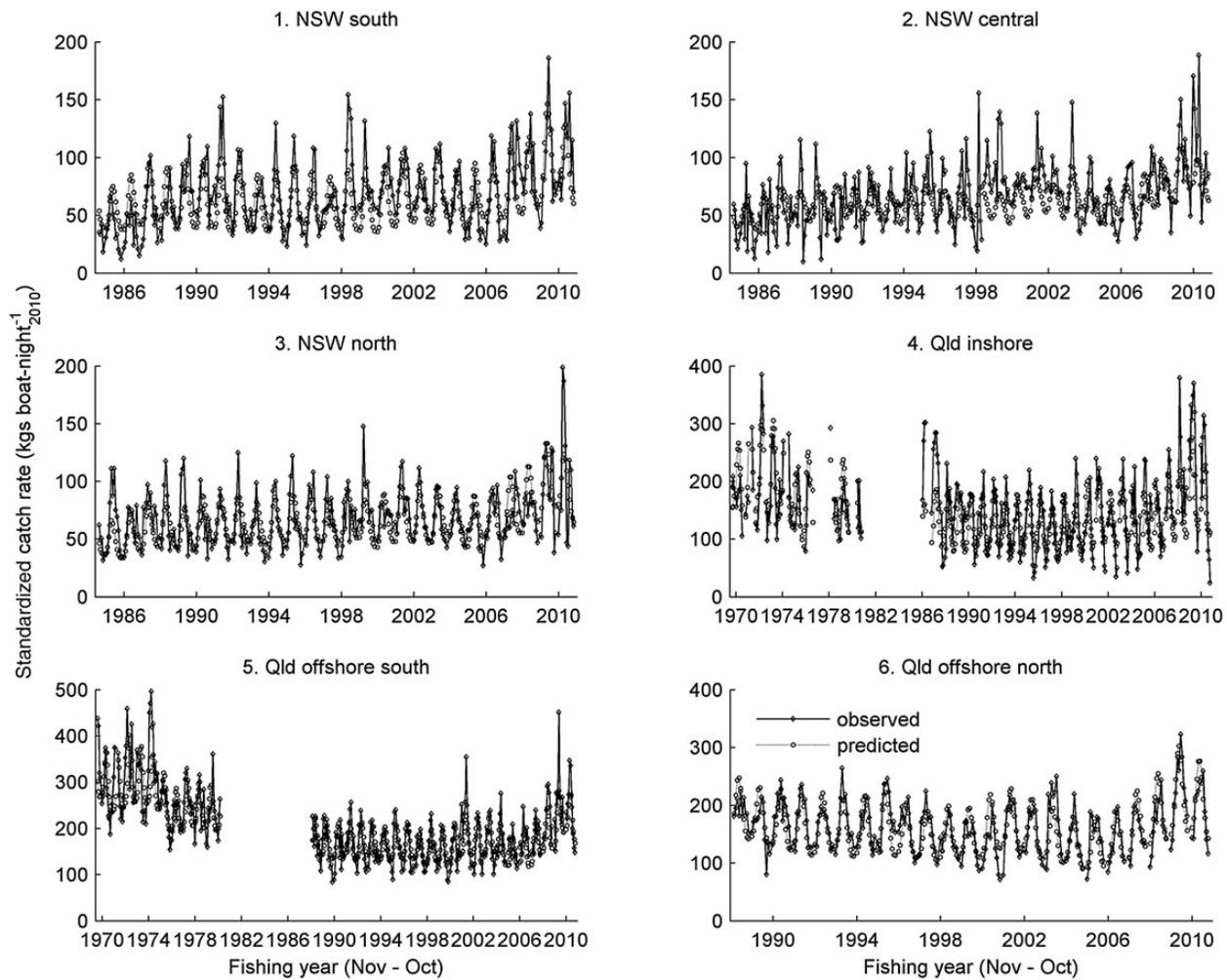


Figure 4. Eastern king prawn observed (standardized) and model-predicted catch rates for each spatial region and month.

variation and implementation error below maximum $E_{status-quo}$ and E_{MSY} total fishing efforts; based on the ratio of 2006–2010 fishing effort to $E_{status-quo}$. If a region was closed to fishing, a proportion of that fishing effort was reallocated to other regions based on probabilities calculated from logbook tallies of each vessel's regional pattern of fishing.

Results

Model calibration and description

The length–spatial model predicted that historical EKP spawning egg production and exploitable biomass, expressed as a median ratio relative to 1958, had declined roughly 40–50% up to 1985 and remained steady through to 2006. The median ratios had increased since 2006, and in 2010 were 60–80% of 1958 levels.

The model fitted the EKP fishery standardized catch rates relatively well, although region 2 EKP catch rates were less seasonal and less predictable (Figure 4). Standard deviations of log-residuals were 0.34, 0.39, 0.24, 0.33, 0.18 and 0.16 for regions 1 to 6 respectively; they were larger in NSW compared with Queensland, and region 4 deviations were inflated by the more variable pre-1989 catch rates from voluntary logbook records. Model calibrations were not influenced by the region 4 EKP recruitment indices due to the limited 5-year time-series (standard deviation of log-residuals = 0.21). Estimated effective sample sizes for the length- and grading-

frequency data were typical for fisheries data (Pennington and Vølstad, 1994), and indicated that prawns within the samples were correlated, not necessarily that the model didn't fit the data (Figures 5 and 6). For region 6 where large EKP were caught, the model predicted the grading data very well (Figure 6).

Roughly 56% of EKP recruitment to the fishery was estimated to enter region 4, 13% in region 1 and 30% in region 2, with little recruitment occurring in region 3 (Table 8). Recruitment steepness was calibrated at 0.36. Typical recruitment modes were estimated in February, December, October and December for regions 1 to 4 respectively. No large yearly variation in catch rates was evident and annual log recruitment standard deviation was estimated at 0.12. EKP mean carapace length at 50% vulnerability was 21 mm in region 1, 25 mm in regions 2 to 4 and 35 mm in regions 5 and 6. Instantaneous natural mortality was calibrated to 0.184 month^{-1} .

Catchability was estimated to peak in January with a low in July for regions 1, 3, 5 and 6. Region 4 catchability peaked in March, with a low in September. The regional amplitude in catchability in these regions was estimated at 20%. Region 2 catchability was less seasonal.

Reference points for MSY and MEY are presented in Table 9. The MEY results were highly dependent on the specified economic parameters, listed in Table 2. The variability in MEY was tabulated for the average number of days currently fished per boat per year

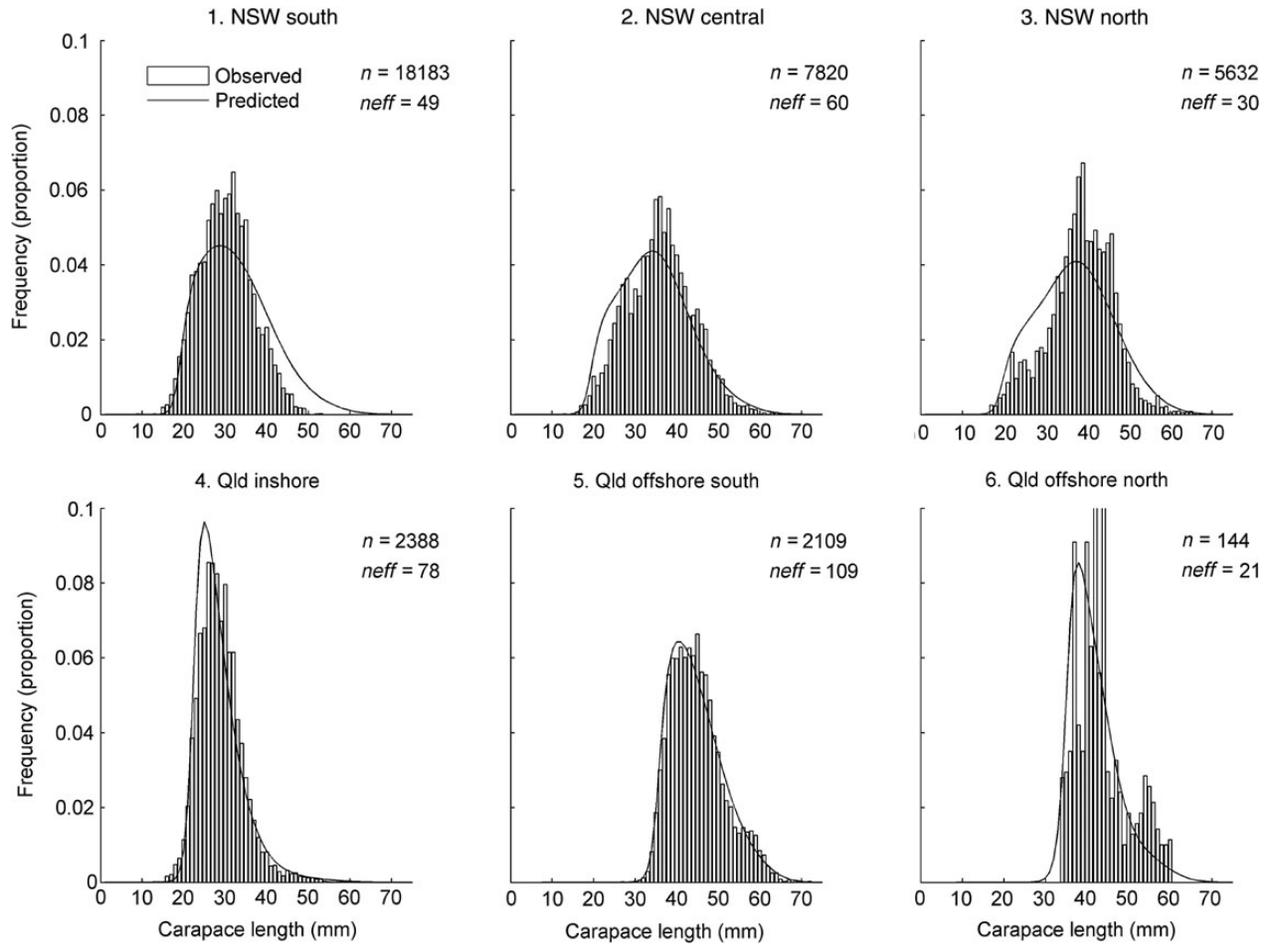


Figure 5. Eastern king prawn observed and model-predicted harvest length frequencies for each region. The plot frequencies were summed over sexes and by effective sample numbers for the months with available data. Mean number of prawns measured (n) and effective numbers ($neff$) per sex and month are shown.

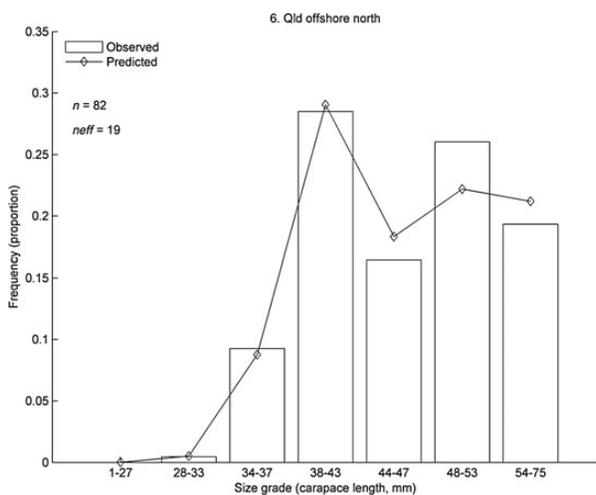


Figure 6. Eastern king prawn observed and model-predicted frequencies of harvest size grading data from Queensland offshore north waters (region 6). The plot frequencies were summed by effective sample numbers over 136 monthly prawn-size-box frequencies. Mean sample number of 5-kg boxes graded (n) and effective numbers ($neff$) per month shown.

(\bar{d} , Table 2), twice this number ($2\bar{d}$) and for variable costs only (Table 9). The level $2\bar{d}$ was included as a relevant illustration for potential effort per boat if the fleet vessel numbers were reduced to allow each vessel much higher fishing capacity. The MEY effort estimates ranged between 7000 and 20 000 boat-days; the lower estimates were applicable for lower values of \bar{d} , and higher fishing costs and power. Fishing effort in 2010 was about 24 000 boat-days.

Mean catch rate reference points, corresponding to MSY and MEY, are plotted in Figure 7. Two versions of MEY catch rates were calculated: one maximized fishing profit against variable costs only (labelled as MEY_v), while the other maximized against both variable and fixed costs (labelled MEY_{vf} and dependent on \bar{d}). These reference points were used as catch-rate thresholds for simulating management procedures 6 to 9. Retrospectively, the catch-rate reference points suggested consistent profitable catch rates in the last three years, 2008–2010, across all regions.

Simulation of management procedures

The results of simulating management procedures were as follows (see Figure 8 and the probabilities of catch-rate control rules closing fishing regions, plotted in Figure 9):

Table 8. Parameter estimates and standard errors for the model calibration ($-\log l = -3253.7$; $\sigma_r = 0.115$).

Parameter	Estimate	Standard error	Estimate transformed
ξ	-0.568	0.089	0.362
Y_1	0.289	0.206	1.335
Y_2	1.171	0.103	3.225
Y_3	-2.713	0.48	0.066
Y_4	1.772	0.083	5.884
μ_1	4.361	0.141	4.361
μ_2	1.918	0.153	1.918
μ_3	-1.165	0.259	-1.165
μ_4	1.949	0.112	1.949
$\kappa_{1...3}$	1.573	0.132	1.573
κ_4	0.819	0.071	0.819
f_{1}^{50}	20.671	0.661	20.671
$f_{2...4}^{50}$	24.483	0.731	24.483
$f_{5...6}^{50}$	35.551	0.193	35.551
δ	0.921	0.027	0.921
M	0.184	0.005	0.184
ρ	0.939	0.281	0.719
s	0.196	0.012	0.196
ϑ_1	-0.455	0.279	-0.455
ϑ_2	1.261	0.236	1.261
ϑ_3	-0.876	0.273	-0.876
ϑ_4	0.521	0.307	0.521
ϑ_5	-0.800	0.137	-0.800
ϑ_6	-0.356	0.179	-0.356

Table 9. Estimated management quantities (95% confidence intervals) for the model calibration.

Quantities	a) Constant 2010 fishing costs and power	b) 3% year ⁻¹ increased costs and power
Harvest (t)		
MSY	3100 (2454:3612)	3100 (2454:3612)
MEY _{vf} (\bar{d})	1253 (641:1854)	1453 (905:1949)
MEY _{vf} ($2\bar{d}$)	1909 (1497:2273)	1962 (1564:2324)
MEY _v	2521 (2176:2828)	2470 (2121:2806)
Annual fishing effort (boat-days)		
E _{MSY}	38 002 (27 035:50 754)	28 300 (20 110:37 663)
E _{MEYvf} (\bar{d})	7470 (3577:11158)	6667 (3970:9531)
E _{MEYvf} ($2\bar{d}$)	12 869 (9425:16467)	9972 (7501:12565)
E _{MEYv}	19 892 (15 552:24 049)	14 307 (10 977:17 676)

The estimates were replicated to describe two scenarios over future years: a) constant 2010 fishing costs and fishing power, and b) 3% year⁻¹ increased costs and power. Variation in maximum economic yields (MEY_{vf}: including both variable and fixed costs) are shown for the 2010 average number of days fished per boat per year (\bar{d} , Table 2), twice ($2\bar{d}$) average number of days and variable costs only (MEY_v: fixed costs and \bar{d} cancelled from profit equation π_y).

Management procedures 1 to 4 (maximum $E_{status-quo} \approx 30\,000$ boat-days year⁻¹)

- There were no significant changes in EKP performance measures (cases 1–4 and 10–13), except that profit under increasing fishing costs and fishing power (cases 10 to 13) declined about 20%.
- Expected annual harvests were ~ 3000 t, at a catch rate of 110 kg boat-day⁻¹.
- Management by regional monthly closures, with *status quo* fishing effort, resulted in no change in egg production or exploitable biomass.

Management procedure 5 ($E_{MEYfv} \approx 8000$ boat-days year⁻¹)

- Compared with procedures 1 to 4, there were 35–50% increases in profit, catch rates, spawning and biomass (cases 5 and 14).
- Annual harvests were more than halved at ~ 1300 t.
- Reduced fishing effort provided larger overall profit but smaller total harvest.

Management procedure 6 ($E_{MSY} \approx 38\,000$ boat-days year⁻¹ and CPUE_{MSY} control rules)

- Compared with procedures 1 to 4, there were no significant changes in performance measures (cases 6 and 15).
- Annual harvests and fishing efforts were highly variable.
- The probability of closing fishing regions after April (half way through the fishing year) was high. The region 4 closure probability was over 50% after February. Increasing fishing costs and fishing power did not significantly change the closure probabilities.
- Catch rate control rules maintained the population status by reducing the length of the fishing season.

Management procedure 7 ($E_{MEYfv} \approx 8000$ boat-days year⁻¹ and CPUE_{MSY} control rules)

- Results (cases 7 and 16) were similar to management procedure 5, with 35–50% increases in profit, catch rates, spawning and biomass compared with procedures 1 to 4.
- Annual harvests were more than halved at ~ 1300 t from 8000 boat-days.
- The probabilities of regional closures were substantially less compared with procedure 6 using E_{MSY}. Regions 1 and 4 had nearly a 20% chance of closure after June. The probabilities were < 5% for regions 5 and 6.
- Reduced fishing effort together with catch-rate control rules maintained higher and more profitable EKP population than *status quo*. Spawning and biomass levels were not significantly higher compared with procedure 5.

Management procedure 8 ($E_{MSY} \approx 38\,000$ boat-days year⁻¹ and CPUE_{MEYv} control rules)

- Compared with procedures 1–4 and 6, there were significant reductions in total fishing harvest and effort (cases 8 and 17). Relative profit, catch rates, spawning and biomass levels were all higher.
- Annual harvests were ~ 1600 t, and total effort was managed at $\sim 13\,000$ boat-days.
- The probability of closing fishing regions after February (4 months into the fishing year) was high.
- Catch rate control rules maintained a higher EKP population status by reducing the fishing year, resulting in a typical closure from March to October.

Management procedure 9 ($E_{MEYfv} \approx 8000$ boat-days year⁻¹ and CPUE_{MEYv} control rules)

- This management resulted in the highest catch rates, spawning and biomass (cases 9 and 18).

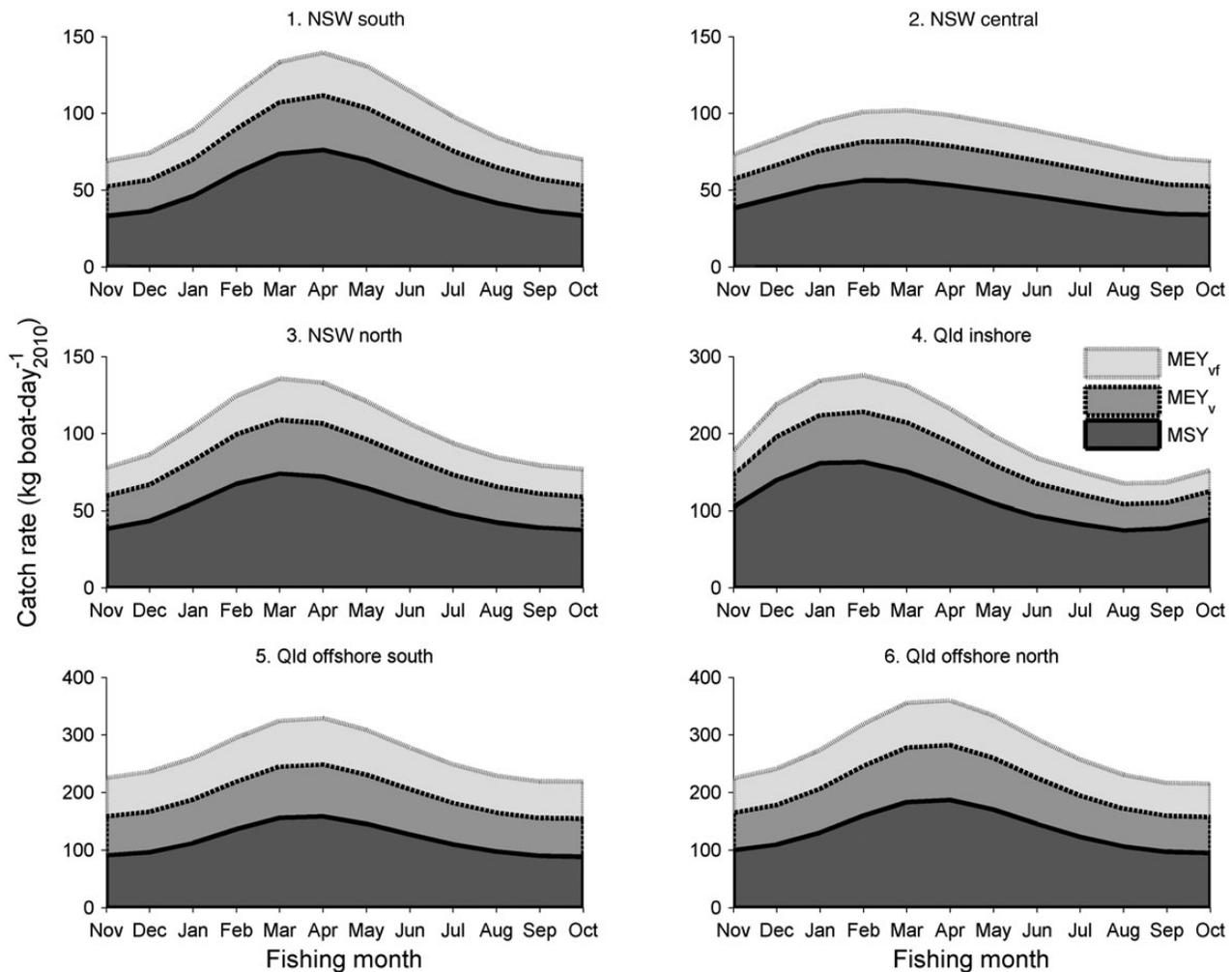


Figure 7. Mean monthly catch rate targets for maximum sustainable yield (MSY), maximum economic yield for variable costs (MEY_v) and MEY_{vf} (d) for variable plus fixed costs by fishing region. Catch rates were standardized to 2010 fishing power.

- Compared with procedures 1 to 4, relative profit was $\sim 50\%$ higher.
- Annual harvests were the lowest of all management procedures, at about 1100 t, with ~ 6000 boat-days effort.
- The closure probabilities were higher compared with procedure 7 with the same fishing effort.
- Despite the lower fishing effort, the catch-rate control rule still reduced the fishing season, with a typical closure from March to October.

Discussion

The results provide a major advance over the previous assessment (O'Neill *et al.*, 2005; Ives and Scandol, 2007), in that EKP has been assessed as a whole stock transcending jurisdictional borders and operational economics have become a research focus. The results outlined management paths to keep EKP fishing sustainable and more profitable.

Our stock steepness estimate of 0.36 (Table 8) was in line with other Penaeid prawn analyses reported by Ye (2000). This is an important parameter describing the relationship between annual

spawning (egg production) and the following year's recruitment (number of new prawns entering the ocean fishery). In Australia, estimates of steepness in the Northern Prawn Fishery have ranged from 0.26–0.36 for the two species of tiger prawns (Dichmont *et al.*, 2001), and the estimate for tiger prawns in the Torres Strait was 0.46 (O'Neill and Turnbull, 2006). Previous analyses of EKP steepness compared values of 0.56, 0.4 and 0.37 and showed management implications of low steepness (O'Neill *et al.*, 2005). The longer assessment time-series, compared with O'Neill *et al.* (2005) and Ives and Scandol (2007), allowed more accurate estimates of EKP productivity.

Management procedures

In the simulations, management procedure 7, which used E_{MEY} and $CPUE_{MSY}$, performed the best in the sense of increased fleet profit and catch rates, and low probability of regional closures. This was followed closely by management procedure 5 which used E_{MEY} with a January fishing closure. For these procedures, combined fleet profit, catch rates, spawning egg production and biomass were all significantly higher than *status quo*. They were also robust to future increases in fishing costs and fishing power. Management procedure 9 resulted in similar increased profit and

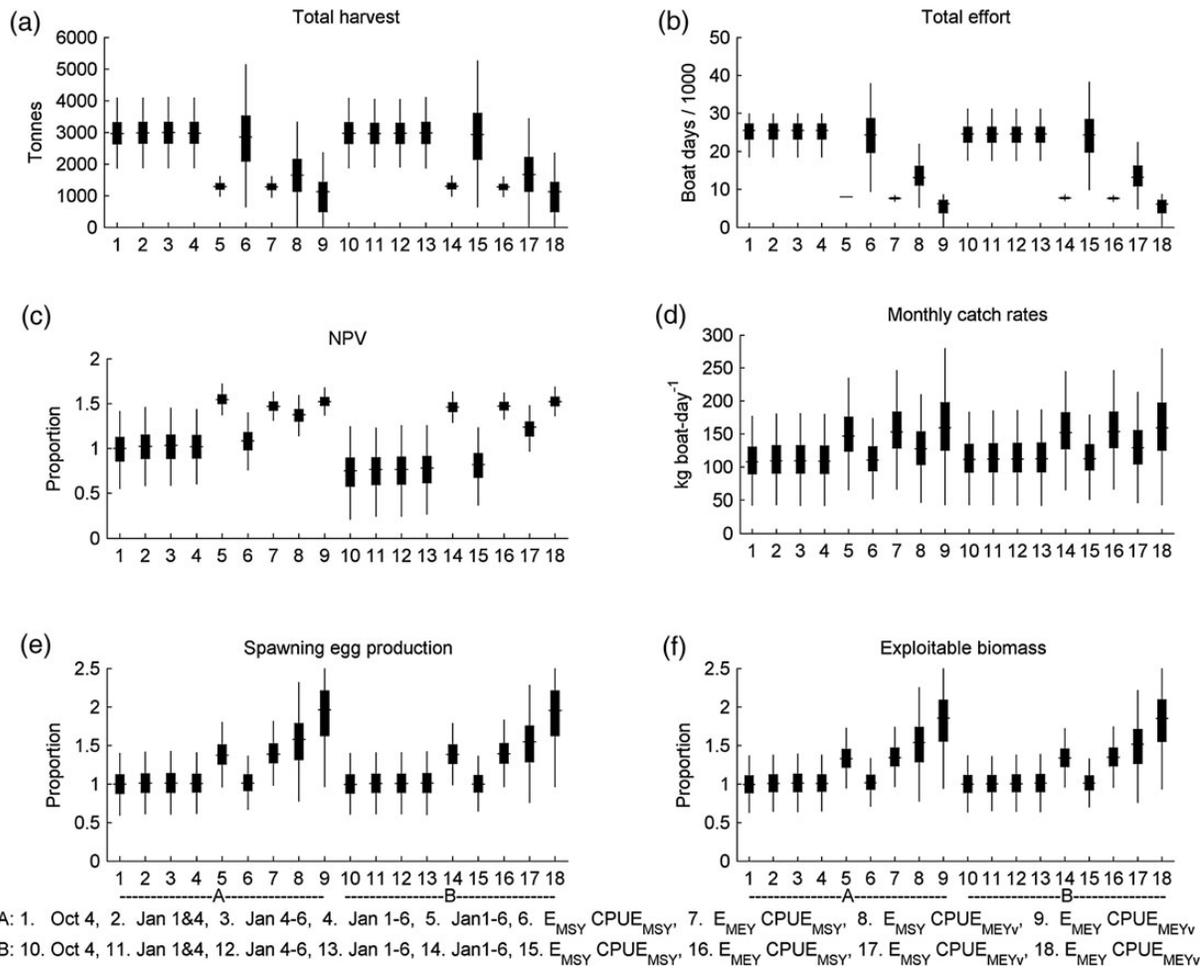


Figure 8. Performance measures over ten future years for nine different EKP management procedures (Table 7); boxes 1–9 are for scenario A (2010 costs and fishing power) and 10–18 scenario B (3% increases in both costs and fishing power). The first row of plots (a) and (b) represented industry functioning, the middle plots (c) and (d) indicated economic conditions, and the bottom plots (e) and (f) measured population change. The relative measures in plots (c), (e) and (f) were scaled against *status quo* strategy 1 (median = 1). The plots display the simulated distributions (1000 samples) around their medians (line in the middle of each box). The bottom and top of each “box” were the 25th and 75th percentiles. The whisker length indicated ~95% coverage of the simulations.

catch rate, but less predictability with potentially short fishing seasons.

A major finding is that it is important to limit fishing effort to a level less than E_{MSY} : catch rate control rules were effective under E_{MEY} but much less so under E_{MSY} , where they successfully reduced effort but caused uncertain harvest and often closed fishing regions midyear.

The setting of the catch-rate trigger required knowledge of where and when EKP were abundant and information on profitable catch rates (Figure 7). In general, EKP recruitment and movement dynamics were known (Braccini et al., 2012b). However, year-to-year variation in timing of recruitment and movement dynamics may occasionally reduce catch rates. No cost-effective monitoring was available to guard against such circumstances, which produce misleading abundance signals. We note that Walters and Martell (2004) caution that in-season management procedures should be used with care in managing total harvests and efforts.

Notwithstanding the above limitations, CPUE $_{MSY}$, in combination with an effort limit of E_{MEY} , was found to be an appropriate trigger point given significant catch-rate observation error. This

trigger point minimized management mistakes due to data errors. Even so, these controls alone may not always be a safeguard against unpredictable situations or issues. Regional changes in fishing effort should be monitored carefully given that hyperstability bias can be caused by temporal changes in fishing power (catchability) and where and how vessels fish.

Analysis showed that single-month fishing closures were not effective at improving industry harvests, economics or population status. However, specific spatial or seasonal closures could still be considered in order to provide vessel repair time for the fleet and to reduce the harvest of small prawns.

An additional ability of the stock operating model was to estimate management procedures for optimal allocation of regional and seasonal levels of fishing, assuming a single jurisdiction. At the time of this research, such predictions were not desired. Fishery managers and stakeholders tabled specific procedures to evaluate (Table 7), with no major alterations to traditional fishing patterns; particularly early-season fishing for Christmas markets. In addition, stakeholder objectives included free movement of vessels, high catch rates, valuable licence units, and equitable access (Dichmont et al., 2013).

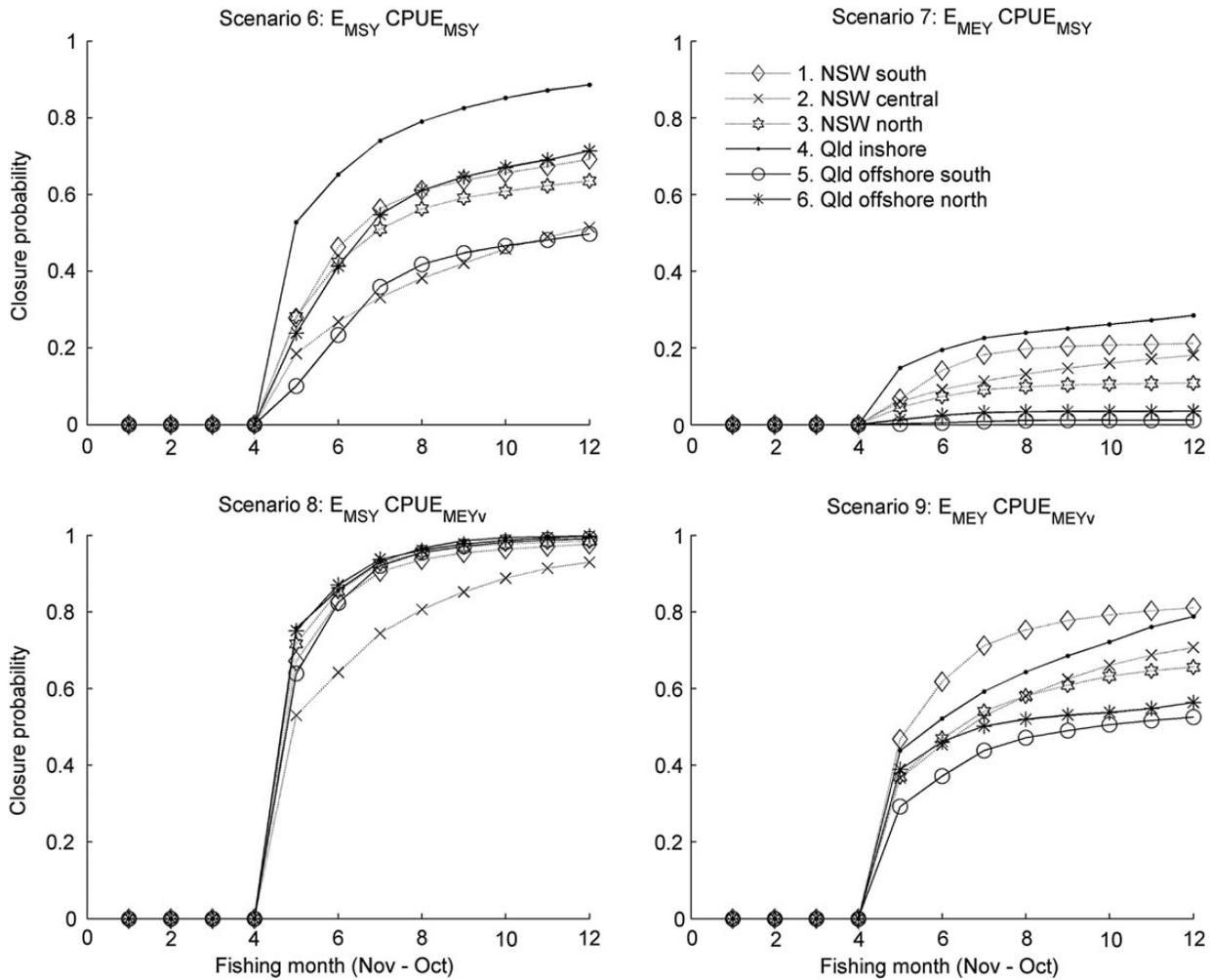


Figure 9. Regional closure probabilities for management performance using catch-rate reference points.

Even though optimal-allocation procedures were not of current interest for EKP, their governance design could be of future benefit across fisheries; for hypothetical examples see (Dichmont *et al.*, 2013). Modelling of innovative patterns of regional and seasonal fishing across fisheries may identify new ways of increasing profit for the fleet as a whole, avoiding excess harvest of small prawns, and improving efficiencies of management and monitoring. Evaluation would require further model dynamics to allow for vessels fishing other otter-trawl sectors in Queensland, including Moreton Bay, saucer scallop, red-spot king prawn and tiger prawn, and catching other valued species in New South Wales, such as cephalopod, school whiting and school prawn.

Reference points

Simulation identified that spawning egg production (S) and exploitable biomass (B) ratios were above reference limits of 50% virgin S_{1958} and 40% virgin B_{1958} . MSY was estimated at ~ 3100 t. Fishing effort estimates for E_{MSY} ranged from 38 000 down to 28 000 boat-days, dependent on the trend in fishing power. Considering decadal management and a potential strong upward trend in fishing power, it would be safer to take E_{MSY} as ~ 28 000 boat-days per year. These values were similar to those estimated by O’Neill *et al.* (2005). The uncertainty surrounding the value of

E_{MSY} was typical for a fisheries assessment, and confirmed that target fishing efforts should not approach this limit due to risks of overfishing and less profitable catch rates (Garcia and Staples, 2000).

Estimates of MEY for EKP were strongly influenced by the reported high costs (variable and fixed) of fishing, the assumed average number of days fished per vessel year (\bar{d}) and fishing power. The ratio of MEY to MSY was especially influenced by the high annual fixed costs (Table 2). The MEY ranged between 1300 t and 2000 t and E_{MEY} between 7000 and 13 000 boat-days. A higher value of \bar{d} significantly increased profit, but reduced the number of vessels, which may negatively impact social objectives of the fishery (Wang and Wang, 2012; Pascoe *et al.*, 2013). Operationalizing MEY in a fishery requires an agreed set of rules, assumptions and strong industry commitment (Dichmont *et al.*, 2010). For MEY_v (estimate for MEY under variable costs only), estimated tonnages were higher at ~ 2500 t and E_{MEY_v} between 14 000 and 20 000 boat-days per year.

Acknowledgements

A special thank you goes to Tony Courtney, Marco Kienzle, Steve Montgomery and Sean Pascoe for their assistance with modelling data and analyses. The Queensland long-term monitoring programme supplied data from their annual EKP recruitment survey.

We gratefully acknowledge the fishery managers, stakeholders and FRDC Project 2008/019 Steering Committee, who contributed to the design of the management procedures.

Funding

The research was supported and funded by the Australian Government's Fisheries Research and Development Corporation (FRDC), the New South Wales Department of Primary Industries and the Queensland Department of Agriculture, Fisheries and Forestry. The FRDC funding and project number was 2008/019.

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Handling editor: Jörn Schmidt

Appendix III: Integrating finite mixture and catch curve models for estimation of survival indicators of stout whiting (*Sillago robusta*)

Integrating finite mixture and catch curve models for estimation of survival indicators of stout whiting (*Sillago robusta*)

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Abstract

A new catch curve methodology is described for estimating annual rates of fish survival. The method analyses individual fish age-abundance data such as length and age by using Gaussian finite mixtures. It was designed to overcome fishery dependent sampling issues, assuming only that fish ages within each length category were sampled randomly and that fish lengths themselves were not. The analysis quantified improved survival rates of stout whiting in waters along Australia's east coast. Estimated survival rates stabilised at about 40-50% between 2009 and 2012, compared to lower estimates below 40% prior to the year 2003. The catch curve mixture model applies naturally to monitoring data on fish age-abundance and is applicable to many fisheries.

Keywords: catch curve, finite mixture model, fish survival, fish mortality, stout whiting, Australia

Introduction

Routine stock assessments are required to monitor indicators of fishing pressure to service management of many fisheries globally. Often a time series of age-abundance data are used to quantify indicators of fish survival or mortality; where fish survival (S) refers to the ratio of abundance between older and younger age groups and the antonym is fish mortality and equal to $\log(-S)$. Fish survival can be quantified from age-abundance data using a range of methods from complex statistical population models (Maunder and Punt, 2013) to simpler catch curve methodologies (Smith et al., 2012). If commercial or recreational sectoral components of data are sampled inconsistently or missing, then estimation of reliable indicators of survival can be difficult. Issues of inconsistent or missing data are relevant for many fisheries and may limit assessments of fish survival from simple analyses of age-abundance data.

Catch curve analysis is one of the most simple and fundamental tools commonly used to estimate fish survival or mortality. The catch curve literature is vast, with recent reviews, recommendations and updates published by Millar (2015) and Smith et al. (2012). Comparable methods for fitting equilibrium age-structured dynamics to time series of fish age-abundance data have also been applied (Fay et al., 2011). The methods analyse patterns of fish age abundance to assess the survival of fish from age a to age $a+1$ year-by-year (cross-sectional) or by cohorts (longitudinal). The historical use of these methods and their estimates in fishery management is mixed due to scientific concerns over their steady state assumptions of constant recruitment and mortality through time.

These scientific concerns, together with issues of inconsistent and missing fishing data, have resulted in developing a modernised catch curve methodology to estimate annual survival fractions of stout whiting (*Sillago robusta*). The new method is described with application to real fish age-abundance data (not simulated) where the variability in sampling was dependent on fish retained by a small fleet of vessels (vessels identified with a Queensland stout whiting sector licence) and their individual spatial-temporal patterns of fishing. This complex but interesting case study fishery provides insights on a catch curve analysis modified to overcome

issues associated with the sample collection of fishery dependent age-abundance data and to evade steady state assumptions. The catch curve methodology was developed from earlier model versions described in Appendix IV (supplementary material).

Stout whiting are small schooling demersal fish caught commercially using Danish seine and otter-trawl methods in subtropical waters along the central east coast of Australia. There are three fishing sectors catching stout whiting and each has different practises, fishing powers and data recording instructions. The sectors are:

- 1) The Queensland stout whiting sector (T_4) commenced target fishing in 1981, with a maximum of five vessels and catch-at-age monitoring authorised each year since 1991. Annual assessments of total allowable catch (TAC) have been conducted since 1997 limiting harvests below 1300 t and down from the peak harvest of 2400 t in 1994.
- 2) The Queensland eastern king prawn (*Melicertus plebejus*) shallow water sector (T_1) commenced ~ 1958 and historically consisted of between 100–300 vessels annually (O'Neill et al., 2014), where significant quantities of stout whiting are taken as non-target by-catch, discarded and not reported. Preliminary estimates of discards ranged 1000–2000 t in the years 2002–2004 (unpublished data; M. F. O'Neill, G. M. Leigh and A. J. Courtney).
- 3) The New South Wales fishing sector (T_{NSW}) consisted of about 100 licences catching both stout whiting and eastern king prawns annually since 1958. Stout whiting annual harvests of 150–600 t were only identified and reported suitably since 1997. No age-abundance monitoring was conducted.

Due to missing sectoral and time-series data, past assessments of stout whiting have focused on simple cross-sectional catch-curve survival indicators calculated from an annual time series of T_4 catch-at-age proportions. The age proportions were determined by length-mediated estimation (Francis and Campana, 2004; Francis et al., 2005), with a random sample of fish length frequencies converted to an age distribution using an otolith based age-length key for each year. Over recent years inconsistent changes in the time series between sampled fish length frequencies and

age-length data had become more obvious once analysed in detail (Fig. 1). The patterns of age structure shifted to older fish from the year 2005 (Fig. 1c), which was not evident in the length of fish harvested (Fig. 1a). Much older fish were observed in the years 2002 and 2010 compared to their surrounding years (Fig. 1c). The lengths of fish harvested was generally similar between years, noting larger fish were caught in the 1995, 2006 and 2010 fishing years (Fig. 1a) without any clear change in the overall seasonal or spatial pattern of fishing. The narrow 50th percentile range of fish lengths sampled each year (Fig. 1a) suggested high sample correlation and small effective sample sizes from the wider fishery area.

The inconsistencies between some years of sampled compositions of fish lengths and age-length data are attributed to high sample correlation, small effective sample sizes and subtle changes in patterns of fishing by fishers. These issues can result in a collection of data that are not random samples of the length composition of the fish population, thereby justifying the decision to not analyse the length composition data and develop a method that does not rely on the assumption that fish lengths are randomly sampled.

Therefore the aim of this paper was to develop a new catch curve analysis to estimate fish survival directly from only the more informative individual age-length samples (without the length frequency data Fig. 1a). This was achieved by joining Gaussian finite mixture, von Bertalanffy growth and catch curve methodology. The new methodology demonstrated improved estimates of fish survival, which was less varied, compared with including other length and catch rate data (see Appendix IV supplementary material and results). For fisheries that monitor fish age-abundance, the data issues, methodology and results herein provide further options for estimating indicators of fish survival.

Materials and methods

Catch curve mixture model

Catch curve analysis is the process to assess the survival of fish age a to age $a+1$ using changes in catch-at-age data (Hilborn and Walters, 1992). The catch curve

mixture model does this using contemporary statistics without the steady state assumptions of constant recruitment and survival. The objective of the analysis was to estimate annual survival fractions from individual fish age-length samples. This was achieved so that the model analysis was conditioned on the assumption that fish ages within each length category were sampled randomly and no longer assumed that the lengths themselves were sampled randomly from the fish population. This assumption aimed to overcome fishery dependent sampling issues.

For standard Gaussian finite mixture models, estimates of mixing proportions π_i , means μ_i and variance matrices V_i define the components i and posterior score probabilities τ that form a multivariate normal distribution (McLachlan and Peel, 2000). Expectation Maximization (EM) algorithm is often used to derive the maximum likelihood estimates (π_i , μ_i and V_i), using software procedures like 'gmdistribution' in Matlab[®] (MathWorks, 2014) and 'EMMIX' in R (McLachlan et al., 2013), when grouping assignments for i are identifiable. However, for many fisheries data the sampled distributions of fish length usually appear with little contrast or separation (unimodal) to estimate the number of age components i freely and accurately. Therefore parametric adjustment to the model means μ_i is proposed so that $\mu_i < \mu_{i+1}$ is logically maintained to help identify components i .

For the stout whiting analysis, we had multiple years k of sequential mixed data \bar{y}_{jk} (samples of matching l_j : fork length mm and a_j : age-group) for each fish j (Fig. 1b and c). The number of sampled aged fish in each year 1991–2013 is denoted n_k , with mixing proportions π_{ki} for each year k and fish age component i , mean length at age μ_i , variance of mean length at age V and individual posterior scores τ_{ijk} for each fish j ; where age component label $i=1\dots9$ corresponded to age groups $a=0\dots8$ years old and $\sum_i \tau_{ijk} = 1$. Posterior scores for each fish are the probabilities (likelihood) of each age components i given the individual fish's length l_j .

The following assumptions were required to enable the analysis herein and to outline the approach for stout whiting:

- Mean fish length at age and constant variance was and based on a externally estimated von Bertalanffy growth curve,
- The number of age components was assumed known and fixed from the data,
- The catch curve approach assumed constant selectivity and that fully recruited fish experience a constant survival rate within a cohort, and
- Survival rates measured the combined effects of both fish mortality and cohort strength. It was not assumed that cohort strength was constant over years.

The algorithm for finding maximum likelihood parameter estimates of fish survival was implemented in Matlab[®] (MathWorks, 2014) using the equations in Table 1 as follows:

1. Calculate and set values for von Bertalanffy growth curve μ_i and V .
2. Define the first fully recruited age component r for catch curve calculation; the peak-plus criterion was used for stout whiting $r = 3$ (Smith et al., 2012).
3. Tally the observed numbers of aged fish n_{ki} for each year k and age component i .
4. For non-recruited fish $i < r$, calculate initial values $\pi_{ki} = n_{ki} / \sum_i n_{ki}$ and

$$\beta_k = 1 - \sum_{i=1}^{r-1} \pi_{ki}.$$
5. Calculate initial values for survival fractions S_q for fully recruited fish $i \geq r$ (equation 1, Table 1). Here the subscript q replaces k to represent survival fractions that can also be calculated for years before $k=1$; from the n_{ki} diagonal cohort calculations.
6. Calculate initial values $\hat{\pi}_{ki}$ for $i \geq r$ (equation 2).
7. EM algorithm (loop calculations until estimates $\hat{\pi}_{ki}$ and \hat{S}_q converge):
 - a. Calculate τ_{ijk} from the mixture density function (equation 3).
 - b. Calculate \tilde{n}_{ki} (equation 4).
 - c. Update $\hat{\pi}_{ki}$ for $i < r$ and β_k (equations 5 ... 8).
 - d. Calculate \hat{S}_q (equation 9).

e. Update $\hat{\pi}_{ki}$ for $i \geq r$ (equation 2).

The calculation of annual fish survival \hat{S}_q followed cohort abundances (diagonals of the truncated \hat{n}_{ki} matrix for $i \geq r$; equations 1 and 9, Table 1). In equation 1 initial values for \hat{S}_q were obtained by comparing two diagonal vectors of cohort abundance. Initial \hat{S}_q was the sum abundance of cohort q divided by the sum abundance of the next younger cohort $q+1$ in the same years for fully recruited fish. To obtain maximum likelihood estimates for \hat{S}_q the update calculations in equation 9 were expanded across the truncated \hat{n}_{ki} matrix so that the observed and fitted numbers match when summed over every diagonal. Equation 9 matched the fitted numbers to the observed ratio of the number of fish in cohort q to the number in all cohorts older than q , where the numbers are summed over all years in which cohort q occurs. The final estimated survival fractions \hat{S}_q applied to a cohort in the year between when it became fully recruited and when the next younger cohort became fully recruited. Therefore S_q cannot be calculated for the final year of data. For confidence intervals on \hat{S}_q , the observed data were resampled at random with replacement to generate 500 separate data sets. Each data set was analysed and results stored. Simple 95% confidence intervals were calculated from the distribution of results.

For this model analysis of stout whiting the direct estimation of von Bertalanffy length-at-age parameters and variance was not considered feasible. This was because the model was conditioned on the assumption that fish ages within each length category were sampled randomly and no longer assumed that the lengths were randomly sampled; the conditional model contained no information on length at age (as opposed to age at length). Therefore survival results were compared for three growth settings: a) $l_\infty = 22.622, \kappa = 0.293, t_0 = -2.342, V = 3.429$; b) $l_\infty = 20.579, \kappa = 0.321, t_0 = -2.668, V = 3.429$; c) $l_\infty = 20.579, \kappa = 0.321, t_0 = -2.668, V = 1.647$. The growth parameters for setting a) were estimated separately outside the catch curve model using the same age-length data (Fig. 1b and Fig. 1c). Settings c) were estimated from catch curve mixture model 2, which included all length frequency and

otolith age data (Appendix IV: supplementary material). Settings b) were a combination of a) and b).

Age data

Stout whiting length and age sampling from the T₄ sector was conducted in 1993–2013 following long term monitoring protocols (Department of Primary Industries and Fisheries, 2007). The sampling was ‘fishery-dependent’, with two 5kg boxes of fish collected from each T₄ vessel’s fishing trip. The provision of boxes-of-fish was dependent on each vessel’s pattern of operation with one box typically from a night-time catch and the other from a day-time catch. The sample times and locations were not controlled, but ungraded (random) fish were supplied from the catch. Any fisher processes of sorting, packing and discarding fish were specified to be separated from the monitoring sample. All fish from each box sample were measured as fork-lengths (mm) for length frequency. From each box, 1 to 3 fish from every 5mm size class were dissected to extract otoliths for aging until a subsample of about thirty fish per size class per year was achieved (length stratified sampling). Historically, the number of fish sampled each year ranged between 300–500 for aging and 3000–20000 for length frequencies dependent on the amount of fishing and catch (Fig. 1). For fish age determination, both otoliths were removed and cleaned, with only the left otolith sectioned. All otolith reading was done without knowledge of fish size, date or location of capture. Age estimates were counts of complete opaque rings. In 2004, fish otoliths from the 1993–2000 years were re-aged independently by Australia’s Central Aging Facility (unpublished report; C. P. Green and K. Krusic-Golub). This was done to standardise fish aging protocols to ensure otolith aging was consistent in time and completed by qualified staff as tested against a reference otolith collection (O’Sullivan, 2007; O’Sullivan and Jebreen, 2007). Final age frequencies were adjusted to age–groups (cohorts) based on fish capture dates, margin widths of the sectioned otoliths and an assumed birth date of 1st January (O’Sullivan and Jebreen, 2007). Verification of a single annual cycle in ring formation, coinciding with spring months in 0+ to 3+ age groups, had been demonstrated for stout whiting otoliths with clear banding (Butcher and Hagedoorn, 2003).

T_1 and T_{NSW} fish age data were not collected historically, so these sectors data were not able to be used to calculate survival indicators.

Results

The patterns of stout whiting length and age by year are displayed in Fig. 1. For the reasons noted in the introduction of this paper, the analysis focused on patterns in the age data (Fig. 1c). The age data suggested a shift to higher survival as shown by the older fish present in 2005–2008. Compared to other years, the cohort frequencies for fully recruited fish (≥ 2 years old) were stronger in 2005–2008. The strength of cohort frequencies as marked for 2–4 year old fish in Fig. 1c, show a marginal decline in strength from 1993–2003, increase to 2008 and then decline and stabilisation thereafter.

The estimated trend in stout whiting survival fractions followed the patterns in cohort strengths (Fig. 2). Survival fractions were lowest between 1993 and 2003. The low survival estimates in these years, particularly 2002, suggest weak recruitment. Higher rates of survival were estimated after 2002, with strong recruitment identified in 2004. Estimated survival stabilised at higher fractions between 2009 and 2012 compared to the low estimates before 2003.

The annual pattern of estimated survivals was not sensitive to the assumed growth curve and variance parameters (Fig. 2). The patterns were in parallel ($\rho = 0.98$), but the scale of the estimates reduced marginally for smaller maximum fish size (l_∞) and variance (V).

Overall, the catch curve mixture model fitted the age frequencies well (Fig. 3). Figure 3 complemented Figure 1c, illustrating that higher survival fractions for cohorts between 2004 and 2006 were driven by the stronger presence of older fish between 2005 and 2008. The age frequency for 3 year old fish in 2008 was unusually strong and did not align with the catch curve prediction. In contrast the low survival fraction calculated in 2002 resulted from fewer older fish prior to 2005.

Discussion

The catch curve mixture model provides an advance over standard catch-curve methodology (Smith et al., 2012). The model analysed the raw individual fish data directly and was focused on estimating survival parameters of fish in the exploited population. The model scaled annual catch-age-proportions (π_{ki}) to follow catch curve age abundances in order to calculate survival fractions (\hat{S}_k). The model requires only input of a representative time series of age-abundance data.

The model solved \hat{S}_k iteratively using the EM algorithm by updating age-abundances to satisfy catch-curves in equations (2) and (9) (Table 1). The inclusion of the parametric von Bertalanffy growth function allowed for separation of age-components i , via maintaining the logical sequences $\mu_i < \mu_{i+1}$ for mean fish lengths. Like in simple catch curve analyses, the age component at full recruitment r was assumed in order to quantify the catch curve process. This setting followed the “Peak Plus” criterion for age of peak abundance (Smith et al., 2012); r can be changed as required for different species or fishing selectivity.

The model measurements of fish survival were not restricted by broad steady state assumptions like in a traditional catch curve. This was because the methodology was free to extract cohort-based information from the age-abundance matrix \hat{n}_{ki} . The model behaviour was only restrictive in that the survival fractions \hat{S}_q were applied equally within each fully recruited cohort q . This still allowed key changes in fish age-abundance and survival to be identified, but the estimated fractions combined effects of both fish cohort strength and mortality. This type of confounding is common in fishery indicators and not essential to separate for application in management. However, comparison of \hat{S}_q results against harvest or standardised catch rate trend data will assist to clarify inferences.

A number of inferences were of note from the analysis of stout whiting. First were the low estimates of fish survival 1993–2003. It appeared the high T_4 harvests of 1300–2400 t taken in 1994–1999 pushed survival rates down (together with catches by other sectors), with the low 2000 and 2002 year estimates driven more by low

recruitment given the corresponding lower harvests of 200–800 t (Fig. 4). The higher fish survivals estimated for the years 2003–2006 indicated stronger recruitment. This correlated from the reduced T_4 harvests and the adoption of by-catch reduction devices by T_1 prawn trawl sector since the year 2000 (Braccini et al., 2012). The estimated survival fractions for the years 2007–2012 had stabilised for those years of harvest (Fig. 4). The catch curve analysis identified significant changes in fish age-abundance and the analysis corrected inconsistent results noted in the two previous models (Appendix IV). Representative and consistent sampling of age data is important for the methodology in order to critically evaluate the validity of age-abundance data.

The annual variability of data and influences of cohort strengths had implications for setting total allowable catches (TAC). For the T_4 sector harvest control rule, direct use of annual estimates of survival fractions in the θ_{k+1} adjustment factor may cause the TAC to vary notably from year to year. This is an undesired behaviour for industry and export markets. Therefore, thresholds on quota change (like for spanner crab, O'Neill et al., 2010) or use of a cube-root or square-root transformation on θ_{k+1} may be required to mitigate year-to-year variation in TAC:

$$\text{TAC}_{T_4,k+1} = \min(\text{TAC}_{T_4,k} \theta_{k+1}, \text{TAC}_{T_4,\text{max}} = 1363\text{t}); \theta_{k+1} = \left(\frac{\bar{S}}{S_{\text{target}}} \right)^{1/x} .$$

The survival target reference point should be set at an average survival rate from years that best represented stable and profitable fishing catch rates (Little et al., 2011). It should be noted that for a transformation on θ_{k+1} , where $x=2$ or $x=3$, it may take the fishery longer to achieve target levels of survival.

The value of applying the catch curve mixture model to other fisheries will depend on the objectives to be achieved. Like the methods and analyses by Francis and Campana (2004) and Francis et al. (2005), the finite mixture method herein estimated fish age-proportions but extended this to provide a formal stock assessment tool to estimate fish survival. It can be of particular use for complex fisheries with many fishing sectors. The methodology is of value to compare alongside existing stock assessment routines, and no assumption on natural

mortality is required. The catch curve mixture model applies naturally to fisheries monitoring data on fish sizes, ages and abundance.

Acknowledgements

The authors gratefully thank past and present monitoring staff who generated and supplied data on the times series of stout whiting age-abundance 1993–2013. The research was supported and funded by the Queensland Government Department of Agriculture and Fisheries.

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Table 1. Catch curve model equations for the EM algorithm. Example calculations are illustrated in the manuscript appendix, Table 2.

Equations	Notes
(1) $\hat{S}_q = \begin{cases} \sum_{m=1}^{end} n_{ki}^q / \sum_{m=1}^{end-1} n_{ki}^{q+1} & \text{for years } < k = 1 \\ \sum_{m=2}^{end} n_{ki}^q / \sum_{m=1}^{end-1} n_{ki}^{q+1} & \text{for years } \geq k = 1 \end{cases}$	Initial survival rates S_q of fish in cohort year q . The notation represents cohort q diagonals of the truncated matrix n_{ki} for fully recruited ages $i \geq r$. m indicates the elements that are summed in the cohort diagonal vectors q and $q+1$.
(2) $\hat{\pi}_{ki} = \beta_k \prod_{q=k-i+r}^{k-1} \hat{S}_q / \sum_{i \geq r} \prod_{q=k-i+r}^{k-1} \hat{S}_q$	Updating equation for π_{ki} age proportions, relative to the abundance of the youngest fully recruited age group in year k . The proportions satisfy the catch curve for $i \geq r$, calculated as the cumulative product of age-based survival.
(3) $\tau_{ijk} = \pi_{ki} f_i(\bar{y}_{jk}) / \sum_i \pi_{ki} f_i(\bar{y}_{jk})$	f is a normal density function for l_j .
(4) $\tilde{n}_{ki} = \sum_{j=1}^{n_k} \tau_{ijk}$	Estimated number of fish in each year k and age component i .
(5) $\pi_{ki}^{(int)} = \pi_{ki}^{(old)} n_{ki} / \tilde{n}_{ki}$	Equations 5 ... 8 are maximum likelihood updates for β_k and π_{ki} for $i < r$. The superscript (int) denotes an intermediate value that still needs to be scaled. The scaling of these two equations ensures that the sum of the new updated values of π_{ki} over i equals to 1.
(6) $\beta_k^{(int)} = \beta_k^{(old)} \sum_{i \geq r} n_{ki} / \sum_{i \geq r} \tilde{n}_{ki}$	
(7) $\pi_{ki}^{(new)} = \pi_{ki}^{(int)} / \left(\sum_{i < r} \pi_{ki}^{(int)} + \beta_k^{(int)} \right)$	
(8) $\beta_k^{(new)} = \beta_k^{(int)} / \left(\sum_{i < r} \pi_{ki}^{(int)} + \beta_k^{(int)} \right)$	
(9) $\hat{S}_q^{(new)} = \hat{S}_q^{(old)} \frac{\left(\sum_{i \geq r} \tilde{n}_{ki}^q \right) \left(\sum_{k=q}^{M_q} \sum_{i \geq r} n_{ki}^{q^*} \right)}{\left(\sum_{i \geq r} n_{ki}^q \right) \left(\sum_{k=q}^{M_q} \sum_{i \geq r} \tilde{n}_{ki}^{q^*} \right)}$	The notation represents cohort q diagonals of the truncated matrix n_{ki} for fully recruited ages $i \geq r$. The double $\sum \sum$ terms sum over the n_{ki} values for fully recruited cohort diagonals q^* positioned to the right (upper side) of cohort q in the same years as cohort q . M_q indicates the final year of data from each cohort q^* .

Fig. 1. Summary of the stout whiting samples by year from the T₄ fishing sector for a) fish lengths recorded from random catch samples, b) fish lengths selected for aging and c) the resulting fish age frequency with cohorts linked for 2–4 year olds. Box plots a) and b) show the respective number of fish sampled each year. The central mark on each box plot is the median, the edges of the box are the 25th and 75th percentiles and the whiskers extend to outline the range of approximately 99% of the data. The fish age frequency in subplot c) is also displayed separately by year in Fig. 3.

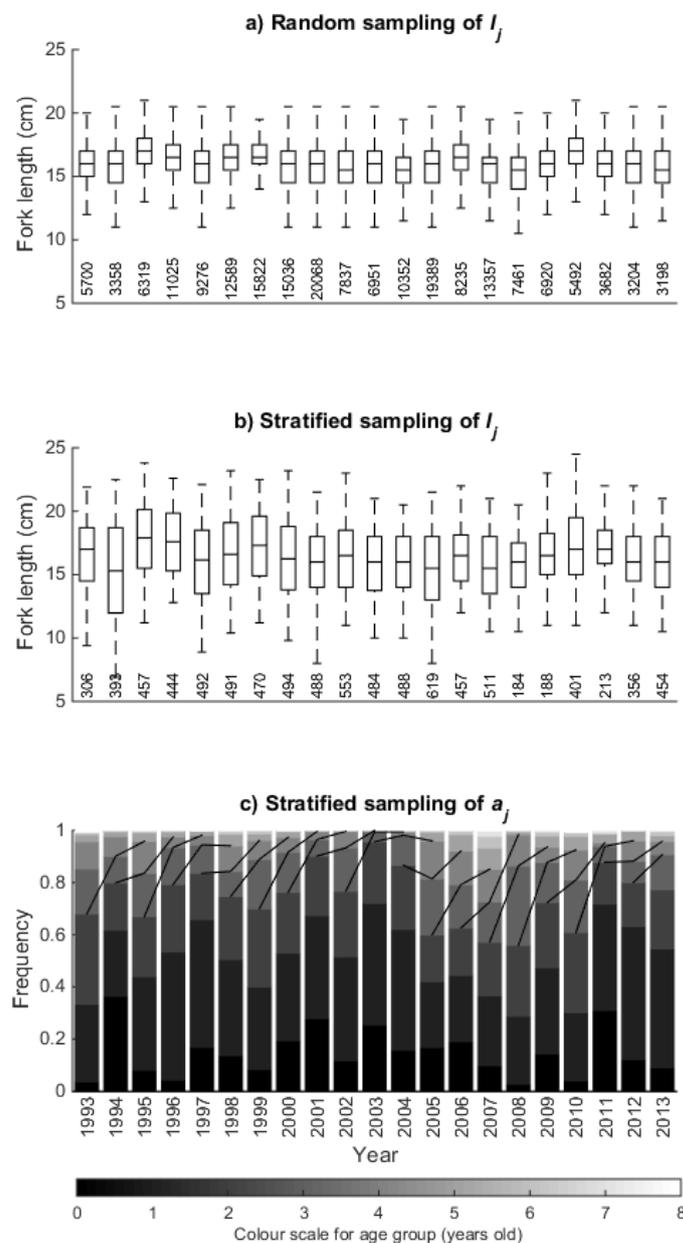


Fig. 2. Estimates of stout whiting survival fractions \hat{S}_q by year for growth settings a) $l_\infty = 22.622, \kappa = 0.293, t_0 = -2.342, V = 3.429$, b) $l_\infty = 20.579, \kappa = 0.321, t_0 = -2.668, V = 3.429$ and c) $l_\infty = 20.579, \kappa = 0.321, t_0 = -2.668, V = 1.647$. 95% confidence interval error bars are shown on all estimates.

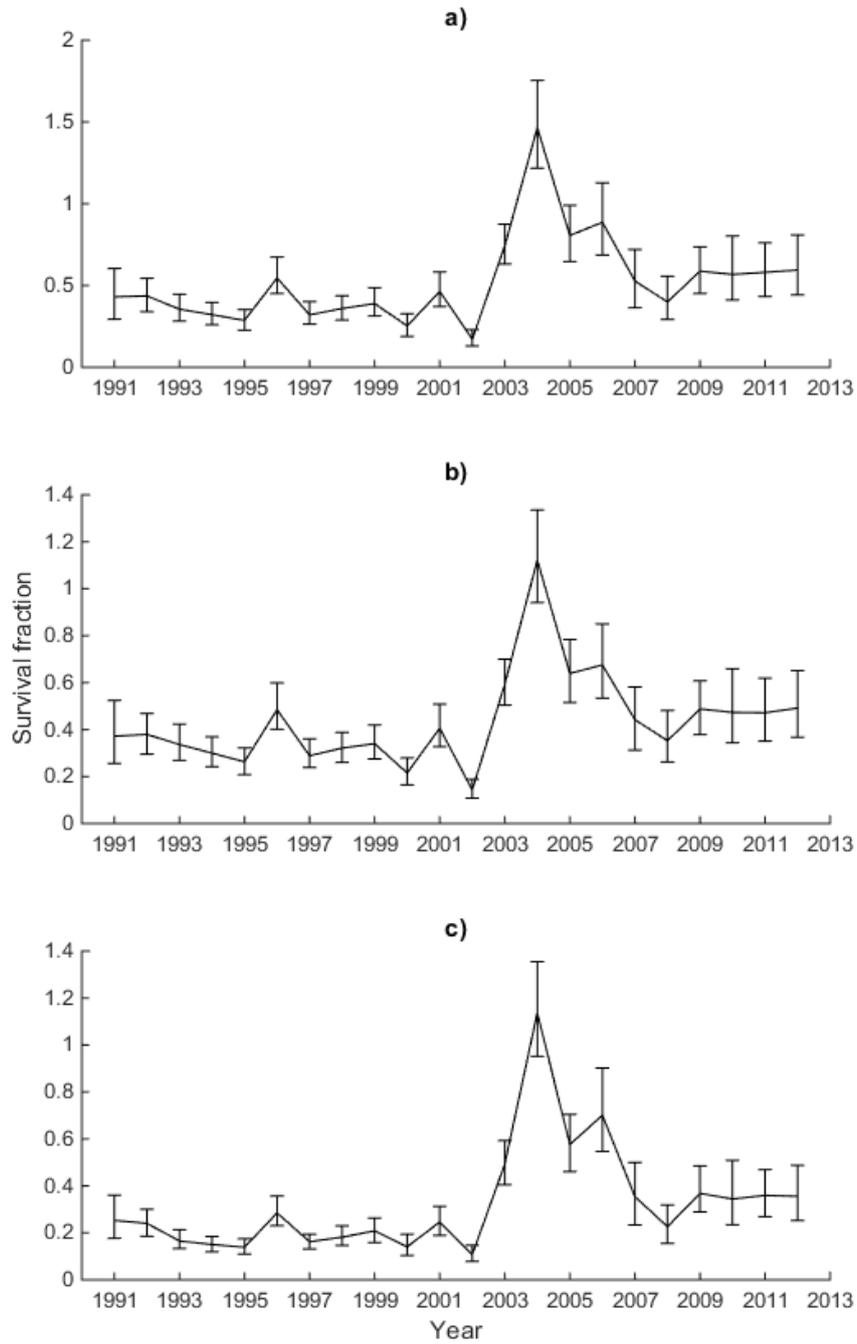


Fig. 3. Comparison of the observed and fitted age frequencies by year.

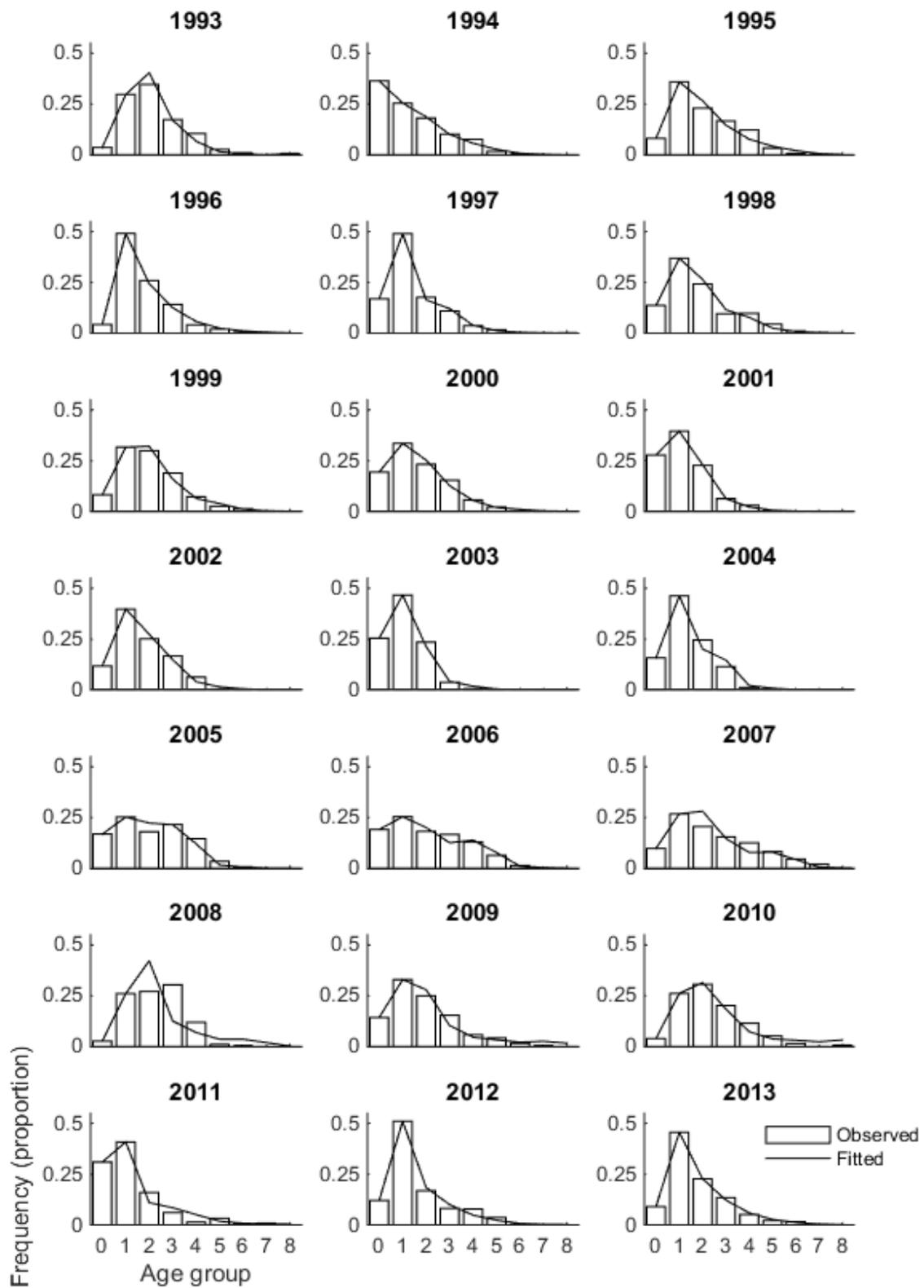
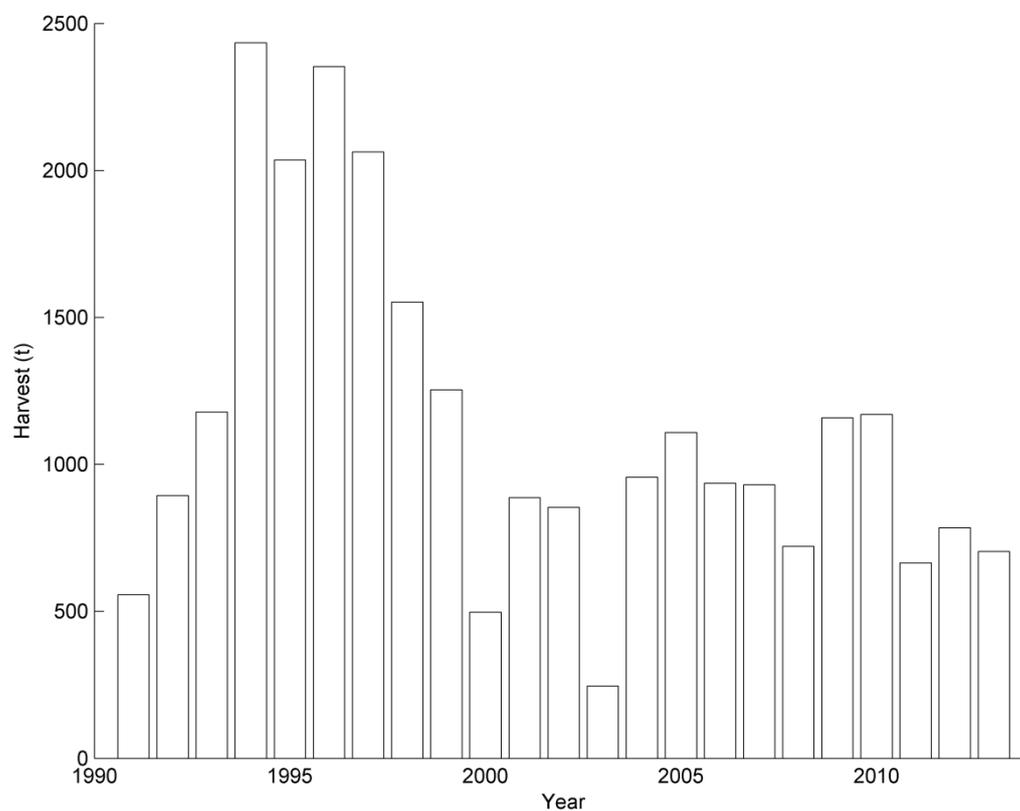


Fig. 4. Stout whiting annual harvest (tonnes) taken by T₄ licensed vessels in Queensland waters.



Appendix

Table 2 demonstrates example calculations for the catch curve model equations from Table 1. For simplicity, the example assumed that all fish were fully recruited, using hypothetical data for five age groups 0...4 and only one iteration of Table 1 equations; the EM algorithm would iterate this many times to seek convergence. Example cohort q is highlight in dark grey for year 1 and age 1. This diagonal vector has 4 elements, $m = 1...4$. Example cohort $q+1$ is highlighted in light grey for year 1 and age 0. This diagonal vector has 4 elements for the same years as cohort q , with $m = 1...4$ ($\text{end}-1 = 5 - 1$). Some example cell calculations are highlighted with blue lines tracing cell precedents. For demonstration only, the calculations in Table 2 were structure as follows:

- The first matrix structured the data year x age.
- N-twiddle (\tilde{n}_{ki}) calculated the number of fish at age component i in each year.
- As named, the matrices 'Diag sum' are the diagonal sums of each cohort relative to each column's position (fish age).
- The matrix 'InitialS' are the initial estimates of S (equation 1, Table 1).
- The matrix 'S adj fac' contains the adjustments to be iterated from S^{old} to S^{new} (equation 9, Table 1).
- The matrix 'S' contains the estimates S^{new} after adjustment.
- The matrices 'Product S' and 'Pi' illustrate the equation 2 (Table 1).

Table 2. Example calculations demonstrating the catch curve model equations from Table 1.

Year	Age					Row sum	N-twiddle					Diag sum					Initial S				Product S				Pi																	
	0	1	2	3	4																																					
1	106	53	32	8	3	202	115.5171	54.7474	23.4632	6.0162	2.2561	282.1061	181.8303	40.4206	8.3297	2.2561	0.47393	0.42857	0.25641	0.37500	1	0.473934	0.203114	0.052081	0.01953	0.571867	0.271027	0.116154	0.029783	0.011169												
2	71	40	30	7	2	150	73.1896	44.4214	21.0528	8.0726	2.3135	103.6973	106.3820	47.0824	16.9574	2.3135	0.60694	0.47393	0.42857	0.25641	1	0.606936	0.287648	0.123278	0.03161	0.487931	0.296143	0.140352	0.060151	0.015423												
3	105	76	56	15	3	255	125.1205	64.3644	39.0654	18.5144	7.9347	223.7808	310.5077	62.1676	26.0301	7.9347	0.51442	0.60694	0.47393	0.42857	1	0.514423	0.312222	0.147973	0.063417	0.490669	0.252411	0.153198	0.072606	0.031117												
4	115	63	18	9	2	207	106.7074	50.7909	26.1280	15.8580	7.5157	214.9998	98.8602	46.1428	23.1022	7.5157	0.47598	0.51442	0.60694	0.47393	1	0.475983	0.244856	0.148612	0.070432	0.515495	0.245367	0.126222	0.076609	0.036308												
5	87	54	18	8	0	167	75.8731	48.7453	23.2019	11.9356	7.2441	171.8026	108.2924	47.8694	20.0148	7.2441	0.64246	0.47598	0.51442	0.60694	1	0.642458	0.305799	0.15731	0.095477	0.454433	0.291888	0.138934	0.071471	0.043378												
6	119	47	48	22	5	241	132.8617	51.3583	32.9956	15.7052	8.0792	255.5385	95.9296	59.5471	24.6675	8.0792	0.38655	0.64246	0.47598	0.51442	1	0.386555	0.248345	0.118208	0.060809	0.551283	0.213105	0.136911	0.065167	0.033524												
7	141	89	34	12	6	282	149.0851	75.8168	29.3073	18.8287	8.9621	241.2301	122.6769	44.5713	26.5515	8.9621	0.50855	0.38655	0.64246	0.47598	1	0.508547	0.196581	0.126295	0.060114	0.52867	0.268854	0.103927	0.066769	0.031781												
8	115	76	28	11	1	231	119.0104	61.1490	31.0971	12.0207	7.7228	179.3361	92.1451	46.8601	15.2659	7.7228	0.51381	0.50855	0.38655	0.64246	1	0.513812	0.261298	0.101006	0.064892	0.515196	0.264714	0.13462	0.052038	0.033432												
9	111	31	15	2	0	159	98.7597	32.1091	16.4980	8.3900	3.2432	185.5973	60.3357	30.9961	15.7630	3.2432	0.32512	0.51381	0.50855	0.38655	1	0.325123	0.167052	0.084954	0.032839	0.62113	0.201944	0.103761	0.052767	0.020397												
10	139	92	35	2	0	268	131.1247	86.7876	28.2167	14.4981	7.3729	131.1247	86.7876	28.2167	14.4981	7.3729	0.66187	0.32512	0.51381	0.50855	1	0.661871	0.215189	0.110567	0.056228	0.489271	0.323834	0.105286	0.054097	0.027511												
Iteration	Age					Row sum	N-twiddle					Diag sum					S				Product S				Pi																	
1	211	100	42	10	3	202	109.4169	55.5385	26.0509	7.8946	3.2791	208.8712	102.8489	45.1891	10.8871	3.2791	1.0675	1.0980	1.1819	1.1076	1	0.50594	0.47059	0.30305	0.41536	0.541668	0.274052	0.128965	0.039082	0.016233												
	178	105	47	10	2	150	72.1583	42.8601	21.6847	10.2045	3.0924	173.6298	99.4544	47.4904	19.1381	3.0924	0.9786	1.0675	1.0980	1.1819	1	0.593974	0.300516	0.141418	0.042856	0.481055	0.285734	0.144565	0.06803	0.020616												
	214	107	65	17	3	255	126.3882	63.1717	37.5223	18.9841	8.9336	209.7359	101.4715	56.5942	25.8058	8.9336	0.9716	0.9786	1.0675	1.0980	1	0.499823	0.296882	0.150205	0.070684	0.49564	0.247732	0.147146	0.074447	0.035034												
	230	109	31	9	2	207	118.5796	45.4158	22.6999	13.4831	6.8217	223.9563	83.3477	38.2998	19.0719	6.8217	0.8046	0.9716	0.9786	1.0675	1	0.382998	0.191431	0.113705	0.057528	0.572848	0.2194	0.109661	0.065136	0.032955												
	179	115	46	13	0	167	84.0259	49.1514	18.8249	9.4091	5.5888	182.2998	105.3767	37.9319	15.5999	5.5888	0.9105	0.8046	0.9716	0.9786	1	0.584955	0.224037	0.111979	0.066512	0.503149	0.29432	0.112724	0.056342	0.033466												
	238	92	61	28	5	241	134.7978	55.2857	32.3397	12.3860	6.1908	243.6222	98.2739	56.2254	19.1070	6.1908	1.0610	0.9105	0.8046	0.9716	1	0.410138	0.239912	0.091886	0.045927	0.559327	0.229401	0.134189	0.051394	0.025688												
	234	119	45	13	6	282	154.5865	73.1448	29.9994	17.5483	6.7210	229.9930	108.8244	42.9882	23.8857	6.7210	0.9304	1.0610	0.9105	0.8046	1	0.473164	0.194063	0.113518	0.043477	0.548179	0.259379	0.106381	0.062228	0.023833												
	181	93	30	11	1	231	131.5863	55.8270	26.4153	10.8339	6.3374	177.7358	75.4065	35.6796	12.8888	6.3374	0.8257	0.9304	1.0610	0.9105	1	0.424262	0.200745	0.082333	0.048161	0.569638	0.241676	0.114352	0.0469	0.027434												
	203	66	17	2	0	159	114.3149	26.1723	11.1039	5.2540	2.1549	201.5706	46.1495	19.5795	9.2643	2.1549	0.7042	0.8257	0.9304	1.0610	1	0.22895	0.097135	0.045961	0.01885	0.718962	0.164606	0.069836	0.033044	0.013553												
	139	92	35	2	0	268	148.2813	87.2557	19.9772	8.4755	4.0103	148.2813	87.2557	19.9772	8.4755	4.0103	0.8891	0.7042	0.8257	0.9304	1	0.588447	0.134725	0.057159	0.027045	0.553288	0.325581	0.074542	0.031625	0.014964												

Appendix IV: Stout whiting catch curve mixture models: supplementary material to Appendix III

Stout whiting catch curve mixture models 1 and 2: supplementary to Appendix III

Michael F. O'Neill

Abstract

A Hierarchical Generalised Linear Model (HGLM) was used to standardise catch rates of stout whiting in Queensland and quantify a learning curve for new vessel operations entering the fishery. New operations were estimated to have 15% higher fishing power after their first cumulative at-sea year. Vessels fishing with the use of sonar technology were estimated to have 10% higher fishing power. The standardised annual catch rate index completed the set of age-abundance indicators for use in monitoring and management of stout whiting. Input of the standardised catch rate into a catch curve mixture model (Model 1) resulted in extremely variable estimates of stout whiting survival between years. This variability was considered implausible and a 2nd model was developed without using the catch rate index (Model 2). The 2nd model analysis suggested low fish survival in years 2000 and 2002. This analysis also highlighted inconsistency of fish length and age data between some years. The reporting of the catch curve results verified the test-application of models 1 and 2 methodology that guided the design of a subsequent model (Appendix III). The methodology for models 1 and 2 provide further analysis options for other fisheries which may have better data.

Introduction

This paper reports on developmental analyses for estimating stout whiting survival (or mortality). The developmental analyses (called model 1 and 2) describe initial theory and results that guided the final model design and outputs as published in Appendix III. Models 1 and 2 aimed to improve accuracy of survival estimates by analysing all fishery monitoring data. This included analysing all fish age and otolith weight data, length frequency data and catch rates. The model contexts are described in the following paragraphs.

Model 1 was designed first to connect the stout whiting standardised catch rate directly with the separate fish-length frequency and age-length-otolith data. In this model the standardised catch rate was used to represent stout whiting abundance and to scale the patterns of age-abundance (from the sampled fish length frequencies and age-length-otolith data). This linkage allowed for the variation in cohort strength (recruitment) and survival fractions to be estimated year by year; i.e. mitigate confounding by separating the signals for recruitment versus survival. The problem of estimated survival or mortality being confounded by cohort strengths is inherent in traditional cross sectional (year-by-year regression) catch-curve methodology, where estimated low survival in a year can imply high rates of fishing mortality or it can imply high recruitment (more new younger fish compared to old). Only repeated annual measures of fish survival or methodology that accounts for variable cohort strengths can resolve this confounder to provide clearer inferences. Unfortunately, the advantages of model 1 and the flexibility of model parameters were concluded to be unsuitable due to the year-to-year variation in the stout whiting data.

Model 2 was designed without catch rates, but still used the same fish-length frequencies and age-length-otolith data to scale age-abundances. As for model 1, the analysis structure assumed the data were sampled randomly from the population in each year. What this means is that the fish length composition data were required to be random samples of ungraded/unsorted landed catches, of which sub-samples of fish age and otolith measurements were taken. The model assumed this fishery-dependent sampling was conducted each year in a consistent and representative pattern between fishing seasons, areas and vessels. Model 2 estimates of survival fractions were still estimated for each cohort. The fractions compared the ratio of fully recruited cohort abundances to the next younger cohort in the same years. By comparing the same years, the survival estimates can be obtained but may be affected by strong or weak recruitment of new fish. The model estimates of survival identified inconsistency between some years of sampled fish-length frequency and age-length-otolith data. Samples where fish length frequencies were measured but not aged were highly correlated and judged to contain little information on survival compared to the age-length samples.

The survival estimates of stout whiting from both model versions 1 and 2 were varied between years. Overall, the scale and trend of survival fractions were comparable to the results in Appendix III, but had higher year-to-year variance. Adjustments to Model 1 (regularisations outlined in Table 6) were applied and noted in the discussion to reduce the variability in cohort strength. The reporting of the results below verified the test-application of models 1 and 2, but also provided the basis for use in other fisheries which may have better data.

Methods

Model versions 1 and 2

The model terminology follows from Appendix III. Stout whiting survival fractions were estimated by joining Gaussian finite mixture, Von Bertalanffy growth and catch curve methodology. Model estimates were solved iteratively using the expectation-maximisation algorithm, by estimating differences in fish abundances by age.

For stout whiting catch curve models 1 and 2, the data consisted of multiple years k of sequential mixed data \vec{y}_{jk} (l_j : fork length mm, o_j : power transformed otolith weight W_j^o , and a_j : age-group) for each fish j . The data were sampled in two parts for l_j and separate sub-sampling of matching l_j - o_j - a_j (Figure 4). The number of all sampled fish in each year 1991–2013 is denoted n_k . The Gaussian finite mixture distributions were defined by the mixing proportions π_{ki} , means $\mu_i^{l,o}$ and covariance matrix $V^{l,o}$, in order to calculate the posterior scores τ_{ijk} ; where age component label $i = 1 \dots 9$ corresponded to age groups $a = 0 \dots 8$ years old. As the a_j data related directly to model predicted posterior scores τ_{ijk} and was not available for all fish, it was used to set $\tau_{ijk} = 1$ where a fish was aged i and not used directly as a third dimension in the mixture model; noting $\sum_i \tau_{ijk} = 1$. The posterior scores are the probabilities of each age component i for each individual fish's data (l_j , o_j and a_j).

The following assumptions were required to enable the analyses:

- Mean fish length at age and variance was assumed constant in time and based on an internally estimated von Bertalanffy growth curve,

- The number of age components was assumed known and fixed from the data,
- The catch curve approach assumed constant selectivity and that fully recruited fish experience a constant survival rate within a cohort, and
- For model 2, survival rates measured the combined effects of both fish mortality and cohort strength. It was not assumed that cohort strength was constant over years. Model 1 separated these effects by using catch rate data.

The overall algorithm for finding maximum likelihood parameter estimates was implemented in Matlab® (MathWorks, 2014) using the equations in Table 1 and Table 2 as follows:

1. Linearize otolith weight with length using the transformation: $o_j = (W_j^o)^{b^{-1}}$, where parameter b was estimated from the power function $W_j^o = al_j^b$.
2. From the data calculate initial values for the EM algorithm: $\mu_i^{l,o}, V^{l,o}, \pi_{ki}$.
3. Define the first fully recruited age component for catch curve calculation; for model 1 the peak criterion $r = 2$ was used and the peak-plus criterion was used for model 2 with $r = 3$ (Smith et al., 2012).
4. EM algorithm (Table 1 or Table 2):
 - a. Calculate derivatives $\frac{\partial \bar{\mu}_i}{\partial \theta}$ for the matrix of growth curve parameters $\bar{\theta}$.
 - b. Calculate τ_{ijk} using mixture density functions and set $\tau_{ijk} = 1$ where a fish had been aged.
 - c. Calculate \hat{n}_{ki} .
 - d. Calculate $\hat{\theta}$ and $\hat{V}^{l,o}$.
 - e. Calculate \hat{S}_k .
 - f. Calculate $\hat{\alpha}_{ki}$.
 - g. Calculate $\hat{\pi}_{ki}$.
 - h. Replace all initial values by their estimated updates: $\hat{\mu}_i^{l,o}, \hat{V}^{l,o}, \hat{\pi}_{ki}$.
 - i. Return and loop until parameter estimates converge.

For the predicted means $\mu_i^{l,o}$ (l and o at age) to be calculated from the Von Bertalanffy growth curve $\hat{\mu}_i^{l,o} = l_\infty^{l,o} \left(1 - \exp\left(-\kappa^{l,o} (t_i - t_0^{l,o})\right) \right)$ (Haddon, 2001), each iteration in the EM algorithm followed a single step of the Gauss-Newton algorithm (θ and ϕ in model 1 or 2).

The derivatives $\frac{\partial \bar{\mu}_i}{\partial \theta}$ were a 6×2 dimensional matrix for each age component i . The matrix cells (1:3,1) were for the fish length derivatives $\frac{\partial \mu_i^l}{\partial l_\infty^l}$, $\frac{\partial \mu_i^l}{\partial K^l}$, and $\frac{\partial \mu_i^l}{\partial t_0^l}$ and matrix cells (4:6,2) for otolith weight derivative $\frac{\partial \mu_i^o}{\partial l_\infty^o}$, $\frac{\partial \mu_i^o}{\partial K^o}$, and $\frac{\partial \mu_i^o}{\partial t_0^o}$ (Table 2, equations 1...3). The cross derivatives between l and o were assumed all zero; matrix cells (4:6,1) and (1:3,2) = 0.

For model 2 the calculation of annual fish survival \hat{S}_k followed cohort abundances (\hat{n}_{ki} matrix diagonals; equation 8, Table 2). The structure of model 2 equation 8 was based on truncation of matrix \hat{n}_{ki} for fully recruited fish (Table 2). \hat{S}_k compared two diagonal vectors of cohort c and $c+1$ abundance. \hat{S}_k was the sum abundance of cohort c divided by the sum abundance of the next younger cohort $c+1$ in the same years for fully recruited fish. The \hat{S}_k ratio therefore represented fish survival in year k .

Table 1. Catch curve model 1 equations.

Equations	Notes
(1) $\tau_{ijk} = \pi_{ki} f_i(\bar{y}_{jk}) / \sum_i \pi_{ki} f_i(\bar{y}_{jk})$	f is a d-dimensional multivariate normal density function, for univariate l_j or multivariate $l_j - o_j$.
(2) $\hat{n}_{ki} = \sum_{j=1}^{n_k} \tau_{ijk}$	Estimated number of fish in each age component i and year k .
(3) $\hat{\theta} = \bar{\theta} + \left\{ \sum_i \left[\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \right] \left(\frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right)^T V_i^{-1} \frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right\}^{-1} \times$ $\left\{ \sum_i \left[\left(\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \bar{y}_{jk} \right)^T - \left(\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \right) \bar{\mu}_i^T \right] V_i^{-1} \frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right\}^T$	Updating equation for parameters of the $a-l$ and $a-o$ growth curves; 2×3 matrix for $l_\infty^{l,o}, k^{l,o}, t_0^{l,o}$. Derivatives are listed in Table 2.
(4) $\hat{V}^{l,o} = \left\{ \sum_k \sum_{j=1}^{n_k} \sum_i \tau_{ijk} (\bar{y}_{jk} - \hat{\mu}_i)(\bar{y}_{jk} - \hat{\mu}_i)^T / \gamma_i \right\} / \sum_k n_k$	The 2×2 covariance matrix for l and o , which can form the parametric relationship $V_i = \gamma_i V$ for each age component i .
(5) $\hat{\phi} = \bar{\phi} + \left[\sum_k \sum_{j=1}^{n_k} \sum_i \frac{\tau_{ijk}}{\gamma_i^3} (\bar{y}_{jk} - \bar{\mu}_i)^T V_i^{-1} (\bar{y}_{jk} - \bar{\mu}_i) \left(\frac{\partial \gamma_i}{\partial \bar{\phi}} \right)^T \frac{\partial \gamma_i}{\partial \bar{\phi}} \right]^{-1} \times$ $\sum_k \sum_{j=1}^{n_k} \sum_i \tau_{ijk} \left\{ \frac{d}{\gamma_i} - \frac{1}{\gamma_i^2} (\bar{y}_{jk} - \bar{\mu}_i)^T V_i^{-1} (\bar{y}_{jk} - \bar{\mu}_i) \right\} \left(\frac{\partial \gamma_i}{\partial \bar{\phi}} \right)^T$	Updating equation for ϕ , that determined the variance scaling factor $\gamma_i = 1 + \phi(a_i - 1)$; ϕ can be scaled relative to the first fully recruited age group (r).
(6) $\hat{S}_k = \frac{\hat{\lambda}_{k+1} n_k}{\hat{\lambda}_k n_{k+1}} \sum_{i>r} \hat{n}_{ik+1} / \sum_{i_{\max} > i \geq r} \hat{n}_{ik}$	Survival rates S_k of fish in year k across all fully recruited ages, based on annual abundance measure λ_k .
(7) $\hat{H}_k = \sum_{\substack{a_i \geq a_r \\ k+a_i-a_r \leq K}} \frac{\hat{\lambda}_{k+a_i-a_r}}{n_{k+a_i-a_r}} \hat{n}_{i, k+a_i-a_r} / \sum_{\substack{a_i \geq a_r \\ k+a_i-a_r \leq K}} \prod_{m=k}^{k+a_i-a_r-1} \hat{S}_m.$	Cohort strength parameters H_k for fish that reach age a_r in year k . The calculation follows matrix diagonals of \hat{n}_{ki} . The denominator is the sum of the cumulative product of age-based survival, with $S_1 = 1$.
(8) $\hat{\alpha}_{ki} = H_{k-a_i+a_r} \prod_{m=k-a_i+a_r}^{k-1} \hat{S}_m$	Age group abundance α_{ik} is calculated to satisfy the catch curve for fish that reach a_r , using the cumulative product of age-based survival.
(9) $\hat{\pi}_{ki} = \left(1 - \frac{\hat{n}_{1k}}{n_k} \right) \hat{\alpha}_{ki} / \sum_{m=a_r}^g \hat{\alpha}_{km}, \hat{\pi}_{1k} = \frac{\hat{n}_{1k}}{n_k}$	Updating equation for π_{ik} age proportions for recruited aged fish.

Table 2. Catch curve model 2 equations.

Equations	Notes
(1) $\frac{\partial \mu_i^{l,o}}{\partial l_\infty} = 1 - \exp\left(-\kappa^{l,o} (t_i - t_0^{l,o})\right)$	Derivative for asymptotic maximum average length l_∞ . t_i is the specified mid-year age of fish in component i .
(2) $\frac{\partial \mu_i^{l,o}}{\partial \kappa^{l,o}} = l_\infty^{l,o} (a_i - t_0^{l,o}) \exp\left(-\kappa^{l,o} (t_i - t_0^{l,o})\right)$	Derivative for annual growth rate labelled κ .
(3) $\frac{\partial \mu_i^{l,o}}{\partial t_0^{l,o}} = -l_\infty^{l,o} \kappa^{l,o} \exp\left(-\kappa^{l,o} (t_i - t_0^{l,o})\right)$	Derivative for the fish age (t_0) at zero length.
(4) $\tau_{ijk} = \pi_{ki} f_i(\vec{y}_{jk}) / \sum_i \pi_{ki} f_i(\vec{y}_{jk})$	f is a d-dimensional multivariate normal density function, for univariate l_j or multivariate $l_j - o_j$.
(5) $\hat{n}_{ki} = \sum_{j=1}^{n_k} \tau_{ijk}$	Estimated number of fish in each year k and age component i .
(6) $\hat{\theta} = \bar{\theta} + \left\{ \sum_i \left[\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \right] \left(\frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right)^T V^{-1} \frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right\}^{-1} \times$ $\left\{ \sum_i \left[\left(\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \vec{y}_{jk} \right)^T - \left(\sum_k \sum_{j=1}^{n_k} \tau_{ijk} \right) \bar{\mu}_i^T \right] V^{-1} \frac{\partial \bar{\mu}_i}{\partial \bar{\theta}} \right\}^T$	Updating equation for parameters $l_\infty^{l,o}, k^{l,o}, t_0^{l,o}$ of the $a-l$ and $a-o$ growth curves.
(7) $\hat{V}^{l,o} = \left\{ \sum_k \sum_{j=1}^{n_k} \sum_i \tau_{ijk} (\vec{y}_{jk} - \hat{\mu}_i)(\vec{y}_{jk} - \hat{\mu}_i)^T \right\} / \sum_k n_k$	The 2×2 covariance matrix for l and o .
(8) $\hat{S}_k = \begin{cases} \sum_{m=1}^{end} n_{ki}^c / \sum_{m=1}^{end-1} n_{ki}^{c+1} & \text{for years } < k = 1 \\ \sum_{m=2}^{end} n_{ki}^c / \sum_{m=1}^{end-1} n_{ki}^{c+1} & \text{for years } \geq k = 1 \end{cases}$	Survival rates S_k of fish in year k . The notation represents cohort c diagonals of the truncated matrix n_{ki} for fully recruited ages ($i > r$). m indicates the cohort vector elements that are summed. n_{ki} contains information on S_k prior to the 1 st year of data $k=1$.
(9) $\hat{\alpha}_{ki} = \prod_{m=k-i+r}^{k-1} \hat{S}_m$	Scaled abundance of age group α_{ki} relative to the abundance of the youngest fully recruited age group in year k . The abundances satisfy the catch curve for fish age components $\geq r$, calculated as the cumulative product of age-based survival. m indicates the \hat{S}_k used.
(10) $\hat{\pi}_{k,1\dots r-1} = \frac{\hat{n}_{ki}}{n_k}; \hat{\pi}_{k,r\dots g} = \left(1 - \sum \hat{\pi}_{k,1\dots r-1}\right) \alpha_{ki} / \sum_{i=r}^g \alpha_{ki}$	Updating equation for π_{ki} age proportions.

Length and age data

Stout whiting length and age sampling from the T₄ sector was conducted 1991–2013 following long term monitoring protocols (Department of Primary Industries and Fisheries, 2007). The sampling was ‘fishery-dependent’, with two 5kg boxes of fish collected from each T₄ vessel’s fishing trip. The provision of boxes-of-fish was dependent on each vessel’s pattern of operation with one box typically from a night-time catch and the other from a day-time catch. The sample times and locations were not controlled, but ungraded (random) fish were supplied from the catch. Any fisher processes of sorting, packing and discarding fish were specified to be separated from the monitoring sample.

All fish from each box were measured as fork-lengths (mm) for length frequency. From each box, 1 to 3 fish from every 5mm size class were dissected to extract otoliths for aging until a subsample of about thirty fish per size class per year was achieved (length stratified sampling). Historically, the number of fish sampled each year ranged between 300–500 for aging and 3000–20000 for length frequencies dependent on the amount of fishing and catch.

For fish age determination, both otoliths were removed and cleaned, with only the left otolith sectioned. All otolith reading was done without knowledge of fish size, date or location of capture. Age estimates were counts of complete opaque rings. In 2004 historical 1993–2000 fish otoliths were re-aged independently by Australia’s Central Aging Facility (unpublished report; C. P. Green and K. Krusic-Golub). This was done to standardise fish aging protocols to ensure otolith aging was consistent in time and completed by qualified staff as tested against a reference otolith collection (O’Sullivan, 2007; O’Sullivan and Jebreen, 2007). Final age frequencies were adjusted to age-groups (cohorts) based on the fish capture dates, the width of sectioned otolith margins and an assumed birth date of 1st January (O’Sullivan and Jebreen, 2007). Verification of a single annual cycle in ring formation, coinciding with spring months in 0+ to 3+ age groups, had been demonstrated for stout whiting otoliths with clear banding (Butcher and Hagedoorn, 2003).

Standardised catch rates of stout whiting

For the Queensland T₄ sector 1991–2013, mandatory shot-by-shot recordings of catches from each vessel were analysed on a daily basis including the number of

hours fished and number of catches (number of deployments or shots of fishing gear) in the day. Target fishing effort where no stout whiting were caught was included. The T_4 catch data were stratified by five fishing zones w33...w38 (Figure 1). Data for vessel and skipper identification, fishing depth and date and associated fishing gears were considered in the statistical modelling.

Commercial catch data reported from New South Wales (T_{NSW}) were collated for the period 1997–2013. The T_{NSW} logbook data represented monthly harvest per vessel in which the number of days of effort was available. No fishing depth or gear data were available. Vessel identification and fishing zone (Figure 1) factors were included in the statistical modelling.

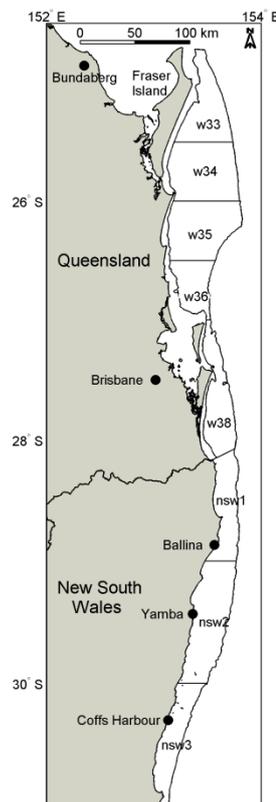


Figure 1. Map of the East Australia stout whiting fishery zoned by analysis regions. Queensland fishing zones (w33...w38) cover offshore water depths between 20 and 50 fathoms. New South Wales fishing zones (nsw1...nsw3) cover offshore water depths up to 50 fathoms.

Two catch rate analyses were conducted separately on T_4 and T_{NSW} catches, due to the different logbook recording systems. The analyses were completed using the statistical software GenStat (VSN International, 2013) and standard errors were calculated for all estimates. Analysis of residuals supported their structures and transformation of catch responses. The importance of individual model terms was assessed formally using Wald (Chi-squared; χ^2) statistics by dropping individual terms from the full model.

The T_4 data were spatially unbalanced and incomplete, with only 2–5 vessels fishing per year in various months and zones between 1991 and 2013. As the T_4 fleet is small, the data potentially contained sources of error variation that may influence standardisation of catch rates. To allow for unequal variances (dispersion) between vessels and the random occurrence of zero catch, a Hierarchical Generalized Linear Model (HGLM) was used assuming normally distributed errors (Lee and Nelder, 2001; Lee et al., 2006; VSN International, 2013). The model response data consisted of the cube root transformation of the daily catch ($\text{kg}^{1/3} \text{ boat-day}^{-1}$) and the expected bias corrected mean followed the Normal distribution third moment $\mu^3 + 3\mu\sigma^2$ (Wikipedia, 2015), with variance $\sigma^2 = \phi V(\mu)$ (VSN International, 2013). The cube root transformation and HGLM was employed to normalise residuals and account for heterogeneity of the data. The optimal box-cox (power) transformation for model normality was about 0.35, suggesting the cube root transformation. The HGLM included fixed ($\mu = \mathbf{X}\boldsymbol{\beta}_1$) and dispersion ($\phi = \exp(\mathbf{X}\boldsymbol{\beta}_2)$) model terms, where \mathbf{X}_1 and \mathbf{X}_2 were the relevant data. The fixed explanatory model terms ($\boldsymbol{\beta}_1$) included the model intercept, interactions between fishing year \times zone, vessel \times effort ($\text{hours}^{1/3}$), zone \times water-depth ($\text{fathoms}^{1/3}$) and the main effects of seasonality, presence/absence of sonar and computer mapping and vessel experience. Seasonality (s) was modelled by four trigonometric covariates, which together modelled an average monthly pattern of catch (Marriott et al., 2013): $s_1 = \cos(2\pi d_y/T_y)$, $s_2 = \sin(2\pi d_y/T_y)$, $s_3 = \cos(4\pi d_y/T_y)$, $s_4 = \sin(4\pi d_y/T_y)$, where d_y was the cumulative day of the year and T_y was the total number of days in the year (365 or 366). As some vessel ownerships had changed over time, a covariate for fishing experience was calculated to follow an exponential learning curve. This

covariate was linear on the natural logarithm scale: $\log(v_y/(1+v_y))$, where v_y was the cumulative number of at-sea fishing days divided by 365.25. The increase in experience was assumed sharpest in the initial fishing years, then levelling out to a limit. The dispersion model terms (β_2) included the main effects for vessels and the incidence of zero catch. Summary of analysis and model terms are in Table 4.

The stout whiting T_{NSW} monthly data were spatially unbalanced but recorded for all zones 1997–2013. No zero catches were evident and lesser covariate data were available. The selected T_{NSW} analysis was a linear mixed model (REML) with normally distributed errors on the log scale (VSN International, 2013). The model included both fixed ($\mathbf{X}\beta$) and random ($\mathbf{Z}\gamma$) terms. Where data (\mathbf{X} , \mathbf{Z}) were relevant and available, the model was fitted to estimate the following fixed terms (β): model intercept, interaction between fishing year \times zone and the main effects of fishing month and effort (logarithm of number of days fished). The random term (γ) quantified the variance and efficiencies between 256 vessels.

The prediction of annual standardised catch rates across the fishery (1991–2013) involved three steps: 1) predict mean catch rates from the models year \times zone terms; 2) impute missing year \times zone predictions; 3) spatially average predictions across zones in each year. These steps followed the spatial standardisation methods of Campbell (2004), Carruthers et al. (2011) and Walters (2003). Mean year \times zone catch rates were calculated using GenStat ‘HGPREDICT’ and ‘VPREDICT’ procedures for the T_4 and T_{NSW} models respectively (VSN International, 2013). The procedures formed standardised predictions by fixing the season, effort, depth, experience and sonar model terms to their average values. Mean catch rates were imputed for year \times zone strata with less than 20 boat-days of fishing (Figure 2d and Table 3). The final predictions were averaged across zones in each year using the area weights (0.16, 0.20, 0.18, 0.09, 0.14, 0.08, 0.08, 0.08) for each zone w33...NSW3 (Figure 1). Standard errors for year \times zone predictions were propagated to produce 95% confidence intervals on the standardised whole-of-fishery annual catch rates. This included calculating standard errors for missing year \times zone means (VSN International, 2013).

Table 3. List of imputed catch rates. The following year \times zone means were imputed similar to the methods of Walters (2003) and Carruthers et al. (2011)

w33.2003 = mean(w33.2002 to w33.2004),
w33.2013 = mean(w33.2012 to w33.2013),
w35.2002 to w35.2007 = mean(w35.2001 to w35.2008),
w35.2011 = mean(w35.2010 to w35.2012),
w36.2003 to w36.2006 = mean(w36.2002 to w36.2007),
w36.2011 to w36.2012 = mean(w36.2010 to w36-.2013),
w38.1991 to w38.1992 = mean(w38.1993 to w38.1995),
w38.2000 to w38.2008 = mean(w38.1999 to w38.2009) and
T _{NSW} 1991 to 1996 = mean 1997 to 2013.

Results

Stout whiting catch rates were analysed for all vessels and areas to estimate the standardised annual abundance indicator for each year k (λ_k). Table 4 lists the model terms used to standardise catch rates for each fishing sector. For the T₄ sector, significant fishing power terms were detected for each vessel operation, at-sea fishing experience, sonar use and hours fishing (Table 4). Fishing using sonar technology increased average catch rates by 10.4% (s.e. = 2.3%). Fishing experience increased average catch rates about 15% after one cumulative at-sea year (\approx 3 calendar years in time; parameter estimate = 0.429, s.e. = 0.083; Figure 2). Average catch rates peaked in the month of May (Figure 2). The 2013 T₄ and T_{NSW} combined catch rate index was equal to 1.02 and up 18% compared to 2012. The 2013 index was about equal to the long term average catch rate 1991–2013 (=1; Figure 2). Inclusion of non-fished zones inflated confidence intervals on the catch rate index (Figure 2).

The standardised annual catch rate λ_k was then input into catch curve model 1. For the analysis the 1+ age group (not 2+ as in model 2) was assumed the age at full recruitment. This was done to make more use of the age data given the extra model parameters for cohort strength. From the analysis the variation in annual estimates of stout whiting survival was deemed large (Figure 3, with Table 6 regularisations

applied). The low estimate of \hat{S}_k was correlated with the decline in catch rates (λ_k) in 2000 (Figure 2a). The variability in estimates between years was considered not reasonable given the expected fish longevity (4–8 years) and inertia in the age-data.

Model 2 estimates of fish survival for most years were more stable and consistent from year to year compared to model 1 (Figure 3). Of note were two very-strong cohort-survivals estimated in 2001 and 2009. These estimates deviated markedly from the overall trend of reduced survival from 1991–2000 and 2002 and then increased thereafter. The higher 2001 survival estimate resulted from a sudden change to older fish aged in 2002 compared to 2001 and 2003 (Figure 4d). This was inconsistent with marginally smaller fish suggested by the length frequency samples in 2002 (Figure 4a). In 2009 the very high survival estimate resulted from larger and older fish present in 2010 samples (Figure 4). The 2001 and 2009 survival fractions suggest strong survival events (low mortality and/or high recruitment event) or highlight data inconsistencies. The low survivals in years 2000 and 2002 suggest diminished recruitment after previous years of high harvest (Figure 5). The estimated growth curves and constant covariance matrix are detailed in Table 5.

Table 4. Summary of statistical analyses of stout whiting catches.

Analysis and components	Statistics
HGLM on T₄ catches	
Number of data	10 812
Response variable	kg ^{1/3} boat-day ⁻¹
Residual variance	4.387
Fixed model terms	(χ^2 statistics, d.f., <i>p</i> -value)
Year × Zone	396.7, 76, <0.001
$f_1(\textit{day})$	197.9, 1, <0.001
$f_2(\textit{day})$	50.6, 1, <0.001
$f_3(\textit{day})$	97.9, 1, <0.001
$f_4(\textit{day})$	51.3, 1, <0.001
Vessel × Hours ^{1/3}	5 963.9, 17, <0.001
Zone × Depth ^{1/3}	63.8, 5, <0.001
$f(\textit{experience})$	25.8, 1, <0.001
Sonar	9.9, 1, 0.002
Dispersion model terms	1184, 17, <0.001
Vessel term	396.7, 16, <0.001
Zero catch term	762.5, 1, <0.001
LMM (REML) on T_{NSW} catches	
Number of data	13 802
Response variable	log(kg) boat-month ⁻¹
Residual variance	1.964
Fixed model terms	(χ^2 statistics, d.f., <i>p</i> -value)
Year × Zone	141.43, 32, <0.001
Month	101.64, 11, <0.001
Log(number of days fished)	988.88, 1, <0.001
Variance component	
Vessels (n =265)	1.134 (s.e. = 0.125)

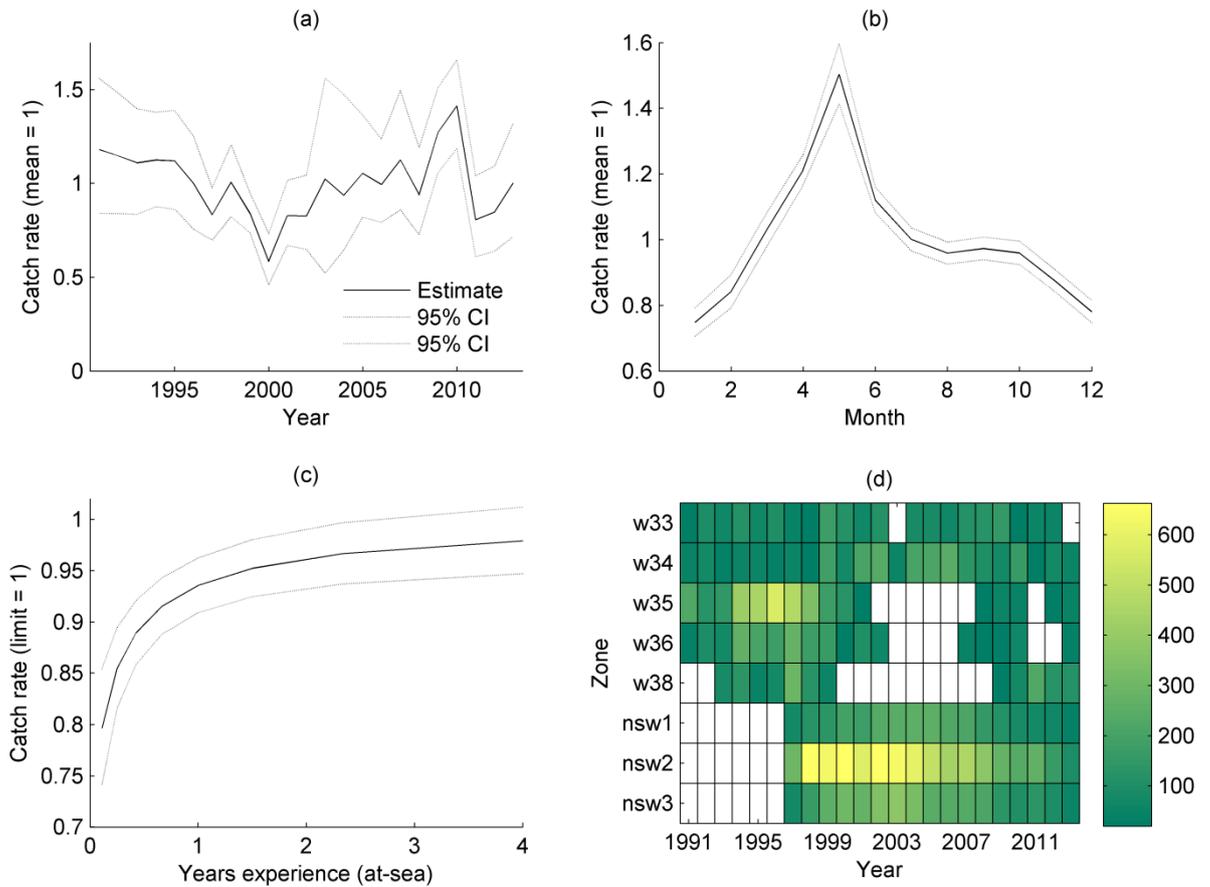


Figure 2. Summary of stout whiting catch rates and data for: (a) final imputed standardised catch rates, scaled proportional to the overall annual mean; (b) seasonal catch rate scaled proportional to the mean; (c) learning curve for at-sea fishing experience showing proportional increases in fishing power relative to the limit; and (d) data frequency boat-days for the year x zone strata, with white grids identifying less than 20 boat-days of fishing and that imputation in (a) was required.

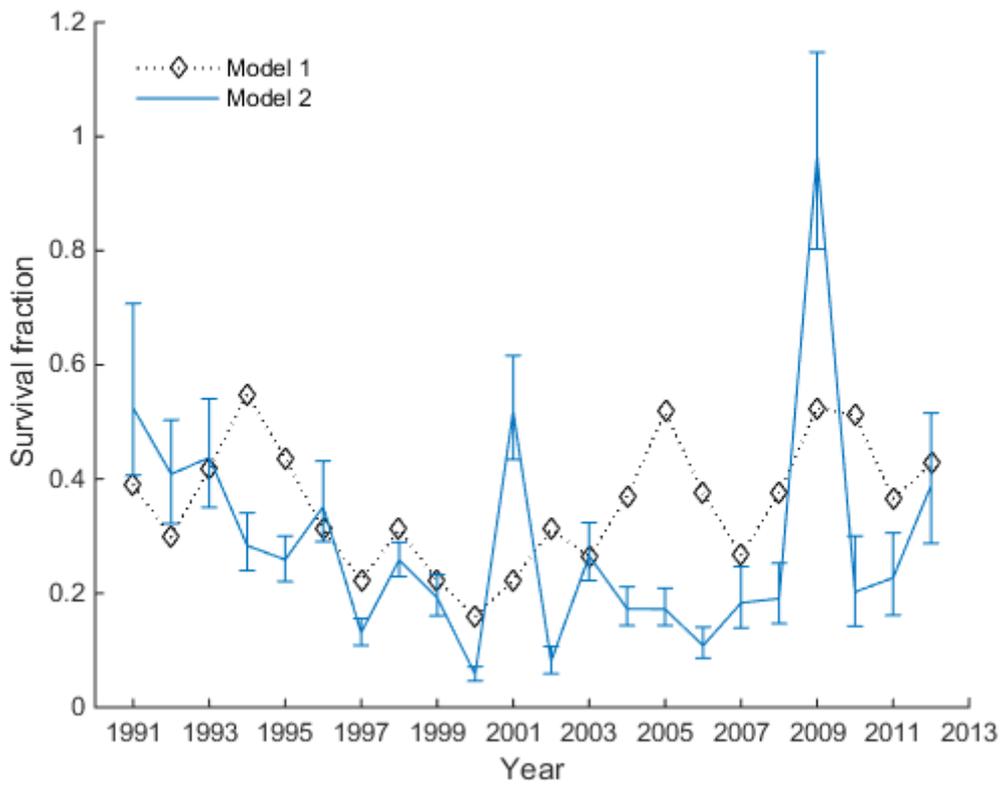


Figure 3. Estimated survival fractions \hat{S}_k of stout whiting as calculated from model versions 1 and 2. Error bars show the 95% confidence intervals of model 2 estimates.

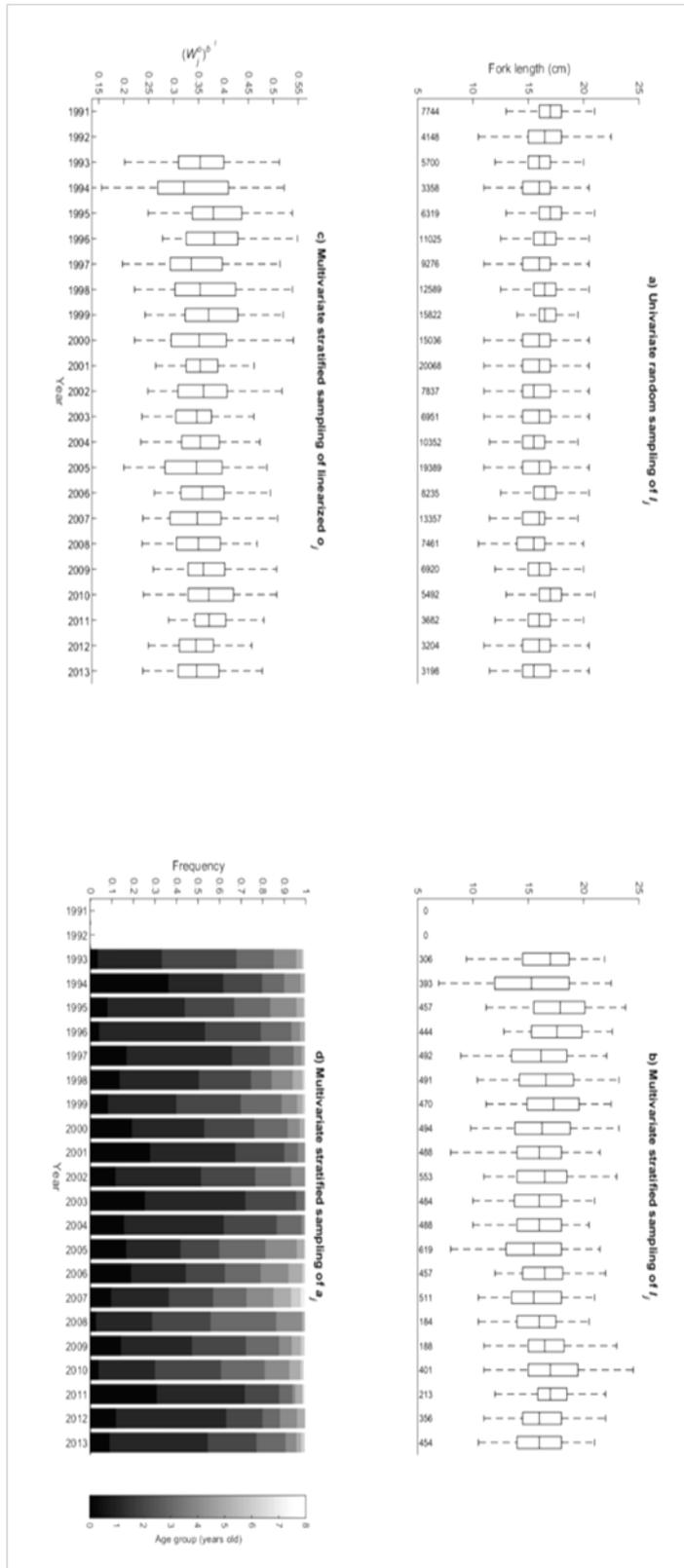


Figure 4. Summary of stout whiting age-abundance samples recorded from the T_4 fishery for a) length frequencies, b–d) matched samples of individual fish length-otolith-age measures. Subplots a) and b) show the annual numbers of fish measured.

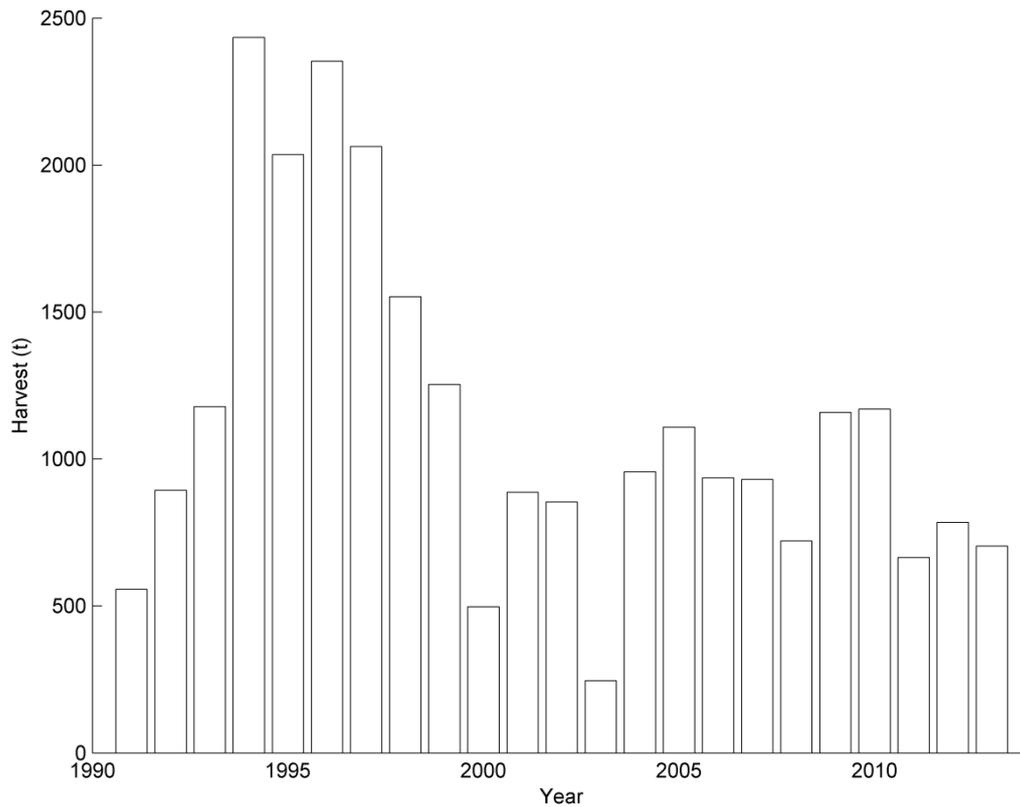


Figure 5. Stout whiting annual harvest (tonnes) taken by T₄ licensed vessels in Queensland waters.

Table 5. Model 2 estimated growth curve and covariance parameters; 95% confidence interval and/or standard error shown in parenthesis.

Parameter estimates	L_{∞}	K	t_0
Fork length l	20.579 (19.905:21.147; 0.308)	0.321 (0.288:0.372; 0.021)	-2.668 (-2.873:-2.395; 0.123)
Linearised otolith weight o	0.568 (0.551:0.587; 0.009)	0.197 (0.179:0.215; 0.009)	-2.942 (-3.145:-2.754; 0.097)
Covariance matrix $V^{l,o}$	$\begin{bmatrix} 1.647 (0.023) & 0.002 (0.00004) \\ 0.002 (0.00004) & 0.0000547 (0.00000091) \end{bmatrix}$		

Discussion

The catch curve mixture models 1 and 2 provided an advance over standard catch-curve methodology (Smith et al., 2012). The models focused directly on estimating growth and survival parameters of a fish population. The model's methods tested

data with and without an annual abundance index (λ_k) to estimate annual survival fractions (\hat{S}_k). The inclusion of the parametric von Bertalanffy growth function allowed for separation of age-components i , via maintaining the logical sequences $\bar{\mu}_i < \bar{\mu}_{i+1}$ for fish length and otolith-weight means. The use of Gaussian finite mixture theory allowed for estimation of survival without all fish being explicitly aged.

For all stock assessments, the use of a reliable trend in standardised catch rates is important to indicate changes in the exploitable population. In model 1 low catch rates correlated with low survival fractions. However, high year-to-year variability of the abundance indicator did affect model performance and obscure estimates of survival. Given the catch rate variability, the internal mechanics of model 1 were tested using restrictions on the annual change in survival (Table 6). The model 1 restrictions (Table 6) were used if the change in estimated fish survival between years exceeded the specified limit of $\pm 30\%$. If exceeded the catch rate abundance index λ_{k+1} was adjusted using equations 2, 3 or 4 (Table 6), where equation 4 specified a upper biological bound on survival $\exp(-0.59)$. The equations were applied at step 4e of the EM algorithm. The application of these restrictions was not successful or desirable and added unwanted complexity. If such model adjustments are required, then the simpler model versions are preferred.

The type of catch curve mixture model to apply in other fisheries will depend on the objectives to be achieved and data quality. Like the methods and analyses by Francis and Campana (2004) and Francis et al. (2005), the finite mixture method herein estimated fish age-proportions but extended to be a formal stock assessment tool to estimate fish survival. It can be of particular use for complex fisheries with many fishing sectors that lack comprehensive catch-effort reporting. The catch curve mixture model applies naturally to fisheries monitoring data on fish sizes, ages and abundance. For stout whiting, the survival estimates were sensitive to the year-to-year variation in the data.

Table 6. Equations for catch curve model 1 regularisation, when age-abundance data have high variance; used for years k .

Equations	Notes
(1) $\hat{S}_k = \max\left(\min\left(\hat{S}_k, \hat{S}_{k-1}\varepsilon\right), \hat{S}_{k-1}\varepsilon^{-1}\right)$	ε specified the limit in annual change in survival from year $k-1$ to k .
(2) $\lambda_{k+1} = \lambda_{k+1}\left(\hat{S}_{k-1}\varepsilon/\hat{S}_k\right)$	Adjust λ_{k+1} if the upper bound was exceeded in equation (12).
(3) $\lambda_{k+1} = \lambda_{k+1}\left(\hat{S}_{k-1}/\hat{S}_k\varepsilon\right)$	Adjust λ_{k+1} if the lower bound was exceeded in equation (12).
(4) $\lambda_{k+1} = \lambda_{k+1}\left(S_{\text{lim}}/\hat{S}_k\right); \hat{S}_k = S_{\text{lim}}$	If $\hat{S}_k > S_{\text{lim}}$, an upper bound on survival can be set as desired (e.g. based on an assumed natural mortality).

Stout whiting catch rates were standardised for both fishing power and spatially unbalanced fishing effort. A Hierarchical Generalised Linear Model (HGLM) was applied to the T_4 catch data to capture heterogeneity of variance in the small fleet (Lee et al., 2006; VSN International, 2013). The HGLM estimated fixed model terms and analysed the dispersion of the errors according to model factors for different vessels and occurrence of zero harvests (Table 4). The cube root transformation was appropriate to normalise catch rates as skewness lay between natural logarithm and square root transformations; Poisson and Gamma log link models did not satisfactorily account for the heterogeneity. For T_{NSW} , many more vessels reported harvests, with a simpler linear mixed model (REML) of log transformation harvests used to standardise catch rates (Table 4).

Two main fishing power effects were identified from the statistical analysis of T_4 harvests. Vessels searching for schools of fish with sonar had 10% higher average catches. This was significantly higher than the 3% estimate for eastern king prawn vessels working the same waters (O'Neill and Leigh, 2007). The estimated at-sea learning curve illustrated how new vessel ownership (new crew operations) improved their fishing power in time (Figure 2c). When new vessel operations commenced in the T_4 sector, they did so with some starting knowledge of spatial fishing areas and techniques. The at-sea learning curve would expect to have greater magnitude if inexperienced operations had commenced fishing.

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Appendix V: Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (*Ranina ranina*) fishery

Using catch rate data for simple cost-effective quota setting in the Australian spanner crab (*Ranina ranina*) fishery

Michael F. O'Neill, Alexander B. Campbell, Ian W. Brown, and Ron Johnstone

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.

For many fisheries, there is a need to develop appropriate indicators, methodologies, and rules for sustainably harvesting marine resources. Complexities of scientific and financial factors often prevent addressing these, but new methodologies offer significant improvements on current and historical approaches. The Australian spanner crab fishery is used to demonstrate this. Between 1999 and 2006, an empirical management procedure using linear regression of fishery catch rates was used to set the annual total allowable catch (quota). A 6-year increasing trend in catch rates revealed shortcomings in the methodology, with a 68% increase in quota calculated for the 2007 fishing year. This large quota increase was prevented by management decision rules. A revised empirical management procedure was developed subsequently, and it achieved a better balance between responsiveness and stability. Simulations identified precautionary harvest and catch rate baselines to set quotas that ensured sustainable crab biomass and favourable performance for management and industry. The management procedure was simple to follow, cost-effective, robust to strong trends and changes in catch rates, and adaptable for use in many fisheries. Application of such “tried-and-tested” empirical systems will allow improved management of both data-limited and data-rich fisheries.

Keywords: catch rate standardization, harvest control rule, management procedure, management strategy evaluation, spanner crab.

Received 19 January 2010; accepted 3 June 2010; advance access publication 4 August 2010.

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Introduction

For many fisheries globally, there continues to be a basic need to develop appropriate indicators, analytical methodologies, and rules for sustainably harvesting marine resources. Complexities of scientific, financial, and practical nature often pose barriers to addressing these needs of management. However, new methodologies offer significant improvements on current and historical approaches. The need to prove the sustainability of fishery stocks requires the development of formalized methods of evaluation and assessment for planning and strategy success (Butterworth and Punt, 1999; Smith *et al.*, 1999). This is a global issue, so approaches are needed to accommodate different species as well as the operational realities of a fishery (Punt *et al.*, 2002; Plagányi *et al.*, 2007). These issues are particularly relevant to the Australian spanner crab (*Ranina ranina*) fishery.

The Australian spanner crab fishery operates across the jurisdictional waters of Queensland and New South Wales between ~22 and 30°S. It is the largest spanner crab fishery of its kind, with annual gross landings between 1500 and 2000 t (Kennelly and Scandol, 2002). Spanner crabs are large, growing to ~15 cm rostral carapace length (~0.75 kg), living in water depths between 10 and 100 m on sandy substrata. They are caught by entangling their legs on tightly strung 32-mm mesh over a flat square or rectangular metal frame enclosing an area of ~1 m²

(Figure 1). In Queensland, the annual spanner crab quota (total allowable catch, TAC) was set historically using an empirical (data-based) management procedure. Since 2002, 90% of the harvests were taken commercially from Queensland waters, and the management procedure has limited tonnages to <2000 t, much less than the harvests that increased exponentially to 3000 t in the early 1990s before the introduction of output controls (Figure 2).

Recently, formal management procedures have been adopted by Australian and international fisheries policy. These procedures contain indicators that measure the state of the fishery (Seijo and Caddy, 2000) and use them in control rules to alter fishing pressure so as to achieve target goals in a fishery (Rademeyer *et al.*, 2007; Smith *et al.*, 2008). They are typically complex, based on theory, and designed for commercial fisheries serviced by quantitative assessment models (such as maximum economic yield: Grafton *et al.*, 2007; Dichmont *et al.*, 2008). Management procedures can also be developed using simple indicators derived from catch or survey data. However, their performance can be uncertain without simulation testing and consideration of uncertainty, conservative management, and data-gathering principles (Dowling *et al.*, 2008; Smith *et al.*, 2008).

Technical reports and government legislation contain many examples of empirical indicators in fisheries management. Most are defined without control rules and response mechanisms or

procedures to modify fishing. Notably, few have been published in peer-reviewed journals detailing their performance in management procedures. Examples of published theoretical and applied systems include the following.

- (i) Data-based procedures using averaged recent catches of sablefish (*Anoplopoma fimbria*) were smoothed with a research survey index of abundance in Canada to provide a practical means of setting annual catch limits in the absence of an acceptable model-based approach (Cox and Kronlund, 2008).
- (ii) For data-limited estuarine fisheries in New South Wales, Australia, simulations and control charts were used to



Figure 1. Entangled spanner crabs (*Ranina ranina*).

identify important changes in annual time-series of harvest and limit trigger points that detected both recruitment and survival failure; accepting a high rate of false triggers (Scandol and Forrest, 2001; Scandol, 2003).

- (iii) Quota management procedures for the South African west coast rock lobster (*Jasus lalandii*) fishery were first implemented in 1997 and later modified in 2000 and 2003 (Johnston and Butterworth, 2005; Plagányi *et al.*, 2007). Notably, the empirical components used catch rates of lobster from the commercial fishery and a fisheries-independent monitoring survey. The rules altered quota directly from that of the previous year based on a weighted average of fishery and survey catch rates divided by their fixed baselines. The maximum change in annual quota was restricted to 10%. The latest management procedures were simulated to show positive trade-offs between resource recovery and future catch objectives, with the ability to adapt to changes in lobster growth.
- (iv) For Australia’s southeastern scalefish and shark fisheries, linear regression of commercial catch rates without any benchmarks was found to keep quotas at their current levels and failed to rebuild resources when needed (Smith *et al.*, 2008). It has been proposed to replace the regression method with a new control rule that compared average catch rates directly against limit and target baselines (Little *et al.*, 2008), with the ability to increase or decrease stock sizes.

As in the fourth example above, the Queensland spanner crab commercial quota was operated by a control rule using linear regression of fishery non-standardized catch rates (Dichmont and Brown, 2010). Between 2002 and 2007, the annual TAC

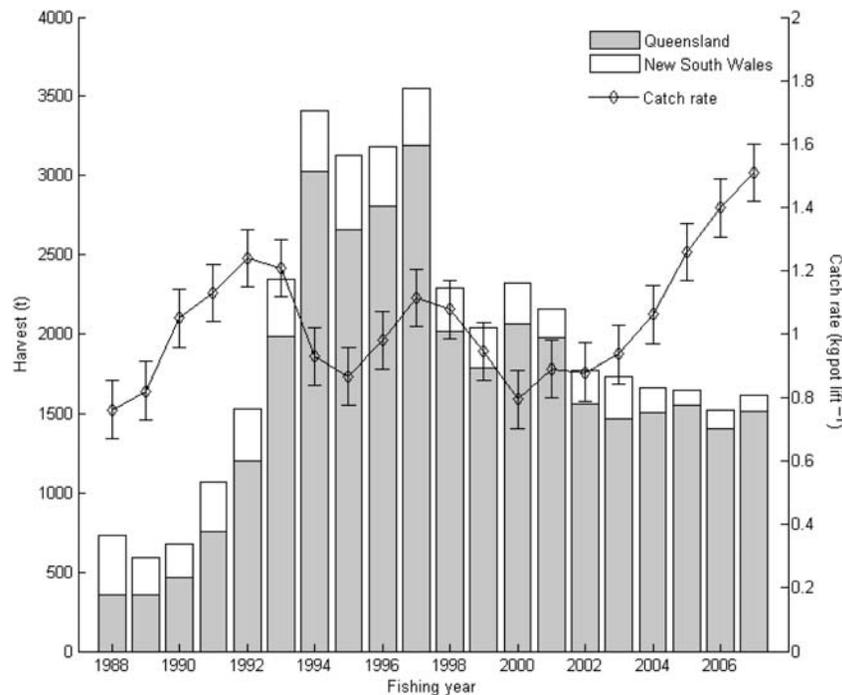


Figure 2. Commercial spanner crab harvest from Queensland and New South Wales waters, overlaid with average catch rates (± 2 s.e.) from Queensland waters.

was assessed every 2 years in relation to performance over the six most recent years. For each of five assessment regions, a regression was fitted to the trend in annual catch rates (Brown, 2006). The proportional difference between the regression's initial and final fitted catch rate was calculated. The proportions were weighted by fishing effort, then averaged across regions to produce a pooled index of proportional change. A 6-year increasing trend in catch rates (2000–2005; Figure 2) resulted in the control rules calculating a 68% increase in harvest quota for the fishing years 2006 and 2007, but the existing management procedure did not accommodate a change of this magnitude. The spanner crab Stock Assessment Group agreed that applying such a large change would have a destabilizing influence on the fishery. The special circumstances Rule 7 provided an “out clause” in cases where additional information indicated that the application of the rules may not be in the best interest of the fishery. In that case, such a large increase in quota would have attracted a great deal more fishing effort, which would later have had to be removed as the quota declined, catch rates would have eventually decreased to unsustainable levels, and landing prices would have declined because the market appeared to be saturated at the then existing quota cap of 1727 t (Brown, 2006; Dichmont and Brown, 2010). Therefore, for the 2006 and 2007 fishing years, a lower quota than calculated by linear control rules was set (1923 t), with the strong support of industry; this was significantly less than the 2901 t calculated.

After failure of the linear harvest control rule, the scientific method for calculating quota was reviewed in 2007 and 2008. Some oversights in the mechanical elements of the linear rules were noted. Comparing initial and final regression catch rates would overestimate the changes in quota when the catch rates were increasing or decreasing, the common “one-way trip” phenomenon in fisheries data (Hilborn and Walters, 1992). The process of comparing the initial and the final catch rates assumed a maximum length of cycle of 5–7 years in the catch rates (Dichmont and Brown, 2010). Increasing trends in non-standardized fishery catch rates are commonly confounded by rises in fishing power (O'Neill and Leigh, 2007). The methods focused on achieving reliable regression fits across too many years. Statistically, this seemed sensible, but the basic mechanism of measuring proportional change between 6 years would result in quite large differences. This was a simple oversight, especially when new quota was being adjusted directly from that of the previous 2 years. Also, full proportional adjustments to quota, compared with unbalanced half-up and full-down arrangements, were applied to preclude the rules progressively driving the quota down in times of the stable or the cyclic change in catch rates (Dichmont and Brown, 2010); statistically, the regression approach would produce non-optimal results at such times.

In response to the need for an alternative approach, we here describe a new management procedure robust to trends in fishing power and cyclic environmental change. Management strategy evaluation (MSE) was used to identify favourable sustainability, industry, and management performance outcomes, using fishery-dependent and fishery-independent standardized catch rate indices together with carefully set baselines. The management procedure and simulation testing further support the application of empirical approaches in fisheries science and management.

Material and methods

Three components were developed to construct and test the performance of empirical indicators in the management procedure. The first component was the standardized catch rate indicators for classifying the status of the spanner crab fishery from (i) the Queensland commercial fleet, and (ii) an independent monitoring survey. The second component was the procedures using the catch rate indicators to set harvest quotas, and the third the simulation dynamics used to evaluate the performance of the management procedure and empirical indicators. In the MSE, the three components were linked in each simulated annual time-step by updating the biological calculations for the spanner crab population, then the standardized catch rates from the exploitable population were calculated, and finally the control rules and the harvest to be taken from the population during the next time-cycle were applied.

Standardized catch rates

Spanner crab standardized catch rates were predicted from generalized linear models (GLMs). The models were fitted using the statistical software package GenStat (2008), and asymptotic standard errors were calculated for all estimates. Stepwise regression was used to select optimal model parameters ($p < 0.05$). Analysis of residuals from each model supported their structure and the use of statistical distributions. The importance of individual model terms was assessed formally using Wald (Chi-squared) statistics by dropping individual terms from the full model (GenStat, 2008).

Commercial data analyses

Commercial catch rates of spanner crabs obtained from industry logbooks between 2000 and 2007 were standardized through a GLM assuming normally distributed errors on a log scale (McCullagh and Nelder, 1989). The model response variable (η) consisted of the log of the daily catch (kg) from each vessel ($n = 51\,166$ catches). Explanatory model terms included the three-way interaction between fishing years, regions, and months, as well as the main effects of individual vessels, their log-transformed fishing effort (the number of net lifts, which was a function of the number of groundlines used, nets per groundline, and lifts per groundline), the spatial resolution of catches based on 30×30 min latitude and longitude grids, and the lunar cycle. The regions represented five latitudinal assessment zones between 23 and 28.17°S (Brown et al., 1999), with the 30-min square grids nested within regions. Lunar cycle was represented by two covariates: (i) a calculated luminance measure that followed a sinusoidal pattern, and (ii) the same lunar data replicated and advanced 7 d (O'Neill and Leigh, 2007). Together, these patterns modelled the cyclic variation in catches corresponding to the moon phase.

The final inclusion in the model was the spanner crab fleet's evolving fishing power. An annual offset schedule (log scale) was derived from a subset of vessel catches with recorded vessel/fishing characteristics ($n = 32\,422$ catches). Through another GLM with equivalent terms to those above, the effect of increased skipper experience in the spanner crab fishery was quantified at three categorical levels of experience, <5 , 5 – 10 , and >10 years. The parameter estimates (β) were combined with the categorical skipper experience data (X) in a simple linear equation to calculate relative changes in catches, under standard conditions, attributable to increased skipper experience: $\log(c) = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$

(Bishop *et al.*, 2004; O'Neill and Leigh, 2007). The logarithm offset (annual schedule) of change in skipper experience was made relative to the year 2000 and calculated by the annual averages minus the average for 2000.

Other fishing-power (catchability) information on which fishers adopted new devices and technologies, and when they were adopted, was considered in the GLM for the subset of vessels. The data were obtained from a purpose-designed survey of past and present Queensland spanner crab vessel owner/operators in 2007. The survey was carried out via a questionnaire, with 60 respondents to the mail-out survey and 48 from the telephone interviews, a total response rate of 83% of the 130 selected spanner crab licence holders. Changes in the following characteristics, and the date of each change, were recorded for each vessel:

- (i) vessel: length, engine rated power, cruising speed, fuel capacity, fuel consumption;
- (ii) on-board technologies: global positioning system, radar, seabed discrimination system, colour sounder;
- (iii) fleet cooperation and communication: radio and mobile telephone;
- (iv) skippering: number of crew and number of years in the fishery;
- (v) winching capacity: line-hauler used and type;
- (vi) fishing effort: soak time, fish at night, overnight trips, number of groundline lifts per day, number of groundlines, number of net frames per groundline;
- (vii) gear: net area, mesh size, thread ply;
- (viii) bait: pilchard or other.

Given little change in these fishing characteristics between 2000 and 2007, their use in the GLM was limited.

The final average annual catch rates were predicted from the full offset model. Predictions were standardized to the mean log offset, log effort, and lunar cycle. Across model factors, predictions were standardized using GenStat's marginal weights policy of averaging over the factor levels for month, region, grid, and vessel (GenStat, 2008). Predicted log-means were rescaled using a common bias-corrected back-transformation of adding half the model variance (McCullagh and Nelder, 1989): $\mu = \exp(\eta + \sigma^2/2)$. The back-transformed means were converted to kg per net lift by dividing by the overall median number of net lifts per day (228.5).

Survey

Since 2000, annual fishery-independent surveys of spanner crab have been conducted in Queensland waters during May, except for 2004 (Brown *et al.*, 2008). Catch rate measures of abundance were collected from 25 areas (6×6 min grids) across the Queensland fishery. In all, 15 individual groundlines (the sampling units), each consisting of ten nets, were set in each area. The net soak times with the number of spanner crabs caught, their gender, and size (rostral carapace length) were recorded. In May 2005, the survey was extended south into northern New South Wales, with the placement of four new areas (Kennelly and Scandol, 2002; Brown *et al.*, 2008).

Survey catches of spanner crabs across the years exhibited a significant component of zero values (26%). As no single statistical distribution can accommodate this inflated zero class, catches

were standardized through a two-component approach, combining mean predictions from binomial regression of zero/non-zero catch and general linear regression on the conditionally distributed log-transformed non-zero catches (McCullagh and Nelder, 1989; Myers and Pepin, 1990; Mayer *et al.*, 2005). The first component relates to the binary response of zero or non-zero catch per groundline, modelled using a logistic transformation with a linear function of the covariates survey area, log-transformation of total net hours per groundline, and year. The second component was for just those catches where the number of crabs caught was not zero. The model response variable (η) consisted of the logarithm of the number of crabs caught per groundline. Explanatory model terms were the same as in the binary analysis. Predicted catch rates from the lognormal model were adjusted using a common bias-corrected back-transformation of adding half the model variance. These catch rates were then multiplied by the binary predicted proportions for non-zero catch to predict the overall standardized average number of spanner crabs per groundline equivalent to the median net hours of fishing.

Management procedure

A management procedure, including harvest control rules, was developed through a series of working group meetings with scientists, managers, and stakeholders between November 2007 and March 2008. From those meetings and initial analyses, certain requirements were defined for the management procedure. These were:

- (i) the need to incorporate catch rates from the fishery and the independent monitoring survey;
- (ii) the need to maintain average catch rates around current profitable (target) levels;
- (iii) the need to maintain quotas around an agreed annual tonnage and set every 2 years;
- (iv) that quota rules were able to perform in strong up and down cycles in catch rates;
- (v) the need to incorporate the flexibility to change target catch rate trigger points;
- (vi) to minimize the frequency of the "crash rule" triggering;
- (vii) the need to minimize trivial changes in quota tonnages.

To meet these requirements, the management procedure followed a process of developing a baseline quota and performance targets for standardized catch rates with range intervals. The base quota (Q_{base}) and target catch rates (fishery = $\bar{c}_{f,\text{target}}$ and survey = $\bar{c}_{s,\text{target}}$) were set by the working group equal to their annual average between 2000 and 2007, and they were fixed. Upper and lower intervals of $\pm 10\%$ were set on target catch rates. The stock performance indicators were the average fishery (\bar{c}_f) and survey (\bar{c}_s) standardized catch rates in the most recent biennial quota period. Standardized catch rates from the fishery and the survey were compared in a decision matrix (Table 1). As no prior evidence was available that either catch rate source was more accurate or reliable than the other, the two indices of spanner crab abundance were given equal weight in the assessment process. The spanner crab quota was calculated from the base quota (Q_{base}) and was made no larger than the maximum tonnage allowed (Q_{max}). New quota was compared with the

Table 1. Decision matrix for setting λ in quota calculation (1), with subscripts u and l indicating upper and lower catch rate thresholds, and θ an average ratio of fishery and survey catch rates from the last 2 years divided by their target (for notation, see Table 3).

Mean catch rates (\bar{c}) Survey (s)	Commercial fishery (f)		
	$\bar{c}_f \leq \bar{c}_{f,target,l}$	$\bar{c}_{f,target,l} < \bar{c}_f < \bar{c}_{f,target,u}$	$\bar{c}_f \geq \bar{c}_{f,target,u}$
$\bar{c}_s \geq \bar{c}_{s,target,u}$	$\begin{bmatrix} 1 \\ 1 \text{ or } \theta \\ \theta \text{ or } 0 \end{bmatrix}$	1	θ_{halfup}
$\bar{c}_{s,target,l} < \bar{c}_s < \bar{c}_{s,target,u}$		1	1
$\bar{c}_s \leq \bar{c}_{s,target,l}$		1 or θ	1

Matrix cell 2,1: if $\bar{c}_s < \bar{c}_{s,target}$, then $\lambda = \theta$, else $\lambda = 1$. Matrix cell 3,1: if $\theta \leq 0.5$, then $\lambda = 0$, else $\lambda = \theta$. Matrix cell 3,2: if $\bar{c}_f < \bar{c}_{f,target}$, then $\lambda = \theta$, else $\lambda = 1$. Matrix cell 1,3: $\lambda = \theta_{\text{halfup}} = (\theta - 1) / 2 + 1$.

tonnage set 2 years earlier. If the new quota was within 5% of the previous quota, then the quota remained unchanged. Quota for Queensland and New South Wales was calculated according to the equation

$$Q_{t+1,t+2} = \min \left[\begin{cases} Q_t, & \text{if } (0.95Q_t \leq \lambda Q_{\text{base}} \leq 1.05Q_t) \\ \lambda Q_{\text{base}}, & \text{otherwise} \end{cases}, Q_{\text{max}} \right], \quad (1)$$

where Q is the quota tonnage for biennial setting in years $t + 1$ and $t + 2$, and λ was from Table 1 (see Dichmont and Brown, 2010, for an extended plain English version of the decision rules).

Simulation

The performance of the management procedure was tested by simulating spanner crab population dynamics, catch rate indices, and harvest. The algorithm driving the simulation used forward-projection methodology similar to that described by Richards *et al.* (1998). The population model tracked annual (time-step t) numbers of spanner crabs by their gender (g), length (l), and age (a) classes (Table 2), using a sample of parameter values (Table 3). Of the population parameters, moderate recruitment productivity (steepness h) and long-lived dynamics (natural mortality and growth) were assumed for testing the performance of the procedure (Table 3). Previous population modelling had failed to identify reliable scenarios of high stock-growth rates for spanner crabs (Brown *et al.*, 1999; Kennelly and Scandol, 2002). Further, juvenile length-at-age data revealed that spanner crabs grow slowly (Kirkwood *et al.*, 2005). Historical harvests from Queensland and New South Wales were tallied between 1960 and 2007 and fed into the model to tune hypotheses for stock status in 2007. The model was then projected forward 50 years to cover three life cycles of spanner crabs and to quantify long-term management performance over the periods of cyclic recruitment and fishing-power increase. After every 2 years, catch rates were simulated (Table 2) and the management procedure was invoked to calculate commercial quota tonnages and harvests taken from Queensland and New South Wales waters. The 50-year projection process from selecting sample parameters to drive the spanner crab stock, to quota management and harvest, was repeated 1000 times in MATLAB™ (2008).

As in most MSE exercises, many modelling scenarios were identified. They covered key uncertainties relating to spanner crab dynamics and the management process. In all, five factor combinations (48 scenarios) were investigated to assess the

performance of the management procedure: (i) three exploitable biomasses to start the projections in 2007 ($B_{2007}/B_0 = 0.2, 0.4,$ or 0.6), (ii) two baselines of catch rate and quota targets (average Q_{base} , $\bar{c}_{f,target}$, and $\bar{c}_{s,target}$; compared with $0.7 Q_{\text{base}}$, $1.3\bar{c}_{f,target}$, and $1.3\bar{c}_{s,target}$ to assess stock rebuilding), (iii) two methods of fixed or updated target catch rates through time, (iv) two states of catch rate (proportional to abundance; compared against hyperstable commercial catch rate biased by 2% annual fishing-power increase), and (v) two intervals on target catch rates to alter the frequency of quota change (± 10 and 20% on $\bar{c}_{f,target}$ and $\bar{c}_{s,target}$, respectively). Simulation results show the sequential interactions of the five factors.

Three approaches were used to assess the effects of the five factors on the management procedure. First, to identify the average effects, the outputs from 50 random simulations for each of the 48 scenarios (simulation parameters were common

Table 2. Equations for simulating spanner crab population dynamics and catch rate indicators of abundance (for notation, see Table 3).

Population dynamics	Equation
Number of spanner crabs:	
$N_{l,a,g,t+1}$	$= \begin{cases} 0.5R_{t+1}\Lambda_l & \text{for } a = 0 \\ N_{l,a-1,g,t} \exp(-M_{a-1}) \\ (1 - \nu_r d_l u_t) \Xi_{l,l} & \text{for } a = 1, \dots, 16 \end{cases} \quad (2)$
Recruitment:	
R_{t+1}	$E_t / (\alpha + \beta E_t) \exp(\epsilon_R)$ (3)
Spawning index—eggs:	
E_t	$\sum_l \sum_a N_{l,a,g,t} m_l f_l$ for $g = \text{female}$ (4)
Start-year exploitable biomass:	
$B_{t,g}$	$\sum_l \sum_a N_{l,a,g,t} \nu_l w_{g,l}$ (5)
Midyear exploitable biomass:	
$B_{\text{mid},t,g}$	$\sum_l \sum_a N_{l,a,g,t} \nu_l \exp(-M_a/2) \sqrt{1 - u_t d_l w_{g,l}}$ (6)
Fishery data indicators—catch rates	
Commercial fishery (f):	
$c_{f,t}$	$q_f q_{\text{inc}} B_{\text{mid},t}^y \tau \exp(\epsilon_f)$ (7)
Survey (s):	
$c_{s,t}$	$q_s B_{\text{mid},t} \exp(\epsilon_s)$ (8)

Table 3. Parameter definitions and uncertainties in simulation.

Modelling components	Equations and values	Notes
Mortality		
M_a	$\zeta = 0.3; M_H = 0.277; M_a = ([a + 1]^{-\zeta} / a_{\max}^{-\zeta}) M_H$	Instantaneous natural mortality (M_a) declined exponentially with age based on assumed shape parameter (ζ); for constant M , $\zeta = 0$. Natural mortality M_H was calculated from the Hoenig (1983) equation for maximum longevity. This was set at 16 years (Kirkwood et al., 2005); $a_{\max} = 16 + 1$, where $a = 0, \dots, 16$
ν_l	$l_{50} = 7 \text{ cm}; l_{95} = 8 \text{ cm}$	Logistic selectivity equation (Haddon, 2001). Full selection attained at minimum legal size, i.e. 10 cm
d_l	$\begin{cases} 0.2 & \text{for } l < 10 \text{ cm} \\ 1 & \text{for } l \geq 10 \text{ cm} \end{cases}$	Discard mortality proportion (Brown et al., 1999). All crabs of legal size are retained
C_t	$(Q_{t,\text{Queensland}} + Q_{t,\text{New South Wales}}) \varepsilon_{ie} + C_{\text{rec}}$, where $C_{\text{rec}} = 2 \times N(11\,476, 2\,051) w_{\text{rec}} / 1000$ and $w_{\text{rec}} = 0.225 \text{ kg}$	Spanner crab harvest (t). A recreational (rec) harvest of 2.6 t for Queensland and New South Wales was included as twice the Queensland average over survey years 1999, 2000, 2002, and 2005 (Higgs, 2001; Henry and Lyle, 2003; Higgs et al., 2007; McInnes, 2008)
ε_{ie}	$B(40.316, 6.794)$	Beta distribution fitted for implementation error on quota (MATLAB, 2008). Median of historical harvest divided by quota limit between 2000 and 2006 was 0.86
u_t	C_t / B_t	Model calculated annual harvest rate
Growth		
Λ_l	$l_{\infty,\text{male}} = 15.6 \text{ cm}; l_{\infty,\text{female}} = 12.2 \text{ cm}; k_{\text{male}} = 0.23; k_{\text{female}} = 0.26;$ $t_{0,\text{male}} = -0.25; t_{0,\text{female}} = -0.24; \sigma = 1 \text{ cm}$	Proportion of crabs in length class l for age category 0 ($a = 0.5$) individuals. Calculated from the normal probability density function, with μ and σ from the von Bertalanffy growth curve for slow growth (Kirkwood et al., 2005)
$\Xi_{l/l}$	For growth parameters see Λ_l ; $E(l) = l_{\infty}(1 - \exp(-k)) + l \exp(-k)$	Growth transition matrix allocating a proportion of crabs in length category l to grow into length l over 1 year. Calculated using the normal probability density function [$E(l)$ and σ] (Sadovy et al., 2007)
$w_{g,l}$	$w_{g,l} = a_g l^{b_g}$, $g = \text{gender}$; $a_{\text{male}} = 0.00011$; $a_{\text{female}} = 0.00022$; $b_{\text{male}} = 3.234$; $b_{\text{female}} = 3.075$	Average crab weight (w , kg) at length (Brown, 1986)
Recruitment		
α, β	$h = 0.4; R_0 = \text{optimized for } B_{2007} / B_0$	Assumed parameters for Beverton–Holt spawner–recruitment [Equation (3); Table 2], defined by steepness (h ; Haddon, 2001). Virgin recruitment (R_0) was optimized to three exploitable biomass ratios in 2007 (0.2, 0.4, and 0.6)
ε_R	$\exp(N[\mu_v, \sigma]); \mu_t = \sin(\pi_t)A; \pi_t = (\pi / 2.2\pi / 13:2.5\pi); A = 0.1; \sigma = 0.25$	Lognormal recruitment error with cyclic bias. The bias was set with a 14-year cycle and amplitude (A), as suggested by autocorrelations from commercial standardized catch rate residuals between 1988 and 2006
m_l	100% for $l \geq 7 \text{ cm}$, else zero	Maturity schedule (Brown, 1986)
f_l	$f = 5.524(l \times 10) - 403.94$	Fecundity schedule measured in thousands of eggs (Brown, 1986)
Fishery		
q_f	$(\prod_{t=1}^n \bar{c}_{f,t} / B_{\text{mid},t})^{1/n}$	Commercial catchability, calculated as the geometric mean of standardized catch rates divided by the modelled midyear biomass

Continued

Table 3. Continued

Modelling components	Equations and values	Notes
q_{inc}	$q_{inc} = 1.02^y \exp(N[0, 0.05]);$ $y = \begin{cases} 0 & \text{for } t = 1, \dots, 10 \\ 1, \dots, 10 & \text{for } t = 11, \dots, 20 \\ 10 & \text{for } t = 21, \dots, 30 \\ 11, \dots, 20 & \text{for } t = 31, \dots, 40 \\ 20 & \text{for } t = 41, \dots, 50 \end{cases}$	Hypothetical 2% annual fishing power increase in commercial catchability (q_t) over the 50-year (t) future projection. The increase was coded with two significant decadal jumps and lognormal error. When not applied, $q_{inc} = 1$
γ	$U(0.2, 0.6)$	Assumed hyperstability coefficient distributed uniformly between 0.2 and 0.6. Lower values flatten the catch rate trend. When not applied, $\gamma = 1$
τ	$\left(\prod_{i=1}^n q_i B_{mid_t} / q_i B_{mid_t} \right)^{1/n}$	Scaler for hyperstable catch rates, calculated as a geometric mean of model-predicted catch rates between 2000 and 2006. When not applied, $\tau = 1$
q_s	As q_f	Survey catchability, calculated as a geometric mean of standardized catch rates divided by the modelled mid-year biomass
ϵ_f	$\exp(N[0, 0.17])$	Lognormal observation error. Standard deviation set to $\sim 10\%$ CV; from commercial statistical analyses
ϵ_s	$\exp(N[0, 0.26])$	Lognormal observation error. Two standard deviations were set from survey statistical analyses. This was coded to allow greater uncertainty, given no within-year survey replication
Q_{base}	For Queensland: $Q_{base} = 1\ 631\ t$; $Q_{max} = 2\ 000\ t$; For New South Wales: $Q_{base} = 150\ t$; $Q_{max} = 200\ t$	Maximum and base tonnages for biennial quota setting in Queensland and New South Wales. New South Wales values were for simulation only, not policy
θ	$[\bar{c}_t / \bar{c}_t, target + \bar{c}_s / \bar{c}_s, target] / 2$	Average ratio of fishery and survey catch rates divided by their target (Table 1)

across factor interactions, $n = 2400$) were analysed through a GLM. For the GLM, analysis of all 1000 simulations was unnecessary (Dichmont *et al.*, 2006c) and would add unrealistically high statistical power (deflating the variance) for comparing meaningful differences between averages. Three performance measures were used as the response variables in GLM: (i) exploitable biomass ratio at the end of the 50-year future projection, (ii) average harvest across the 50-year future projection, and (iii) frequency of setting new quota tonnages across the 50-year future projection. The interaction of assumed exploitable biomasses in 2007 [Factor (i) above] and target baselines [Factor (ii)] represented clearly different states for the analyses. The three-way interaction of these terms with Factors (iii), (iv), and (v) were the focus of interpretation. Second, all 1000 simulations were used for graphic presentation of means and to construct appropriate 95% prediction intervals for annual variation in performance measures. To finish, regressions of mean predictions for the 48 scenarios were used to assess the impact of recruitment and observation errors on conclusions over the 50-year projection. Three random error terms ϵ_R , ϵ_F and ϵ_S were compared at zero, half, and full variance (Table 3) over 10, 25, and 50 years. Definition of the regression analyses were

$$\bar{m}_{iyv_1} = \begin{cases} y + \beta_y \bar{m}_{iyv_2} \\ y + \beta \bar{m}_{iyv_2} \end{cases},$$

where \bar{m}_{iyv_1} was the mean performance measure for scenario i , year y , and full variances v_1 ; \bar{m}_{iyv_2} was the mean performance measure for scenario i , year y , and half or zero variances v_2 ; β represented the slope parameters to be estimated. Non significant F -tests comparing full and reduced models and β coefficients were used as statistical measures of no impact of random noise on performance measures.

Results

Establishing target catch rate indicators

Commercial catches of spanner crabs between 2000 and 2007 were standardized from two statistical analyses (Table 4). The first explored the standardization of a number of potential fishing-power covariates from a subset of 103 commercial vessel operations. The covariates covered data representing fishing experience, vessel specification (e.g. vessel size, total engine power, fuel capacity), use of navigational aids (such as a global positioning system, radar, echosounder, and mobile telephone/radio), and fishing practices (such as overnight trips, use of line-haulers, gear soak time, number of net lifts per day, net area, number of crew). For the years analysed, there was little change in the use of many of these covariates (Table 5), and their inclusion in the linear model was not significant and excluded ($p > 0.05$). Significant fishing-power terms were detected for each vessel operation, three levels of skipper experience, and the logarithm of the number of net lifts (Table 4). The parameter estimates showed that fishers with >5 years experience had at least 8% better average catch rates than fishers with <5 years experience (log parameter estimates for fishing experience: <5 years = -0.1341 , s.e. = 0.0172 ; >10 years = -0.0458 , s.e. = 0.0152 ; fishers with 5–10 years of experience were set at the reference level of 0).

For the second analysis of all commercial catches, the logarithm of the number of net lifts was the most significant model

Table 4. Summary of the analysis from each GLM.

Parameter	Commercial catches		Survey catches	
	Subset of data	All data	Zero/non-zero	Non-zero
Summary of analysis				
Number of data	32 422	51 166	2 804	2 085
Regression mean deviance	20.94	27.043	17.246	33.498
Residual mean deviance	0.312	0.335	0.912	1.048
Regression d.f., residual d.f.	628, 31 793	751, 50 414	39, 2 764	39, 2 045
Adjusted r^2	0.562	0.539	0.2	0.367
Wald statistics, d.f.				
Vessel	3 361.92, 102	7 262.04, 219	–	–
Number of net lifts (log)	10 365.38, 1	14 547.97, 1	–	–
Fishing year.region.month	1 638.56, 304	1 969.92, 304	–	–
Fishing area (grid)	911.72, 46	1 414.8, 54	–	–
Luminance	3.49*, 1	5.34, 1	–	–
Luminance advance 7 days	7.05, 1	7.37, 1	–	–
Skipper experience	83.5, 2	Offset	–	–
Location	–	–	384, 32	1 091.5, 32
Number of net hours (log)	–	–	5.2, 1	35.2, 1
Year	–	–	15, 6	93.3, 6

–, Model term not applicable to the analysis.

*Model term significance $p = 0.062$, otherwise $p < 0.05$. For the commercial and survey (non-zero) analyses, F statistics can be derived by dividing the Wald statistics by their degrees of freedom (d.f.).

Table 5. Summary of average spanner crab fleet characteristics (covariates) weighted by the number of days fished by each vessel between 2000 and 2007.

Covariate	Mean	Median	Minimum	Maximum	Std deviation
Vessel length (m)	9.288	8.5	5.5	21.3	2.771
Engine rated power (hp)	288.2	250	60	751	120.2
Fuel capacity (l)	977.5	600	150	8 500	1 451
Fuel use per day (l)	220.7	180	70	550	120.2
Cruising speed (knots)	16.33	15	7	36	4.46
GPS (p)	1	1	1	1	0
Radar (p)	0.343	0	0	1	0.475
Sounder (p)	1	1	0	1	0
Seabed discrimination system (p)	0.0364	0	0	1	0.187
Mobile phone/radio (p)	1	1	1	1	0
Overnight trips (p)	0.311	0	0	1	0.463
Fish at night (p)	0.0902	0	0	1	0.287
Line hauler (p)	1	1	1	1	0
Lifts of groundlines (n)	6.656	6	4	16	1.726
Groundlines (n)*	3.122	3	2	4	0.345
Nets per groundline (n)*	14.18	15	10	30	1.904
Soak time (min)	65.33	60	30	120	17.91
Net area (m ²)	0.879	0.88	0.196	1	0.131
Mesh size (mm)	33.05	31.75	25	50.8	4.854
Mesh ply rating	9.23	9	3	12	2.297
Crew (n)	0.622	1	0	4	0.544
Skipper experience (years)*	9.835	9	0	34	5.919
Bait, pilchard (p)	0.829	1	0	1	0.377

p, proportion; n, number.

*Significant change in covariate between fishing years ($p < 0.05$).

term (parameter estimate = 0.851, s.e. = 0.007; Table 4), indicating that daily catch and effort were not covered by a simple 1:1 relationship. Average net lifts per vessel day declined by 15% between 2000 and 2007, with the coefficient mitigating the standardized catch rate for the reduction in net lifts. Catches of crabs were significantly different between vessels, years, months, regions, and fishing grid within regions

(Table 4). The logarithm offset (annual schedule) of change in the fleet’s fishing power attributable to changing skipper experience was small, just a 2% increase between 2000 and 2007. Also of minor significance was the effect of lunar cycle, with average catch rates 3% higher over the waxing crescent and first quarter of the phases. Figure 3 illustrates the relative standardized annual average catch of crabs per net lift. The

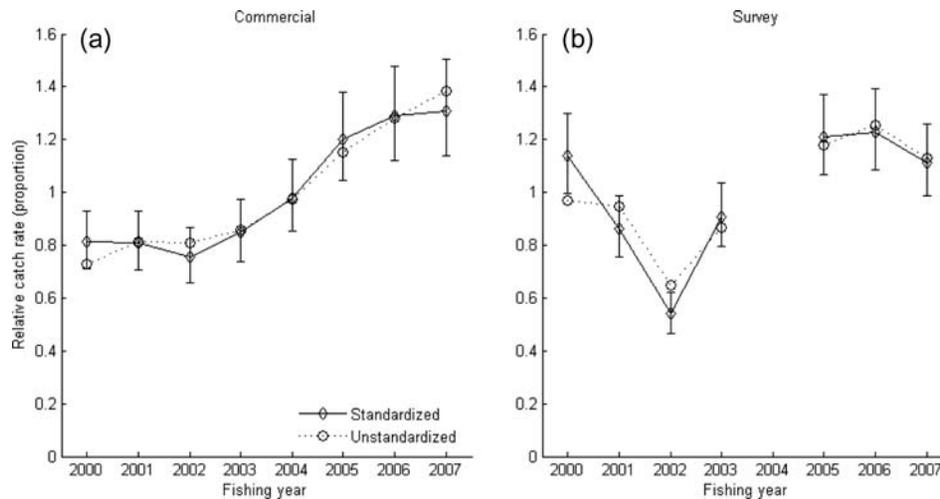


Figure 3. Standardized and unstandardized annual catch rates of spanner crabs relative to their mean (=1) for the (a) commercial fishery and (b) the fisheries-independent monitoring survey. Error bars indicate 95% confidence intervals on standardized catch rates.

Table 6. Summary of the GLM three-way interactions for the three performance measures: the Wald statistics and probabilities of no significant difference between two methods of calculating target catch rates, two catch rate states, and two catch rate thresholds for each simulated performance measure.

Three-way interaction terms: Factor (i) (biomass ratio 2007) × Factor (ii) (target baselines) × c	Exploitable biomass	Harvest	Frequency of quota change
Factor (iii): method for calculating $\bar{c}_{f,target}$ and $\bar{c}_{s,target}$ (fixed or updating through time)	36.742*, 0.001	18.519*, 0.001	72.35*, 0.001
Factor (iv): catch rate states (proportional to abundance or biased)	6.242*, 0.044	8.871*, 0.012	20.47*, 0.014
Factor (v): catch rate thresholds (10 or 20%)	0.522, 0.770	3.731, 0.155	37.23*, 0.001

Number of simulations = 2400. *F*-statistics equal to the Wald statistics divided by their degrees of freedom (d.f. = 2).

*Significant model term.

overall average fishery catch rate was 1.043 (s.e. = 0.085) kg of crab per net lift.

Survey catches of spanner crabs showed that 74% of groundlines caught crab. These proportions changed significantly with location and year (Table 4). The proportions increased significantly with logarithm of net hours of fishing (parameter estimate = 0.527, s.e. = 0.231). Analysis of non-zero catches also showed differences between location and year (Table 4), and catches increased significantly with logarithm of net hours of fishing (parameter estimate = 0.576, s.e. = 0.097). The relative product of predicted probabilities of catching crab and average non-zero catches of crab are illustrated in Figure 3. The average survey catch rate was 13.971 (s.e. = 1.307) crabs per groundline, standardized to a total soak time of 8.811 net-hour.

Simulations that support lower quota and higher catch rate targets

Simulations were structured to describe five possible effects on the performance of the management procedure (the five factors listed in the “Simulation” section above). Results were very dependent on the projection starting biomass in 2007 and the target baselines associated with the biomass levels between the years 2000 and 2007 ($p < 0.001$). After adjusting for these terms through three-way interactions (Table 6), significant differences were identified between the methods of calculating target catch rates and their states over all three performance measures. For catch rate thresholds, only the frequency of quota change demonstrated a significant difference.

Figure 4 illustrates the differences in average performance statistics (for exploitable biomass, harvest, and frequency of quota change) between the 48 scenarios examined. The differences were not influenced much by the number of projection years or the extent of simulation random error (Table 7). For the average quota and catch rate baselines selected by management, the exploitable biomasses at the end of the 50-year projection were lower when the starting biomass ratios in 2007 were 0.2 and 0.4 (scenarios 1–8 and 17–24; Figure 4). The declines were greatest when fishing power/hyperstability biased the commercial catch rates. Biennial updating of average baselines resulted in lower biomasses when comparing scenarios 1–8. In contrast, biomass ratios increased when average baselines were adjusted up conservatively by 30% (scenarios 9–16, 25–32, and 41–48), and biennial updating of adjusted baselines resulted in further increases especially from low biomass ($B_{2007}/B_0 = 0.2$) scenarios 13–16. Average biomass ratios were only the same at the beginning and the end of the simulations when starting biomasses were high ($B_{2007}/B_0 = 0.6$) and baselines were set at their average (scenarios 33–40). No significant differences in average biomass resulted between using either 10 or 20% intervals on catch rate triggers (Table 6 and Figure 4).

The harvest outcomes shown in Figure 4 show that tonnages were only maintained at their average (~1532 t) when starting biomass ratios were at 0.4 or 0.6 in 2007 and average baselines were used (Figure 4, scenarios 17–24 and 33–40); otherwise, average harvests were <1532 t. Average harvests were generally lowest when updating 30% adjusted baselines, marginally higher

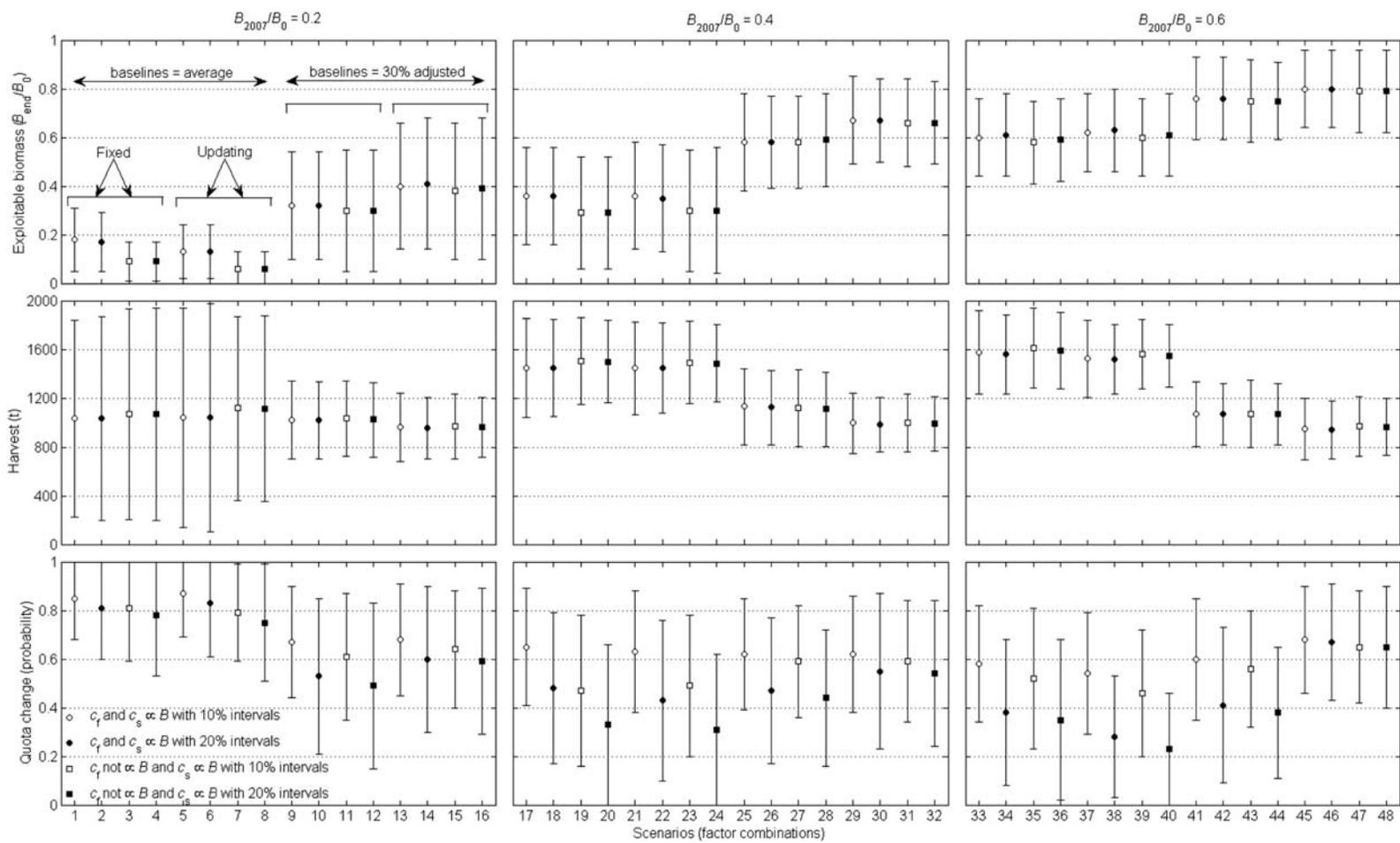


Figure 4. Exploitable biomass, harvest, and quota performance measures (means and 95% prediction intervals for a simulation outcome) for each scenario. The top row of subplots represents the exploitable biomass at the end of the 50-year projection, the middle row the harvest across the 50-year projection, and the bottom row the probability of having to change quota every 2 years. The legend identifies scenarios with different catch rate assumptions [Factor (iv)] and intervals [Factor (v)]. As annotated in the top left subplot, every group of four means and intervals from left to right corresponds to alternating the fixed and updating setting [Factor (iii)] for target catch rates ($\bar{c}_{f, target}$ and $\bar{c}_{s, target}$), and every group of eight corresponds to alternating the two baselines [average and 30% adjusted; Factor (ii)] settings. Each column of subplots corresponds to the three different biomass ratios assumed in 2007 [$B_{2007}/B_0 = 0.2, 0.4,$ and 0.6 ; Factor (i)].

Table 7. Statistical measures for comparing 50-year projections against shorter 25- and 10-year projections.

Performance measure and variance	F-statistics; p-value	Correlation estimate (s.e.)
$B_{\text{end}}/B_0 \times 0.5(\eta_r, \eta_b \text{ and } \eta_s)$	2.33; 0.101	0.926 (0.010)
$B_{\text{end}}/B_0 \times 0(\eta_r, \eta_b \text{ and } \eta_s)$	1.77; 0.175	0.836 (0.017)
Harvest $\times 0.5(\eta_r, \eta_b \text{ and } \eta_s)$	1.37; 0.258	0.930 (0.017)
Harvest $\times 0(\eta_r, \eta_b \text{ and } \eta_s)$	1.44; 0.241	0.813 (0.025)
Quota change $\times 0.5(\eta_r, \eta_b \text{ and } \eta_s)$	0.11; 0.899	0.684 (0.022)
Quota change $\times 0(\eta_r, \eta_b \text{ and } \eta_s)$	1.12; 0.328	0.457 (0.036)

The *F*-statistics conclude that there was no significant difference in the performance of the management procedure (as illustrated in Figure 4) between projections of 10–50 and 25–50 years. Linear regression coefficients illustrate significant ($p < 0.001$) correlation between results with full variance against 0.5 and zero variance on simulation recruitment (η_r) and observation (η_f and η_s) errors.

when commercial catch rates were biased, and not significantly different between 10 and 20% intervals on catch rate triggers (Table 6 and Figure 4). Large harvest variances were associated with the low biomass ($B_{2007}/B_0 = 0.2$) and average baselines scenarios 1–8. For these scenarios, Figures 5 and 6 scenario 1 illustrated erratic setting of quota and no biomass rebuilding even with 12% of the quotas set to zero and 69% of the non-zero quota set below base. For the 30% adjusted baselines, quota tonnages increased with rising biomass; more so when rebuilding from the lower B_{2007}/B_0 ratio (scenarios 9, 25, and 41; Figure 5).

Significant differences in the probability of varying the quota were detected across all factors (Table 6). For all low-biomass scenarios (1–8), the probability of quota change every 2 years was highest at $\sim 80\%$ (Figure 4). The probability of varying the quota was lowest when biomass was high, updating average baselines, fishing power and hyperstability-biased commercial catch rates, and 20% intervals were set as catch rate triggers (Figure 4). Overall, the probability of varying the quota every 2 years was $\sim 60\%$.

Interestingly, the management procedure resulted in a large range of quota tonnages across stock sizes, the scatterplot and probability statistics showing the chances of setting the quota correctly or incorrectly (Figure 6). For scenario 1, base and above-base quotas were being set incorrectly at low stock sizes, even assuming no hyperstability or fishing-power biases. For the other scenarios in Figure 6, most quotas were set at base tonnage, with larger quotas generally set at higher biomasses. There was a small probability of setting quota tonnages at the maximum cap of 2200 t.

Discussion

The results here using the Australian spanner crab fishery have provided significant insight into how the approach taken to this and other fisheries requires certain core attributes to maximize the chances of sustainable stock management. These include aspects of the procedure, from appropriate standardization of fishery and independent monitoring data, to setting baseline indicators and numerical models for MSE. These components are pertinent to science and management globally. For Australian spanner crabs, the components were successfully brought together in a quantitative assessment tool that permits simple, rapid, cost-effective quota setting. The findings related to the management procedure are discussed further below.

When faced with uncertainty, do not set generous baselines

Simulations that identified precautionary levels of quota and catch rate baselines were required to ensure robust performance of the management procedure. This resulted in higher simulated biomasses and catch rates of crabs with less variable total harvests. This outcome was demonstrated to be consistent and robust against assumptions on uncertain crab population dynamics and biases on catch rate indicators. Importantly, the baseline settings were critical, because the rules operated towards target catch and catch rates. In a typical data-limited fishery, this would require balancing knowledge of the fishery, the life-history characteristics of the species, and political opinion on sustainable harvest. When set too generously, the rules incorrectly set high quotas at low population sizes (e.g. scenario 1; Figure 6) and overruled the three precautionary behaviours in the management system: (i) quota increases above baseline only if both catch rate indices are above their target; (ii) a “half-up” principle restricts quota increases above baseline to half the full proportional increase; (iii) quota reductions are by the full proportional decrease. In choosing baselines, it was important to consider four key aspects: (i) lower-than-perceived stock sizes, (ii) biased fishery catch rates that result in lower biomass, higher quota, and less responsive quota change, (iii) a base quota of less than the average harvest, and (iv) updating baseline catch rates towards targets that are higher than average. No risks to the population of choosing between simple 10 or 20% catch rate intervals were found. When large population size or high productivity of the stock was assumed, average baselines proved sustainable, as illustrated by biomass scenarios 0.4 and 0.6 B_{2007}/B_0 (Figure 4).

MSEs through simulation models have been used internationally to investigate the appropriate levels of fishing and the use of reference points in many fisheries (Dichmont *et al.*, 2006a; Little *et al.*, 2007). Monte Carlo methodology is often used to allow for adequate model parameter and process uncertainties (Richards *et al.*, 1998). Here, we generally followed these conventional procedures, but differed in that the operating model for spanner crabs was not conditioned to abundance indices or stock assessments. Instead, the stock–recruitment parameter for virgin recruitment, with steepness and other biological parameters fixed, was tuned to hypothetical stock sizes in 2007 ($B_{2007}/B_0 = 0.2, 0.4, \text{ or } 0.6$) using the time-series of total harvest from Queensland and New South Wales. The simulation approach provided flexibility to examine a number of uncertainties about the spanner crab population, allowing a robust set of indicators and quota rules to be selected.

Keep management procedures practical and simple and use the available data

The management procedure was developed as a co-management approach between managers, scientists, and the fishing industry. The rules met predefined requirements and provided transparency to the quota-setting process. They were built from industry suggestions to use a baseline quota, baseline catch rates, and half-up/full-down principles to increase/decrease quota, respectively. Importantly, the use of quota and catch rate baselines allowed sufficient flexibility to allow for adaptation to the reasons for change (e.g. stock rebuilding), but they still operated under the overall principles.

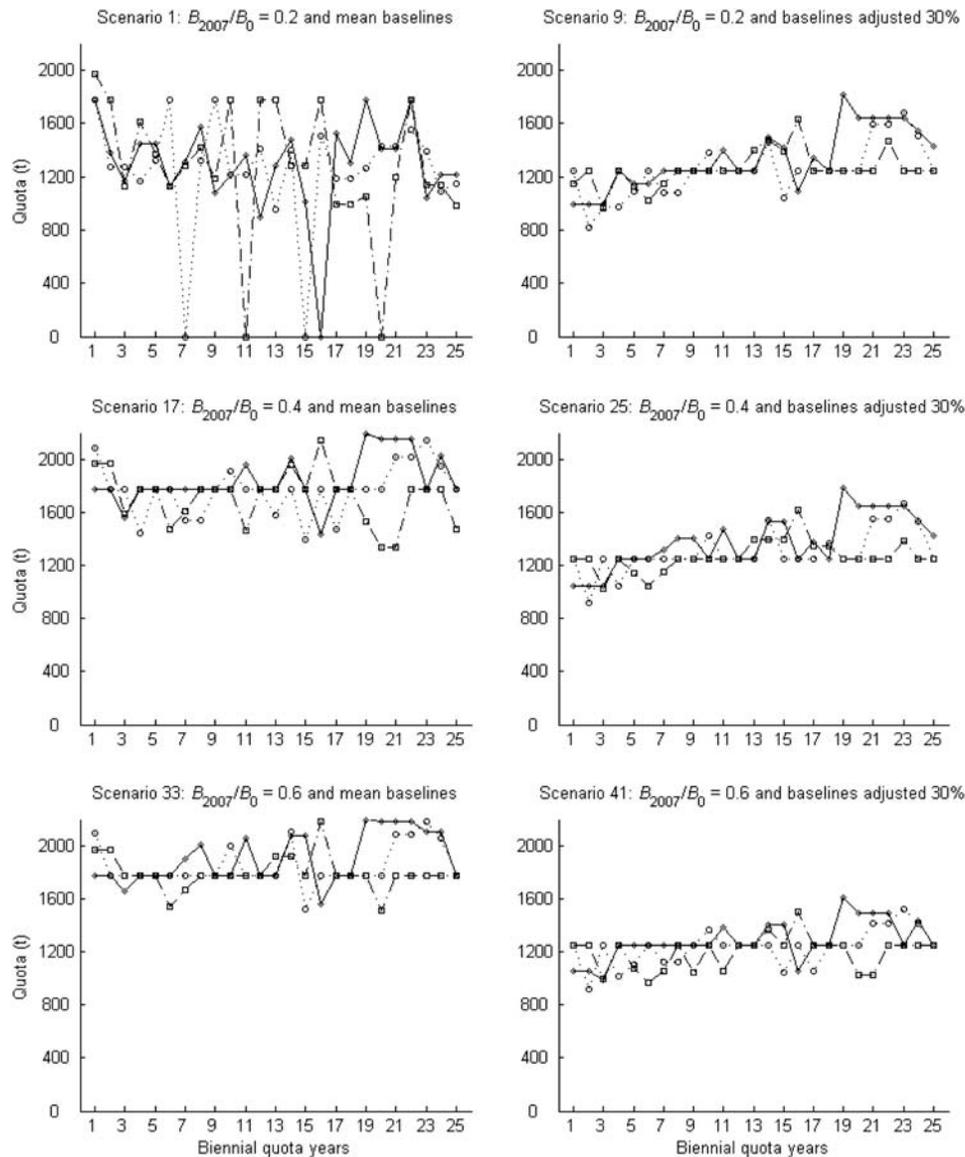


Figure 5. Comparison of expected quota behaviour from three random time-series selected under six scenarios. Catch rate baselines were all fixed, assumed proportional to abundance, with an interval width of $\pm 10\%$.

As with all quotas, the setting process followed multiple rules. Decisions were applied to select the base-quota multiplier (λ) depending on whether the standardized catch rates fell inside or outside the thresholds (Table 1), testing if the calculated new quota was within $\pm 5\%$ of previous quota, and capping to the maximum allowed tonnage. Although there were multiple steps to follow, they were simple and relatively quick to run, easy to understand, transparent to industry, responsive to changing population indices, and inexpensive (except for the cost of a fishery-independent abundance survey). Another advantage was that the process removed the need to run time-consuming stock assessment models and avoided the uncertainties associated with dynamics of spanner crabs (Kirkwood *et al.*, 2005). Although quotas were set every 2 years, the rules could be run annually. Also, the system would allow discrete responses of setting quotas into categories to be achieved. This would appeal to stakeholders and management because it minimizes unnecessary quota

change and administration compared with continuous mathematical functions (Dichmont *et al.*, 2006b; Cox and Kronlund, 2008; Little *et al.*, 2008).

A limitation of the quota process was that population status would not be known. The empirical rules could not set fishing effort or harvest accurately to obtain target biomasses above those that support maximum sustainable yield ($> 0.35-0.4B_0$; Figure 6). This was because of the multiplicative effect of more-variable recruitment and catch rate sampling (observation) error at larger population sizes. In those cases, a range of tonnages was still set above and below the base quota. Only population model procedures with greater certainty can perform better at achieving target biomasses (Rademeyer *et al.*, 2007). The crab resource may be underutilized if the real population size were high (e.g. scenarios 33–48; Figure 4). In addition, as highlighted by Cox and Kronlund (2008) and found here, the performance of empirical rules was very dependent on the level of population

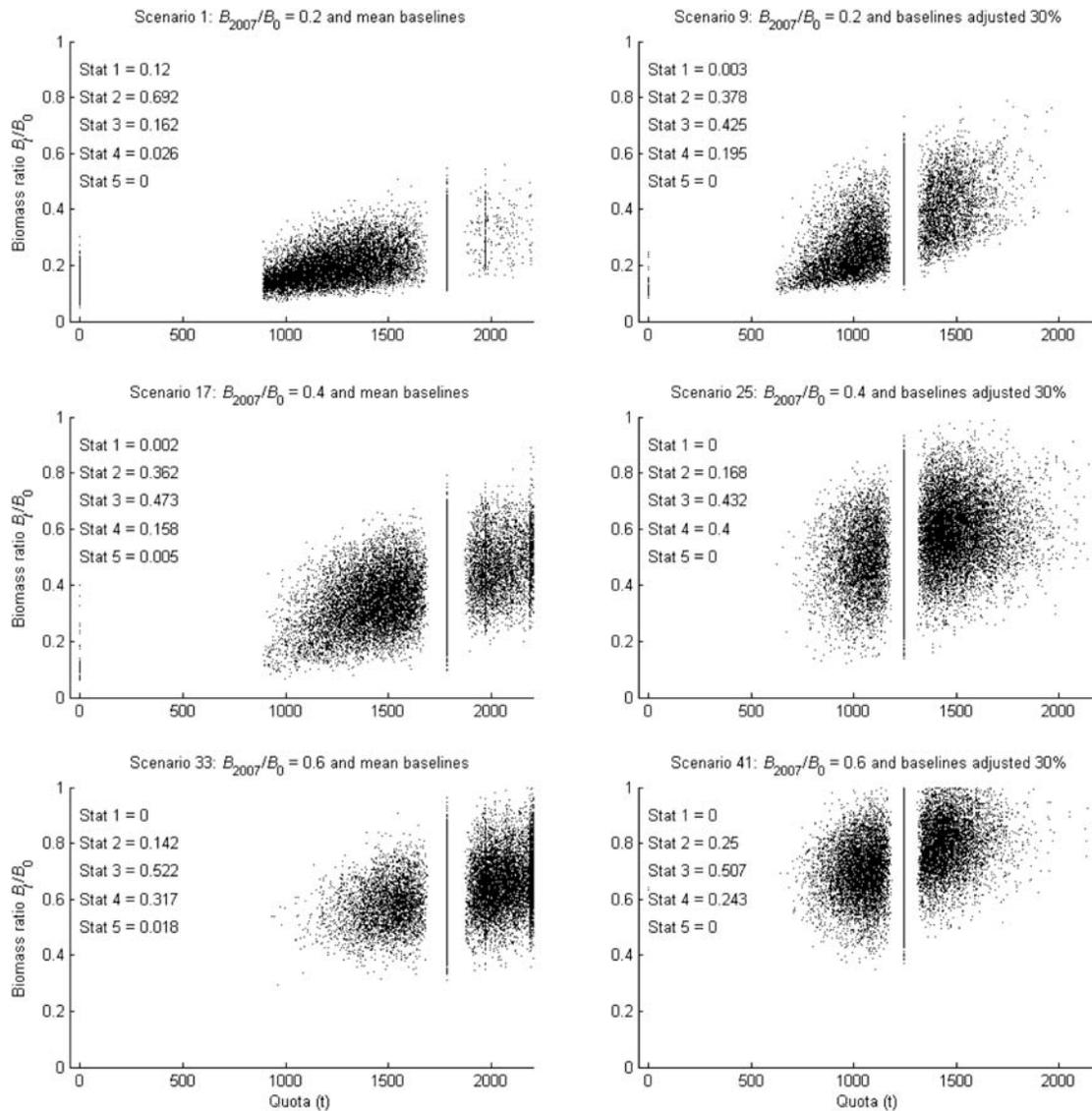


Figure 6. Simulated performance of quota setting against exploitable stock size for six scenarios. Statistics show the proportion of quotas set at zero tonnage (Stat 1), non-zero tonnages less than base (Stat 2), base (Stat 3), and above base (Stat 4); $n = 25\,000$ points per subplot. Catch rate baselines were all fixed, assumed proportional to abundance, with an interval width of $\pm 10\%$.

size present when the baselines were set. Problems of catch rate non-linearity and uncertainty of lower-than-perceived population size were overcome by setting precautionary quota and catch rate baselines. Abundance indices generated from a more temporally and spatially replicated fishery-independent survey would minimize some of the problems and remove the need for including fishery data (Skalski, 1990; Brown, 2001).

Standardize catch rates using appropriate statistical models

General linear models were used to analyse log-transformed commercial weights of spanner crab. The transformation model is common and was appropriate for spanner crabs, because catches were many, right-skewed, non-zero, and with normally distributed residuals. A large subset (63%) of the commercial catch information was first analysed with data on skippers' years of fishing experience (Table 4), thus quantifying the improvement in the

fleet's fishing experience. At that time, the resulting improvements (fishing-power offset) had limited practical effect on standardized catch rates. Even so, documenting change in fishing-power variables is essential, because operators will always aim to improve their efficiency.

Survey catches of spanner crab were standardized using a two-component approach. The methodology was particularly applicable to these discrete-count data that exhibited a significant zero class and moderate non-zero catch sizes. The models more accurately reflected the properties of the data than the old fashioned $\log(y + 1)$ transformation. Overall, the conditional log-normal model provided the best goodness-of-fit statistics and normal residual plots, as found by Mayer *et al.* (2005). However, further enhancement through more general modelling might be possible using the techniques described in other studies (Faddy, 1998; O'Neill and Faddy, 2002; Podlich *et al.*, 2002). These two-component approaches do not rely on the standard distributional

assumptions, but instead a model based on a generalized Poisson process.

Conclusions

This research paper has described a new empirical management procedure for Australian spanner crabs. Notably, it has also highlighted an approach of how to apply statistical and mathematical tools in setting harvest-decision rules. The empirical rules were simple to follow, cost-effective, flexible to changes in fishery conditions, and adaptable for use in many fisheries. When stock status and dynamics are uncertain, precautionary levels of quota and catch rate baselines are suggested to ensure sustainable and profitable fishing. The nature of this result was consistent with many numerical publications which suggest the setting of quotas below the maximum sustainable yield. This was because of the uncertainty surrounding the real values of sustainable harvest and their year-on-year variability. The system described here solved earlier problems of overestimating increases and decreases in quota and assessed fishing-power bias on catch rates. Further, the results demonstrated the technical advantages and increased potential for sustainable management gained from using this empirical baseline approach. The adaptive capacity that this management procedure provides has significance for improving our ability to manage data-poor and data-rich fisheries sustainably. In that context, the continued application and the development of these techniques warrants consideration in fisheries management into the future across all fisheries.

Acknowledgements

The Department of Employment, Economic Development and Innovation funded the project. The fishery catch rate standardization work would not have been possible without the data collated by many people. Special thanks go to Mai Tanimoto and Chris Barber for their assistance with the fleet survey and to the licence holders and skippers who contributed detailed information on their vessels and operations to examine fishing-power change. The long-term monitoring programme supplied data from their annual spanner crab survey, which provided independent information about the fishery. We gratefully acknowledge the members of the Spanner Crab Stock Assessment Group who contributed to the evolution of the management procedures, and Richard Freeman and other industry members who made a significant contribution to the process. Finally, we thank the anonymous reviewers for their valued comments.

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doi:10.1093/icesjms/fsq095