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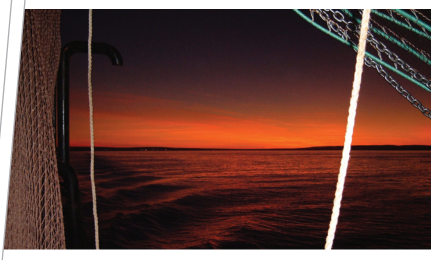

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Developing techniques to estimate total allowable catches for the NPF major prawn species

FRDC Project 2007/018
FINAL REPORT • September 2010

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Australian Government
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1. NON TECHNICAL SUMMARY

2007/018	**Developing techniques to estimate total allowable catches for the NPF major prawn species**

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OBJECTIVES:

1) Development of techniques for calculating and delivery of TAC estimates for the two tiger prawn species and non-tiger prawn species that include both biological and economic information
2) Estimation of fishing power effort creep of the fishery
3) Assessment of the species distribution for tiger and endeavour prawns to enable splitting group specific catch and effort data
4) Evaluation of economic efficiency under different TACs

NON TECHNICAL SUMMARY:

OUTCOMES ACHIEVED TO DATE

1. This project first assessed how many TACs are necessary to effectively manage the fishery. Then, given these results, the project developed new methods to assess the relevant species (or groups) and methods relating to standardising catch rates (based on a fishing power analyses), as well as considering optimal vessels size under various TAC conditions.

2. Assessment methods for each major target species or group was developed.

3. Two methods to mention are the development of the size structured model for the tiger prawn stocks and the Bayesian biomass dynamic models (for "data poor" stocks such as the blue endeavour prawns). The NPF RAG adopted both these methods for the Standard NPF assessment in 2010 onwards to manage the tiger prawn fishery.

4. The projects newly developed assessment methods have been reviewed by the NPFRAG over several meetings (and at times by NORMAC).

Presently, the NPF fishery is managed with two distinct seasons: a predominantly banana prawn season and a mainly tiger and endeavour prawn season. The main purpose of this research was to establish how many TACs might be necessary to effectively manage the tiger prawn component of the fishery, which consists of at least 4 commercial species. Moreover, to develop methods that will be used to set TACs for these key species. Within this project an analysis was performed in order to estimate the degrees of substitution between the catch of the different tiger prawn species. The results indicate the two species of tiger prawns and the economic bycatch species (e.g. endeavour prawns) are not separable. The most practical means to manage the tiger prawn fishery as outputs is via a combined species-group tiger prawn TAC. For the banana prawn stocks it is clear (from historical and present behaviour) that both common and redlegged banana prawns can be targeted with little bycatch of the other prawn species. Based on these results, the project therefore developed assessment methods for tiger prawns as a group, with endeavour prawns as an economic bycatch.

A suite of assessment models could be applied given the range of biological and economic data available for these stocks and the associated fleets. Previous assessments (before this project) did not include the size data that has recently become available, and for this project new methods have been developed: a size-structured model for the data rich species (two tiger prawn stocks) and a Bayesian hierarchical biomass dynamic model for the information poor species (endeavour prawn stock, specifically the blue endeavour prawn stock). The advantages of the size-structured model include the greater inclusion of available data (specifically catch and survey length-frequency data as well as tagging data), and therefore less use of pre-specified parameters (for example selectivity is estimated). The size-structured model also allows grade-specific prices to be considered, and has greater flexibility in terms of fitting fishing effort to estimate season length, thus providing a useful tool for evaluation of the trade-off between TAC and season duration/timing (as recognised by the NPF RAG).

Updates to the Fishing Power model and series have been undertaken, in that the extent and treatment of technology changes since 2002 have been reviewed, and the 2003 fishing power models have been re-fitted and coefficients re-estimated using all the latest available data (1970 to 2007). There was a new model developed and this was used in the assessment. These fishing power models were incorporated as input in the NPF Assessment in 2010, an assessment that utilises a bio-economic model.

Thus in this project, the existing dynamic bio-economic model was applied to estimate Total Allowable Effort (TAE) and Total Allowable Catches (TACs). A critical element of this project was to take what was learnt from the: (1) newly developed size-structured model and the (2) recently developed Bayesian hierarchical biomass dynamic model and integrate then into a single bio-economic model. Furthermore, the present bio-economic model was extended to include almost any combination of assessment model (size, biomass dynamic and delay difference).

This approach of being able to evaluate any combination of assessment model is both unique and pioneering and created the opportunity to explore the sensitivity of the different models and species combinations to a range of uncertainties. When model uncertainty is eliminated the greatest variation in future catches seems to be due to uncertainty in the economic parameters.

However, between model uncertainty was also high and it was important that the model combination selected was based on scientific principles rather than a selection based on the actual TAC. When reviewed by the NPRAG, this framework was acknowledged as novel and a valuable contribution to the analysis of uncertainty for tiger and endeavour prawns. The NPF RAG therefore selected the best combination of models, these being the size model for both species of tiger prawns and the Bayesian hierarchical model for blue endeavour prawns. *This model is now the basis of the most recent NPF Assessment – 2010 onwards.*

As banana prawns are not included in this combined species-group TAC for tigers and endeavour prawns, a separate set of approaches for setting TACs is required for these stocks. During the project and with feedback from the RAG (and later NORMAC) the banana prawn stocks were spilt into two banana prawn stock-regions. The demarcation of the boundary between the two stock regions is presented in the report of which NORMAC chose one of the boundaries east of Pearce Point in the Joseph Bonaparte Gulf and south of a boundary at 12° latitude. At this stage, the project (verified by the NPF RAG) considers that it does not have any quantitative assessment method that can be adequately applied to Eastern banana prawn stock-region (mostly common banana prawns). The extreme spatial and temporal variation in the catch rate data (and therefore one's ability to predict the size of recruitment in advance) is one of the major underlying factors that will undermine any assessment. It is unlikely that this situation will change in the near future.

The only option is to rely on empirical methods based on historical catch and effort data to set TACs for banana prawn stock regions. As an alternative, an Updated TAC method (as recommended by NORMAC on the basis of a Cost Benefit Analysis – the relevant sections included with permission herein) could be applied to the stock. This method sets a constant TAC with a potential of an increase in the TAC (an Update) if the recruitment survey index is medium or high. However there is considerable uncertainty in the relationship between the survey index of abundance of recruits and the subsequent observed catches. For the other stock-region (the Western banana prawn stock-region - predominantly red-legged banana prawns), a preliminary assessment model was developed. Key sensitivities are highlighted and some preliminary model results are presented and compared to a separate Bayesian hierarchical biomass dynamic model to the redlegged prawn stock in the Western region.

As highlighted, changes to the NPF fishing fleet is anticipated with the introduction of output controls and the final section provides a preliminary analysis of the potential optimal vessel size under various conditions. Vessels were found to be currently close to their optimal size given average historic prices and current stock conditions.

Thus to summarise, significant progress has been made in this project with the development of techniques for the estimation of total allowable catches (TACs) for the major prawn species in the Northern Prawn Fishery (NPF). These techniques include novel and newly applied assessment methods that have been reviewed by the NPFRAG over several meetings (and at times by NORMAC), and applied in the most recent NPF Assessment in 2010 even before moving to ITQs.

KEYWORDS: Total Allowable Catch, TAC, Northern Prawn Fishery, NPF, prawn species

2. ACKNOWLEDGMENTS

The NPF Ltd is acknowledged for its exceptional support in providing access to data. The project benefitted from the extensive feedback from the members of the Northern Prawn Fisheries Resource Assessment Group (RAG). Financial support for this project is provided in part by the FRDC and the CSIRO Wealth from Ocean Flagship. The industry is thanked for their data. AFMA provided the VMS data.

3. BACKGROUND

The Northern Prawn Fishery (NPF) is one of Australia's most valuable fisheries in terms of total landed value, and is the most valuable fishery managed by the Australian Commonwealth government. The fishery has an explicit management objective of maximizing economic returns. In 2007-2008, the gross value of product was around A$74m (ABARE, 2009).

The fishery is currently managed using a combination of input controls, primarily seasonal closures and individual transferable gear units. The latter places restrictions on the amount of headrope that vessels can tow. Over the last decade, the fleet size has more than halved, from 133 vessels in 1998 to 52 in 2008.

Part of the recent reduction in fleet size was facilitated by government investment in the fishing industry. In 2005 the Federal Government announced a $220 million adjustment package to help secure the sustainability of the Commonwealth fish stocks and a profitable future for Australia's fishing industry. In response, the Australian Fisheries Management Authority (AFMA) proposed that a new harvest strategy framework be implemented for all Commonwealth-managed fisheries by 2008. Initiatives proposed under this framework are still being implemented at this stage (post 2008). The framework set in place the 'goalposts' for managing catches of commercial stocks by setting agreed target and limit reference points and clear decision rules for each species.

In order for the Northern Prawn Fishery (NPF) to be part of the adjustment package commitment was sort from the industry to move towards a system of output controls (that is quota control, specifically Individual Transferable Quotas (ITQs)). Output control via a system of quota normally involves setting a global Total Allowable Catch (TAC) for each commercial species (if possible) and then having the means to distribute on the basis of allocation rules ITQs to each fishing unit. The allocation rules are outside of the remit of this project. Suffice to state, that since the NPF is historically managed via a fishing effort (input) control system, the onus was on the establishment of a means to assess what methods were available to estimate for each prawn stock (if possible) a Total Allowable Catch (TAC).

The Northern Prawn Fishery Management Advisory Committee (NORMAC) in 2006 discussed the preliminary advice from Northern Prawn Fishery Resource Assessment Group (NPFRAG) on changes needed in stock assessment to meet the requirements of an ITQ management system. As a consequence, NORMAC and the NPFRAG agreed to endorse the development of research proposals to support the likely output control management for the NPF, and to facilitate the development and implementation of the ITQ system with a time line of 2010 (deadline provided at the time of submission of this project proposal).

For the NPF to complete its transition to a quota management system within this timeline, it was essential to begin research on methods of estimating appropriate total allowable catches (TACs) and to begin to develop corresponding management procedures as soon as possible. The

NORMAC meeting in March 2006 also discussed the research needs for the transition of the NPF to a TAC system and supported the development of this proposal. In its June 2006 meeting, the NPFRAG further discussed, recommended modifications to, and endorsed a pre-proposal, from which this project's proposal has developed. So, this project was developed in close consultation with the NPF RAG and NORMAC, which are comprised of representatives of the industry, management authorities and other stakeholders. These events essentially frame the background context within which this project developed and was completed.

4. NEED

The transition to a quota system requires research on methods of estimating total allowable catches (TACs). The NPF is a multi-species fishery. However, stock assessments have only been undertaken on two out of the eight commercial species. Controlling catch of only two prawn species cannot secure the long-term sustainability of the whole NPF. Therefore, a whole-fishery approach must be adopted, and assessments of each stock needs to be extended to a greater number of species. Estimating TACs for annual species like the commercial prawns in the NPF is challenging because recruitment and subsequent catches are greatly influenced by environmental variables that fluctuate widely. In the NPF, biological parameters are not uniformly known for all prawn species, and the characteristics of population dynamics differ from species to species. A tier-approach should be applied here like the SESSF, i.e. a formal stock assessment will be done for species supported by sufficient data; for others more empirical methods may be adopted. It is well known that the move from input to output control causes major changes to the catch rate data and can cause a major break in the time series thereof.

A key management objective in the NPF is the maximisation of economic profits. TACs will, therefore, have to reflect this economic objective. Although the theory of maximum economic yield (MEY) is well established, such a management target has not been implemented in any fishery (at the time this project proposal was tabled). Achieving such a target requires both methodological development and analysis of a number of factors not previously considered when setting TACs in fisheries. In summary, this project was designed to meet the strategic need and provide the science, tools and technical support for the successful transition of the NPF to a quota management system.

Presently, the NPF fishery is managed with two distinct seasons: a predominantly banana season and a mainly tiger and endeavour prawn season. From historical and present behaviour, it is clear that both common and redlegged banana prawns can be targeted with little bycatch of other prawn species. However, a key aspect of this project was to evaluate the degree to which individual species can be targeted in the tiger (and endeavour) prawn component/season(s) of the fishery. The purpose was to establish how many TACs might be necessary to effectively manage this tiger prawn component of the fishery, which consists of at least 4 species, and how many TACs might be necessary to practically manage the banana prawn stocks.

Thus in summary, the evaluation of output controls for this fishery has become a priority with the recommendation from NORMAC that the fishery be managed via output controls. This project was established with the main objective of developing techniques for calculating and delivery of, TAC estimates for the two tiger prawn species and non-tiger prawn species that include both biological and economic information thus meeting the need that methods to estimate TACs be evaluated.

5. OBJECTIVES

The main objectives of the project "*Developing techniques to estimate total allowable catches for the NPF major prawn species*" as listed in the original proposal were to contribute to the:

1) Development of techniques for calculating and delivery of TAC estimates for the two tiger prawn species and non-tiger prawn species that include both biological and economic information

2) Estimation of fishing power effort creep of the fishery

3) Assessment of species distribution for tiger and endeavour prawns to enable splitting group specific catch and effort data

4) Evaluation of economic efficiency under different TACs

No changes were made to these objectives during the course of the project. The extent to which each has been achieved is the subject of this report in full (including appendices).

Here we merely highlight that all of these objectives have been completed and can summarise it as such:

- Techniques have been developed to estimate TACs for the two tiger prawn stocks (e.g. a newly applied size structured model) as well as the non-tiger prawn species (e.g. Bayesian hierarchical biomass dynamic models). The biological and economic data on the stocks and fishery are integrated within a bio-economic assessment. The bio-economic model was extended to include almost any combination of assessment model (the above mentioned models and an updated previously applied delay-difference model).
- Updates to the Fishing Power model and series have been undertaken (to estimate fishing power creep), in that the extent and treatment of technology changes since 2002 have been reviewed, and the 2003 fishing power models have been re-fitted and coefficients re-estimated using all the latest available data (1970 to 2007). These fishing power models were incorporated as input in the NPF Assessment in 2010.
- As part of the overall analysis of assessing distribution of species, the splitting of catches into species was updated. The statistical approaches used to build the species distribution models from previous studies was further refined and both the tiger and endeavour species split models were calibrated with a consolidated data-set that includes the data collected in this project. The refinement and calibration of these species split models have improved the accuracy of the catch estimates at the species level.
- The economic efficiency under different TACs has been evaluated. A restricted profit function for the fishery was estimated to determine the optimal vessel characteristics and output levels as a guide to how the fleet may adjust under an ITQ system. Vessels were found to be currently close to their optimal size given average historic prices and current stock conditions.

6. METHODS

This project firstly assessed how many TACs were necessary to effectively manage the fishery. Then, given those results, the project developed new methods to assess the relevant species (or groups) and methods relating to standardising catch rates based on a fishing power analyses, whilst considering optimal vessel size under various TAC conditions.

The methodology applied in this project can best be described as a series of steps. Each separate step involved a separate and distinct method/ quantitative analysis, and although these are linked, the actual methods cannot be combined easily into one series of functional relationships (equations). We thus provide a brief technical explanation of each step and its associated methodology separately, and described in detail their dependencies. The detailed technical descriptions are included in the Appendices.

The methodological steps (Figure 1) can be described in the following manner:

Step 1. Establish number of TACs to be set in each fishery (Figure 1).

Within the fishery, generally banana prawn stocks are fished separately to tiger and endeavour prawn species. Therefore two separate analyses were undertaken. For the tiger prawn fishery, the analysis had to establish how many TACs might be necessary to effectively manage the tiger prawn component of the fishery (i.e. could TACs be realistically set for each of the tiger prawn species or conversely, could a single TAC be used to manage the whole tiger prawn fishery?). The method that was applied to the tiger prawn component of the fishery was a production analysis of targeting ability (a Bayesian multi-output distance function approach). In addition to this research, various other techniques were applied to the banana prawn species, however only after considering the partition of the species into banana prawn stock regions (see Step 2 – below).

Step 2. Collate and update input data (catch and effort for individual stocks) and re-estimate fishing power using new data (Figure 1)

> Step 2a) <u>Update data on estimating catch distributions</u> (and magnitude) for individual prawn species and models (the “species split models”). Any assessment of the tiger prawn component of the fishery requires models to estimate catch for each species as detailed landings data are at a species group level only.

Step 2b). Provide an update of the fishing power analysis for incorporation of new estimated time series into assessment of tiger prawn stocks. Technological advances and changes in the size (and geographic extent – temporal and spatial distribution) of the fleet are such that the previous analysis of fishing power was in need of an update. This update was relevant to both the actual model and data.

Step 2c) Partition the banana prawn stocks in sub-regions. Present options for the division of the banana prawns stocks into two separate stock-regions, that is, partition the NPF banana prawn fishery into Eastern and Western regions for separate allocation.

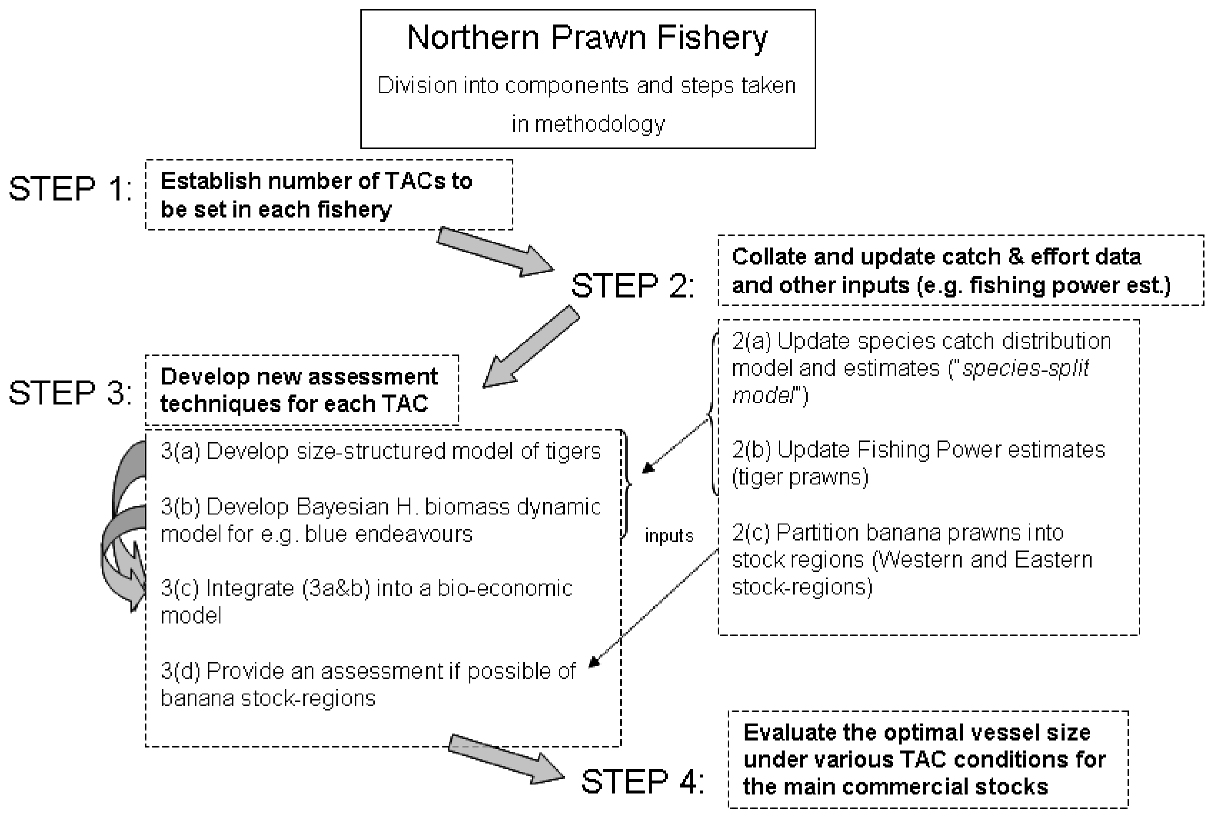

Figure 1. The main steps defining the overall methodology applied in the project.

Step 3. Develop new and novel assessment techniques for the prawn stocks (each considered separately) (Figure 1).

Step 3a) Develop a size-structured model for the data "rich" stocks such as the two tiger prawn species (brown and groove) for which length frequency data is available.

Step 3b) Apply Bayesian hierarchical biomass dynamic models to assess the less data “rich” stocks such as the blue endeavour prawns. In addition, in order to ascertain the utility of this approach and provide validity to any results we tested the method against the same stocks in Step 3a), that is, the brown and grooved tiger prawn stocks.

Step 3c) Develop an integrated model bio-economic model for the tiger and endeavour prawn component of the fishery that combines the product from 4a (the size structured model) and 4b (the Bayesian hierarchical biomass dynamic model) and the NPF bio-economic model[1].

Step 3d) Provide an approach for setting output controls for the banana prawns stock regions (stocks) (depending on the boundary of the stock region defined in step 2b). As the two regions are the Western and the Eastern region, the Eastern region relies on the method presented in a cost benefit analysis (CBA) of common banana prawns that was undertaken as part of an assessment of the economic benefits of output controls in the NPF. The Western banana prawn stock region comprises an area in the Joseph Bonaparte Gulf and has been assessed with two methods (i) a quarterly biomass dynamic model and (ii) Bayesian hierarchical biomass dynamic model.

Step 4. Evaluate the optimal size of vessels under various TAC output conditions (Figure 1).

Strictly Step 4 does not directly follow Step 3, however it forms the basis of an in-depth analysis of economic efficiency in the fleets and the potential impact of output control. As an economic analysis, it contributes and validates the data inputs and assumptions in the integrated bio-economic model (Step 3c).

Although not listed as a “*Step – 5*”, the final task was to take what has been achieved in this project (after review by the RAG) and include these new approaches (particularly 3c&d) in the most recent NPF Assessment (2010) and present estimated input (TAEs) and output (TACs) control measures for each of the stock/stock regions of the fishery[2].

In the sections below we summarise elements of the method applied for each step. We do this as concisely as possible, without a detailed reference to every assumption and all the data used (the details of assumptions are explicit in the extensive set of manuscripts presented in the

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[1] A critical element of this project was to take what was learnt from the: (1) the newly developed size-structured model (this project) and the (2) recently developed Bayesian hierarchical biomass dynamic model (this project) and integrate them into a single bio-economic model. An updated version of the previously applied delay difference was still included in the suite of assessment models as a sensitivity test required an analysis of the relative impacts of previous versus new approaches was required.

[2] This task has been completed – see NPF RAG Assessment 2009/10. AFMA R-2008/0824.

appendices; that are referenced; a few of which have been published in peer reviewed international journals).

6.1 Establish number of TACs for output control

An evaluation was undertaken of the number of potential TACs essential for prawn fisheries (tiger/endeavour component of fishery) by considering the ability of the fleet to target individual species (Step 1 – Figure 1). In order to estimate the targeting ability of fishing vessels an econometric analysis is applied to the Tiger prawn and endeavour component of the fishery as an example. In the analysis, the Morishima elasticities of substitution are derived from a multi-output distance function to examine fishers' ability to control output mix in a fishery about to move to ITQ management. The parameters of the model are estimated using Bayesian techniques to avoid potential endogeneity bias (Appendix 3 contains a detailed manuscript of this study as a reference). In most fisheries productivity studies, production is generally assumed to be either non-joint in input quantities, such that the production of a single output can be modelled as a function of a set of inputs, or that production is joint in input quantities, but is separable, such that a composite measure of a set of outputs can be modelled as a function of a set of inputs. In both cases, a single output measure is obtained and used in the estimation of the production function. Some form of multi-output function is required when the technology is believed to be both joint in inputs and non-separable. A number of primal multi-output functional forms with different characteristics exist. These include multi-output production functions where one species is considered the dependent variable and the other species are included as covariates (Felthoven and Morrison, 2004; Orea *et al*, 2005), and distance functions in which ratios of the outputs appear as covariates.

The general form of the multi-output production function may be given by

$$y_1 = f(y_{m>1}, x_k)$$

where y_m is the level of output of species m, and x_k is the level of input k (where inputs include vessel characteristics as well as the size of fish stocks). Orea et al (2005) estimated the model using logged values of the dependent and independent variables, while Felthoven and Morrison (2004) proposed a generalised linear transformation function using the square root of the covariates.

The multi-output distance function can be expressed as

$$D(x,y) = \frac{\min}{\psi}\left\{\psi > 0 : \left(\frac{y}{\psi}\right) \in P(x)\right\}$$

where *P(x)* is the set of feasible output vectors obtainable from the input vector *x* (Orea et al, 2005), and *D(x,y)* represents the distance to the production frontier. In practice, the output distance function is estimated as

$$-\ln y_1 = f(\ln(y_m / y_1), \ln x_k) - \ln D$$

which is effectively a standard production frontier model with one output as the dependent variable and the others as covariates in ratio. The multi-output distance function has had broad use in many industries (e.g. Grosskopf *et al.*, 1995; Coelli and Perelman, 2000; Morrison Paul *et al.*, 2000, Fare *et al.*, 2005; Lee, 2005), but only limited applications in fisheries (Fousekis, 2002; Huang and Leung, 2007; Pascoe *et al.*, 2007). The approach adopted in this study was the translog multi-output distance function (see Appendix 3).

6.2 Collate and update data for input into models

6.2.1. Update data on estimating catch distributions

An initial task was to update data on estimating catch distributions (the "species split models") (Step 2a – Figure 1). The methodology (Appendix 4) we use for partitioning catch biomasses into the component species parallels directly to that described Venables, Kenyon *et al.* (2006). In particular we build generalized linear models for catch allocation using the following predictors: (1) location, specified by Longitude and Latitude, (2) spatially static predictors [distance from land, depth, and average percent mud in the sediment], (3) a temporal variable: time of year for periodic variations within the year, and (4) the elapsed number of days since January 1st 1970 for a long-term trend (Appendix 4 outlines the method in its full extent).

The spatially static variables are measured at the 6-minute grid cell level, which matches the spatial scale of measurement used by the logbook records themselves. The response, that is the quantity for which we will construct models, as in the previous study is: (a) The proportion of grooved tiger prawns, *P. semisulcatus*, in the total catch, and b) The proportion of red endeavour prawns, *M. ensis*, in the total endeavour catch. Since there are only two species in each group, once the proportion of one is known, the proportion of the other is the complementary fraction.

6.2.2. Provide an update of the fishing power analysis

The approach to estimating relative fishing power for the NPF tiger prawn fishery has traditionally been to fit a statistical linear model to logbook data, to predict daily catch rates (on a log scale) from a suite of terms that represent abundance, vessels, skippers and technology (Bishop, Venables, Dichmont *et. al*., 2008) (Step 2b – Figure 1) (Appendix 5). This approach is well-known (Maunder and Punt, 2004); however in the prawn fisheries of the NPF, the fitting of such models is compromised by confounding between vessel terms and prawn abundance.

This confounding is due to a confluence of factors. Firstly, the fishery has been actively managed by input controls which have resulted in changes in nets or fleet composition and consequently in swept area capacity. The fleet is a modern industrial one, and adoption of innovations in fishing technology has been rapid (for example see Robins, Wang and Die, 1998). Previous research has concluded that the logbook data alone could not fully resolve the fishing power issues, because of this confounding between vessel technology changes, movements of vessels and local abundance (Bishop *et al*,. 2008). To compensate for any unavoidable deficiencies in the data, the fishing power models for the NPF tiger prawn fishery have the feature that some of the coefficients (e.g. for technology that could not be well-estimated from the available data) were fixed (or offset) at values obtained from external evidence including expert knowledge and judgment.

Previous models that have been used for recent annual stock assessments up until 2007 are referred to as “the 2003 models” in the present report. They are the basic low, basic high and spatial high models described in Dichmont, Bishop, Venables *et al.* (2003) and Bishop *et al.* (2008). Each model is of the form:

$$\log(C_{ijkt}) = \alpha_0 + \gamma \log(f_{ijkt}) + \sum\nolimits_q \alpha_q X_{qjkt} + \sum\nolimits_p \beta_p \log(V_{pik}) + \sum\nolimits_h g(i,k,h)\delta_h + \varepsilon$$

where

C_{ijkt} denotes the daily catch weight of tiger prawns plus half the endeavour prawns, of vessel *i* fishing in area *j*, year *k* and month *t*;

f_{ijkt} represents effort, hours trawled per day;

X_q are terms to represent abundance and availability: (including year, month, area);

V_p are 1 to *p* continuous vessel, gear and skipper characteristics;

$g(i,k,h)$ functions *g* of categorical vessel, gear and skipper characteristics;

ε an error term assumed independent and homoscedastic;

The basic relative fishing power for the fleet each year was the arithmetic mean of per vessel fishing powers, weighted for the effort of each vessel that year.

$$R_{k,i/s,j} = \frac{\sum\limits_{ik} f_{ik}(\exp(c_{ik} - c_{sk}))}{\sum f_{ik}}$$

The relative fishing power each year (relative to 1970, $\frac{R_{k,i/s,j}}{R_{1970,i/s,j}}$), and the fishing power each year relative to the previous year $q_{inc} = \frac{R_{k,i/s,j}}{R_{k-1,i/s,j}}$ were calculated.

Since 2003 there have been considerable changes in the fleet and to summarise, the aim was to evaluate to what extent new technologies are impacting on the fleet, and could changes be made to the characterisation of these technical changes in the model in order to reduce the number of offsets in the analysis. Moreover, the reduction in the fleet size has resulted in changes in the spatial extent of the fishery. In that regard, there are two interacting factors that contribute to potential change in fishing power: (1) the actual reduction in fleet number and (2) the effect that a smaller fleet has on its ability to search and catch prawns in terms of its reduced spatial searching and catching power.

Thus, the present study addresses objective 2 of the TAC Project: *Update the fishing power series and develop a pre-ITQ fishing power series of estimates*. To achieve this objective,

a) “The 2003 models” were re-fitted, and the coefficients re-estimated, using all the latest available data to 2007.

b) The extent and treatment of technology changes since 2002 were reviewed and there is less need for some of the offsets previously applied (see results)

c) A major change in the fishery since 2002 has been a reduction in fleet size (from 97 vessels in 2003 to 51 vessels in 2007). We investigated whether reducing the fleet size has had any impact on the fishing power of the fleet.

d) Improvements to the fishing power models were also investigated and implemented. This new method produced estimates with narrower confidence bounds and on the basis of this result there is now no requirement for a high and low version of the fishing power series of estimates. This new "single time series estimate" of the fishing power model has been adopted.

6.2.3. Partition the banana prawn stocks in sub-regions

The banana prawn catch in the NPF consists of two biological species, namely *Penaeus merguiensis* (common banana prawns) and *P. indicus* (red-legged banana prawns), which are undifferentiated in the catch. Common banana prawns are caught throughout the NPF, often in aggregations close to the surface and in relatively shallow water. By contrast, red-legged banana prawns are confined to a number of discrete regions in the West of the NPF and are caught in relatively deep water by trawl methods more reminiscent of tiger prawn trawling.

Ideally, to manage both biological species, a separate TAC would be set for both. Since the catch is undifferentiated, however, for practical purposes the best approximation to this situation is for the banana prawn component of the NPF fishery to be partitioned spatially into two regions and a separate banana prawn TAC be set for each (Step 2c – Figure 1). The method relied on a set of criteria for setting the partition (Appendix 6). Three evident criteria for a spatial partitioning of the TAC regions are, possibly in increasing order of importance:

- The interface between the two spatial regions should be clear and precise and, as well separated as possible from the normal operation of the fishery,
- The interface should be simple to specify, making compliance simple for the industry, and easy to ensure by the management authority

The western partition should contain as much of the red-legged banana catch, and as little of the common banana catch, as possible.

6.3 Develop new and novel assessment techniques for the prawn stocks

6.3.1 Develop a size-structured model for tiger prawn species

Three species in Australia's Northern Prawn Fishery (*Peneaus semisulcatus*, P. *esculentus*, and *Metapenaeus endeavouri*) are assessed using a size-structured population dynamics model which operates on a weekly time-step (Step 3 – Figure 1). The parameters of this multi-species population dynamics model, which include annual recruitment, fishery and survey selection patterns, parameters which define the size-transition matrix, and recruitment patterns, are estimated using data on catches, catch-rates, length-frequency data from surveys and the fishery, survey indices and tag release-recapture data.

The model allows for the technical interaction among the three species a result of bycatch when targeting one or the other species. The results from the multi-species stock assessment form part of the basis for evaluating the time-series of catches (by species) and levels of fishing effort (by fishing strategy) which maximize net present value. The bio-economic model takes into account costs which are proportional to catches, and those which are proportional to fishing effort, as well as fixed costs. The sensitivity of the results is examined by changing the assumptions regarding the values for the economic parameters of the bio-economic model as well as those on which the assessment are based. Appendix 7 provides in detail the model, assumptions and the estimation procedure and data used.

In common with previous stock assessments of the tiger and endeavour prawns (e.g. Dichmont *et al.*, 2003), the population dynamics model operates on a weekly time-step:

$$\underline{N}_{k,y,w+1,s} = \mathbf{X}_{k,s}\mathbf{H}_{k,y,w,s}\underline{N}_{k,y,w,s} + 0.5\underline{R}_{k,y,w+1} \qquad (1)$$

where $N_{k,y,w,s,l}$ is the number of prawns of species *k* and sex *s* in length-class *l* (1mm length-classes between lengths of 15 and 55 mm) alive at the start of week *w* of year *y* ($\underline{N}_{k,y,w,s}$ denotes the vector of numbers by length), $\mathbf{H}_{k,y,w,s}$ is the survival matrix for species *k* and sex *s* during week *w* of year *y* (a diagonal matrix with $e^{-Z_{k,y,w,l}}$ on the diagonal), $\mathbf{X}_{k,s}$ is the growth matrix (the probability of an animal of species *k* and sex *s* in size-class *i* growing into size-class *j*) during a week, $\underline{R}_{k,y,w}$ is the recruitment of species *k* to the population during week *w* of year *y*:

$$R_{k,y,w,l} = \begin{cases} \alpha_{k,w}\, R_{k,\tilde{y}(y,w)} & \text{if } l = 15\,\text{mm} \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

$\alpha_{k,w}$ is the expected fraction of the annual recruitment for species *k* that occurs during week *w*, $R_{k,\tilde{y}}$ is the recruitment of species *k* during 'biological year' $\tilde{y}$, and $\tilde{y}(y,w)$ is the 'biological year' corresponding to week *w* of year *y*:

$$\tilde{y}(y,w)=\begin{cases} y & w<40 \\ y+1 & \text{otherwise}\end{cases} \tag{3}$$

Total mortality, $Z_{k,y,w,l}$, on animals of species *k* in length-class *l* during week *w* of year *y* is given by:

$$Z_{k,y,w,l}=M_k+F_{k,y,w,l} \tag{4}$$

where M_k is the average (over week) weekly instantaneous rate of natural mortality (assumed to be independent of sex, length and time), and $F_{k,y,w,l}$ is the fishing mortality on animals of species *k* in length-class *l* during week *w* of year *y*.

Equation (3) implies that the 'biological year' ranges from week 40 (roughly the start of October) until week 39 (roughly the end of September) while Equation (2) implies that recruitment contributes only to first length-class considered in the model. Growth is assumed to be time-invariant (seasonally and annually) and the annual recruitment pattern (defined by $\alpha_{k,w}$) is assumed to be the same each year in the absence of data to parameterise seasonal growth and time-dependent recruitment patterns.

The spawner stock size index for species *k* and calendar year *y*, $\tilde{S}_{k,y}$, is computed using the equation:

$$\tilde{S}_{k,y}=\sum_w \beta_{k,w}\sum_l \omega_{k,l}\frac{1-e^{-Z_{k,y,w,l}}}{Z_{k,y,w,l}}N_{k,y,w,\text{fem},l} \tag{5}$$

where $\beta_{k,w}$ is a relative measure of the amount of spawning by species *k* during week *w*, and $\omega_{k,l}$ is the proportion of females of species *k* in length-class *l* which are mature.

For the purposes of this study, it is assumed that the probability that an animal in size-class *i* grows into size-class *j* during each time-step is governed by a normal distribution, i.e. for each species *k*:

$$X_{k,s,i,j}=\int_{L_j}^{L_{j+1}}\frac{1}{\sqrt{2\pi}\sigma^I_{k,s}}\exp\left(-\frac{\{L+0.5-(L_i+I_{k,s,i})\}^2}{2(\sigma^I_{k,s})^2}\right)dL \tag{6}$$

where $\sigma^I_{k,s}$ determines the variability in the growth increment for animals of species *k* and sex *s*, $L_{i/j}$ is the lower limit of size-classes *i* / *j*, and $I_{k,s,i}$ is the growth increment for animals of species *k* and sex *s* in size-class *i*, determined according to a von Bertalanffy growth curve parameterised in terms of $\kappa_{k,s}$ and $\ell_{\infty,k,s}$, i.e.:

$$I_{k,s,i}=(\ell_{\infty,k,s}-L_i)(1-e^{-\kappa_{k,s}}) \tag{7}$$

Annual recruitments for the years for which information on catches and survey indices of recruitment is available (1970-2008) are treated as estimable parameters while those for (future) years are assumed to be related to $\tilde{S}_{k,y}$ according to a Ricker stock-recruitment relationship:

$$\hat{R}_{k,y+1}=\tilde{\alpha}_k\tilde{S}_{k,y}\,e^{-\tilde{\beta}_k\tilde{S}_{k,y}} \tag{8}$$

where $\hat{R}_{k,y}$ is the conditional mean for the recruitment during biological year *y* (i.e. the recruitment from October of year *y*-1 to September of year *y*) based on the stock-recruitment relationship, and $\tilde{\alpha}_k$ and $\tilde{\beta}_k$ are the parameters of the stock-recruitment relationship.

The relationship between the actual recruitment for future year *y* and the conditional mean based on the stock-recruitment relationship is given by:

$$R_{k,y} = \hat{R}_{k,y}\, e^{\eta_{k,y}} \qquad \eta_{k,y+1} = \rho_{r,k}\eta_{k,y} + \sqrt{1-\rho_{r,k}^2}\,\xi_{k,y+1} \qquad \xi_{k,y+1} \sim N(0;\sigma_{r,k}^2) \quad (9)$$

where $\rho_{r,k}$ is the environmentally-driven temporal correlation in recruitment (account needs to taken of the possibility of environmentally-driven temporal correlation because the residuals about the fit of Equation 9 exhibit auto-correlation), and $\sigma_{r,k}$ is the (environmental) variability in recruitment about the stock-recruitment relationship.

Fishing mortality and catch

Catch in the model is a function of weekly stock size, the level of fishing effort expended each week, the relative fishing power of the fleet in that year, the relative availability of each species in each week, the size selectivity of the fishing gear, and the catchability of the species. The fishing mortality on animals in length-class *l* during week *w* of year *y*, $F_{k,y,w,l}$, is given by:

$$F_{k,y,w,l} = A_{k,w}\,\gamma_{y,w}\,S_{k,l}^F\,(q_k^G E_{y,w}^G + q_k^B\,E_{y,w}^B) \qquad (10)$$

where $E_{y,w}^{G/B}$ is the effort during week *w* of year *y* 'targeted' towards *P. semisulcatus* (G) and *P. esculentus* (B), $q_k^{G/B}$ is the catchability coefficient for the fishing strategies targeting *P. semisulcatus* (G) and *P. esculentus* (B), $A_{k,w}$ is the relative availability of animals of species *k* during week *w*, $\gamma_{y,w}$ is the relative efficiency of the two fishing strategies during week *w* of year *y*, and $S_{k,l}^F$ is the selectivity of the fishery on animals of species *k* in length-class *l* (assumed to be a logistic function of length).

The catch (kg) of prawns of species *k* of size class *l* during week *w* of year *y* ($Y_{k,y,w,l}$) is given by:

$$Y_{k,y,w,l} = \sum_s w_{k,s,l}\,\tilde{Y}_{k,y,w,s,l} \qquad (11)$$

where $w_{k,s,l}$ is the mass of animals of species *k* and sex *s* in length-class *l*, and

$$\tilde{Y}_{k,y,w,s,l} = \tfrac{F_{k,y,w,l}}{Z_{k,y,w,l}} N_{k,y,w,s,l}(1-e^{-Z_{k,y,w,l}}) \qquad (12)$$

Total mortality as a function of length does not depend on sex as both fishery selectivity and natural mortality are assumed to be independent of sex. However, dimorphic growth means that mortality due to the fishery is sex-specific.

Economic model

The economic model estimates the flow of costs and revenues from fishing over time. It differs from the previous bioeconomic model (Dichmont *et al*., 2008) in that it incorporates fixed as well as variable costs, and allows for prices to depend on prawn size. The objective function involves the maximisation of the net present value (NPV) of the flow of profits over time, from the first year (taken to be 2008 in this study) to the terminal year of the simulation (taken to be 2050), given by:

$$NPV = \sum_{y=1}^{T-1} \pi_y \Big/ (1+i)^{y-1} + \left[\pi_T / i\right] \Big/ (1+i)^{T-1} \qquad (13)$$

where *i* is the rate of interest (the discount rate, assumed to be 5% per annum in this study), π_y is the profit during year *y*, and π_T is the level of profit during the terminal year. Profits were assumed to continue at the level π_T indefinitely on the basis that the system is in equilibrium.

The level of profits in each year (including the terminal year) are given by:

$$\pi_y = \sum_w \left\{ \sum_k \sum_l v_{k,y,w,l} Y_{k,y,w,l} - VC_{y,w} \right\} - \Omega_y V_y \qquad (14)$$

where $v_{k,y,w,l}$ is the average price per kilogram for animals of species *k* in length-class *l* during week *w* of year *y*, $VC_{y,w}$ is the total variable costs during week *w* of year *y*, Ω_y is the average annual fixed costs associated with a vessel operating during year *y* and V_y is the number of vessels operating during year *y*. The model assumes that all of the catch ($Y_{k,y,w,l}$) is landed, which is not unreasonable since the fishery is currently managed using input controls and therefore no incentives exist to high grade or otherwise discard any of the catch. The combined term $v_{k,y,w,l} Y_{k,y,w,l}$ represents the revenue each week associated with each species and length class.

Variable costs include labour, fuel (and oil) costs, and other material costs. Maintenance and repair costs are also assumed to be variable (i.e. relate to the amount of fishing effort) for the purposes of the model. Crew are currently paid a share of the revenue, while other material costs are proportional to the size of the catch in weight. Variable costs, therefore, are given by:

$$VC_{y,w} = \sum_k \sum_l \left[(c_L v_{k,y,w,l} + c_M \right] Y_{k,y,w,l} + (c_k + c_F) E_{y,w} \qquad (15)$$

where c_L is the share cost of labour, c_M is cost of packaging and gear maintenance (assumed to be proportional to the fishery catch in weight), c_K is the cost of repairs and maintenance per unit of effort, $c_{F,y}$ is the cost of fuel and oil per unit of effort during (future) year *y*, and $E_{y,w}$ is the total effort ($E_{y,w} = E^G_{y,w} + E^B_{y,w}$).

Fixed costs (Ω_y) include a measure of the opportunity cost of capital, depreciation, and other annual vessel costs (i.e. those not related to the level of fishing effort) such that:

$$\Omega_y = W_y + (o+d) K_y \qquad (16)$$

W_y is the annual vessel costs, o is the opportunity cost of capital (equal to the interest rate $o=i$), d is the economic depreciation rate, and K_y is the average value of capital (vessel plus gear) in year *y*.

The key choice variable in the model is fishing effort by fishing strategy, week and year. Effort for the first seven years of the projection period is selected to maximize Equation (13), with effort for the seventh and all future years set to that for the seventh year (Dichmont *et al*., 2008). A key reason for only estimating a subset of the possible time-series of effort levels is that effort converges to a constant value when the dynamics are deterministic and because the results of the model are only used to set effort levels for the two years following the year for which the most recent data are available. Further, the reliability of forecasts of economic parameters (input and output prices) decreases with length of forecast, so attempting to use the model to determine optimal effort levels over anything other than the relatively short term would be unrealistic. Maximization of Equation (13) is subject to the constraints that annual profit is non-zero, i.e. $\pi_y \geq 0$ (ensuring that the model does not "close" the fishery or reduce effort to a level that would result in short term losses in order to obtain longer term gains), and that effort for each fishing strategy cannot drop below half of that for 2007 (2777 days).

6.3.2 Apply Bayesian hierarchical biomass dynamic models to assess "data poor" stocks

Conventional biomass dynamics models express next year's biomass as this year's biomass plus surplus production less catch. These models are typically applied to species with several age-classes but it is unclear how well they perform for short-lived species with low survival and high recruitment variation. In this study we apply Bayesian hierarchical biomass dynamic models to assess the "data poor" stocks (e.g. blue endeavour) (Step 3b- Figure 1). This is a unique modification of the typical biomass dynamic models (which previously have not worked that well in the NPF) that are able to share information among stocks to provide priors at a "hyper parameter" level as well as simultaneously considering both process and observation error. This means that regions with poor contrast and information in the data can draw information from informative regions.

In order to check this method, it was first applied to the "data rich" species (i.e. the tiger prawn species). Once this check was complete the method was then applied to Blue Endeavour prawns which are defined here as "data poor" ("data poor" as the key biological parameters are unknown particularly biological data needed for parameterisation of size and/or delay difference models but not for Bayesian biomass dynamic models) (Appendices 8-10 provide detailed applications of this method to grooved tiger prawns, brown tiger prawns and blue endeavour prawns, respectively).

Two alternative versions of the standard biomass dynamics model (Standard) were constructed for short-lived species by ignoring the "old biomass" term (Annual), and assuming that the biomass at the start of the next year depends on density-dependent processes that are a function of that biomass (Stock-recruit). These models were fitted to catch and effort data for the tiger prawns stocks (brown and grooved) and the blue endeavour stock using a hierarchical Bayesian technique. The results from the biomass dynamics models were compared to those from more complicated weekly delay-difference models. A variety of formulations of the biomass dynamic models have been developed and examined (review in Quinn and Deriso 1999). An implicit assumption of most biomass dynamics models is that natural mortality is not very high so that a fairly large proportion of the biomass at the start of the next (annual) time-step consists of the biomass at the start of the current time-step. However, the suitability of these models and their assumptions have rarely been examined for short-lived species such as tropical prawns and squids that exhibit high annual recruitment variation and for which the catch comprises only a single age class.

As the catch-effort data are the main reliable information we have for prawns, biomass dynamics models seem to be the most appropriate tool for stock assessment. In this method, we assume prawns in each stock region is biologically independent of prawns in other stock regions, i.e., there is no spawner or larvae migration among the four stock regions. For stock region *s*, the deterministic version of the biomass dynamics model can be written as:

$$B_{s,y} = B_{s,y-1} + r_s B_{s,y-1}\left(1 - \frac{B_{s,y-1}}{K_s}\right) - \sum_{f=1}^{4} C_{s,f,y-1}\,, \qquad (1)$$

where *B* is biomass (in ton), *r* is the intrinsic growth rate, *K* is the carrying capacity, *C* is the catch. The subscript *y* is year, *s* is stock, and *f* is fleet.

The values for the parameters in equation 1 were estimated by fitting them to data on catch-per-unit-effort (CPUE). For a multi-stock, multi-fleet fishery the model-estimate corresponding to the catch-rate for stock *s*, fleet *f*, and year *y*, $\hat{U}_{s,f,y}$ is:

$$\hat{U}_{s,f,y} = q_{s,f} P_y B_{s,y}\,, \qquad (2)$$

where $q_{s,f}$ is the catchability coefficient for stock *s* and fleet *f*, and P_y is the relative fishing power during year *y*. The observed catch-rate was assumed to be log-normally distributed about its expected value in common with most applications of biomass dynamics models (Polacheck et al. 1993; Meyer and Millar 1999):

$$U_{s,f,y} \sim \text{log-normal}\{\ell\text{n}(\text{E}[\hat{U}_{s,f,y}], \tau_{U,s,f})\} \qquad (3)$$

where $\tau_{U,s,f}$ is the precision (the inverse of the variance) of the observation error for the catch-rate data for fleet *f*. $\tau_{U,s,f}$ is allowed to differ among fleets because it would not be expected that fleets that target a species and which take it as by-catch would lead to indices of abundance with the same extent of precision as would be the case for a target fleet.

We assumed that deviations about the expected biomass are log-normally distributed (Meyer and Millar 1999; Chaloupka and Balazs 2007), i.e.:

$$B_{s,y} \sim \text{log}-\text{normal}\{\ell n(E[B_{s,y}]), \tau_{B,s}\} \qquad (4)$$

where $\tau_{B,s}$ is the precision of the process error for stock *s*. The prior for the biomass at the start of the first year of the modelled period is assumed to be the same as for the carrying capacity for stock *s*.

It is necessary to specify prior distributions for all of the parameters of the model to implement each of the three state-space models within a hierarchical Bayesian framework. Under the assumption that the population growth parameter and catchability are unlikely to differ substantially among stocks, it was assumed that *r*, *K* and *q* for each stock and fleet were log-normally distributed about a common mean, i.e. these parameters for each stock are random effects about a common mean, i.e.

$$\begin{aligned} &r_s \sim \text{log-normal}(\mu_r, \tau_r) \\ &K_s \sim \text{log-normal}(\mu_K, \tau_K) \\ &q_{s,f} \sim \text{log-normal}(\mu_{q,f}, \tau_{q,f}) \end{aligned} \tag{5}$$

Where μ_r and $\mu_{q,f}$ are the prior means for *r* and fleet-specific catchability, τ_r and $\tau_{q,f}$ are the corresponding prior precisions, and *a* and *b* are the lower and upper limit of the uniform distribution. Collectively, these parameters are known as hyper-parameters (Harley and Myers 2001; Su *et al*. 2001). We assumed a normal distribution, N(M_θ, T_θ), for μ_θ, where θ is either *r* or *q*. Bayesian hierarchical models have the advantages that there is no need to specify the values for the parameters of the priors, but rather those of the hyper-parameters, and that the results of models are less sensitive to the values for parameters of the hyper-prior than those of the prior. We specified values for the means (M_θ) of these hyper-priors (McAllister *et al*. 2004; Askey *et al* 2007) by considering results from non-hierarchical Bayesian models and set the values for T_θ to large values so that the hyper-priors were relatively non-informative, but still proper (Gelman 2006). The values for the precision hyper-parameter T_θ were set using a half–Cauchy distribution (Gelman 2006).

The hyper-priors for the τ_θ, as well as the priors for the observation precisions, $\tau_{U,s,f}$, and the process precisions, $\tau_{B,s}$, were set to proper, but reasonably non-informative gamma distributions with mean 1 and variance 1000, i.e., $gamma(0.001, 0.001)$.

In summary, the hierarchical structure of the alternative biomass dynamic models contain the following levels:

Hyper-priors: M_θ assigned, T_θ half-Cauchy distribution;

Hyper-priors: $\mu_\theta \sim$ N(M_θ, T_θ), $\tau_\theta \sim$ G(0.001, 0.001);

Hyper-parameters: μ_K, μ_r, $\mu_{q,f}$, τ_K, τ_r, $\tau_{q,f}$;

Priors: log(K_s)~N(μ_K, τ_K), log($B_{s,y}$)~N(log(E[$B_{s,y}$], $\tau_{B,s}$), log(r_s)~N(μ_r, τ_r), log($q_{s,f}$)~N($\mu_{q,f}, \tau_{q,f}$), $\tau_{U,s,f}$~G(0.001, 0.001), $\tau_{B,s}$~G(0.001, 0.001);

Parameters: K_s, r_s, $q_{s,f}$, $B_{s,1970}$, $\tau_{U,s,f}$ $\tau_{B,s}$;

Data: $U_{s,f,y}$.

Given the assumptions regarding the nature of the state-space model, the priors for the parameters and those for hyper-priors, the posterior distribution is proportional to:

$$p(\mu_K)p(\tau_K)p(\mu_r)p(\tau_r)p(\underline{\mu}_{q,f})p(\underline{\tau}_{q,f})$$
$$p(\underline{K}_s \mid \mu_K,\tau_K)p(\underline{B}_{1970,s} \mid \mu_K,\tau_K)p(\underline{r}_s \mid \mu_r,\tau_r)p(\underline{q}_{s,f} \mid \underline{\mu}_{q,f},\underline{\tau}_{q,f})p(\underline{\tau}_{B,s})p(\underline{\tau}_{U,s,f}) \quad (6)$$
$$\prod_{s,y}\left(p(B_{s,y} \mid B_{s,y-1},K_s r_s,C_y,\tau_{B,s})\prod_f p(U_{s,f,y} \mid B_{s,y},q_{s,f},P_y,\tau_{U,s,f}) \right)$$

where the underlined parameters denote a vector or matrix over stock *s*, fleet *f*, and/or year *y*.

The Gibbs sampler, a Markov chain Monte Carlo (MCMC) technique, implemented using the WinBUGS package (http://www.mrc-bsu.cam.ac.uk/bugs) was used to sample parameter vectors from the posterior distribution (Eqn. 6). Three Markov chains were conducted based on dispersed initial values, and the results of the first 4,000 cycles of each chain taken as the burn-in period. The results of an additional 60,000 cycles from the three chains were saved, which formed the basis for further analysis. Whether the MCMC algorithm converged adequately to the posterior was evaluated by visually examining the three chains for each parameter in Eqn. 6 and using the Gelman-Rubin diagnostic statistic (Best et al. 1996). From these estimated parameters, we derive the management parameter, the maximum sustainable yield MSY for stock *s*:

$$MSY_s = \frac{r_s K_s}{4}. \quad (7)$$

6.3.3 Develop an integrated bio-economic model

A framework is described whereby effort levels and their associated catches consistent with maximizing the net present value of fishery profits over time can be calculated when each harvested prawn species is modelled using a different population dynamics model. The modelling framework (the integrated bio-economic model) includes the three prawn species (*Penaeus semisulcatus, P. esculentus*, and *Metapenaeus endeavouri*) in Australia's Northern Prawn Fishery and three population dynamics models (size-structured, delay-difference, and biomass dynamics) (Step 3c) (Appendix 11 provides a detailed manuscript of this study as a reference).

The delay-difference and size-structured population dynamics models are specified by Dichmont *et al*. (2003) and Punt *et al*. (2010) respectively and Appendix 7. The applications of the biomass dynamics model are based on the "standard" model of Zhou *et al*. (2010), i.e.:

$$B_{i,s,y+1} = [B_{i,s,y} + r_{i,s}(1 - B_{i,s,y} / K_{i,s}) - C_{i,s,y}]e^{\tau_{i,s,y} - \sigma_{i,s}^2/2} \qquad \tau_{i,s,y} \sim N(0;\sigma_{i,s}^2) \qquad (1)$$

where $B_{i,s,y}$ is biomass of stock *s* of species *i* at the start of year *y*, $r_{i,s}$ is the intrinsic rate of growth for stock *s* of species *i*, $K_{i,s}$ is the carrying capacity for stock *s* of species *i*, $C_{i,s,y}$ is the catch (in mass) of prawns of stock *s* of species *i* during year *y*, and $\sigma_{i,s}$ is the standard deviation of the process error for stock *s* of species *i*. The economic objective function is the maximisation of the net present value (NPV) of the flow of profits over time, from the first year (taken to be 2008 in this study) to the terminal year of the simulation (taken to be 2050), given by:

$$NPV = \sum_{y=1}^{T-1} \pi_y \Big/ (1+o)^{y-1} + \left[\pi_T / o\right] \Big/ (1+o)^{T-1} \tag{2}$$

where o is the discount rate (equivalent to the opportunity cost of capital and assumed to be 5% per annum in this study), π_y is the profit during year y, and π_T is the level of profit during the terminal year. Profits were assumed to continue at the level π_T indefinitely on the basis that the system is in equilibrium.

The level of profits in each year (including the terminal year) are given by:

$$\pi_y = \sum_i \tilde{R}_{i,y} - \sum_f (c_K + c_{F,y}) E_y^f - \Omega_y V_y \tag{3}$$

where $\tilde{R}_{i,y}$ is the net revenue obtained from catches of species i during year y (net revenue being revenue less costs which are proportional to the size of the catch), E_y^f is the effort expended by fishing strategy f (that targeted towards *P. semisulcatus* or *P. esculentus*) during year y, c_K is the cost of repairs and maintenance per unit of effort, $c_{F,y}$ is the cost of fuel and grease per unit of effort during (future) year y, V_y is the number of vessels (assumed to be 52 for the analyses of this study), Ω_y is the average fixed costs associated with a vessel operating during year y, and includes a measure of the opportunity cost of capital, such that:

$$\Omega_y = W_y + (o+d)\Psi_y \tag{4}$$

W_y is the annual vessel costs (i.e. those not related to the level of fishing effort), o is the opportunity cost of capital (equivalent to the discount rate as noted above), d is the economic depreciation rate, and Ψ_y is the average value of capital during year y.

The choice of the appropriate formula for net revenue for species i during year y, $\tilde{R}_{i,y}$, depends on the model of the population dynamics, i.e.:

$$\tilde{R}_{i,y} = \begin{cases} \sum_l \left[(1-c_L)v_{i,y,l} - c_M\right] \sum_w Y_{i,y,w,l}^{\mathrm{Siz}} & \text{Size-structured model} \\ \left[(1-c_L)\bar{v}_{i,y} - c_M\right] \sum_w Y_{i,y,w}^{\mathrm{Del}} & \text{Delay-difference model} \\ \left[(1-c_L)\bar{v}_{i,y} - c_M\right] \sum_s E[Y_{i,y,s}^{\mathrm{Bio}}] & \text{Biomass dynamics model} \end{cases} \tag{5}$$

where $v_{k,y,l}$ is the average price per kilogram for prawns of species i in size-class l during (future year) y, $\bar{v}_{k,y}$ is the average price per kilogram for prawns of species i during (future year) y, $Y_{i,y,w,l}^{\mathrm{Siz}}$ is the catch (kg) of prawns of species i in size-class l during week w of year y (based on the size-structured model), $Y_{i,y,w}^{\mathrm{Del}}$ is the catch of prawns of species i during week w of year y (based on the delay-difference model), $E[Y_{i,y,s}^{\mathrm{Bio}}]$ is the expected catch of prawns of species i in stock area s during year y (based on the biomass dynamics model), c_L is the share cost of labour (labour costs are assumed to be proportional to fishery revenue), and c_M is cost of packaging and gear maintenance (assumed to be proportional to the fishery catch in weight).

The expected catch of prawns of species *i* in stock area *s* during year *y* based on the biomass dynamics model is the average over draws from the Bayesian posterior distribution as well as future sequences of process error (i.e. $\tau_{i,s,y}$ in Equation 1).

The population dynamics in the delay-difference and size-structured models require estimates of fishing effort by week while the annual total effort used to update the population dynamics in the biomass dynamics model is the annual effort by stock area. For the analyses of this study, the effort by week (and fishing strategy) is computed by multiplying the annual effort by the proportion of effort by week (where, for consistency with previous analyses, the proportion of effort by week is set to the average proportion of effort by week over 2003-7), given by:

$$E_{w,y}^{wf} = \varepsilon_w^f E_y^f \qquad (6)$$

where $E_{w,y}^{wf}$ is the effort expended by fishing strategy *f* during week *w* of year *y*, and ε_w^f is the proportion of total effort expended by fishing strategy *f* during week *w* (such that $\sum_w \varepsilon_w^f = 1$). This proportion is assumed to be static over time (see Punt *et al.* (2010) for analyses that explore the sensitivity of the outcomes of the economics model to different assumptions regarding the proportion of effort by week). The proportion of effort that occurs in each stock area is assumed to be time-invariant and is selected to maximise Equation 2.

The key choice variable in Equation 2 is fishing effort by fishing strategy and year. Effort for the first seven years of the projection period is selected to maximize Equation 2, with effort for the seventh and all future years set to that of the seventh year (Dichmont *et al*., 2008). A key reason for only estimating a subset of the possible time-series of effort levels is that annual effort converges over time to a constant value when the dynamics are deterministic. Moreover, the results of the model would only be used to set harvest and effort levels for the two years following the year for which the most recent data are available. Maximization of Equation 2 is subject to the constraints that annual profit is non-zero, i.e. $\pi_y \geq 0$, that a boat cannot fish for more than seven days each week, and that effort cannot be less than half of that during 2007.

Further constraints have been imposed (when maximising Equation 2) in that effort (and hence catch) is zero if the average spawning biomass over the five years before the year for which an effort (or catch) is needed is less than 50% of S_{MSY} (the stock size corresponding to MSY). However, this constraint does not impact the results of this analysis given the current size of the modelled species.

In terms of parameter estimation, Dichmont *et al*. (2003), Punt *et al*. (2010) and Zhou *et al*. (2010) respectively describe the approaches used to estimate the values for the parameters of the delay-difference, size-structured and biomass dynamics models. The values for parameters of the economics model (c_K, $c_{F,y}$, c_L, c_M, d, K_y, $\bar{v}_{k,y}$, and $v_{k,y,l}$) are set to those in Table 5.2 of Punt *et al*. (2010) (Appendix 5 – this study).

Model outputs and scenarios

The results from the economics model are summarized by the expected catch for 2008, C_{2008}, the long-term catch under an MEY strategy, C_{MEY}, the number of fishing days for 2008, E_{2008}, the number of fishing days in 2014 and later under an MEY strategy, E_{MEY}, the ratio of S_{MEY} to S_{MSY} [3] for each species, and the relative profit. The first two of these quantities are reported by species, and the second two are reported for the fishing strategy which targets *P. semisulcatus* and for that which targets *P. esculentus*. The relative profit is the profit for the scenario under consideration relative to that of the reference case scenario (all species modelled using the size-structured model). The stock sizes in 2007 relative to S_{MSY} and S_{MEY} are also reported to indicate the extent of recovery needed to move each species to the target level. The results for the biomass dynamics model are averages over draws from the posterior distribution and over future sequences of process error. The biomasses by stock area from the biomass dynamics model are aggregated across the entire NPF for comparability with the results from the size-structured and delay-difference models. The scenarios (Table 1) examine various choices regarding which species are modelled using which estimation frameworks.[4] Although, Table 1 is not a fully-balanced design, it rather reflects the fact that the data for *M. endeavouri* are less informative than those for *P. semisulcatus* and *P. esculentus*, and hence that it is more likely that the biomass dynamics model will be applied to *M. endeavouri* than any of the other species.

Table 1. The model configurations by prawn species which define the scenarios considered in the analyses of this study. "Size", "Delay" and "Biomass" respectively refer to the size-structured, delay-difference and biomass dynamics models.

Case	***P. semisulcatus***	***P. esculentus***	***M. endeavouri***
Reference	Size	Size	Size
1	Delay	Delay	Delay
2	Biomass	Biomass	Biomass
3	Size	Size	Biomass
4	Delay	Delay	Biomass
5	Size	Biomass	Biomass
6	Delay	Biomass	Biomass
7	Biomass	Size	Biomass
8	Biomass	Delay	Biomass

[3] The calculations of MSY are based on the assumption of deterministic dynamics for all species (including those modelled using the biomass dynamics model).

[4] The software is written so that either the size-structured model or the delay-difference model can be applied, but not both simultaneously.

6.3.4 Provide an approach for setting output controls for the banana prawns stocks

The banana prawn catch in the NPF consists of two biological species, namely *Penaeus merguiensis* (common banana prawns) and *P. indicus* (red-legged banana prawns), which are undifferentiated in the catch. In order to set TACs for the two species, the recommendation is for the banana prawn component of the NPF fishery to be partitioned spatially into two regions (and a separate banana prawn TAC be set for each). The recommended dividing line includes an East-West North division extending north from Peace Point (129.3567^{o}E) along the same longitude. This partition creates an Eastern Banana prawn stock region and a Western Banana prawn stock region.

In this project the options for setting output controls and the impacts thereof for Eastern Banana prawn stock region was evaluated as part of a cost benefit analysis (CBA)[5]. A summary of the method is provided below (Step 3d – Figure 1).

For the Western banana prawn stock region in the absence of an assessment, the default would be to rely on an *ad hoc* empirical approach as developed in the CBA – the constant TAC (which relies on choosing a quantile of the observed catches). Alternatively in this project, two preliminary assessments of the Western banana prawn stock region have been developed (a quarterly difference model and a Bayesian Hierarchical biomass dynamic model). The method for both of these is also described below (also part of method Step 3d – Figure 1).

Eastern Banana Prawn region: Cost Benefit Analysis
Strictly when this study was undertaken (Appendix 12) no decision had been made on the boundary between the eastern and western banana stock regions however the method remains exactly the same and has been party repeated in the most recent NPF Assessment (2010). The key aspect of the cost-benefit analysis is its direct comparison with the *status quo*, that is, the input controlled system, with the same future potential catches. As all indices are computed relative to an input controlled system - it is the relative change, between revenues (in one system versus the other) and costs (in one system versus the other) that are estimated. The implications are such: the main performance indicator (profit) under a simulated output controlled system is compared to the potential benefits obtainable under an input controlled system and since this indicator represents the incremental gains relative to the current *status quo*, it is termed *incremental profit.*

[5] At the time of the analysis the boundary between the Eastern and Western banana stock regions had not been reviewed by the RAG (and NORMAC) thus previous analyses use an alternative boundary. The latest RAG assessment (2010) for banana prawns which relies on the research in this project uses the most recent boundary as reviewed by the RAG.

As all indices are computed relative to the input control case it is the relative change (thus deltas (Δs)), between revenues and costs that matter. As profit is normally revenue minus costs, the incremental profit (IP_y) in the analysis is given by:

$$\begin{aligned} IP_y &= \Delta Revenue_y - \Delta Cost_y \\ &= \left((\tilde{p}_y(1-c) - o)C_y^{\mathrm{mod}} - (p(1-c) - o)C_y^{obs} \right) - v(E_y^{\mathrm{mod}} - E_y^{obs}) \end{aligned} \quad (1)$$

where IP_y is the incremental profit in year y, C_y^{mod} and C_y^{obs} are the model estimated and observed (actual) catches respectively, E_y^{mod} and E_y^{obs} are the model estimated and observed effort levels (boat days fished) respectively, p is the average banana prawn price, $\tilde{p}_y$ is the assumed price received in year y, c is the crew share of revenue (c=0.23), o is other variable costs associated with the catch (e.g. freight, packaging, o=\$1060) and v is the average variable cost per boat day fished (v=\$4000) (data from 2008 tiger prawn assessment see NPFRAG (2008)).

In the base scenario, it is assumed that $\tilde{p}_y = p = 8000$ per tonne. That is, there is no price premium. In other scenarios, a price premium is assumed to exist in years when the TAC is binding and fishers have an incentive to improve their quality by fishing slower. That is,

$$\tilde{p}_y = \begin{cases} 8000 \quad where\ TAC_y \geq C_y^{obs} \\ (8500,\ \ 9000\ \ or\ \ 9500) \quad where\ TAC_y < C_y^{obs} \end{cases} \quad (2)$$

where TAC_y is the total allowable catch in year y. The TAC was set in a range of ways depending on the scenario examined. In the second scenario, TACs were set as a constant level over all years, but the constant TAC level was varied between the 10 per cent and 100 per cent quantiles of the observed catches.

In the third set of scenarios, the TAC is updated based on a pre-season recruitment survey estimate of the catch and the *cv* is the assumed *coefficient of variation* representing the accuracy of the recruitment survey. Recruitment survey indices for banana prawns were obtained from Milton *et al.* (2008). At present, a preliminary evaluation of an actual relationship between the recruitment index and catches indicate that a relationship does exist but the *cv* is likely to be in the region of 0.35 at the very best (and greater, that is 0.4 and above, thus we assumed a value of 0.4 for all the analyses).
The *cv* of the recruitment survey versus observed catch was also varied between 10 per cent and 100 per cent. A *cv* of 10 per cent implies that the relationship is assumed to be known very well, whereas a *cv* of 100 per cent assumes a very poor connection between the recruitment survey index and the subsequent catch.

As a preliminary harvest control rule an initial TAC (C_{min}) is set based a quantile of the historical catches and after this first step the pre-season recruitment survey is used to *increase* the TAC if the recruitment survey indicates the potential catch is greater than initial TAC (C_{min}).

$$TAC_y = \begin{cases} C_{\min} \quad where\ C_y^{obs} \leq C_{\min} \\ 1000 + 0.42 C_y^{survey}\ \ where\ C_y^{obs} > C_{\min} \end{cases} \quad (3)$$

In Equation 3 we use the observed catches because we do not have a long enough abundance series to generate C_y^{survey}. In reality, the HCR should be modified such that it relates to the survey index but this task is outside the scope of this project. Furthermore, the potential future catch (here drawn from the historically observed catch) may not be the same as the TAC since the TAC can be set higher than what is available. Therefore, the catch in each year in the model under an output control system is either the observed catch (when the TAC is set too high) or the TAC. This can be mathematically expressed as

$$C_y^{\text{mod}} = \begin{cases} C_y^{obs} & where\ TAC_y \geq C_y^{obs} \\ TAC_y & where\ TAC_y < C_y^{obs} \end{cases} \tag{4}$$

The model effort in each year was derived from the assumed catch, and given by

$$E_y^{\text{mod}} = \alpha_y \exp(\beta_y C_y^{\text{mod}}) \tag{5}$$

Where α_y and β_y are year specific coefficients derived from the observed cumulative catch and effort data each year.

Western Banana Prawn stock region – Quarterly biomass dynamic difference model on redlegged banana prawns

A discrete population model was constructed for red-legged banana prawns in the Joseph Bonaparte Gulf (Western banana prawn stock region) as follows. Appendix 13 provides a detailed manuscript of this study as a reference. The model time-step is quarterly (3 month quarters), with the number of prawns in year *y* and quarter *s* ($N_{y,s}$) given by:

$$N_{y,s+1} = N_{y,s}\, e^{-M_s} - C_{y,s} + R_{y,s+1} \qquad \text{for } s = 1 \text{ to } 3 \tag{1}$$

and

$$N_{y+1,1} = N_{y,4}\, e^{-M_4} - C_{y,4} + R_{y+1,1} \qquad \text{for } s = 4 \tag{2}$$

where

$N_{y,a}$ is the number of recruited prawns (those corresponding to a size large enough to be fished) at the start of quarter *s* in year *y* (which refers to a calendar year),

$R_{y,s}$ is the number of recruits (number of 6-month old prawns) which are added to the population at the end of each quarter *s* in year *y*,

M_s denotes the natural mortality rate during quarter *s* (assumed in the Reference case to be constant throughout the year), and computed by multiplying the weekly natural mortality estimate by 13 (weeks) to reflect a quarterly mortality rate; and

$C_{y,s}$ is the predicted number of prawns caught during quarter *s* in year *y*, with catches arbitrarily assumed taken as a pulse at the end of each quarter.

Given catches are recorded in units of mass, the predicted number of prawns caught during quarter s in year y is computed from the following relationship:

$$C_{y,s} = A_{y,s} F_{y,s} N_{y,s} e^{-M_s} \tag{3}$$

where

$A_{y,s}$ is the relative availability for quarter s and for year y, with an availability vector being applied to the early period 1970-1987 and a separate vector to the 1988-2006 (i.e. post end of year NPF closure) and 2007 (first season closure) periods; and

$F_{y,s}$ is the fished proportion in quarter s and year y of a fully selected age class.

The fished proportion reflects the catch by mass ($C^{mass}{}_{y,s}$) in quarter s and year y as a proportion of the exploitable ("available") component of biomass:

$$F_{y,s} = C^{mass}{}_{y,s} \big/ B^{ex}_{y,s} \tag{4}$$

with

$$B^{ex}_{y,s} = w_s N_{y,s} e^{-M_s} A_{y,s} \tag{5}$$

where

w_s is the average mass of prawns during quarter s.

One of the biggest challenges in constructing a realistic model of *P. indicus* relates to improved information on growth, and in particular quarterly changes in growth. Length frequency data that span a number of periods through the year are needed to better inform this aspect of model development. As a first step, this preliminary model used the female (because the male growth is too slow on its own) von Bertalanffy growth parameters and assumed that individual mass increases through the year. An average length and mass of prawns was thus calculated for each quarter, assuming a median birth date of October.

The number of recruits at the end of quarter s in year y is assumed to be related to the spawning stock size six months previously (i.e. during two quarters previously) by a modified Beverton-Holt stock-recruitment relationship (Beverton and Holt, 1957), allowing for annual fluctuation about the deterministic relationship for Quarters 1 and 2:

$$\begin{aligned} R_{y,s+1} &= \frac{\alpha B^{sp}_{y,s-1}}{\beta + \left(B^{sp}_{y,s-1}\right)^{\gamma}} e^{(\varsigma_{y,s} - (\sigma_R)^2/2)} && s = 1, 2 \\ R_{y,s+1} &= \frac{\alpha B^{sp}_{y,s-1}}{\beta + \left(B^{sp}_{y,s-1}\right)^{\gamma}} && s = 3, 4 \end{aligned} \tag{6}$$

where

α, β and γ are spawning biomass-recruitment relationship parameters (note that cases with γ > 1 lead to recruitment which reaches a maximum at a certain spawning biomass, and thereafter declines towards zero, and thus have the capability of mimicking a Ricker-type relationship – the Reference Case has γ=1),

$\varsigma_{y,s}$ reflects fluctuation about the expected recruitment for year *y* and quarter *s*, which is assumed to be normally distributed with standard deviation σ_R (which is input in the applications considered here); these residuals are treated as estimable parameters in the model fitting process, and a single set of residuals is estimated for Quarters 1 and 2 because almost all spawning is assumed to occur during this half of the year and is assumed driven by the same environmental influences each year;

$B^{sp}_{y,s}$ is the spawning biomass at the start of quarter *s* in year *y*, computed as:

$$B^{sp}_{y,s} = f_s \cdot w_s \cdot N_{y,s} \tag{7}$$

where

f_s is a relative index of the amount of spawning during quarter s.

In order to work with estimable parameters that are more meaningful biologically, the stock-recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, K^{sp}, and the "steepness", *h*, of the stock-recruitment relationship, which is the proportion of the virgin recruitment that is realized at a spawning biomass level of 20% of the virgin spawning biomass. Equation (6) can be rewritten in terms of the "steepness" *h*, defined as the fraction of pristine recruitment R_0 that results when spawning biomass drops to 20% of its pristine level, i.e.:

$$hR_0 = R\left(0.2B^{sp}_0\right) \tag{8}$$

which yields the following for the deterministic component of the formulation:

$$R\left(B^{sp}_{y,s}\right) = \frac{4h \cdot R_0 \cdot B^{sp}_{y,s}}{B^{sp}_o(1-h) + B^{sp}_{y,s}(5h-1)} \tag{9}$$

It follows that the total spawner stock size and recruitment for calendar year *y* are given respectively by:

$$B^{sp}_y = \sum_s B^{sp}_{y,s} \tag{10}$$

$$R_y = \sum_s R_{y,s} \tag{11}$$

The resource is assumed to be at the deterministic equilibrium (corresponding to an absence of harvesting) at the start of 1980, the initial year considered here. The model estimates the pre-exploitation quarter 1 spawning biomass, from which the starting number of prawns can be calculated using Equation (7), and it follows:

$$R_{0,1} = \left(1 - e^{-M_1}\right) \cdot B_{0,1}^{sp} / \left(f_1 \cdot w_1\right) \tag{12}$$

and similarly for the pristine numbers and recruitment levels in the remaining quarters, which can then be added together to provide total spawning biomass and recruitment values for the year. The model sets the starting spawning biomass in the first quarter $B_{0,1}^{sp} = K^{sp}$. Given the total pre-exploitation spawning biomass B_0^{sp}, it follows that:

$$B_0^{sp} = \frac{\sum_s f_s \cdot w_s \cdot R_{0,s}}{\left(1 - e^{-M_s}\right)} \tag{13}$$

which can be solved for R_0, and hence the stock recruit parameters. The model is fitted to all available CPUE data for each of the four quarters.

Western Banana Prawn stock region – Bayesian Hierarchical biomass dynamic model

The method applied to this region (and predominately the redlegged banana prawn stock – Appendix 14) is the same method as applied to the two tiger prawns species and blue endeavour prawns (see method as outlined above in section 6.3.2 - Apply Bayesian hierarchical biomass dynamic models to assess "data poor" stocks).

6.4 Preliminary evaluation of potential changes to fleet after introduction of output controls

A restricted profit function for the fishery was estimated (Step 4 – Figure 1) to determine the optimal vessel characteristics and output levels as a guide to how the fleet may adjust under an ITQ system. The key objective of the study was to estimate the average optimal vessel size and catch, taking into consideration expected changes in prices and stock conditions. Appendix 15 provides a detailed manuscript of this study as a reference. The move to ITQs in the fishery will provide incentives for fishers to adjust their activity levels in response to these conditions, and any estimation of future TACs will need to take into account the expected future cost structure of the industry as well as expected changes in input and output prices. An advantage of using a profit function to estimate the optimal size and activity levels is that it allows for variation in both inputs and outputs, with both assumed to be endogenous with respect to their relative prices.

Following Squires (1987) and Andersen *et al.* (2008), the most general form of the restricted profit function is given as *HR(p,z)*, where *HR* is the short-term restricted profit defined as total revenue less the variable costs, p is a vector of variable input and output prices, and z is a vector of quasi-fixed inputs. The function is restricted because it depends on the existing level of quasi-fixed inputs. Total profits can be given by $HT(p,p_z,z)=HR(p,z)-p_z{}'z$, where p_z is a vector of the (market) user prices of the quasi-fixed inputs. From Hotelling's lemma (Hotelling 1932), $\delta HR(p,z)/\delta p = Q(p,z)$ and $\delta HR(p,z)/\delta z = -p_z*$, where $Q(p,z)$ is the profit maximising level of outputs or inputs given the set of prices and the level of quasi-fixed factors, and p_z* is the shadow prices of the quasi-fixed factors. The optimal level of the quasi-fixed factors is determined by equating the shadow price to the service price, such that $\delta HR/\delta z=p_z$ (Squires 1987).

Given this, the optimal equilibrium level of inputs and outputs (i.e. after quasi-fixed factors have been optimised) is given by $\delta HR(p,z*(p,p_z))/\delta p$, where $z*(p,p_z)$ is the long run equilibrium level of the quasi-fixed factors given the set of prices. Although restricted profit functions have been estimated for a wide range of industries, relatively few attempts to estimate profit functions have been made in fisheries (Squires 1987, 1988; Asche *et al.* 2007; Andersen *et al.* 2008). This is most likely due to a lack of an appropriate time series of economic information in most fisheries.

A range of functional forms of the profit function are available, the most frequently used being the translog. This is a relatively flexible functional form, because it does not impose assumptions about constant price elasticities nor elasticities of substitution between inputs and outputs. The full description of the translog is presented in Appendix 15.

7. RESULTS/DISCUSSION

7.1 Targeting ability of fishing vessels: an econometric analysis

Pascoe *et al*. (Appendix 3) provide a detailed analysis of the ability for vessels to target stocks such that only one species is consistently landed. In their analysis the catch of each separate stock reflects multiple outputs in a production sense. Since tiger prawns are clearly targetable (from banana prawns), the analysis concentrates on the tiger prawn fishery. Testing whether there is a low or high degree of substitution amongst these multiple outputs provides an indication of the need for species-group TACs or separate species TACs, respectively.

The tiger prawn fishery catch composition varies over the season, with brown tiger prawns caught mostly at the start of the season, with grooved tiger prawns and blue endeavour prawns caught mostly at the end of the season. This is suggestive of some degree of targeting ability related to the relative seasonal abundance. Generally, stock abundance on the fishing grounds of brown tiger prawns peaks before that of the grooved tiger prawns.

A Bayesian estimation technique was used to estimate degrees of substitution of the outputs (aka. catch) of each species caught in the tiger prawn fishery (Pascoe *et al.*, Appendix 3). The results indicate that, although a small degree of substitution is possible between endeavour prawns and tiger prawns, it is slight. Further, historically there have been few economic incentives to actively target endeavour prawns. Discussions on this matter (at NPF RAG meetings) have suggested that endeavour prawns can be classified as an economic bycatch of tiger prawn effort – indeed this work supports that assumption in the present stock assessment.

The asymmetry in the elasticities of substitution between the two tiger prawn species suggests that catches of predominantly brown tigers can be taken with relatively low levels of bycatch of grooved tiger, but catches of predominantly grooved tigers will generally include brown tiger prawns. This is generally consistent with the catch compositions that appear to indicate some degree of targeting of brown tiger prawns early in the season. The Morishima elasticities of substitution (MES) for the two tiger prawn species were estimated for each week of the tiger prawn season over the last three years of the data (2005-2007) assuming average input levels (i.e. $\ln(\bar{x}) = 0$) (Figure 2).

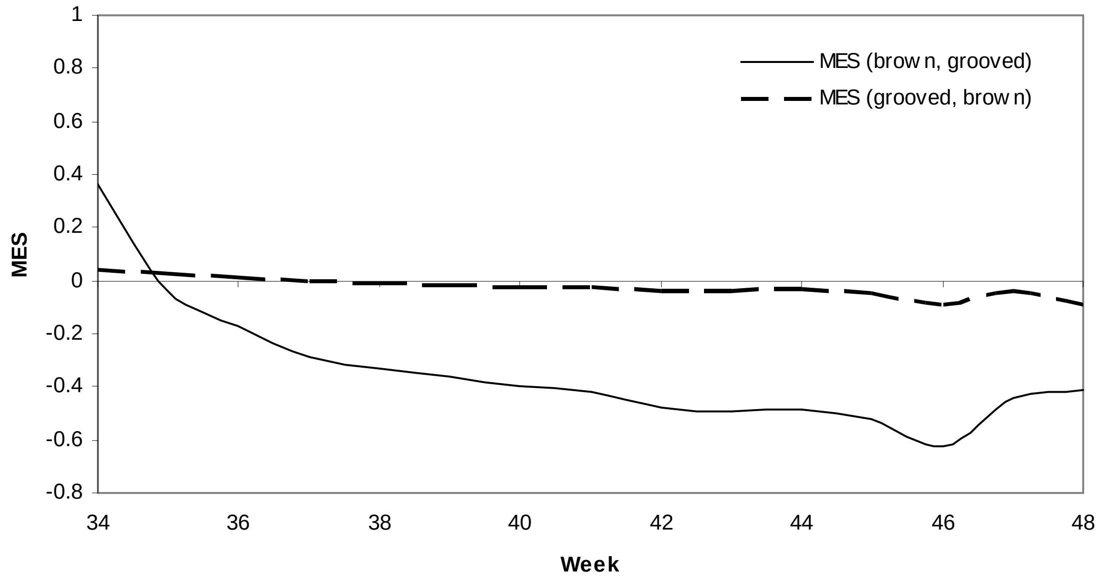


Figure 2. Average MES by week over the tiger prawn season, 2005-07 (Figure 3.3 in Appendix 3)

For most of the season, a substitution relationship appears to exist between brown and grooved tiger prawns, suggesting an ability to target brown tigers and avoid grooved tigers to some extent. This relationship, however, is still relatively weak, and a complimentary relationship may exist at the very start of the season. In contrast, there is little relationship between the partial exploitation rates for grooved tiger prawn and those for brown tigers. This suggests that the ability to target grooved tigers and exclude brown tigers is limited, with catches of grooved tigers sometimes including bycatch of brown tigers and other times not within the same period. These results are consistent with the results at the mean.

Thus as a summary, in terms of the two tiger prawn stocks, although there are times when predominantly brown tigers are landed with relatively lower levels of bycatch of grooved tiger prawns, catches of predominantly grooved tiger prawns will generally include brown tiger prawns. Stated simply, the two species of Tiger prawns and the economic bycatch species (e.g. Endeavour prawns) are not separable. The most practical means to manage the fishery as outputs is via a combined tiger prawn species-group TAC which would indirectly also control catches of endeavour prawns.

Based on these results, the project therefore developed assessment methods for tiger prawns as a group with endeavour prawns as an economic bycatch i.e. a single TAC for the tiger prawn fishery. However, before presenting the set of assessment techniques applied to tiger prawns as a group with endeavour prawns as an economic bycatch, we divert to the species split exercise in order to provide an outline of progress with this methodology.

7.2 Update species split of catch groups and determine split for the endeavour group

The endeavour species split model has been updated with the new endeavour prawn samples that were collected from the fleet (see Appendix 4). The statistical technology used to build the species distribution models (Venables *et al*., 2006) was further refined and both the tiger and endeavour species split models were calibrated with a consolidated data-set that includes the data collected in this project.

The refinement and calibration of these species split models have improved the accuracy of the catch estimates at the species level, particularly for endeavour prawns as the commercial endeavour catch data collected by Venables *et al*. (2006) had a limited coverage in both spatial and temporal scales. This was a significant contribution to the research within the project as estimates of catch and effort for the key species is an important element of any assessment.

7.3 Estimated fishing power trends

Updates to the Fishing Power model and series (Appendix 5) have been undertaken and the following was completed: (1) the extent and treatment of technology changes since 2002 have been reviewed and (2) the 2003 fishing power models presently used in the assessment have been re-fitted and therefore the coefficients re-estimated using all the latest available data (1970 to 2007), and (3) a new model based on the past models but emphasising the spatial changes in the fishery was developed.

Over the last decade as the fishing fleet has reduced in size, it has been noticed by several studies that the spatial extent of the fishery has changed. There has always been a concern that this aspect needed to be included in the fishing power models, thereby resulting in a preliminary spatial model being developed in 2003 which has always been used as a sensitivity test in the assessment.

A new model (to be referred to as the 2009 integrated model – Figure 3) has been developed that integrates the features of the 2003 basic and spatial models, but also adds new statistical methods that best captures spatial changes. The NPRAG agreed that the ‘2009 model’ is the best estimate of fishing power in the fishery, and agreed to use the 2009 model mid-high as a sensitivity scenario. These fishing power models have now been incorporated into the most recent NPF Assessment (2010).

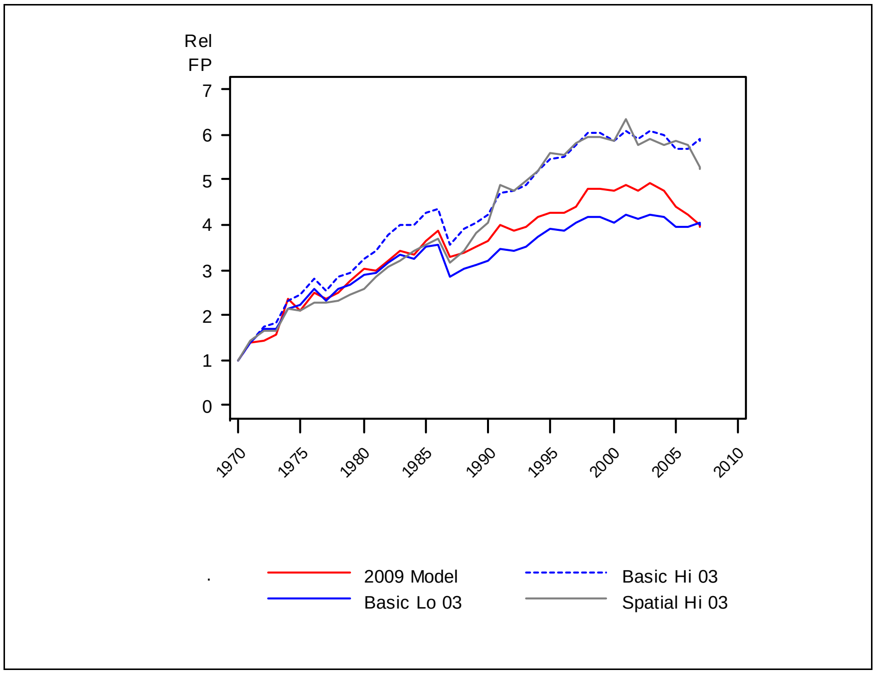


Figure 3. Cumulative relative fishing power from 2009 integrated model compared to three series from 2003

7.4 Banana Prawns: Species Split – Banana prawns into regions

As banana prawns are not included in this combined species-group TAC for tigers and endeavour prawns, a separate set of approaches for setting TACs is required for these stocks. However, rather than separate these species based on identifying the species at sea, the NPFRAG and NORMAC agreed that these two species should rather be geographically separated.

The banana prawn catch in the NPF consists of two biological species, namely *Penaeus merguiensis* (common banana prawns) and *P. indicus* (red-legged banana prawns), which are undifferentiated in the catch. In order to set TACs for the two species, the recommendation is for the banana prawn component of the NPF fishery to be partitioned spatially into two regions (and a separate banana prawn TAC be set for each). Two possible dividing lines are presented (Appendix 6), although here we only comment on the one tabled by the NPF RAG (November 16^{th}-17^{th} 2009 meeting) as a recommendation to go forward to NORMAC for a decision.

The recommended dividing line includes an East-West division extending north from Peace Point (129.3567^{o}E) along the same longitude (Figure 4). As it is a North-South line it creates a division of the banana stocks into a Western region and Eastern region, with at the very least a conservative 65% of the redlegged banana stock in the Western region and only 0.9% of the common banana prawn stock. The Eastern region has correspondingly the balance of the proportions (35% and 99.1%, of redlegged banana prawns and common banana prawns, respectively). Further deliberations by the RAG have the region now defined as a zone demarcated by the North/South line as noted, as well as a line of latitude (at 12°S); however NORMAC must confirm acceptance of this boundary.

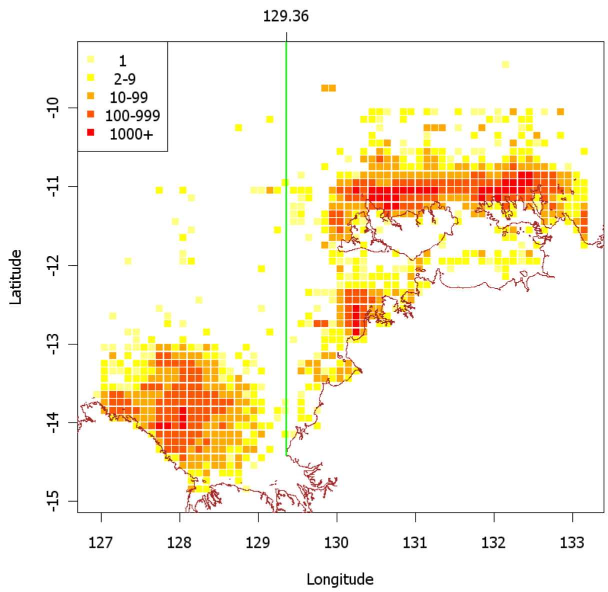


Figure 4. The division chosen to partition the banana prawns stocks into two stock regions (a Western and Eastern stock region). Data show total nominal effort for area presented for 6 minute grid squares for 1990-2008. Note, the RAG recommended the 12°S line of latitude also be part of the demarcation of the areas and NORMAC must confirm acceptance of this boundary.

7.5 Develop new assessment techniques: size structured model

A suite of assessment models could be applied given the range of biological and economic data available for these stocks and the associated fleets. Since each species of endeavour and tiger prawns have very different biology and risk of being overfished, it is essential that, where possible, species are assessed separately and then these are combined in the economic component of the assessment.

This is similar to the present assessment system (Dichmont *et al*. 2008). However, the present assessment has not included the size data that has recently become available and requires more biological information for endeavour prawns than is presently available. As a result, new methods have been developed: a size-based model for the data rich species and a hierarchical biomass dynamic model for the information poor species. Aging animals such as prawns is problematic.

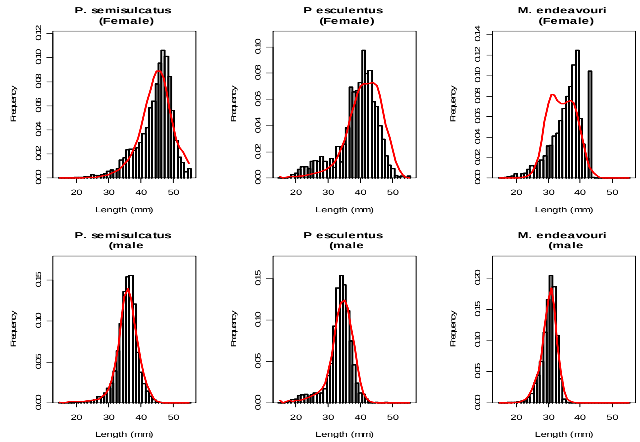
A major contribution of this project is the development of a size-structured assessment (Punt *et al.*, Appendix 7). The parameters of this multi-species population dynamics model, which include annual recruitment, fishery and survey selection patterns, parameters which define the size-transition matrix, and recruitment patterns, are estimated using data on catches, catch-rates, length-frequency data from surveys and the fishery, and tag release-recapture data (see Punt *et al.*, Appendix 7).

The advantages of the size-structured model include the greater inclusion of available data (specifically catch and survey length-frequency data as well as tagging data), and therefore less use of pre-specified parameters (for example selectivity is estimated, not knife-edge); whereas in the delay difference model this was originally not the case.

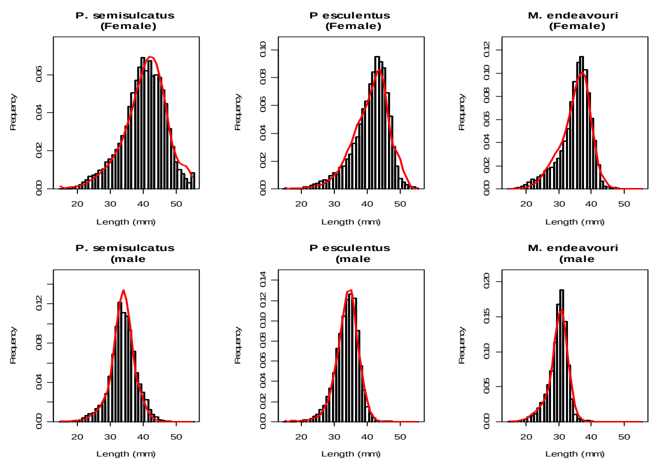
The size-structured population dynamics model also allows grade-specific prices to be considered unlike the delay-difference model which is forced to assume that price is independent of size. This has implications in terms of both optimal level of catch as well as optimal timing of catch. The model has greater flexibility in terms of fitting potential alternative effort regimes for different assumptions regarding season length. Importantly, since it still uses weekly time intervals, this model provides a useful tool for evaluation of the trade-off between TAC and season duration/timing (as recognised by the NPF RAG) (Figure 5) by estimating the optimal fishing pattern while estimating the profit into the future.

Model fits to the data are shown in Figure 6 (the observed length-frequencies and model-predictions from size-structured population dynamics model) and Figure 7 (observed survey indices and model-predictions from the size-structured population dynamics model for the “recruitment” and “spawning” surveys). The fits to the length-frequency data (aggregated over year; Figure 6) indicate that the model is capable of capturing the broad features of the catch and survey length-frequency data adequately. The model is also able to follow the survey indices fairly well (Figure 7), although the extent of additional variation (i.e. variation beyond that expected given sampling errors), is relatively high (an additional CV ranging from 0.11 to 0.40, with these CVs being largest for *M. endeavouri*).

(a) Catch length-frequency



(b) “Spawning” survey length-frequency



(c) “Recruitment” survey length-frequency

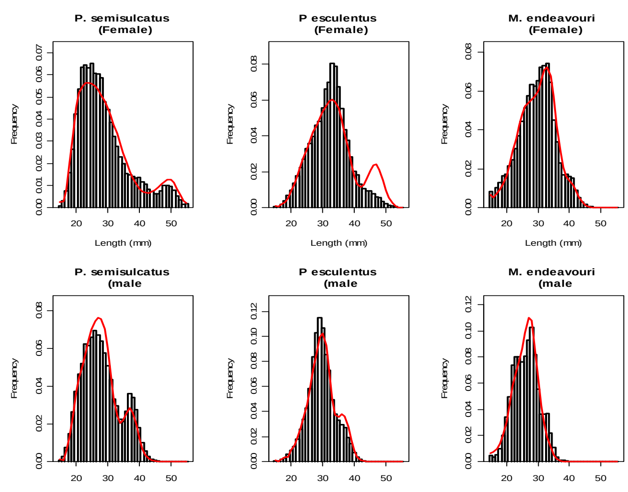


Figure 6. Observed length-frequencies (bars) and model-predictions from the base-case size-structured population dynamics model (line). The values shown are averages over the years for which data are available (with weights proportional to effective sample sizes).

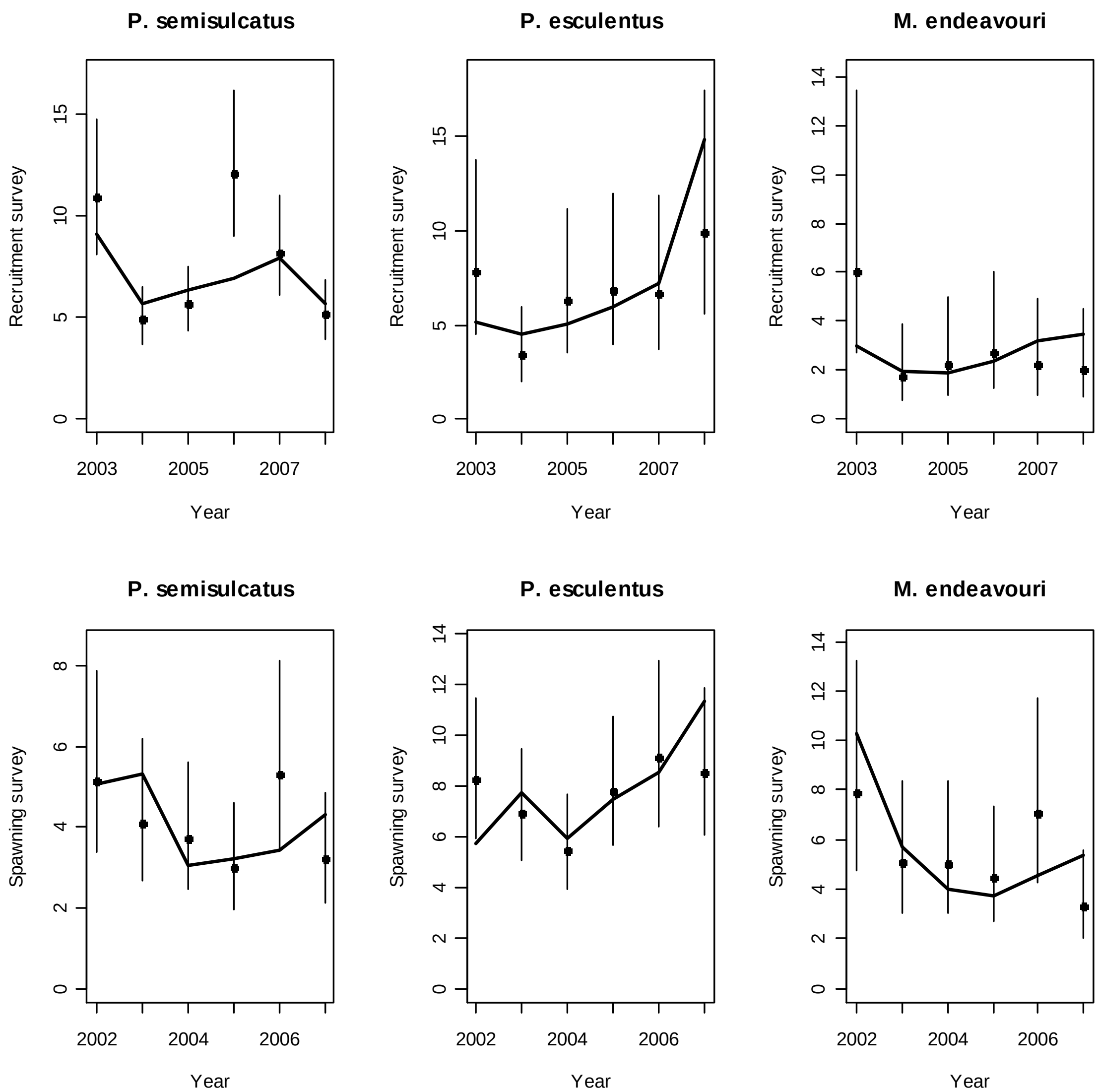


Figure 7. Observed survey indices (dots) and model-predictions from the base-case size-structured population dynamics model (lines) for the “recruitment” and “spawning” surveys (upper and lower panels respectively). The vertical lines are 95% confidence intervals based on the sampling error and the maximum likelihood estimate for the extent of additional variation.

The size-structured model is however, much more computationally demanding than the delay difference model. The key output from the stock assessment is the time-trajectory of spawning stock size (Figure 8). The qualitative trends in the estimates of these quantities for the historical period (1970-2007) are insensitive to the form of the population dynamics model and the inclusion (or otherwise) of the survey data. However, the absolute values for some of the model outputs are quite sensitive to these specifications. This is most evident for the first and last years of the assessment period for *P. esculentus*, with the delay-difference model suggesting a decline in abundance in the last year while the size-structured model suggests an increase. This difference is primarily due to different treatments of the recruitment indices (which are treated as indices of recruitment biomass in the delay-difference model, but as a measure of selected biomass in the size-structured model). Generally, the relative trends of the models (delay-difference versus size structured) are not that different, although absolute values for some of the model outputs are quite sensitive to the model specified, the assumptions and the economic estimates.

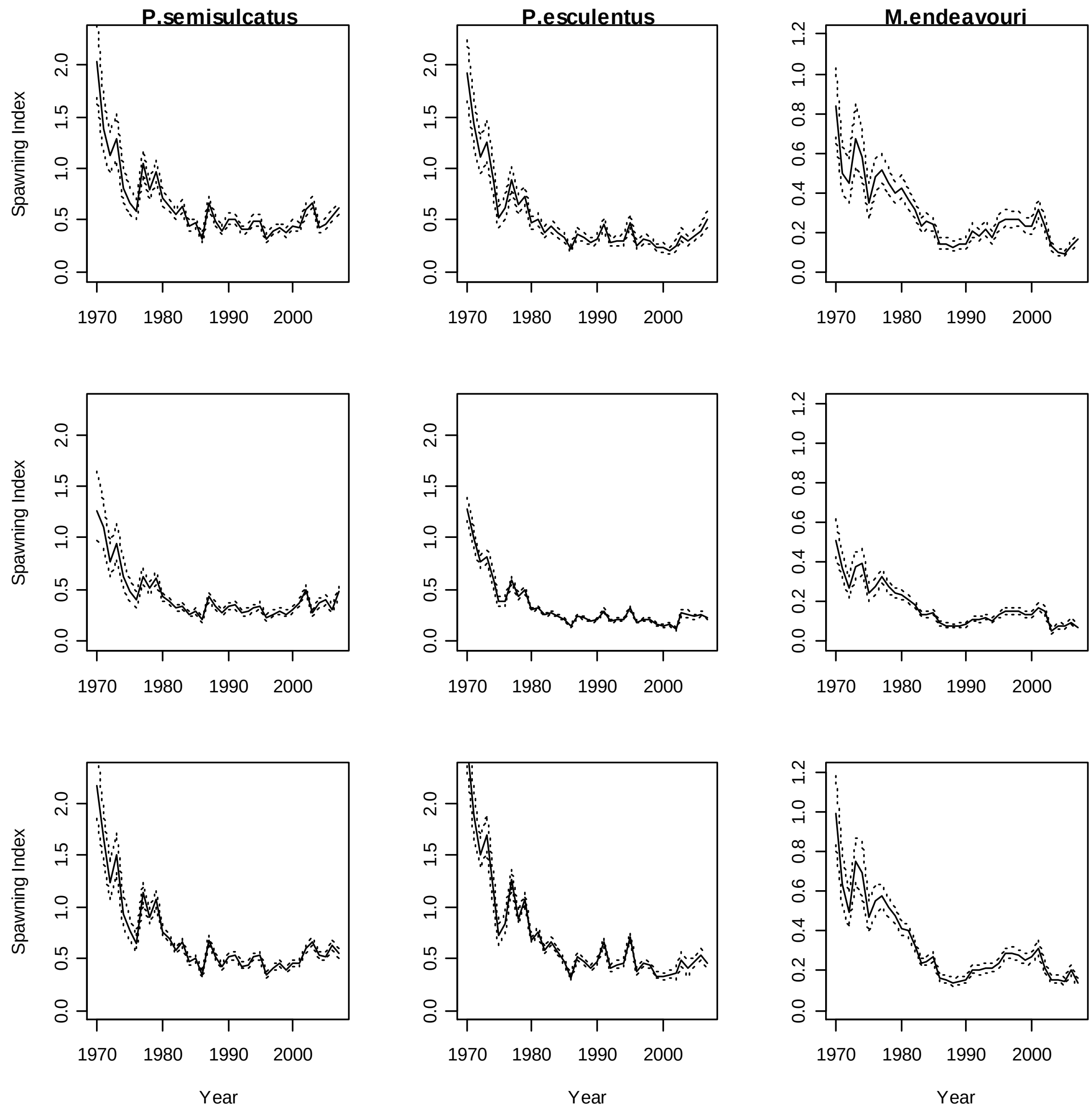


Figure 8. Time-trajectories of spawning stock size from the base-case size-structured population dynamics model (upper panels), a variant of this model in which the survey data are ignored (centre panels) and the delay-difference model (lower panels). The dotted lines indicate 90% confidence intervals.

Table 2. Summary of the outcomes of the integrated economics model. The values in parentheses for the reference case denote 90% confidence intervals. The annotated footnotes below provide a summary of each of the sensitivity tests and the assumptions made.

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Reference[1]								
P. semisulcatus	1039	1447	1.331	1.414	1.063	3587	5602	100
	(839-1253)	(1386-1536)	(1.309-1.356)	(1.339-1.499)	(1.008-1.118)	(2777-4217)	(5422-5896)	(93-108)
P. esculentus	852	1231	1.164	1.250	1.073	2777	4370	
	(783-927)	(1148-1303)	(1.134-1.203)	(1.166-1.362)	(1.002-1.161)	(2777-2777)	(4197-4542)	
M. endeavouri	325	646	1.218	0.796	0.653			
	(278-372)	(593-699)	(1.191-1.259)	(0.724-0.888)	(0.587-0.727)			
P1[2]								
P. semisulcatus	860	1500	1.293	1.428	1.104	2828	5812	92
P. esculentus	719	1284	1.090	0.712	0.653	2777	3592	
M. endeavouri	192	649	1.296	0.544	0.420			
P2[3]								
P. semisulcatus	824	1608	1.239	0.964	0.779	2777	5392	115
P. esculentus	695	1313	1.081	0.705	0.652	2777	3861	
M. endeavouri	311	691	1.190	0.555	0.467			
E1[4]								
P. semisulcatus	852	1439	1.340	1.414	1.056	2777	5526	127
P. esculentus	833	1222	1.181	1.250	1.058	2777	4264	
M. endeavouri	307	644	1.233	0.796	0.645			
E2[5]								
P. semisulcatus	1213	1456	1.321	1.414	1.071	4406	5688	82
P. esculentus	871	1240	1.147	1.250	1.090	2777	4482	
M. endeavouri	343	647	1.201	0.796	0.662			
E3[6]								
P. semisulcatus	1025	1478	1.297	1.414	1.091	3526	5938	122
P. esculentus	851	1247	1.131	1.250	1.104	2777	4562	
M. endeavouri	324	649	1.183	0.796	0.672			
E4a[7]								
P. semisulcatus	1298	1290	1.470	1.414	0.962	4729	4327	42
P. esculentus	1094	1131	1.305	1.250	0.957	3687	3562	
M. endeavouri	394	618	1.370	0.796	0.581			
E4b[8]								
P. semisulcatus	852	1491	1.280	1.414	1.105	2777	6097	113
P. esculentus	833	1253	1.118	1.250	1.118	2777	4640	
M. endeavouri	307	650	1.170	0.796	0.681			
E4c[9]								
P. semisulcatus	1263	1211	1.529	1.414	0.924	4574	3889	34
P. esculentus	1041	997	1.437	1.250	0.869	3471	2777	
M. endeavouri	381	578	1.500	0.796	0.531			

(Table 2 Continued)

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
E5[10]								
P. semisulcatus	1189	1396	1.486	1.414	0.952	4314	4858	101
P. esculentus	917	1200	1.167	1.250	1.071	2777	3994	
M. endeavouri	297	602	1.408	0.796	0.565			
E6[11]								
P. semisulcatus	1002	1363	1.390	1.528	1.099	3522	5394	96
P. esculentus	928	1210	1.130	1.280	1.132	2777	4078	
M. endeavouri	295	626	1.207	0.723	0.599			
E7[12]								
P. semisulcatus	1027	1447	1.330	1.414	1.063	3534	5579	98
P. esculentus	851	1246	1.133	1.250	1.103	2777	4583	
M. endeavouri	324	648	1.195	0.796	0.666			
E8[13]								
P. semisulcatus	1062	1447	1.332	1.414	1.063	3840	5601	100
P. esculentus	504	1231	1.164	1.250	1.073	1395	4371	
M. endeavouri	247	646	1.218	0.796	0.653			

[1]Based on the size-structured population dynamics model, uses all of the available data, uses grade-specific prices, assumes that effort is distributed across the season as in 2003-7, and assumes a fixed fleet of 52 vessels. Unless specified otherwise, the configuration of the population dynamics and economics models for each sensitivity test match those for the reference case.

[2]No survey data;

[3]Delay-difference population dynamics model (prices are independent of grade)

[4]Discount rate = 4%

[5]Discount rate = 6%

[6]Prices increase by twice the reference case forecast rate

[7]Prices decrease at the historic rate of increase (4% pa) until 2015

[8]Rate of change in fuel cost is twice that for the reference case

[9]Prices decrease at the historic rate of increase (4% pa) and the fuel cost crashes in 2009 and then recovers at 8% p.a.

[10]Weekly distribution of effort is estimated (1 July – 31 December for the *P. semisulcatus* fishing strategy; 1 April – 31 December for the *P. esculentus* fishing strategy). Effort is constrained not to exceed seven days per week per vessel.

[11]The weekly distribution of effort depends on the effort expended (linearly interpolated between three levels)

[12]Prices are independent of grade

[13]Free entry and exit of vessels (each vessel is allowed to fish for 135 days; the average number of days fished per vessel over the period 2003-2007)

A series of sensitivity tests were run and the results are presented in Table 2. Table 2 includes annotations that list the range of sensitivity tests.

The reference case analysis (see Table 2) suggests that two of the three species (*P. semisulcatus* and *P. esculentus*) were above the spawning stock size at which MSY is achieved, S_{MSY}, in 2007 and also above the spawning stock size corresponding to MEY, S_{MEY}. In contrast, the third species *M. endeavouri* was estimated to be below S_{MSY} and S_{MEY}, the latter by quite a considerable extent. This pattern is robust among the various sensitivity tests (note that S_{2007}/S_{MSY} is the same for all of the sensitivity tests which vary the assumptions of the economic model because S_{MSY} is only impacted by assumptions related to the biological characteristics of the stocks). However, ignoring the survey data or basing the assessment on the delay-difference model suggests that both *P. esculentus* and *M. endeavouri* are currently below S_{MSY}.

As expected, S_{MEY} is larger than S_{MSY}. However, the extent to which this is the case depends on species, the method of assessment, and the values for the parameters of bio-economic model. The average (across cases in Table 2) values for S_{MEY}/S_{MSY} are 1.33, 1.16, and 1.22 for *P. semisulcatus*, *P. esculentus*, and *M. endeavouri* respectively.

There are considerable differences among the sensitivity tests in all of the output quantities and the extent of among-sensitivity test variation exceeds that attributable to parameter uncertainty (Table 2). In other words, between model uncertainty was also high and it was important that the model combination selected was based on scientific principles rather than selecting based on the actual TAC. Some quantities are, however, much less sensitive to the assumptions of the bio-economic model than others. For example, the profit, relative to that for the reference case analysis, has a coefficient of variation of 30% among the sensitivity tests. In contrast, the coefficient of variation for the total catch over species at MEY (average across sensitivity tests of 3331t) is only 7.5%.

The among-sensitivity test variation in the total catch over species for 2008 is higher than the variation among sensitivity tests in the catch at MEY (14.6% vs. 7.5%). This result is perhaps not unexpected because, while both the catch for 2008 and the catch at MEY depend on the values for the biological parameters of the stock assessment, as well as the assumptions and parameter values for the bio-economic model, the catch for 2008 also depends on the estimate of recruitment for the forthcoming year. Here we refer the reader to the Appendix for further details, suffice to state that depending on the model used and the estimates of recruitment in the latter year, the models provide different estimates of the status of the stock.

In summary, the impact of the biological model (and the data used to estimate its parameters) consequently can have a substantial impact on the key outputs of the bio-economic model.

7.6 Development of Bayesian hierarchical biomass dynamic models

A suite of Bayesian hierarchical biomass dynamic models were also developed and tested for use in the NPF (Appendices 8-10). This is a unique modification of the typical biomass dynamic models (which previously have not worked that well in the NPF) that are able to share information among stocks to provide priors at a “hyper parameter” level as well as simultaneously considering both process and observation error. This means that regions with poor contrast and information in the data can draw information from informative regions. The can also potentially enable separate TACs to be produced for different regions of the fishery.

These models are not as data intensive as the delay-difference model above, largely because they use annual-time intervals, which means they are less computationally demanding. They are performing well for grooved tiger prawns (as a test of the method and an ability to compare between methods) but not as well for brown tiger prawns. These models have also been applied successfully to blue endeavour prawn (Figure 9a&b, Figure 10), and for all three species combined (the two tiger stocks and the endeavour prawns) providing an additional technique for comparative integrated model analyses.

For the grooved tiger prawns the same information presented for blue endeavours in Figure 9 and 10 is presented in Appendix 8 (Figure 8.2 and Figure 8.5). Similarly, for the brown tiger prawns the same information presented for blue endeavours in Figure 9 and 10 is presented in Appendix 9 (Figure 9.3, 9.4 and Figure 9.5).

The hierarchical Bayesian biomass dynamics model fits the CPUE data of the two tiger prawn fleets fairly well (Figure 9). However, the model performs better for some stocks and the pattern appears to differ between the two fleets (Figures 9a and 9b). The grooved tiger prawn fleet has a lower observation error for Stocks 1 and 2, while the brown tiger prawn fleet has a lower observation error for Stocks 3 and 4. These results are in line with commercial catch data in these regions.

Estimated biomass tends to be high in the early years and gradually reduces before 1990 (Figure 10). The status of Stock 4 is slightly better than other stocks. The result indicates that biomass was below the B_{msy} level of all stocks in 2007. The median carrying capacity K is similar among stocks, varying between 1642 and 1879 t. The median intrinsic growth rate *r* ranges from 0.38 to 0.78 for the four stocks. The estimated total MSY is slightly under 1000 tonnes.

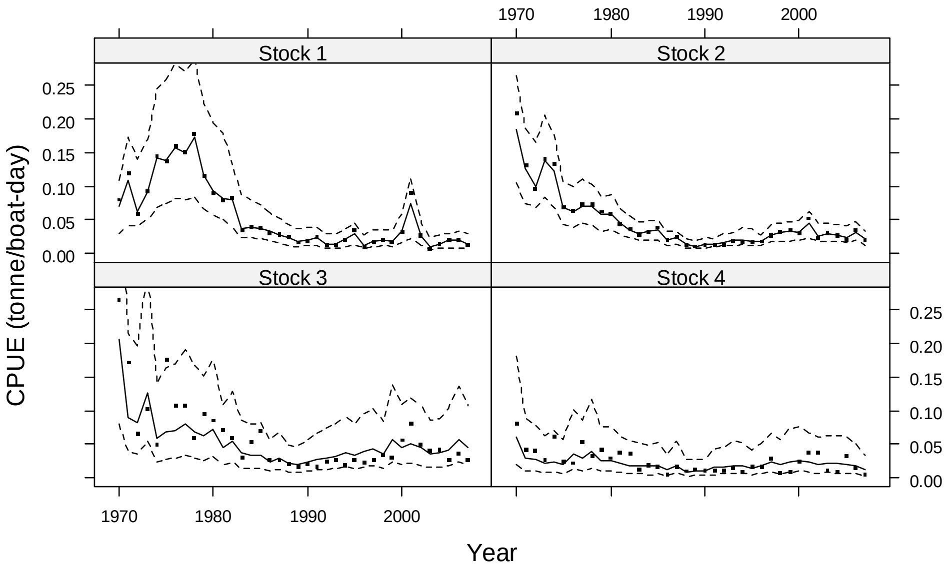


Figure 9a. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the semi fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

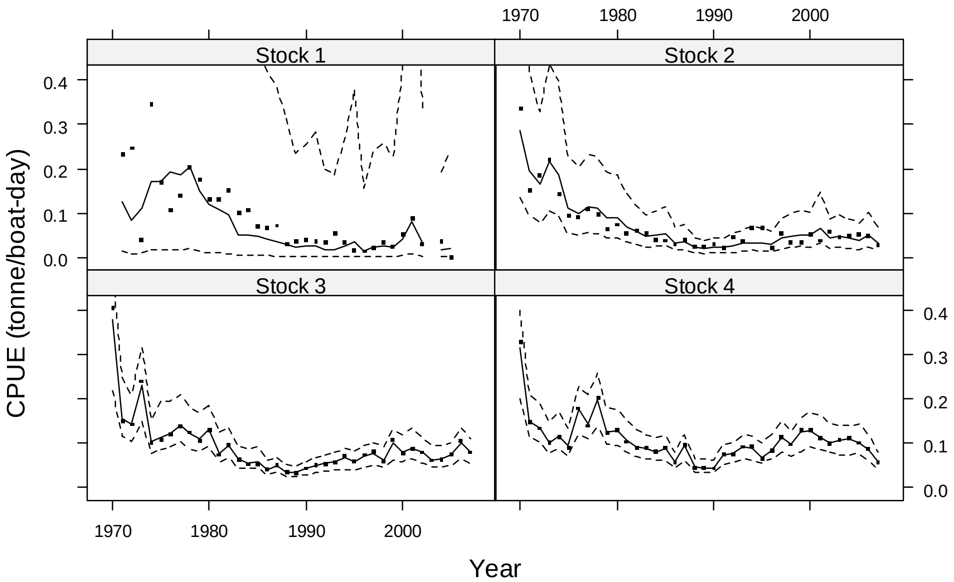


Figure 9b. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the escu fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

The fleet targeting *P. esculentus* has a higher catchability than the fleet targeting P. semisculentus (compare Figure 9a to Figure 9b). This is consistent with the observation that blue endeavour tends to associate with brown prawns in their distribution.

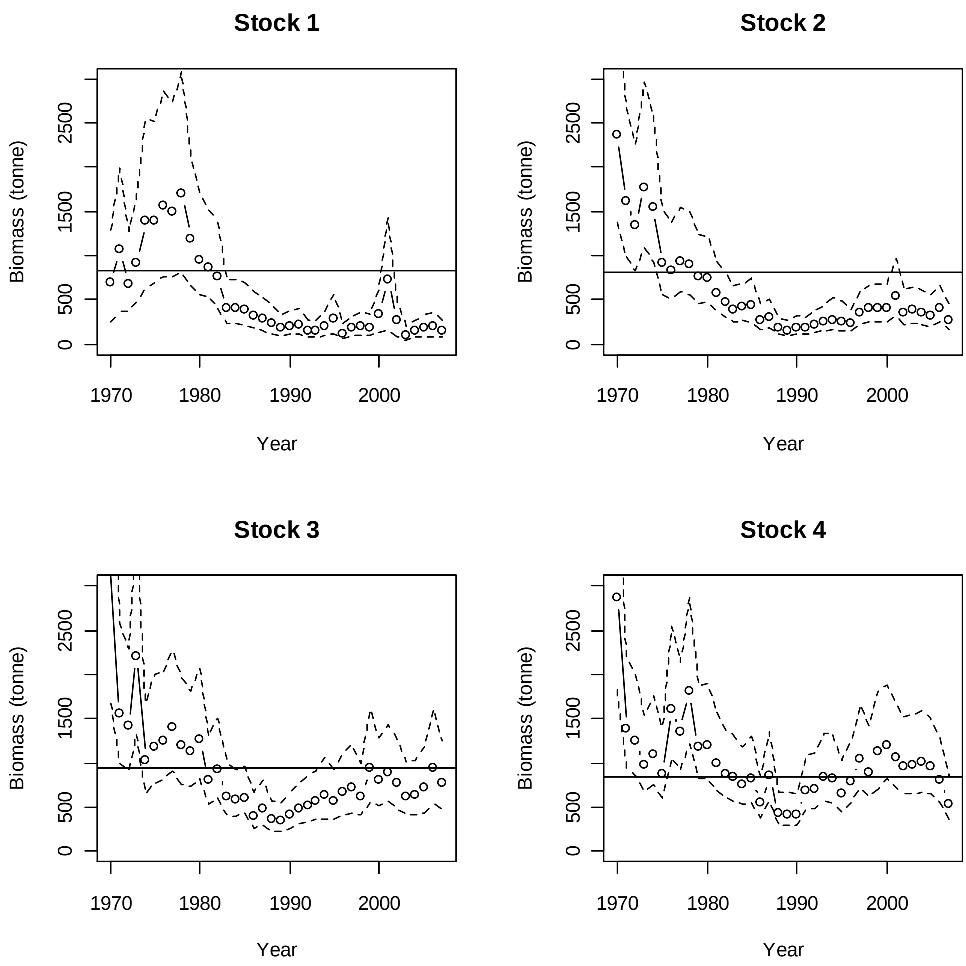


Figure 10. Posterior median biomass from 1970 to 2007. The horizontal line is the median B_{msy}.

7.7 An integrated bio-economic model

This fishery uses a dynamic bio-economic model to estimate TAE and, in the future, TACs. These models join the stock assessment models with the economic model. Given that it is clear that different species have different degree of data richness, a critical element of this project was to take what was learnt from the: (1) re-application of the established delay-difference model, (2) the newly developed size-structured model (this project) and the (3) recently development of the Bayesian hierarchical biomass dynamic models (this project) and integrate then into a single bio-economic model.

Therefore, the present bio-economic model was extended to include almost any combination of assessment model (the above mentioned: size-structured, delay-difference, and biomass dynamics models) (Punt *et al.*, Appendix 11).

This approach is both unique and pioneering and created the opportunity to explore the sensitivity of the different models and species combinations to a range of uncertainties (Table 1).

The results for the nine cases in Table 1 are summarized in Table 3. Even though the time-trajectories of spawning stock size in Figure 8 are qualitatively very similar, there are marked differences in results among the nine cases. For example, while all cases indicate that $S_{\mathrm{MEY}}/S_{\mathrm{MSY}} > 1$, the size of the spawning stock relative to S_{MSY} and S_{MEY} in 2007 is sensitive to how each species is modelled. For example, *P. semisulcatus* is estimated to be above S_{MSY} and S_{MEY} for cases 1, 3 and 5 (cases in which *P. semisulcatus* is modelled using the size-structured population dynamics model). In contrast, only the reference case, and cases 3 and 4, suggest that *P. esculentus* is above S_{MSY} and S_{MEY}.

There is considerable between-case variation in the 2008 and long-term catch corresponding to MEY (for example, between-case CVs of 12.0%, 16.2% and 4.9% for C_{2008} for *P. semisulcatus*, *P. esculentus*, and *M. endeavouri* respectively). However, the total catch aggregated over species is less variable (CVs of 10.1% for C_{2008} and 4.2% for C_{MEY}). The analysis in which the size-structured population dynamics model is used for all three species leads to highest catches (and effort levels) for 2008, but case 8 (delay-difference model for *P. esculentus* and biomass dynamics model for the other two species) leads to highest catch corresponding to MEY.

In summary, when model uncertainty is eliminated (i.e. only one type of model is used e.g. the size based model), the greatest variation in future catches (especially the first year of the prediction) seems to be due to uncertainty in the economic parameters. However, between model uncertainty was also high and it was important that the model combination selected was based on scientific principles rather than selecting based on the actual TAC.

The approach of this study provides a flexible framework that enables species which differ in terms of available data and which are consequently modelled using different population dynamics models to be used to estimate net present value and consequently the catch and effort levels which maximize net present value. The framework currently includes three population dynamics models (size-structured, delay-difference and biomass dynamics).

When reviewed by the NPRAG this framework was acknowledged as novel and a valuable contribution to the analysis of uncertainty for tiger and endeavour prawns. The NPF RAG also therefore selected the best combination of model, being the size structured model for both species of tiger prawns, and the Bayesian hierarchical model for blue endeavour prawns. This series of model choices formed the basis of the reference base case in the most recent NPF annual assessment (2010).

Table 3. Summary of the outcomes of the integrated economics model. Summary statistics include the expected catch for 2008, C_{2008}, the long-term catch under an MEY strategy, C_{MEY}, the number of fishing days for 2008, E_{2008}, the number of fishing days in 2014 and later under an MEY strategy, E_{MEY}, the ratio of S_{MEY} to S_{MSY} for each species, and the relative profit.

Case	C_{2008} (t)	C_{MEY} (t)	$S_{\mathrm{MEY}}/S_{\mathrm{MSY}}$	$S_{2007}/S_{\mathrm{MSY}}$	$S_{2007}/S_{\mathrm{MEY}}$	E_{2008} (days)	E_{MEY} (days)	Relative profit
Reference								
P. semisulcatus	1039	1447	1.331	1.414	1.063	3587	5602	100
P. esculentus	852	1231	1.164	1.250	1.073	2777	4370	
M. endeavouri	325	646	1.218	0.796	0.653			
Case 1								
P. semisulcatus	824	1608	1.239	0.964	0.779	2777	5392	115
P. esculentus	695	1313	1.081	0.705	0.652	2777	3861	
M. endeavouri	311	691	1.190	0.555	0.467			
Case 2								
P. semisulcatus	715	1668	1.169	1.032	0.883	2777	5875	115
P. esculentus	539	1268	1.025	0.746	0.728	2777	4157	
M. endeavouri	293	793	1.011	0.577	0.571			
Case 3								
P. semisulcatus	852	1450	1.265	1.348	1.065	2777	5623	106
P. esculentus	833	1235	1.071	1.158	1.081	2777	4420	
M. endeavouri	294	857	1.083	0.584	0.539			
Case 4								
P. semisulcatus	824	1616	1.234	0.969	0.786	2777	5462	121
P. esculentus	695	1330	1.077	0.728	0.677	2777	4100	
M. endeavouri	296	853	1.023	0.523	0.511			
Case5								
P. semisulcatus	900	1468	1.277	1.375	1.076	2980	5921	96
P. esculentus	606	1323	1.094	0.686	0.627	2777	3382	
M. endeavouri	320	819	1.112	0.515	0.463			
Case 6								
P. semisulcatus	824	1621	1.223	0.965	0.789	2777	5542	120
P. esculentus	596	1340	1.052	0.704	0.669	2777	3792	
M. endeavouri	311	830	1.027	0.493	0.480			

(Table 3 Continued)

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Case 7								
P. semisulcatus	740	1677	1.212	1.016	0.838	2777	5143	87
P. esculentus	833	1242	1.079	1.183	1.096	2777	4569	
M. endeavouri	287	717	1.101	0.655	0.595			
Case 8								
P. semisulcatus	739	1757	1.148	1.026	0.894	2777	5972	122
P. esculentus	695	1332	1.065	0.719	0.676	2777	4058	
M. endeavouri	284	710	1.027	0.608	0.592			

7.8 Banana Prawns – Eastern Region

At this stage, the project (verified by the NPF RAG) considers that it does not have any quantitative assessment method that can be adequately applied to common banana prawns. The extreme spatial and temporal variation in catch rate data (and therefore one's ability to predict the size of recruitment in advance) is one of the major underlying factors. It is unlikely that this situation will change in the near future.

As such, the NPF RAG will not be able to use quantitative assessment methods to determine a TAC for these species. As an alternative, empirical methods based on historical catch and effort data could be used to set TACs for common banana prawns and other species (if necessary). An example of such a method was presented to NORMAC (68 and 69) as part of the NPF ITQ Cost Benefit Analysis (CBA) of ITQ options. A relevant section of the report is presented here with permission from the authors (Appendix 12). This analysis was funded jointly by the CBA and TAC projects as the core elements of the analysis were required for both.

Three scenarios were evaluated: (1) Constant TAC, (2) Updated TAC (no price premium), and (3) Updated TAC – price premium. The objective of the analysis was to evaluate the magnitude of the *incremental profit*. The output statistic (incremental profit) was supplemented with additional metrics presented in Table 4. These are the percentage (%) of the times the incremental profit is greater then the profit in an input system (*status quo*), the % times the incremental profit is the same as the *status quo*; and the % times the incremental profit is less than the *status quo*. Note a negative incremental profit does not imply that total absolute profit will be negative.

For the Constant TAC scenario the number of times the incremental profit is greater than the *status quo* (as a percentage) is in the region of 50-56 per cent depending on the quantile value (Table 4). This is high and results in a positive average incremental profit relative to the input system (in the region of \$0.39 - \$0.83 million). However, with every benefit there comes a trade-off since the proportion of times the incremental profit is less than the input controlled system is in the range of 11-22 per cent (Table 4). These values reflect the times the stock is productive in a particular year (potential catch greater than 5000 tonnes); however if the TAC is set low relative to the availability of the stock, lower benefits (in terms of potential revenue) are obtained.

Table 4. Additional metrics for the performance indicator (incremental profit) versus the three scenarios assuming the recruitment survey index versus observed catch relationship's *cv*=0.4 for a range of restrictive TAC settings (quantile of observed catches = 0.2, 0.3 and 0.4).

	Constant TAC			**Updated TAC - no price premium**			**Updated TAC - price premium ($1 per kg)**		
Quantile	**0.2**	**0.3**	**0.4**	**0.2**	**0.3**	**0.4**	**0.2**	**0.3**	**0.4**
% times > *status quo* (input controls)	56	50	50	47	42	41	53	47	43
% times < *status quo* (input controls)	22	17	11	9	7	5	3	3	3
% times same as *status quo* (input controls)	22	33	39	44	51	53	44	51	54
Average incremental profit ($millions)	0.83	0.54	0.39	0.83	0.60	0.50	2.05	1.78	1.61

The Updated TAC-no price premium scenario allows the management system by using the pre-season recruitment survey to reduce the proportion of times the incremental profit is less than the profit in the current input system (the *status quo*) - to be in the range of 5-9 per cent (Table 4) compared to the 11-22 per cent for the same metric in the case of the Constant TAC scenario. The possibility of obtaining a price premium ($1/kg) decreases the proportion of times the incremental profit is less than the profit in the input control system further to 3 per cent (across the range of quantile values considered) (Table 4). The average incremental profits in this case (Updated TAC-price premium) are even greater compared to the Constant TAC than the scenario with no price premiums.

The highest value for average incremental profit ($2.05 million (Table 4) for the fleet as a whole, or around $40k a boat) occurs when there is a price premium and the TAC is very conservative (thus restrictive) i.e. a TAC of 1680 tonnes, based on a quantile value of the observed catch of 0.2 (Table 4). Without a price premium, average additional profits are relatively small - between $8k and $15k a vessel depending on the harvest control rule (HCR).

On the basis of these results NORMAC recommended that the Updated TAC method should be applied to Eastern banana prawn stock region – a method that sets a constant TAC with a potential of an increase in the TAC if the recruitment survey is medium or large. Future research will focus on the characteristics of the harvest control rule under an Updated TAC control rule.

7.9 Banana Prawns - Western Region (red-legged banana prawns)

Plagányi *et al (Appendix 13).* provide a summary of a preliminary assessment model developed for red-legged banana prawns (*Penaeus indicus*). Quarterly time steps are used to represent the dynamics and the model is fitted to available catch and effort data. These data are standardised using a fishing power series derived specifically for red-legged banana prawns. Key sensitivities are highlighted and some preliminary model results are presented. Although a preliminary assessment of resource status and reference level estimates are provided, the primary purpose of the analysis was to seek comments from the Northern Prawn Fishery RAG (November 16th-17th 2009 meeting) as to the proposed methodology. The preliminary model fits are shown in Figure 11 (model-predicted CPUE versus nominal per quarter) and Figure 12 (average annual nominal CPUE data and overall model-predicted commercially available biomass).

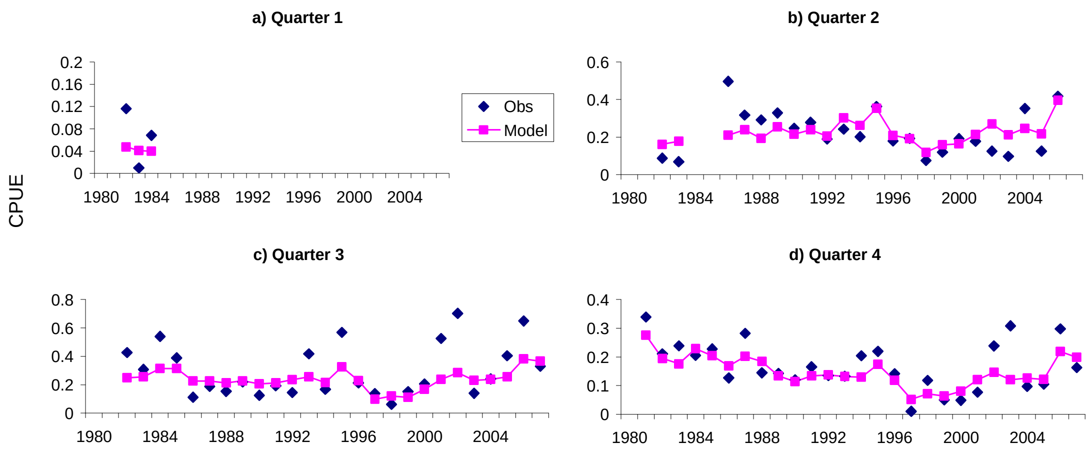


Figure 11. Comparisons between the nominal CPUE data for each quarter (quarter) and model-predicted CPUE values using the base-case model version.

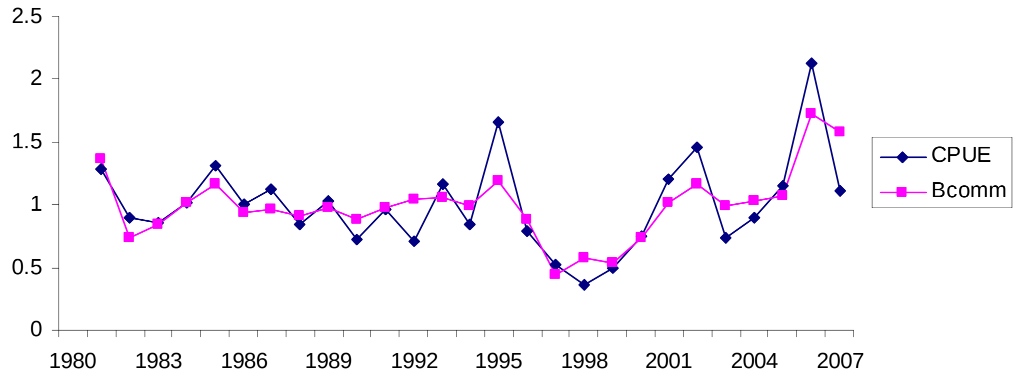


Figure 12. Comparisons between the average annual nominal CPUE data and overall model-predicted commercially available *P. indicus* biomass.

The model fits to each of the quarters separately, but as an additional diagnostic the quarterly predictions were added together for the purposes of comparison with the annual averaged CPUE values (Figure. 12). The model fit is reasonable, particularly over the most recent period. Key sensitivities are highlighted (Appendix 13) and some preliminary model results presented. A preliminary assessment of resource status and reference level estimates is provided.

Appendix 14 is an application of Bayesian hierarchical biomass dynamic model to the redlegged prawn stock in the Western region. Both of these Appendices (13 and 14) represent preliminary models of this region and will be further subject to review by the NPF RAG. For interest the estimates of B/Bmsy for redlegged banana prawns are presented in Figure 13. As noted these results are preliminary.

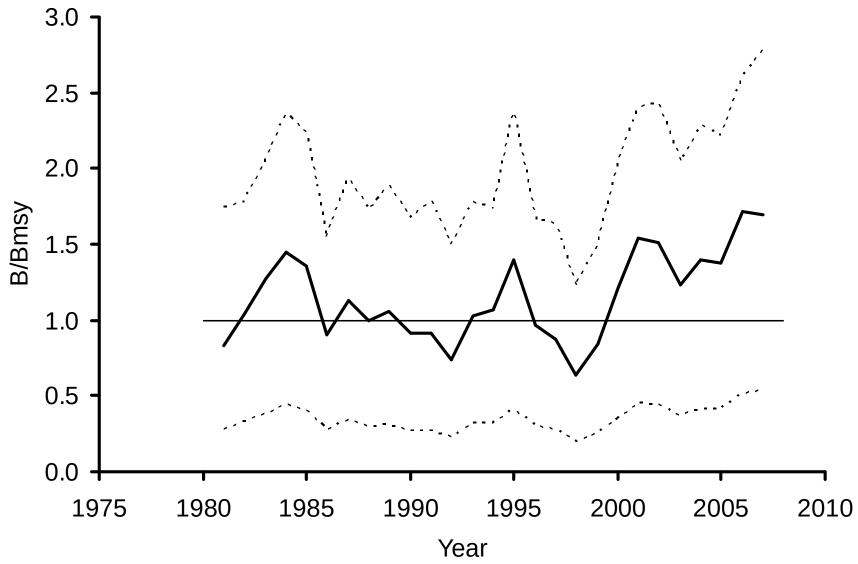


Figure 13. Posterior median time trajectory for the red legged banana prawns' ratio of B/B_{msy} in JBG. The dotted lines are the 2.5% and 97.5% credible intervals.

7.10 Fleet Impacts: optimal vessel size

As highlighted, changes to the NPF fishing fleet is anticipated with the introduction of output control and the final section analyses the potential optimal vessel size under various TAC conditions. A restricted profit function for the fishery was estimated to determine the optimal vessel characteristics and output levels as a guide to how the fleet may adjust under an ITQ system (Appendix 15).

Vessels were found to be currently close to their optimal size given average historic prices and current stock conditions (Figure 14). However, higher tiger prawn stocks are expected to result in the average size of vessels increasing, with rising fuel prices also likely to result in capital being substituted for fishing days.

The optimal vessel engine power was estimated under a set of price conditions (Figure 14a), and this used to estimate the optimal catch of each species. The resultant estimates of optimal vessel size and output levels, and the impact of prices on these estimates, are illustrated in Figure 14. Given the price assumptions in the bioeconomic model and the associated stock size at MEY, vessels are likely to increase their engine power (and presumably their overall size) by around 20 per cent in the long run.

Fuel use is expected to decrease by around 20 per cent relative to the average over the period of the data for a wide range of prices (Figure 14b), suggesting that larger engines are partially being substituted for days fished. This particularly large decrease is mostly driven by the relatively high fuel prices. However, lower levels of fuel consumption were optimal for all price scenarios (both inputs and outputs), suggesting that cost savings through effort reduction would more than offset reduced revenue arising from the subsequently lower catches.

The optimal individual catches per vessel of the two species groups are also lower given the price assumptions.[6] There is a general apparent “shift” from banana prawns to the more valuable tiger prawns as prawn prices decrease, and fuel prices increase. The optimal catch of banana and tigers prawns is around 80 and 85 per cent respectively of their average over the period 1994-95 to 1995-96, *ceteris paribus* at the assumed long run relative fuel and prawn prices in the bio-economic model (Figures 14c and 14d).

[6] As noted by a reviewer, the introduction of ITQs will result in a price for quota that has not been considered in the analysis. This may also affect optimal input usage as input demand is related to optimal output supply. However, as the optimal output is less that their current harvest level, and quotas are likely to exceed the optimal output, then quotas are likely to be non-binding and the shadow price effectively zero.

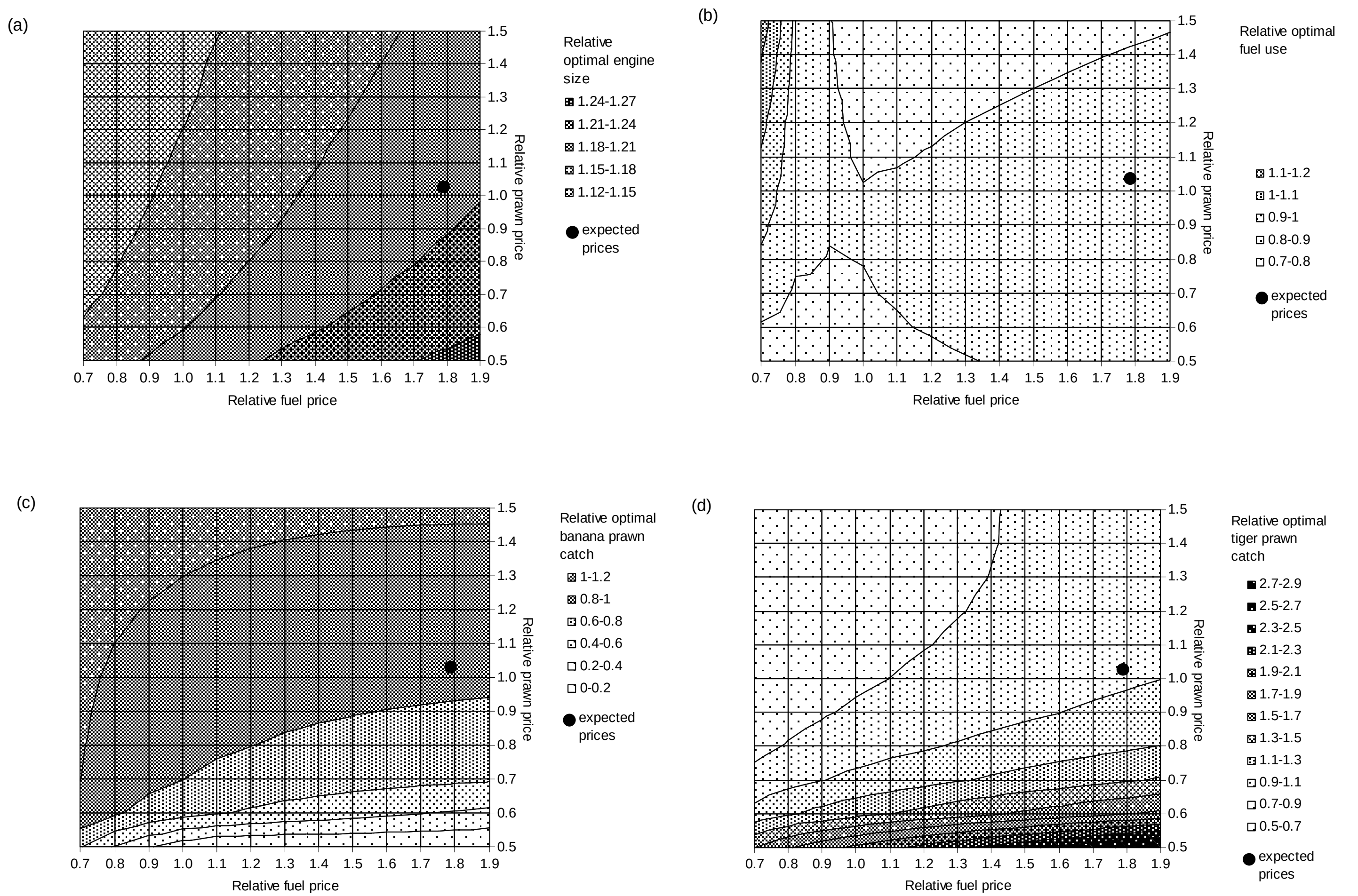


Figure 14. Optimal input use and catches: a) engine power, b) fuel use, c) banana prawn catch, and d) tiger group catch

8. BENEFITS AND ADOPTION

Industry and AFMA (with support from the NPFRAG and NORMAC) have been the main beneficiaries and have also adopted most of the methods developed within this project.

In terms of dirtect contact with these beneficiaries, the results of this project have been reported to the NPFRAG on several occasions, and to the NORMAC and AFMA committees. For one of the most recent of these (as an example), the project was the main agenda item and filled two of the days at the NPFRAG meeting on the 16th-17th November 2009, including:

- Optimal vessel size and output (Dr Sean Pascoe)
- Size Model (tiger prawns) and Mixed/Integrated model (Dr Cathy Dichmont)
- Fishing power in the NPF (Dr Janet Bishop)
- Species distribution of Banana prawns (Dr Bill Venables)
- Red-legged banana prawns (Dr Eva Plaganyi)

The methods in this project are now applied in the NPF Assessment (reflecting adoption by the beneficiaries) and the most recent NPF Assessment was presented at the May 2010 RAG meeting in Brisbane.

The RAG has extensively reviewed **all** the methods developed by the project so far and have had detailed input to the project. This is much appreciated. In terms of progress against communication and extension plan, several of the methods have also been submitted (with approval from FRDC) to journals:

- Pascoe, S, Punt, A., Dichmont, C.M., accepted. Targeting Ability in Australia's Multispecies Northern Prawn Fishery: a Bayesian multi-output distance function approach. European Review of Agricultural Economics.
- Pascoe, S, Vieira, S., Dichmont, C.M., Punt, A.E., re-submitted. Optimal vessel size and output in the Australian northern prawn fishery: a restricted profit function approach. Australian Journal of Agricultural and Resource Economics.
- Zhou, S., Punt, A.E., Deng, A., Dichmont, C.M., Ye, Y., Venables, W.N. 2009. Modified Bayesian biomass dynamics model for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Marine and Freshwater Research. 60.
- André E. Punt, Roy A. Deng, Catherine M. Dichmont, Tom Kompas, William N. Venables, Shijie Zhou, Sean Pascoe, Trevor Hutton, Rob Kenyon, Tonya van der Velde, and Marco Kienzle., 2010. Integrating size-structured assessment and bio-economic management advice in Australia's Northern Prawn Fishery. ICES Journal of Marine Science.

9. FUTURE DEVELOPMENT

Future research involves the in-depth evaluation of Harvest Strategies (HS) under output controls taking into account extensive outputs from this project (the full range of methods developed: the size structured models, the Bayesian Hierarchical biomass dynamic models and the integrated bio-economic model that incorporates the latter mentioned methods).

It is important to note that this project is developing methods for setting TACs that will feed directly into the development and evaluation of Harvest Strategies (HS) under output controls. This latter component is a separate project ("Developing and testing harvest strategies for the NPF under input and ITQ controls AFMA project 2006/828"). Harvest strategies consist of three essential parts: *monitoring*, *assessment*, and *harvest control rules* and this project provides a detailed analysis of the *assessment* component.

The Eastern Banana Prawn TAC setting trial in 2010 did not accurately set a TAC appropriate to the scale of the actual catch under inputs, and the method needs to be reviewed urgently.

10. PLANNED OUTCOMES

This project first assessed how many TACs are necessary to effectively manage the fishery. Then, given these results, the project developed new methods to assess the relevant species (or groups) and methods relating to standardising catch rates (based on a fishing power analyses), as well as considering optimal vessels size under various TAC conditions. A planned outcome was to effectively integrate these new methods (which are outputs) within the assessment process after feedback from the RAG. Therefore the project met the planned outcome that it directly addresses the requirement for the NPF to move to a TAC management system, which is NORMAC's response to the Ministerial Direction.

Significant progress has been made in this project with the development of techniques for the estimation of total allowable catches (TACs) for the major prawn species in the Northern Prawn Fishery (NPF). An additional planned outcome was to present during the project progress at each stage to the NPF Resource Assessment Group (RAG) and obtain feedback on the research outputs. This planned outcome was achieved.

Two methods to mention are the development of the size structured model for the tiger prawn stocks and the Bayesian biomass dynamic models (for "data poor" stocks such as the blue endeavour prawns). The NPF Assessment adopted both these methods in 2010. Thus as a planned outcome, both the size structured model and the Bayesian biomass dynamic models have been integrated into the bio-economic assessment that sets MEY as a target (the basis of the NPF Annual Assessment).

These newly applied assessment methods that have been reviewed by the NPFRAG over several meetings (and at times by NORMAC), and a significant part of this project as a planned outcome is the handing over of these methods to the Harvest Strategy project.

This project developed methods for setting TACs that will now feed directly into the development and evaluation of Harvest Strategies (HS) under output controls. This latter component is a separate project (*Developing and testing harvest strategies for the NPF under input and ITQ controls: AFMA project 2006/828*).

11. CONCLUSION

A critical part of establishing and setting combined species-group TACs, is to acknowledge the characteristics of the fleet/stock technical interactions and the spatial/temporal dimensions of the NPF fishery. The very nature of the harvesting process impacts on: (1) the monitoring of catches where species are not identified but rather recorded as a group, (2) species and groups are often caught together, yet (3) the biology of each species are reasonably different with different risks of overfishing - meaning that species need to be assessed separately but managed as a non-separable harvesting unit with Maximum Economic Yield as the target reference point.

On the basis of research in this project (and a final decision from NORMAC), three separate species-group TACs could be set in the NPF:

- tiger (and endeavour) prawns
- banana prawns - Eastern stock-region (which are predominantly redlegged banana prawns)
- banana prawns - Western stock-region (which are predominantly common banana prawns).

Each of these is discussed in detail separately, in terms of models, procedures, assumptions, additional information, NPRAG and/or NORMAC feedback, and actions and decisions, in this report.

Table 5 which was previously presented at a RAG meeting during the project has now been updated after further development of the types of assessment models in the project. It is clear from Table 5 that all relevant tasks have been completed.

In summary, significant progress has been made in this project with the development of techniques to estimate total allowable catches (TACs) for the major commercial prawn species in the NPF, using a range of alternative assessment approaches; including novel methods such as a framework that provides for a mixture of models in an integrated analysis. All these methods have been extensively reviewed by the NPFRAG and their comments have been included in the analyses. The NPFRAG is acknowledged for their feedback and support.

Table 5. Summary table of models developed for the different target species and their progress. “Completed” are those for which the results are robust, “Estimated” means the work has been undertaken but further tests of the results need to be undertaken, “Estimated but large uncertainty” indicates that it is unlikely the method would work well with that species, “Not applicable” (N/A) is that this method would not be applied (with reason supplied).

Species and model type	**P. semisulcatus** (grooved tiger prawn)	**P. esculentus** (brown tiger prawn)	**M. endeavouri** (blue endeavour prawn)	**M. ensis** (red endeavour prawn)	**P. indicus** (red-legged banana prawns)	**P. merguiensis** (common banana prawns)	**Economic and TAC**
Bayesian hierarchical biomass dynamic model (annual)	Completed	Completed by with large uncertainty	Completed	N/A	Completed	N/A no assessment possible	Completed
Delay difference (Dichmont *et al.* 2003) (weekly)	Completed	Completed	Completed	N/A - biological parameters unavailable	N/A - see below	N/A no assessment possible	Completed
Difference model (quarterly)	N/A - not necessary, given above	N/A - not necessary, given above	N/A - not necessary, given above	N/A - biological parameters unavailable	Completed (preliminary)	N/A – no assessment possible	N/A
Size model (weekly)	Completed	Completed	Completed	N/A - biological parameters unavailable	N/A biological parameters unavailable	N/A – no assessment possible	Completed
Data based TAC setting system	N/A - given MEY target	N/A - given MEY target	N/A - given MEY target	N/A - given MEY target	Only consider, if no assessment possible – draft method provided	Completed (NPF Cost Benefit Analysis project)	Included in NPF Cost Benefit Analysis project completed

12. REFERENCES

ABARE. 2009. Australian Fisheries Statistics 2008, Canberra: ABARE.

Andersen, T.B., Roll, K.H. and Tveterås, S. 2008. The price responsiveness of salmon supply in the short and long run, Marine Resource Economics 23: 425-437.

Asche, F., Gordon, D.V. and Jensen, C.L. 2007. Individual Vessel Quotas and Increased Fishing Pressure on Unregulated Species, Land Economics 83: 41-49.

Askey, P.J., Post, J.R., Parkinson, E.A., Rivot, E., Paul, A.J., *et al.* 2007. Estimation of gillnet efficiency and selectivity across multiple sampling units: a hierarchical Bayesian analysis using mark-recapture data. *Fisheries Research* 83, 162-174.

Best, N., Cowles, M.K., and Vines, K. 1996. 'CODA Convergence Diagnosis and Output Analysis Software for Gibbs Sampling Output.' (MRC Biostatistics Unit: Cambridge.)

Bishop, J. 2006. Standardizing fishery-dependent catch and effort in a complex fishery where technology changed. Rev. Fish. Biol. Fisheries 16:21-38.

Bishop, J., Venables, W.N., Dichmont, C.M., Sterling, D.J. 2008. Standardizing catch rates: is logbook information by itself enough? ICES Journal of Marine Science 65: 255–266

Chaloupka, M. and Balazs, G. 2007. Using Bayesian state-space modelling to assess the recovery and harvest potential of the Hawaiian green sea turtle stock. *Ecological Modelling* 205, 93-109.

Coelli, T.J. and Perelman, S. 2000. Technical Efficiency of European Railways: A Distance Function Approach. Applied Economics 32(15): 1967-76.

Dichmont, C. M., Deng, A., Punt, A. E., Ellis, N., Venables, W. N., Kompas, T., Zhou, S., and Bishop, J. 2008. Beyond biological performance measures in management strategy evaluation: Bringing economics and the effects of trawling on the benthos. Fisheries Research 94: 238–250.

Dichmont, C.M., Punt, A.E., Deng, A., and Venables, W. 2003. Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery. Fish. Res. 65, 335–350.

Färe, R., Grosskopf, S., Noh, D.-W. and Weber, W. 2005. Characteristics of a polluting technology: theory and practice, Journal of Econometrics 126: 469-492.

Felthoven, R.G. and Morrison Paul, C.J. 2004. Multi-Output, Nonfrontier Primal Measures of Capacity and Capacity Utilization, American Journal of Agricultural Economics 86: 619-633.

Fousekis, P. 2002. Distance vs. ray functions: an application to the inshore fishery of Greece, Marine Resource Economics 17: 251–267.

Gelman, A. 2006. Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis* 1, 515-534.

Grosskopf, S., Margaritis, D. and Valdmanis, V. 1995. Estimating output substitutability of hospital services: A distance function approach. European Journal of Operations Research 80: 575-587.

Harley, S.J., and Myers, R.A. 2001. Hierarchical Bayesian models of length-specific catchability of research trawl surveys. *Canadian Journal of Fisheries and Aquatic Sciences* 58, 1569-1584.

Hotelling, H. 1932. Edgeworth's taxation paradox and the nature of demand and supply functions, Journal of Political Economy 40: 577-616.

Huang, H. and Leung, P. 2007. Modeling protected species as an undesirable output: The case of sea turtle interactions in Hawaii's longline fishery, Journal of Environmental Management 84: 523-533.

Maunder, M.M., and Punt, A.E. 2004 Standardizing catch and effort data: a review of recent approaches. Fisheries Research, 70: 141-159

McAllister, M.K., Hill, S.L., Agnew, D.J., Kirkwood, G.P., and Beddington, J.R., 2004. A Bayesian hierarchical formulation of the DeLury stock assessment model for abundance estimation of Falkland Islands' squid (*Loligo gahi*). *Canadian Journal of Fisheries and Aquatic Sciences* 61, 1048-1059.

Meyer, R., and Millar, R.B. 1999. BUGS in Bayesian stock assessments. *Canadian Journal of Fisheries and Aquatic Sciences* 56, 1078-1086.

Milton, D.A., R.A. Kenyon, C. Burridge, M. Zhu, R. Pendrey, T. van der Velde, A. Donovan and M. Kienzle 2008. An Integrated Monitoring Program for the Northern Prawn Fishery 2006/08. (R05/1024 l 30/09/2008).

Morrison Paul, C .J., Johnston, W. E. and Frengley G. A. G. 2000. Efficiency in New Zealand Sheep and Beef Farming: The Impacts of Regulatory Reform. Review of Economics and Statistics 82(May):325-37.

NPFRAG, 2008. Bio-Economic Model Status of Tiger Prawn Stocks at the end of 2007 in the NPF, *Report of the NPFRAG*. CSIRO, Brisbane.

Orea, L., Alvarez, A. and Morrison Paul, C.J. 2005. Modeling and Measuring Production Processes for a Multi-species Fishery: Alternative Technical Efficiency Estimates for the Northern Spain Hake Fishery, Natural Resource Modeling 18: 183-213.

Pascoe, S., Koundouri, P. and Bjorndal, T. 2007. Estimating targeting ability in multi-species fisheries: a primal multi-output distance function approach. Land Economics 83(3): 382-397.

Polacheck, T., Hilborn, R., and Punt, A.E. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. *Canadian Journal of Fisheries and Aquatic Sciences* 50, 2597-2607.

Punt, André E., Roy A. Deng, Catherine M. Dichmont, Tom Kompas, William N. Venables, Shijie Zhou, Sean Pascoe, Trevor Hutton, Rob Kenyon, Tonya van der Velde, and Marco

Kienzle., 2010. Integrating size-structured assessment and bio-economic management advice in Australia's Northern Prawn Fishery. ICES Journal of Marine Science (in press).

Quinn, T.J., and Deriso, R.B. 1999. 'Quantitative Fish Dynamics.' (Oxford University Press: New York.)

Robins, C.M., Wang, Y.-G. & Die D. 1998. The impact of Global Positioning Systems and plotters on fishing power in the Northern Prawn Fishery, Australia. Can. J. Fish. Aquat. Sci., 55, 1645-1651.

Squires, D. 1987. Long run profit functions of multiproduct firms, American Journal of Agricultural Economics 69: 558-569.

Squires, D. 1988. Production Technology, Costs, and Multiproduct Industry Structure: An Application of the Long-Run Profit Function to the New England Fishing Industry, The Canadian Journal of Economics / Revue canadienne d'Economique 21: 359-378.

Su, Z., Adkison, M.D., and van Alen, B.W. 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. *Canadian Journal of Fisheries and Aquatic Sciences* 58, 1648-1662.

Venables, W. N., R. A. Kenyon, et al. 2006. Species Distribution and Catch Allocation: data and methods for the NPF, 2002-2004, Australian Fisheries Management Authority: 190.

Zhou, S., Punt, A. E., Deng, R., Dichmont, C. M., Ye, Y., and Bishop, J. 2010 (in press). Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Marine and Freshwater Research 00: 00–00.

APPENDIX 1. INTELLECTUAL PROPERTY

Some of the manuscripts presented in Appendices 3-15 are submitted or published papers. This research should be cited as the paper rather than the report (refer to Section 8 “Benefits and Adoption” for a list of papers published or in press).

APPENDIX 2. STAFF

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APPENDIX 3. IMPLICATIONS OF TARGETING ABILITY FOR OUTPUT CONTROLS IN AUSTRALIA'S MULTISPECIES NORTHERN PRAWN FISHERY: A BAYESIAN MULTI-OUTPUT DISTANCE FUNCTION APPROACH

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3.1 Abstract

The degree to which individual species can be targeted will influence how quotas are set in multispecies fisheries managed through individual transferable quotas (ITQs). In this paper, Morishima elasticities of substitution are derived from a multi-output distance function to examine fishers' ability to control output mix in a fishery about to move to ITQ management. The parameters of the model are estimated using Bayesian techniques to avoid potential endogeneity bias. The results suggest that the ability of fishers to change their output mix is relatively limited, and a single quota may be sufficient to control catches of the key species.

Keywords: Targeting behaviour; multi-output distance function; Morishima elasticities of substitution; fisheries management; Bayesian estimation..

3.2 Introduction

Rights based management, and individual transferable quota (ITQ) management systems in particular, are becoming increasingly applied to fisheries. In most fisheries subject to ITQs, individual species are regulated as if each were harvested in a separate production process (Squires, 1987), and hence each species would require a separate total allowable catch (TAC). However, production in multi-species fisheries is often assumed by economists to be joint, with several species caught simultaneously using all inputs (Squires *et al.*, 1998). If such functions truly represent fishing technology, then the imposition of TACs that are inconsistent with the composition of the catch may result in over-quota catch of at least some species, depending on the profitability of continuing fishing and discarding the over-quota catch. The existence of both over-quota catch of some species and underutilized quota of others is common in most fisheries managed using output controls (Sanchirico *et al.*, 2006).

The need to set a TAC for each individual species in a multispecies fishery depends on the ability of fishers to target individual species as well as the incentives to target. Targeting ability implies that fishers are able to influence their catch composition directly, either through using different types of gear, or fishing in different areas (Branch and Hilborn, 2008). Catch compositions can also be changed by varying when fishing occurs owing to seasonal changes in abundance or availability. Hence, fishers' catch composition will depend on their decisions of when, where and how to fish. Their ability to respond to market and management-induced incentives will depend on the relative importance of the temporal, spatial and technological aspects of targeting.

Relatively few studies have attempted to estimate targeting ability empirically. Earlier studies used a revenue function approach to determine the responsiveness of catch composition to relative prices (Kirkley and Strand, 1988; Campbell and Nicholl, 1994). More recently, Pascoe *et al.* (2007) used a multi-output distance function approach and derived Morishima elasticities of substitution (MES) as measures of the ability of fishers to control their output mixes. The MES originally derives from the profit function, and represents the responsiveness of the input or output mix to changes in relative prices, but can also be estimated indirectly from the primal production function (Blackorby and Russell 1981,1989) with a similar interpretation. Similar measures have been used to determine the potential for output substitution in hospital service provisions (Grosskopf *et al.*, 1995), and the potential to reduce pollution by electricity utilities, with pollution being considered an undesirable output (Fare *et al.*, 2005; Lee, 2005).

An ability to alter the output mix in fisheries in response to price changes, ceteris paribus, indicates a degree of targeting ability. An advantage of the primal production function approach over the revenue or profit function approaches is that individual catch and input data for fisheries are generally more readily available than information on prices paid and received by individual fishers.

The purpose in this paper is to determine the extent to which fishers can target individual species within Australia's multispecies northern prawn fishery, which is expected to move to ITQ management in 2012. A multi-output distance function was estimated, and the degree of substitutability in the output mix measured as Morishima elasticities of substitution. The distance function was estimated using Bayesian techniques to address potential endogeneity problems often associated with output distance functions (O'Donnell, 2007). Low substitutability or complementarity in outputs would suggest that setting TACs for each species individually may be unnecessary. Conversely, high degrees of substitutability may indicate the need for separate TACs. Jointness and separability in the production process are also examined. The implications of these factors for ITQ management and TAC setting in the fishery are examined in light of the broader set of incentives facing fishers.

3.3 The Northern Prawn Fishery

The northern prawn fishery (Figure 3.1) is one of Australia's most valuable fisheries in terms of total landed value, and is the most valuable fishery managed by Australian Commonwealth government. The fishery has an explicit management objective of maximizing economic returns. In 2007-08, the gross value of product was around A$74m (ABARE, 2009). The fishery is currently managed using a combination of input controls, primarily seasonal closures and individual transferable gear units. The latter places restrictions on the amount of headrope that vessels can tow. Over the last decade, the fleet size has more than halved, from 133 vessels in 1998 to 52 in 2008. In 2005 and 2006, 43 vessels left the fishery as part of a $150 million national government buyback scheme. In return for government assistance to restructure, the fishery had to agree that it would move to management through ITQs.

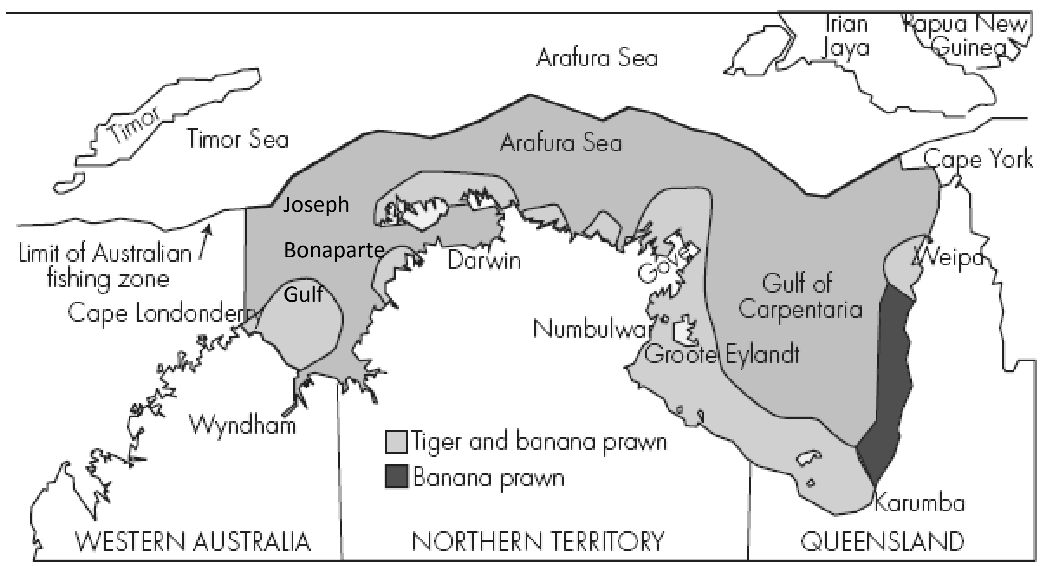

Figure 3.1. The Australian northern prawn fishery (Vieira and Hohnen, 2007).

The fishery occurs over two "seasons" each year, and can effectively be considered as two separate fisheries – namely a "banana prawn fishery" and a "tiger prawn fishery"[7]. The start and end dates of each season differ among years but the banana prawn season is generally from March/April to June while the second season generally covers August to October. The length of each season is currently modified to adjust exploitation rates on the various species given differences in their status relative to target and limit reference points.

The banana prawn season is dominated by white banana prawns (*Fenneropenaeus merguiensis*). Most activity in this fishery takes place along the Queensland coast on the eastern side of the

[7] A third fishery exists in the Joseph Bonaparte Gulf based in red-legged banana prawns (*Fenneropenaeus indicus*). This species is highly targetable with little bycatch. The fishery is relatively small in terms of catch and number of active participants, and is excluded from the analysis.

Gulf of Carpentaria (GoC), and is based on spawning aggregations of banana prawns. Small quantities of tiger and endeavour prawns are caught also as bycatch, although there are strict limits on the quantities that may be retained to prevent targeting of these species at that time.

The tiger prawn fishery is largely based on the western side of the GoC and across the top of the Northern Territory. The key species caught in the fishery are brown tiger prawns (*Penaeus esculentus*), grooved tiger prawns (*P. semisulcatus*) and two endeavour prawn species (*Metapenaeus endeavouri* and *M. ensis*). Relatively small quantities of banana prawns are also caught, as well as a number of other commercially valuable prawn, fish, cephalopod and other crustacean species.

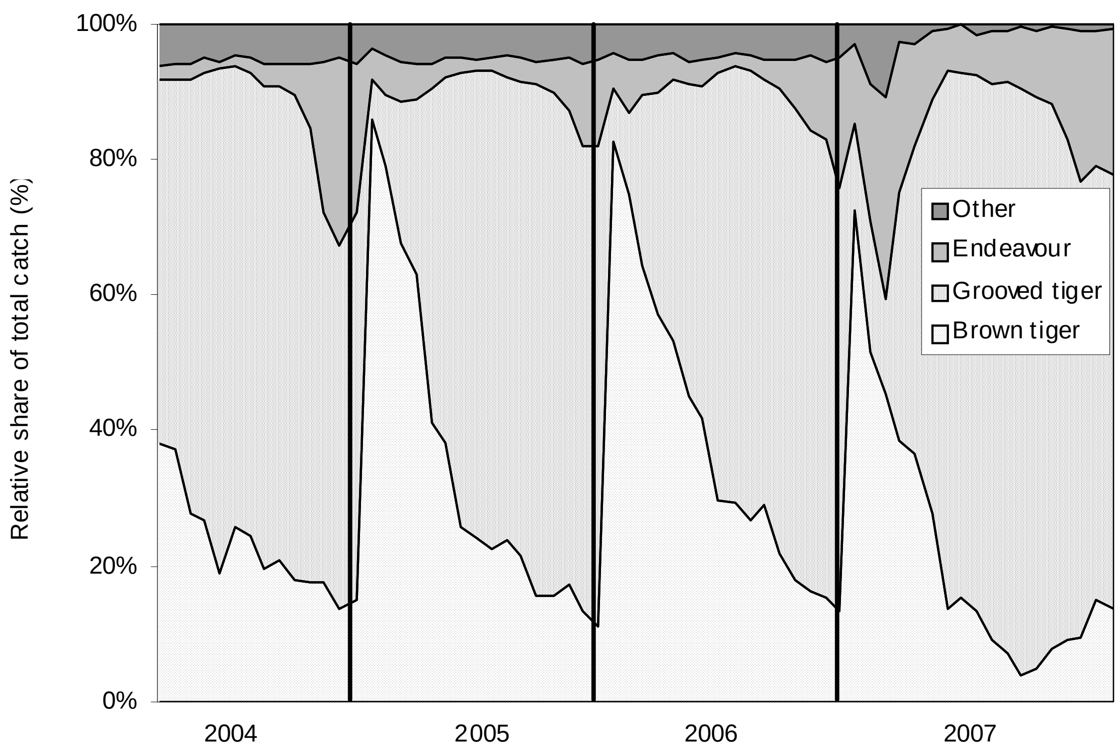

Figure 3.2. Weekly catch composition, tiger prawn fishery, 2004-07. In 2004, the fishery was opened on 1 September, whereas in 2005 to 2007 the fishery was opened on 1 August.

For all intents and purposes, the banana prawn fishery is effectively a single species fishery. Consequently, this study focused on the potential targeting of the tiger, endeavour and king prawn species. The catch composition varies over the season, with brown tiger prawns caught mostly at the start of the season, and endeavour prawns caught mostly at the end of the season (Figure 3.2). This is suggestive of targeting ability related to the relative seasonal abundance. Generally, stock abundance of brown tiger prawns peaks before that of the grooved tiger prawn, whereas endeavour prawn abundance peaks towards the end of the year.

3.4 Modelling output substitution

In most fisheries productivity studies, production is generally assumed to be either non-joint in input quantities, such that the production of a single output can be modelled as a function of a set of inputs, or that production is joint in input quantities, but is separable, such that a composite measure of a set of outputs can be modelled as a function of a set of inputs. In both cases, a single output measure is obtained and used in the estimation of the production function. Some form of multi-output function is required when the technology is believed to be both joint in inputs and non-separable.

A number of primal multi-output functional forms with different characteristics exist. These include multi-output production functions where one species is considered the dependent variable and the other species are included as covariates (Felthoven and Morrison, 2004; Orea *et al*, 2005), and distance functions in which ratios of the outputs appear as covariates.

The general form of the multi-output production function may be given by

$$y_1 = f(y_{m>1}, x_k) \tag{1}$$

where y_m is the level of output of species m, and x_k is the level of input k (where inputs include vessel characteristics as well as the size of fish stocks). Orea et al (2005) estimated the model using logged values of the dependent and independent variables, while Felthoven and Morrison (2004) proposed a generalised linear transformation function using the square root of the covariates.

The multi-output distance function can be expressed as

$$D(x, y) = \frac{\min}{\psi}\left\{\psi > 0 : \left(\frac{y}{\psi}\right) \in P(x)\right\} \tag{2}$$

where $P(x)$ is the set of feasible output vectors obtainable from the input vector x (Orea et al, 2005), and $D(x,y)$ represents the distance to the production frontier.[8] In practice, the output distance function is estimated as

$$-\ln y_1 = f(\ln(y_m / y_1), \ln x_k) - \ln D \tag{3}$$

which is effectively a standard production frontier model with one output as the dependent variable and the others as covariates in ratio. The multi-output distance function has had broad use in many industries (e.g. Grosskopf *et al.*, 1995; Coelli and Perelman, 2000; Morrison Paul *et al.*, 2000, Fare *et al.*, 2005; Lee, 2005), but only limited applications in fisheries (Fousekis, 2002; Huang and Leung, 2007; Pascoe *et al.*, 2007).

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[8] This is further detailed in the following section.

Indirect measures of the MES can be derived from the production function and distance function (Blackorby and Russell, 1981; Grosskopf *et al.*, 1995), respectively given by

$$MES_{y_m y_n} = y_m\left[\frac{\partial^2 y_1}{\partial y_m\, \partial y_n}\Bigg/\frac{\partial y_1)}{\partial y_n}\right] - y_m\left[\frac{\partial^2 y_1}{\partial y_m^2}\Bigg/\frac{\partial y_1}{\partial y_m}\right] \quad m,n \neq 1 \tag{4}$$

$$MES_{y_m y_n} = y_m\left[\frac{\partial^2 D(x,y)}{\partial y_m\, \partial y_n}\Bigg/\frac{\partial D(x,y)}{\partial y_n}\right] - y_m\left[\frac{\partial^2 D(x,y)}{\partial y_m^2}\Bigg/\frac{\partial D(x,y)}{\partial y_m}\right] \quad \forall m,n \tag{5}$$

A negative value indicates that the outputs are substitutes, while a positive value indicates complementarity. The size of the MES is a measure of the strength of the substitute/complementarity relationship.

A criticism of the output distance function is the potential for endogeneity bias resulting from outputs appear as covariates in the distance function, as well as the normalisation of the outputs by the dependent variable (Kumbhakar and Lovell, 2000; Atkinson *et al.* 2003; Felthoven and Morrison Paul, 2004). This criticism is often disputed, with some arguing that the output ratios (y_m/y_1) are more likely to be exogenous than values of y_m used in other multi-output transformation functions (Kumbhakar and Lovell, 2000), and hence distance functions may be less susceptible to endogeneity bias than alternative multi-output models. Further, as the distance function represents a radial expansion of all outputs, given the set of inputs, the ratio $y_{m,i}/y_{1,i}$ remains constant and hence can be assumed to be exogenous (Morrison Paul and Nehring, 2005). This latter argument, however, is also seen as weakness of distance functions, because it implies that any increase in efficiency increases all outputs by the same proportion, and that any random shock affects all outputs equally (Orea *et al.*, 2005). The alternative production function approach, such as those used by Orea *et al* (2005) and Felthoven and Morrison Paul (2004), overcomes this particular problem, but in doing so creates additional problems. In particular, production technology properties will vary depending on which species is chosen as the dependent variable. Further, estimates of output substitution elasticities represent the degree to which the outputs other than that used as the dependent variable can be substituted. For a clear target species/bycatch relationship, this may be appropriate as varying the bycatch mix given the catch of the target species may be of interest. However, when attempting to assess the degree to which species may be targeted, this functional form is inappropriate.[9]

[9] A reviewer suggested that failure to account for uncertainty and risk aversion considerations may also result in inefficient estimates (see, for example, Koundouri and Nauges, 2005; Koundouri *et al.*, 2009). Inclusion of an explicit risk function, however, would be at the expense of estimating the inefficiency term, rendering a distance function inoperable. Further, a recent study suggests that estimates of flexible risk preferences from production data are unreliable, and suggests that "emphasis on the estimation of flexible risk preferences in production studies has been misplaced, and future efforts are likely to be more fruitfully employed elsewhere" (Lence, 2009, p 596)

3.4.1 The translog multi-output distance function

The approach adopted in this study was the translog multi-output distance function. The translog distance function with M *(m = 1, 2, … , M)* outputs *Y; K (k = 1, 2, … , K)* inputs *X*; and for *I (i = 1, 2, … , I)* firms can be given by:

$$\begin{aligned}\ln D_i &= \alpha_0 + \sum_m \alpha_m \ln y_{m,i} + 0.5 \sum_m \sum_n \beta_{m,n} \ln y_{m,i} \ln y_{n,i} \\ &+ \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\ &+ \sum_k \sum_m \beta_{k,m} \ln x_{k,i} \ln y_{m,i} + v_i\end{aligned} \tag{6}$$

where D_i is the distance from the production possibility frontier ($0 \le D_i \le 1$), $y_{m,i}$ and $x_{k,i}$ are the outputs and inputs respectively, and v_i is a stochastic error term, assumed to be N[0, σ]. The distance function assumes joint production and non-separability of outputs from inputs. If the alternative assumption of separability is valid, then production is effectively forced to be joint (Livernois and Ryan, 1989). The validity of the assumptions of both non-jointness and separability can be explicitly tested.

The output distance function is homogeneous of degree one in outputs (Shephard, 1970). In order to maintain the homogeneity conditions, the constraints $\sum_m \alpha_m = 1, \sum_n \beta_{mn} = \sum_m \beta_{km} = 0$ need to be imposed, while symmetry restrictions require $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$. The homogeneity restrictions can be imposed through normalizing the function by one of the outputs (e.g. $y_{1,i}$), and the model can be expressed as a standard production frontier by moving the distance measure to the right hand side of the equation. Further, technical change over the period of the data can be captured by including a time variable, *t*, into the model. This results in:

$$\begin{aligned}\ln y_{1,i} &= \alpha_0 + \sum_{m \neq 1} \alpha_m \ln y^*_{m,i} + 0.5 \sum_{m \neq 1} \sum_n \beta_{m,n} \ln y^*_{m,i} \ln y^*_{n,i} \\ &+ \sum_k \alpha_k \ln x_{k,i} + 0.5 \sum_k \sum_l \beta_{k,l} \ln x_{k,i} \ln x_{l,i} \\ &+ \sum_k \sum_{m \neq 1} \beta_{k,m} \ln x_{k,i} \ln y^*_{m,i} \\ &+ \gamma_1 t + \gamma_2 t^2 + \sum_k \gamma_k t \ln x_{k,i} - \ln D_i + v_i\end{aligned} \tag{7}$$

where $y^*_{m,i} = y_{m,i}/y_{1,i}$ and the distance measure is equivalent to the inefficiency term (i.e. $-u_i = -\ln D_i$). For estimation purposes, the negative sign on the dependent variable can be ignored (i.e., we use $\ln y_{1,i}$ rather than $-\ln y_{1,i}$). This results in the signs of the estimated coefficients being reversed, but is more consistent with the expected signs of parameters in conventional production frontiers. The rate of technological change each period can be determined by $\partial y_{1,i} / \partial t = y_{1,i} (\gamma_1 + 2\gamma_2 t + \sum_k \gamma_k \ln x_{k,i})$, where $y_{1,i} = exp(ln y_{1,i})$.

Several definitions of non-jointness in input quantities have been developed (see Kohli, 1981; 1983; Lau, 1978; Livernois and Ryan, 1989), although a definition most relevant to fisheries production is that of “almost non-joint” technologies (Lau, 1978). A technology is said to be almost non-joint in input quantities if there exists individual, quasi-concave, non-negative, non-decreasing production functions for each output *i=1,..,I* in a production set *Y*, such that $Y_i = f_i(X_{1i},...,X_{ni};Z)\ \forall i$ and $\sum_i X_{ni} = X_n \quad \forall n$, where Y_i is the level of output *i*, X_{ni} is the level of variable input *n*=1,…,*N* directed at producing output *i* (such that the sum of the directed inputs equals the total level of those inputs used, X_n), and *Z* is a vector of fixed inputs. That is, production of one output does not diminish the available supply of the input for the production of other outputs. This can be examined empirically by imposing additional restrictions on the model ($\alpha_m = 0\ \forall\ m$, $\beta_{m,n} = 0\ \forall\ m,n$ and $\beta_{k,m} = 0\ \forall k,m$), and estimating the model as a single output translog production function (i.e. $\ln y_{1i} = \alpha_0 + \sum_k \alpha_k \ln x_{k,i} + 0.5\sum_k\sum_l \beta_{k,l} \ln x_k \ln x_{l,i} - \ln D_i + v_i$).

Separability of outputs and inputs requires the optimal mix of outputs to be independent of the input levels. This can be tested by imposing the restrictions $\beta_{km} = 0\ \forall k,m$ on equation (5). In terms of estimating targeting behaviour, separability is less of an issue. Separability of outputs and inputs enables the transformation function to be written as $G(Y) = L(X;Z)$, where *G(Y)* effectively aggregates the outputs into a single composite measure (Livernois and Ryan, 1989). However, non-separability implies that a multi-output distance function is more appropriate as a functional form.

3.4.2 Model Estimation

The main criticism of the multi-output distance function is the potential for endogeneity bias to affect the parameter estimates. This can be avoided by using Bayesian estimation techniques (Fernandez et al 2000, O’Donnell 2007). Following Griffin and Steel (2007), the functional form of the output distance function (equation 4) can be represented by $\ln y_1 = N(\alpha + x_i^{'}\beta - D_i, \sigma^2)$ where $N(\mu,\sigma^2)$ denotes a normal distribution with mean μ $(= \alpha + x_i^{'}\beta - D_i)$ and variance σ^2, x_{it} is the set of covariates (the logarithms of the inputs and normalised outputs of the other species), *D* is the distance from the frontier (i.e. the inefficiency component) and σ^2 is the variance of the error term. The parameters of the model are assigned generally uninformative priors, in this case given by $\beta \sim N(0,\Sigma)$, where Σ is the variance-covariance matrix, that values for which are set so that there is essentially no *a priori* information about the β. Various assumptions about the distribution of *D* are often used in efficiency literature, the two most common being the half normal distribution $D \sim N^+(0,\lambda)$ and the truncated normal distribution $D \sim N^+(\xi,\lambda)$, where λ itself is unknown and has a prior gamma distribution $\lambda \sim Ga(0,\lambda_0)$. The value of ξ is also unknown, and assumed to be normally distributed with very high variance so that prior is uninformative.

The models were implemented in WinBUGS,[10] which utilises a Markov Chain Monte Carlo (MCMC) technique for generating parameter vectors from the posterior distribution. A Gibbs sampler is used to generate a sequence of values based on an initial vector of parameters and the outcomes of the previous estimate (hence generating a Markov Chain). The Gibbs sequence converges to a stationary distribution that is independent of the starting values, and represents the distribution of the parameters of interest.

3.5 Data

Daily logbook data over the period 1995 to 2007 were combined with information on vessel characteristics. While a longer period of logbook data was available (back to 1970), the analysis was restricted to post-1995 due to substantially different management structures being in place before 1995. Within the data set, each logbook record is classified as either relating to the tiger prawn or banana prawn fishery. Only observations that were coded as relating to the tiger prawn fishery were used. The daily data were aggregated into weekly values, as these were considered more appropriate given the sequential nature of the fishery.

Logbook information only records the catch of prawns as tigers, endeavours, bananas and kings. Data from scientific surveys taken from each area over each week of each season were used to separate the total catch of tiger prawns into their separate species (Venables and Dichmont, 2004). Equivalent species split information was also available to separate endeavour prawns. However, the data for the two endeavour species were combined because reliable stock information at the species level was not available for endeavour prawns, and as they form only a relatively small proportion of the total catch. All other species (banana, king and other prawns) were aggregated into an “other” category, representing between 2 and 10 per cent of the total catch each week.

The inputs in the production function were headrope length, engine power (kW) and hours fished over the week. From 2006, vessels were able to use quad gear (four nets – two off each beam) rather than twin gear (two nets – one off each beam) although incurred a penalty in terms of headrope length if they did so. A dummy variable was used to capture the effects of this for vessels that used quad gear. Moon phase is also believed to affect the availability of prawns, with catch rates being generally higher at or following the new moon (Salini *et al.*, 2001). The moon phase expressed as an index of luminosity ranging from zero (new moon) to 100 (full moon). A summary of the main vessel information included in the analysis is presented in Table 3.1.

Weekly biomass estimates for the two tiger prawn species are estimated directly through regular stock assessments (Dichmont *et al*., 2003), but only a single composite endeavour prawn biomass estimate was available at a weekly level. The biomass estimates were converted to an index with the base being the average over the period as a whole. For the “other” prawn species, average catch per unit of effort (CPUE) was used as a proxy measure of stock abundance in order to derive the stock index. The use of CPUE as a stock index in production functions raises

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[10] WinBUGS is freely available software that can be downloaded at http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml. The truncated normal and half normal distributions requires an additional component that can be downloaded from http://www.winbugs-development.org.uk/.

several issues (Pascoe and Coglan, 2002). However, given the relatively small contribution to total catch by the "other" species (less than 5 per cent over the period of the data), it is unlikely that any problems associated with the use of the index will substantially influence the results.

Table 3.1. Summary of data used in the analysis

	Average vessel catch per week (kg)				Average hours fished per week	Average vessel characteristics			Number of active boats
	Brown tiger	Grooved tiger	Endeavour	Other		Engine	Head-rope	Vintage	
1995	669	833	437	92	80	316	13	26	125
1996	736	952	420	88	76	305	13	24	127
1997	691	1007	413	94	81	325	13	24	129
1998	655	1083	494	91	79	329	13	23	130
1999	576	1147	351	88	76	331	13	23	129
2000	590	1123	375	87	75	337	13	22	121
2001	445	1241	422	86	75	345	12	22	116
2002	283	1390	325	89	77	361	12	21	114
2003	245	1455	397	92	80	366	11	20	98
2004	209	1434	452	92	79	368	11	20	96
2005	384	1251	284	91	79	379	10	19	89
2006	428	1201	342	92	79	382	10	19	77
2007	406	1256	373	88	76	379	11	18	51

Catch of each species was divided by the stock index to produce an index of partial exploitation rate (i.e. $f_{i,m} = C_{i,m} / S_m$), and this was used as the output measures in the model. The degree to which partial fishing mortalities for individual species vary in a particular time period can provide an indication of the ability of fishers to alter their fishing behaviour to influence their catch (Rijnsdorp *et al.*, 2006). This involves an implicit assumption that the stock elasticity is equal to 1, consistent with the stock assessment process that assumes catch rate is linearly related to biomass.

Zero catches of any species were nominally changed to a value of 0.01 to avoid problems when logging the data. This affected less than 1% of the observations for each of the three main species, but almost two thirds of the "other" catch category. Observations with small values for hours fished (less than 10 hours in a week) or small values of catch (less than 100 kg in a week) were also removed as these either represented data errors or a breakdown of the vessel. These observations represented less than 1% of the total data set. The final panel data set included 24,035 observations from 164 vessels that operated over the 13 year period. The data were logged and normalized such that the mean (logged) value was zero. A time variable was included to capture technical change. This was an annual variable rather than weekly as it is most likely that changes in technologies would occur between the seasons rather than during them.

3.6 Results

The Gibbs sampler was initialized using the estimates of the α and β parameters derived from a normal maximum likelihood estimation of the model parameters. With the exception of the truncated normal distribution assumption for the inefficiency term (*D*), convergence[11] of the MCMC algorithm was obtained by 5,000 replications and the models were run for a further 25,000 replications that were used in the final analysis. The original 5,000 replications were discarded as "burn-in". For the truncated normal distribution assumption, the β parameters converged within 5,000 replications, but the α and D had not converged even after 100,000 replications. Instead, an inverse relationship between α and D was observed, with the α values constantly increasing and the D constantly decreasing (suggesting an expanding frontier and increasingly inefficient fleet).

3.6.1 Model specification and production elasticities

A number of different model specifications were also tested (Table 3.2), including the translog production function given in Equation 7, a Cobb-Douglas production function where the cross product and squared terms are set to zero, and variations of these models with different assumptions about the distribution of the inefficiency term (half normal or truncated normal).

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[11] Convergence was determined initially by examining the history plots over both the full series and the burn-in period. For the final model, a more formal examination of convergence was also undertaken using the convergence diagnostic recommended by Geweke (1992), which compared posterior means at the start (runs 5,000-10,000) with those at the end of the sequence (runs 25,000-30,000) and tested for statistical difference based on the standard deviations of each. Fernandez *et al*. (2000) also notes difficulties with the truncated normal distribution.

The model was also tested for separability and non-jointness in production. The Deviance Information Criterion (DIC) was used to determine the most appropriate functional form, with lower values of the criterion indicating more appropriate models. The translog production frontier was found to be the most appropriate functional form (Table 3.2), based on the DIC values.

Table 3.2: Specification tests[a]

Model specification	$\overline{D}$	$\hat{D}$	p_D	*DIC*
Half normal	27745.0	27575.5	169.576	27914.6
Truncated normal	27750.6	27575.6	174.981	27925.5
Cobb-Douglas	45973.1	45821.9	151.176	46124.3
Separability	28636.7	28474.5	162.245	28799.0
Non-joint	95355.9	95205.3	150.634	95506.6

(a) $\overline{D}$ is the posterior mean of the deviance given by -2*(log likelihood); $\hat{D}$ is an estimate of $\overline{D}$ based on the posterior mean of the parameters; p_D is the effective number of parameters; $DIC = \overline{D} + p_D = \hat{D} + 2p_d$

The non-separable nature of the production process indicates that a multi-output functional form of the model is appropriate. Rejecting the assumption of non-joint production does not necessarily imply that the output is produced in fixed proportions. That is, the production technology may not be *purely* joint, but just *mostly* joint. Under such technology, the composition of the output mix may have some discretionary element. This is expected to be the case in most fisheries, where fishers may be able to increase the proportion of one species or another in the catch by varying their targeting behaviour, although the resultant output is still a combination of several species (Pascoe *et al.*, 2007).

Zero was not included in the 95% credibility intervals for most of the parameters of the translog model (Tables 3.3 and 3.4), roughly equivalent in concept to being significantly different from zero at α=0.05. Given that $\ln(\bar{x}) = 0$, the coefficients for the inputs represent their production elasticities at the mean level of all inputs. The posterior median for the elasticity relating to hours fished was less than 1, suggesting diminishing returns to effort each week. The lower 2.5th percentile of the elasticity relating to engine power did not include zero. While engine power can increase the area swept per unit of time, other factors – such as time fished and headrope length – have a greater impact on total catch. Increasing headrope length was estimated to produce a less than proportional increase in catch (elasticity = 0.82 at the posterior mean).

Table 3.3: Parameter estimates

	Mean	*Standard deviation*	*2.50%*	*median*	*97.50%*
Constant	0.784	0.020	0.746	0.784	0.824
Ln(Brown tiger)	-0.312	0.002	-0.316	-0.312	-0.308
Ln(Endeavour)	-0.224	0.002	-0.229	-0.224	-0.220
Ln(Other)	-0.052	0.002	-0.056	-0.052	-0.048
Ln^2(Brown tiger)	-0.056	0.001	-0.057	-0.056	-0.055
Ln^2(Endeavour)	-0.060	0.001	-0.061	-0.060	-0.059
Ln^2 (Other)	-0.010	0.000	-0.011	-0.010	-0.009
Ln(Brown)*ln(Endeavour)	0.048	0.001	0.047	0.048	0.050
Ln(Brown)*ln(Other)	0.010	0.001	0.009	0.010	0.011
Ln(Endeavour)*ln(Other)	0.009	0.001	0.007	0.009	0.010
Ln(Hours fished)	0.885	0.022	0.843	0.885	0.927
Ln(Engine power)	-0.015	0.065	-0.141	-0.015	0.116
Ln(Headrope)	0.820	0.082	0.659	0.820	0.980
Ln^2(Hours fished)	-0.101	0.011	-0.123	-0.101	-0.080
Ln^2(Engine power)	-0.113	0.096	-0.299	-0.114	0.074
Ln^2 (Headrope)	-0.673	0.116	-0.901	-0.674	-0.445
Ln(Hours)*ln(Engine power)	0.045	0.045	-0.044	0.045	0.132
Ln(Hours fished)*ln(Headrope)	-0.010	0.057	-0.121	-0.011	0.101
Ln(Engine power)*ln(Headrope)	0.235	0.198	-0.153	0.236	0.620
Ln(Brown tiger)*ln(Hours fished)	0.002	0.003	-0.004	0.002	0.008
Ln(Brown tiger)*ln(Engine power)	0.042	0.008	0.027	0.042	0.057
Ln(Brown tiger)*ln(Headrope)	0.056	0.009	0.038	0.056	0.074
Ln(Endeavour)*ln(Hours fished)	-0.016	0.004	-0.023	-0.016	-0.008
Ln(Endeavour)*ln(Engine power)	0.078	0.010	0.059	0.078	0.097
Ln(Endeavour)*ln(Headrope)	-0.085	0.012	-0.108	-0.085	-0.062
Ln(Others)*ln(Hours)	0.059	0.003	0.054	0.059	0.065
Ln(Others)*ln(Engine power)	-0.031	0.006	-0.043	-0.031	-0.018
Ln(Others)*ln(Headrope)	-0.059	0.007	-0.073	-0.059	-0.045

Time	0.039	0.005	0.029	0.039	0.048
$Time^2$	-0.003	0.000	-0.004	-0.003	-0.002
Time*ln(Hours fished)	-0.001	0.003	-0.007	-0.001	0.005
Time*ln(Engine power)	0.023	0.010	0.002	0.023	0.044
Time*ln(Headrope)	-0.083	0.013	-0.108	-0.083	-0.058
Quad gear (dummy variable)	-0.029	0.003	-0.034	-0.029	-0.023
Ln(Moon illumination)	-0.223	0.110	-0.437	-0.223	-0.006
σ^2	24.330	3.813	17.670	24.050	32.650
λ	0.186	0.002	0.182	0.186	0.189

It has been shown that there is a trade-off between flexibility and theoretical consistency when using flexible functional forms such as the translog. For theoretical consistency, the distance function needs to be non-decreasing, linearly homogenous and convex is outputs, as well as decreasing in terms of inputs. Following Sauer *et al.* (2006), the models were tested for monotonicity and curvature at the mean (i.e. $(x,y)=1$; $ln(x)=0$, $ln(y)=0$), and using the mean values of the posteriors. Only engine power and headrope length were considered appropriate input variables to include in this analysis as hours fished is a capital utilization variable rather than an input *per se*. The first derivatives were positive and the second derivatives were negative for both inputs, as expected, and consistent with the monotonicity requirement, and convexity conditions also held at the mean of the posteriors. For the outputs, homogeneity was imposed through the structural form of the model. Similarly, the first and second derivatives had the expected signs, and convexity conditions were also met.[12]

Table 3.4: Derived[a] parameters from homogeneity conditions

	Mean	*Standard deviation*
Ln(Grooved tiger)	-0.412	0.003
Ln^2(Grooved tiger)	0.008	0.002

[12] O'Donnell and Coelli (2005) suggest a further advantage of the Bayesian approach is that is it possible to directly impose curvature conditions during the estimation process, and a method for doing so is in WinBUGS is illustrated in Griffin and Steel (2007) using the so-called "ones trick". Imposing these conditions in WinBUGS, however, can result in slow convergence and mixing, requiring a substantially larger number of model runs. Given the considerable time taken for the 30,000 runs of each model (about 21 hours each, and 70 hours for the truncated normal distribution model which had 100,000 runs), the conditions were not imposed but tested retrospectively.

Implicit cross products		
Ln(Grooved tiger)*ln(Brown tiger)	-0.003	0.001
Ln(Grooved tiger)*ln(Endeavour)	0.003	0.001
Ln(Grooved tiger)*ln(Other)	-0.009	0.001
Implicit input cross products		
Ln(Grooved tiger)*ln(Hours fished)	-0.045	0.006
Ln(Grooved tiger)*ln(Engine power)	-0.089	0.014
Ln(Grooved tiger)*ln(Headrope)	0.089	0.017

a) Values were estimated from 1,000 random draws from the distributions of the appropriate β parameters.

3.6.2 Elasticities of substitution

The primary objective of the study was to determine the degree of targeting ability of fishers. The derived output elasticities of substitution were estimated at the data means (i.e. $\ln(\bar{y}) = \ln(\bar{x}) = 0$) and estimates of β drawn from their probability distribution (Table 3.5), with positive values indicating complementarily (i.e. join production) and negative values indicating substitutability (i.e. targeting).

The columns in Table 3.5 represent the "target" species, while the rows represent the bycatch or "substitute" species. The greatest potential for substitution appeared to be between endeavour and brown tiger prawns. Given that brown tiger prawn catches peak at the start of the season while endeavour prawn catches tend to peak at the end of the season, such a result is not surprising. In general, endeavour prawns appear to have the greatest (although still slight) degree of targeting ability, although this is also expected to be opportunistic. Endeavour prawns attract a similar price to banana prawns, which is about half the price of tiger prawns. As a result, the incentive to target endeavour prawns is low, and it is likely that apparent targeting represents unexpected larger catches of endeavour prawns which fishers continue to exploit rather than search elsewhere for tiger prawns.[13]

[13] Distributions around these mean MES values were not estimated.

Table 3.5. Mean MES elasticities of substitution at the mean input and output levels[a]

	Tiger prawns		Endeavour	
	Grooved	Brown	prawns	Other
Grooved		-0.354	-0.541	-0.374
		(0.006)	(0.010)	(0.026)
Brown	0.048		-0.689	-0.428
	(0.013)		(0.012)	(0.026)
Endeavour	0.028	-0.576		-0.434
	(0.013)	(0.007)		(0.026)
Other	0.207	-0.558	-0.701	
	(0.026)	(0.017)	(0.020)	

a) Values were estimated from 1,000 random draws from the distributions of the appropriate β parameters. Figures in parentheses are the estimated standard deviations

The asymmetry in the elasticities of substitution between the two tiger prawn species suggests that catches of predominantly brown tigers can be taken with relatively low levels of bycatch of grooved tiger, but catches of predominantly grooved tigers will generally include brown tiger prawns. This is generally consistent with the catch compositions illustrated in Figure 3.2 that appear to indicate some degree of targeting of brown tiger prawns early in the season.

For the “other” species, these do not necessarily appear in the catches of the main three species, but these main species will generally appear in catches dominated by “other” species. As with endeavour prawns, large catches of “other” species is most likely opportunistic as the prices are low relative to the tiger prawn species.

The MES estimates in Table 3.5 are at the mean levels of partial exploitation rate and inputs. Output is dominated by different species in different weeks (Figure 3.2). The MES for the two tiger prawn species were estimated for each week of the tiger prawn season over the last three years of the data (2005-2007) assuming average input levels (i.e. $\ln(\bar{x}) = 0$) (Figure 3.3). For most of the season, a substitution relationship appears to exist between brown and grooved tiger prawns, suggesting an ability to target brown tigers and avoid grooved tigers to some extent. This relationship, however, is still relatively weak, and a complimentary relationship may exist at the very start of the season. In contrast, there is little relationship between the partial exploitation rates for grooved tiger prawn and those for brown tigers. This suggests that the ability to target grooved tigers and exclude brown tigers is limited, with catches of grooved tigers sometimes including bycatch of brown tigers and other times not within the same period. These results are consistent with the results at the mean.

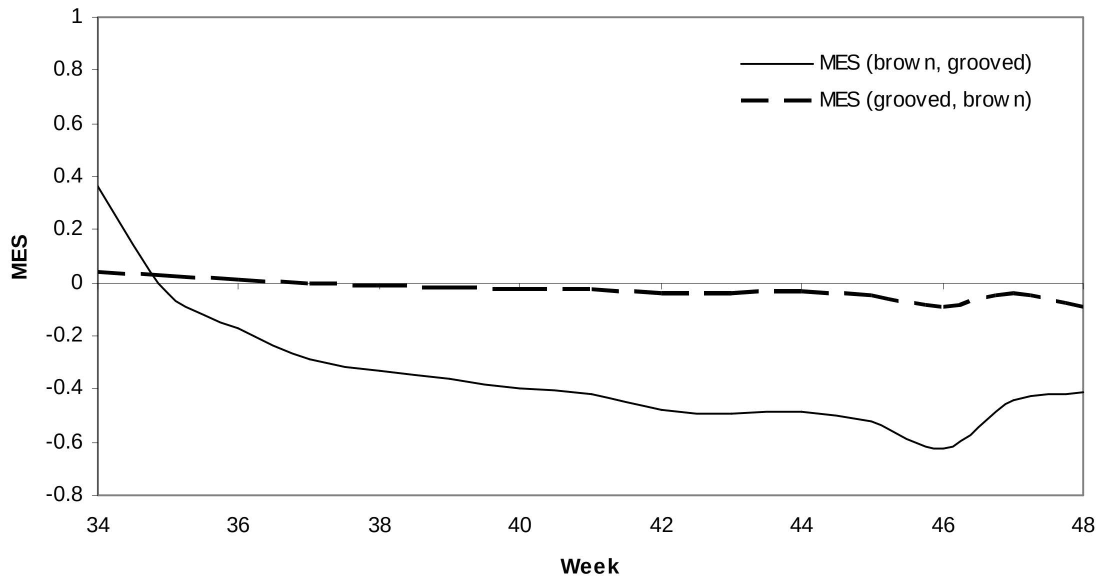

Figure 3.3. Average MES by week over the tiger prawn season, 2005-07.

3.7 Discussion

3.7.1 Output distance functions and fisher incentives

While the focus of this paper has been on assessing targeting behaviour in anticipation of a move to ITQ controls, the use of an output distance function is unlikely to be valid if ITQs were already in place. Under input controls, fishers face incentives to maximise outputs given their level of inputs, so an output oriented function is likely to be appropriate. However, if ITQs was already in place, fishers would have an incentive to take their quota with minimum input use, and hence an input distance function may be appropriate. Profit functions may be more appropriate still as these will account also for the potential to change inputs that are quasi-fixed in the short term, and also adjust their output mix (if possible) because fishers also have an incentive to adjust their entire input and output mix to maximise profits under ITQs. Catch and effort data under an ITQ system may also be compromised, as incidental overquota catch is likely to be discarded, so landing records may not represent actual catch mixes, and estimates of targeting ability based on these data may be distorted.

Prices for the two tiger prawn species are identical as they are not distinguished on the market, nor sold separately. As a result, there was no price-induced incentive to target one species or the other. With species-specific TACs and hence individual quotas, the incentive structure will change, and incentives could be generated to target individual species if possible. However, an ability to target due to location would still be apparent in the data even if incentives to target do not exist (as catch compositions would vary) because the fleet is widely dispersed over the area of the tiger fishery. As noted in the results based on observed behaviour, for much of the season the ability to target grooved tiger prawns and exclude brown tiger prawns (and other prawn species) is negligible.

3.7.2 Targeting ability a necessary but not sufficient requirement for separate quotas?

The purpose of the analysis was to determine the ability of fishers to target individual species based on observed behaviour. Being able to target individual species is a necessary, but not sufficient, condition for targeting to take place. Targeting behaviour will also depend on the set of incentives facing the operator. These largely relate to the relative profitability of each targeting activity, which in turn will depend on the price of the species caught, the relative stock abundance and the costs of fishing. When setting TACs for individual species in an output-controlled fishery, both the ability to target and the incentives to target need to be considered simultaneously.

For the northern prawn fishery, the critical questions for TAC setting involve whether or not to set separate TACs for the two tiger prawn species, endeavours, bananas and other prawns, and whether it is practical in terms of identifying different species. From the model results, endeavour prawns are generally targetable, but it is likely that “target” catches of endeavours are largely opportunistic. Catches of endeavour prawns exceeded tiger prawns in only 2 per cent of the observations. This small proportion of relatively “clean” catch is the most likely explanation for the greater (but still small) elasticity of substitutability between endeavour and tiger prawns in Table 3.5. Given that prices for endeavour prawns are roughly half those for tiger prawns, fishers are unlikely to target endeavours in preference to tigers, but may seek endeavour prawns if tiger prawn quota is limited or exhausted. Similarly, “targeted” catches of banana prawns are likely to be purely opportunistic (if not accidental) during the tiger prawn season. Banana prawn prices are similar to those for endeavour prawns. It is worth landing banana prawns if caught, but generally not worth actively seeking banana prawns during the tiger prawn season.

Tiger prawns dominate the fishery in terms of both value and quantity of catch. Hence, if any species are likely to be able to be subjected to TACs, then it is most likely to be the tiger prawns. For the two tiger prawn species, the lack of a strong substitution or complementary relationship creates difficulties if TACs are set for each tiger prawn species separately. Brown tiger prawn catches can only be limited by limiting fishing activities in the weeks that they dominate the catch. If the TAC for brown tiger prawns is filled at the start of the season, any over-quota catch of brown tiger prawns taken later in the season (when grooved tiger prawns dominate) will most likely be discarded. This may potentially be a problem for brown tiger prawns as these are currently believed to be more vulnerable to overexploitation. Setting a conservative TAC for brown tiger prawns to enable stock recovery would require a similarly conservative TAC for grooved tiger prawns despite the negative elasticity of substitution.

Setting separate TACs for the two tiger prawn species may create a number of practical difficulties. These species are not readily differentiable by fishers. In addition, both attract the same market price, so there is no incentive to differentiate the species. Sorting the species in the catch would be difficult and add additional costs to the fishing operation in terms of forgone fishing time. The potential for mislabelling of product – deliberate or unintentional – would be high.

As there is a seasonal element to the catch (Figure 3.2), the continued use of seasonal closures combined with a single TAC for the two tiger prawn species may remain the most appropriate means of limiting tiger prawn catches. In multispecies fisheries where several species are caught jointly, no single management measure is likely to be successful in achieving the optimal yield for all species (Sutinen, 1999).

Introducing ITQs into the fishery will change the set of incentives facing fishers, and hence may change their targeting behaviour. Evidence of changed targeting behaviour following the introduction of ITQs has been observed in other fisheries (e.g. Branch and Hilborn, 2008). Based on past behaviour, relatively little white banana and endeavour prawn catch is taken other than as bycatch of tiger prawns during the tiger prawn season. This appears to be more opportunistic harvesting than pre-meditated targeting. Given the low prices of these species relative to tiger prawns and the high costs of fishing, it is unlikely that these species will be substantially targeted even if the incentive structures change in the fishery. A single TAC for tiger prawns will be more readily enforceable that separate TACs for the separate tiger prawn species. This may need to be combined with seasonal closures as indicated above to ensure brown tiger prawns are not overexploited. This will reduce the efficiency gains that may be achieved under a pure ITQ program, but the additional costs involved with a pure ITQ system is not likely to be offset by the additional benefits.

3.8 Conclusions

Despite its obvious relevance to fisheries management, output substitutability as an indicator of fishers' ability to alter their output mix based on historic data is rarely examined. The multi-output distance function approach offers considerable advantages over dual profit and cost functions as catch and effort data are generally more readily available than economic data. Perceived endogeneity problems attributed to distance functions can be overcome using Bayesian estimation techniques, and reliable estimates of output substitution can be derived. While this study is not the first to estimate multi-output distance functions in fisheries, nor the first to estimate multi-output distance functions using Bayesian techniques, it is the first to use these techniques for tactical fisheries management decision making. The analysis demonstrates that consideration needs to be given not just to the technical ability of fishers to adjust their output mix, but the set of incentives they face and the impact these will have on fishers' targeting behaviour.

3.9 Acknowledgements

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3.10 References

ABARE. (2009). Australian Fisheries Statistics 2008, Canberra: ABARE.

Atkinson, S.W., Cornwell, C. and Honerkamp, O. (2003). Measuring and decomposing productivity change: stochastic distance function estimation versus data envelopment analysis, *Journal of Business and Economic Statistics* 84: 284-294.

Battese, G. E. and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20: 325-332.

Blackorby, C. and Russell, R. R. (1981). The Morishima Elasticity of Substitution; Symmetry, Constancy, Separability, and Its Relationship to the Hicks and Allen Elasticities. *Review of Economic Studies* 48(1): 147-58.

Blackorby, C. and Russell, R.R. (1989). Will the real elasticity of substitution please stand pp? (A comparison of the Allen/Uzawa and Morishima Elasticities), *American Economic Review* 79 882-888.

Branch, T. A. and Hilborn, R. (2008). Matching catches to quotas in a multispecies trawl fishery: targeting and avoidance behavior under individual transferable quotas. *Canadian Journal of Fisheries and Aquatic Sciences* 65(7): 1435-1446.

Campbell, H. F. and Nicholl, R. B. (1994). Can purse seiners target yellowfin tuna? *Land Economics* 70(3): 345-353.

Coelli, T.J. and Perelman, S. (2000). Technical Efficiency of European Railways: A Distance Function Approach. *Applied Economics* 32(15): 1967-76.

Dichmont, C. M., Punt, A. E., Deng, A., Dell, Q. and Venables, W. (2003). Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery. *Fisheries Research* 65: 335-350.

Färe, R., Grosskopf, S., Noh, D.-W. and Weber, W. (2005). Characteristics of a polluting technology: theory and practice, *Journal of Econometrics* 126: 469-492.

Felthoven, R.G. and Morrison Paul, C.J. (2004). Multi-Output, Nonfrontier Primal Measures of Capacity and Capacity Utilization, *American Journal of Agricultural Economics* 86: 619-633.

Fernández, C., Koop, G. and Steel, M. (2000). A Bayesian analysis of multiple-output production frontiers, *Journal of Econometrics* 98: 47-79.

Fousekis, P. (2002). Distance vs. ray functions: an application to the inshore fishery of Greece, *Marine Resource Economics* 17: 251–267.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. in Bernardo, J., Berger, J., Dawid, A.P. and Smith, A.F.M. (eds.), *Bayesian Statistics 4*. Oxford, UK: Oxford University Press, pp 169-193.

Griffin, J. and Steel, M. (2007). Bayesian stochastic frontier analysis using WinBUGS, *Journal of Productivity Analysis* 27: 163-176.

Grosskopf, S., Margaritis, D. and Valdmanis, V. (1995). Estimating output substitutability of hospital services: A distance function approach. *European Journal of Operations Research* 80: 575-587.

Huang, H. and Leung, P. (2007). Modeling protected species as an undesirable output: The case of sea turtle interactions in Hawaii's longline fishery, *Journal of Environmental Management* 84: 523-533.

Kirkley, J. E. and Strand, I. E. (1988). The technology and management of multi-species fisheries. *Applied Economics* 20(10): 1279 - 1292.

Kohli, U. R. (1981). Nonjointness and Factor Intensity in U.S. Production. *International Economic Review* 22(1): 3-18.

Kohli, U. (1983). Non-Joint Technologies. *Review of Economic Studies* 50(1): 209-19.

Koundouri, P., Laukkanen, M., Myyra, S. and Nauges, C. (2009). The effects of EU agricultural policy changes on farmers' risk attitudes, *European Review of Agricultural Economics* 36: 53-77.

Koundouri, P. and Nauges, C. (2005). On production function estimation with selectivity and risk considerations, *Journal ofAgricultura1 and Resource Economics* 30: 597-608.

Kumbhakar, S.C. and Lovell, C.A.K. (2000). *Stochastic frontier analysis.* Cambridge, UK: Cambridge University Press,

Lau, L. J. (1978). Applications of profit functions. In Fuss, M. and McFadden, D. (eds.) *Production Economics: A Dual Approach to Theory and Applications. Volume I: The Theory of Production*. Amsterdam: North-Holland, 133-216.

Lee, M. (2005). The shadow price of substitutable sulfur in the US electric power plant: A distance function approach, *Journal of Environmental Management* 77: 104-110.

Lence, S.H. (2009). Joint estimation of risk preferences and technology: flexible utility or futility?, *American Journal of Agricultural Economics* 91: 581-598.

Livernois, J. R. and Ryan, D. L. (1989). Testing for Non-jointness in Oil and Gas Exploration: A Variable Profit Function Approach. *International Economic Review* 30(2): 479-504.

Morrison Paul, C .J., Johnston, W. E. and Frengley G. A. G. (2000). Efficiency in New Zealand Sheep and Beef Farming: The Impacts of Regulatory Reform. *Review of Economics and Statististics* 82(May):325-37.

Morrison Paul, C.J. and Nehring, R. (2005). Product diversification, production systems, and economic performance in U.S. agricultural production, *Journal of Econometrics* 126: 525-548.

O'Donnell, C.J. (2007). Estimating Output Distance Functions, *Australasian Meeting of the Econometric Society*, Brisbane, 3-6 July.

O'Donnell, C.J. and Coelli, T.J. (2005). A Bayesian approach to imposing curvature on distance functions, *Journal of Econometrics* 126: 493-523.

Orea, L., Alvarez, A. and Morrison Paul, C.J. (2005). Modeling and Measuring Production Processes for a Multi-species Fishery: Alternative Technical Efficiency Estimates for the Northern Spain Hake Fishery, *Natural Resource Modeling* 18: 183-213.

Pascoe, S. and Coglan, L. (2002). Contribution of unmeasurable factors to the efficiency of fishing vessels: an analysis of technical efficiency of fishing vessels in the English Channel. *American Journal of Agricultural Economics* 84(3): 45-57.

Pascoe, S., Koundouri, P. and Bjorndal, T. (2007). Estimating targeting ability in multi-species fisheries: a primal multi-output distance function approach. *Land Economics* 83(3): 382-397.

Rijnsdorp, A.D., Daan, N. and Dekker, W. (2006). Partial fishing mortality per fishing trip: a useful indicator of effective fishing effort in mixed demersal fisheries. *ICES Journal of Marine Science* 63: 556-566.

Sauer, J., Frohberg, K. and Hockman, H. (2006). Stochastic efficiency measurement: the curse of theoretical consistency. *Journal of Applied Economics* 9(1): 139-165.

Salini, J., Brewer, D., Farmer, M. and Jones, P. (2001). Lunar periodicity of prawns and by-catch in trawls from the Gulf of Carpentaria, northern Australia. *Marine Biology* 138: 975-983.

Sanchirico, J.N., Holland, D., Quigley, K. and Fina, M. (2006). Catch-quota balancing in multispecies individual fishing quotas. *Marine Policy* 30: 767-785.

Shephard, R.W. (1970). *Theory of Cost and Production Functions*. Princeton: Princeton University Press.

Squires, D. (1987). Public regulation and the structure of production in multiproduct industries: and application to the New England otter trawl industry. *Rand Journal of Economics* 18(2): 232-47.

Squires, D., Campbell, H., Cunningham, S., Dewees, C., Grafton, R.Q., Herricks Jr., S.F., Kirkley, J., Pascoe, S., Salvanes, K., Shallard, B., Turris B. and Vestergaard, N. (1998). Individual transferable quotas in multispecies fisheries. *Marine Policy* 22(2): 135-60

Sutinen, J.G. (1999). What works well and why: evidence from fishery-management experiences in OECD countries. *ICES Journal of Marine Science* 56: 1051-1058.

Venables, W.N. and Dichmont, C.M. (2004). A generalised linear model for catch allocation: an example from Australia's Northern Prawn Fishery. *Fisheries Research* 70(2-3): 405-422.

Vieira, S. and Hohnen, L. (2007). Australian Fisheries Surveys Report 2007: Results for Selected Fisheries, 2004-05 and 2005-06, *ABARE Report Prepared for the Fisheries Resources Research Fund*. ABARE, Canberra.

APPENDIX 4. UPDATED SPECIES DISTRIBUTION DATA AND MODELS

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4.1 Introduction

Both the tiger and endeavour prawn catches in the NPF are mixtures of two biological species. The tiger prawns are composed of 'Brown' tiger prawns, *Penaeus esculentus* and 'Grooved' tiger prawns, *P. semusulcatus*. Endeavour prawns are composed of 'Blue' endeavour prawns, *Metapenaeus endeavouri* and 'Red' endeavour prawns, *M. ensis*. The assessments are for each component species separately. This leads to the need for a procedure to partition the total catch weight into component species. Devising such a method is known as the 'species split' problem.

4.1.1 Background

In 2001 a risk analysis of the NPF, (Dichmont, Die *et al.* 2001), had shown that the static species split model then in use for the tiger prawn assessment could be much improved by using a parametric statistical model that was dynamic in the sense that it took account of regular temporal changes over the year. It also raised the possibility that there had been a shift in species proportions that had become quite volatile in the (then) recent seasons, but it was impossible to establish if this was a real phenomenon or if it was an artefact of sparse and irregular sampling.

This led to the AFMA Species Distribution project, (Venables, Kenyon *et al.* 2006), which reported in January 2006. Its main results and recommendations included the following:

1. It refined the statistical technology used to build the species distribution models and calibrated them with new data. The models use only six predictor variables, but very non-linearly and with interactions. These were *Latitude*, *Longitude*, *Distance from dry land*, *Depth*, *Percent mud* and *Day of the year*. The first five of these were measured at the 6 minute grid square scale, the same spatial scale as is used by the logbook records.
2. It used extra data which came from the NPF monitoring surveys as an out-of-season component, and from the data acquisition arm of the project itself which came from in-season sampling. With this extra data and new technology it revised the species split model for tiger prawns in important ways, but keeping the same fundamental philosophy. It also gave some support to the possibility that the apparent long-term fluctuations shown in the

Risk report were probably mostly due to irregular and sporadic sampling rather than to a serious shift in population proportions.

3. It showed that endeavour prawns could also be split into the two component species using essentially identical statistical models to those recommended for use with tiger prawns. The endeavour prawn data available for calibrating these models, however, was somewhat lacking in recent years and it recommended that some effort be given to collecting more data. This was becoming available from the NPF monitoring surveys in any case but as the models are not static in time, additional data from within the season was also needed. Prior to this no endeavour species split model had been produced.
4. The issue of a long-term trend in tiger prawn proportions could not be fully resolved, however, and the project recommended that some additional data be collected periodically and used to check the continuing reliability of the species split models.

The present study is one such follow-up from the species distribution project.

4.1.2 Aims of the present study

This component of the TAC project has the following informal objectives:

1. To design a sampling scheme and collect additional in-season data with particular focus on endeavour prawn species.
2. To revise the historical data sets and incorporate all new data into a consolidated data set.
3. To recalibrate the tiger and endeavour species split models with the consolidated data set and provide them for use in tiger and endeavour assessments for the NPF.
4. To examine the stability of the models and recommend on future precautionary sampling that may be needed to monitor the stability of the species proportions.

4.2 Data sets

Twelve studies were used to contribute data to this consolidated data set, the same as were used in the Species Distribution project. Each is now identified by a 2-letter code, which are listed in Table 4.1 in Addendum 2. Figure 4.10, Table 4.2 and Table 4.3, also in Addendum 2, give some idea of the relative contribution of the studies in terms of shots, as well as the spatial and temporal coverage of each. Finally, Figure 4.11 (Addendum 2) illustrates the relative sampling intensity by tiger stock region.

Several features of this record should be noted.

1. The data which has been collected since 2004 is new to this study. The NPF Monitoring project has contributed much of this, but all out of season and only in the Gulf of Carpentaria.
2. The present TAC Species Split component collected in season data. Endeavour prawns were a priority, and some effort was made to collect data outside the Gulf of Carpentaria, where sampling has been very sparse and sporadic. Gathering samples outside the Gulf was only

partly successful, however, and may need further sampling if this becomes a key region in future.

4.3 Catch allocation models

4.3.1 Predictors and response

The methodology we use for partitioning catch biomasses into the component species parallels directly that described in full in Chapter 9 of (Venables, Kenyon *et al.* 2006). In particular we build generalized linear models for catch allocation using the following predictors:

1. Location, specified by **`Longitude`** and **`Latitude.`**
2. Spatially static predictors: distance from land, (**`Rland`**), depth, (**`Depth_av`**), and average percent mud in the sediment, (**`Mud_av`**),
3. A temporal variable: time of year (**`PDay`**) for periodic variations within the year,
4. The elapsed number of days since 1970-01-01, (**`Day`**), for a long-term trend.

The spatially static variables are measured at the 6-minute grid cell level, which matches the spatial scale of measurement used by the logbook records themselves.

The response, that is the quantity for which we will construct models, as in the previous study is

a) The proportion of grooved tiger prawns, *P. semisulcatus*, in the total catch, and

b) The proportion of red endeavour prawns, *M. ensis*, in the total endeavour catch.

Since there is only two species in each group, once the proportion of one is known, the proportion of the other is the complementary fraction.

4.3.2 Model form and construction

Again we follow the methods used in (Venables, Kenyon *et al*. 2006), for reasons presented there. We use generalized additive models fitted by the methods described in (Wood 2006) and implemented in his **`mgcv`** package for the R software environment.

Model construction was described in detail in the earlier report. The final model chosen, which remains our present choice for the working catch allocation model, has a quasi-binomial family, with logistic link and a linear predictor containing the following terms:

- An *isotropic* term in location, written as **`s(Longitude, Latitude)`**,
- A tensor spline term in time of year and distance from dry land, written as **`te(PDay, Rland),`** *constrained to be periodic in time of year,*
- A tensor spline term in time of year and depth, written as **`te(PDay, Depth_av)`**, *constrained to be periodic in time of year,*
- A smooth term in percent mud, written as **`s(Mud_av)`**,

- For non-stationary models, a smooth term in elapsed time, written as **`s(Day)`**.

One innovation we have used with this study is the periodic constraint placed on the time of year variable in the tensor spline terms. This ensures that the model achieves a continuous smooth transition between 31 December of one year and 1 January of the next, as seems natural. This was not quite achieved in previous models, but as no commercial fishing occurs in the end of year period, so the change makes little difference to catch allocation.

The same model form is used for both tiger and endeavour prawns, and the model performance checks do not differ greatly from those shown in the pervious report.

It is important to note that the form of the model fitted to the catch proportions is quasi-binomial with a logistic link. Since this is a quasi-likelihood model, the usual methods for model selection which rely on likelihood comparisons, such as the use of AIC, are not available. Some approximate significance tests are available, but with such large samples the value of such tests is limited. All terms appear to show very high significances.

4.3.3 Long-term stability

The non-stationary model was fitted as a check on the long-term stability of the species proportions. Plots of these components are shown in Figure 4.1 and Figure 4.2 below. While these show some apparent instability, the component is measured in the logistic scale, and in this scale the absolute variation should not be considered great.[14]

[14] In both endeavour and tiger prawns, the additional data even since the report made to the RAG in April 2008 shows a slight downturn in the deviation of the long-term trend, i.e. if there is a movement it appears to be towards stability. This is a very weak.

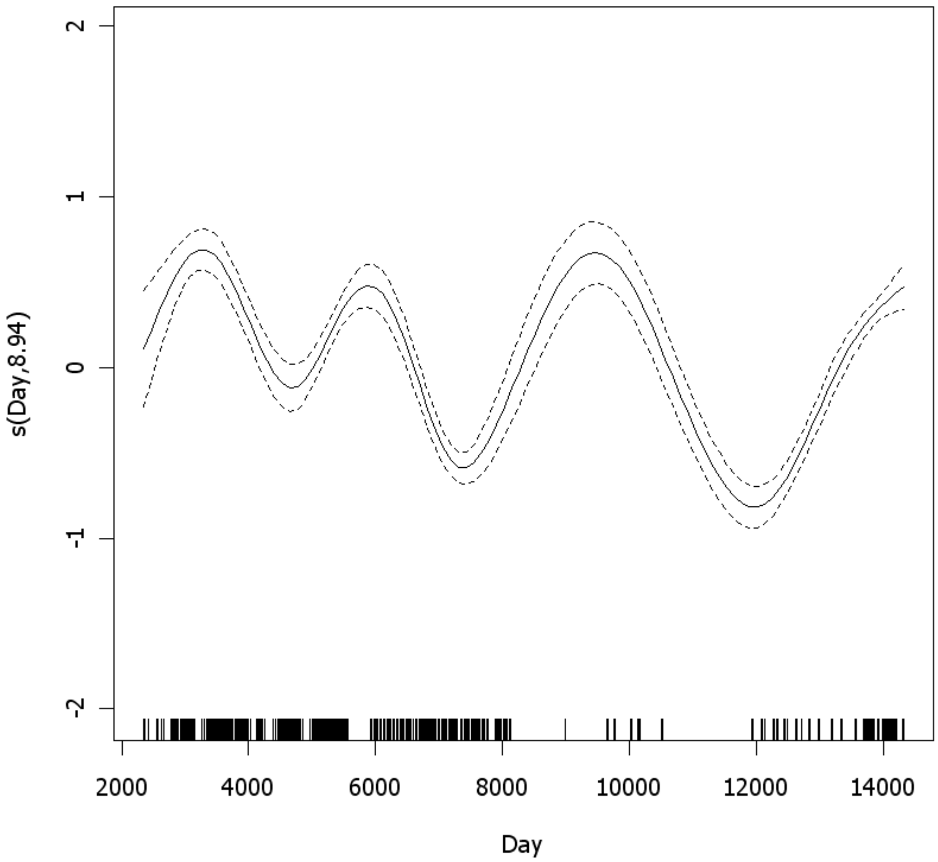


Figure 4.1: Long-term trend component for endeavour prawn species composition. The fine hairs at the bottom of the diagram indicate the times when sampling was conducted.

These terms are significant in the statistical sense, as will often be the case with very large samples as we have here, but in practical terms their effect on catch allocation is small. In the working catch allocation models we therefore use the stationary model 3 above. There are two practical reasons for this. Since sampling only started in 1976, there is no way to use a non-stationary model for catch allocation prior to that time or into the future. Secondly, the sporadic nature of the sampling in time will mean that this component will not be very stably estimated, anyway. This is somewhat confirmed by the apparently irregularities in the curves are linked with sampling times.

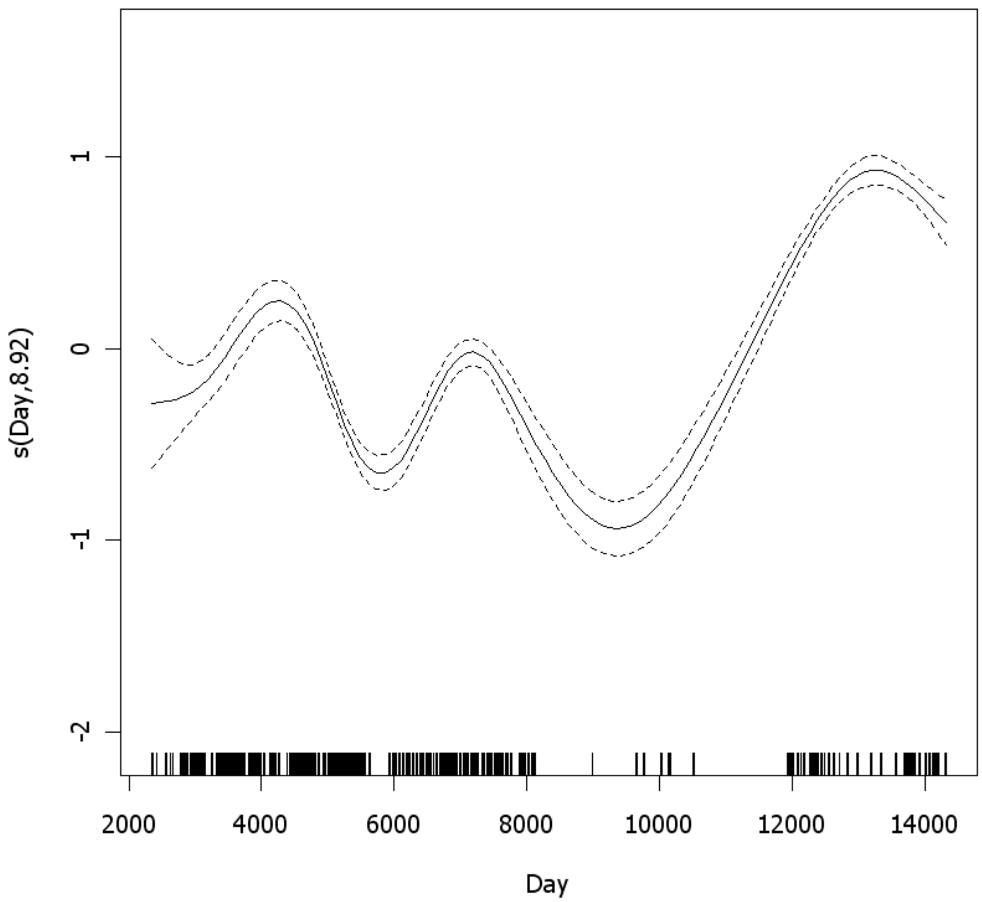


Figure 4.2: Long-term trend component for tiger prawn species composition. The fine hairs at the bottom of the diagram indicate the times when sampling was conducted.

The rising proportion of *P. semisulcatus* in recent times, though not great, seems very consistent with, and persistent from, the two precious studies. This is not surprising, but the possibility of an overall decrease in the brown tiger proportion of the total tiger prawn catch will need to be monitored into the future, at some level of sampling.

4.3.4 Stable components of the models

For completeness we show here graphical representations of the four stationary components of what we have called Model 3 in the above discussion. These are difficult to interpret, but are shown here for comparison with previous studies, with which they appear to be entirely comparable. Figure 4.3 shows the additive components for tiger prawns and Figure 4.5 for endeavour prawns. The two dimensional terms are shown as contour diagrams. For the periodic terms perspective diagrams are given below the main plots in Figure 4.4 and Figure 4.6, for tiger and endeavour prawns respectively.

The **`s(Mud_av)`** component for tiger prawns shows fairly clearly a rising proportion of *P. semisulcatus* with rising percent mud, and hence a fairly strong link with the underlying sediment. This has been know for some time and was used in a major way in the first tiger species split model of Somers. This is not so evident for endeavour prawns, but there is a suggestion of it, particularly for very high percent mud regions.

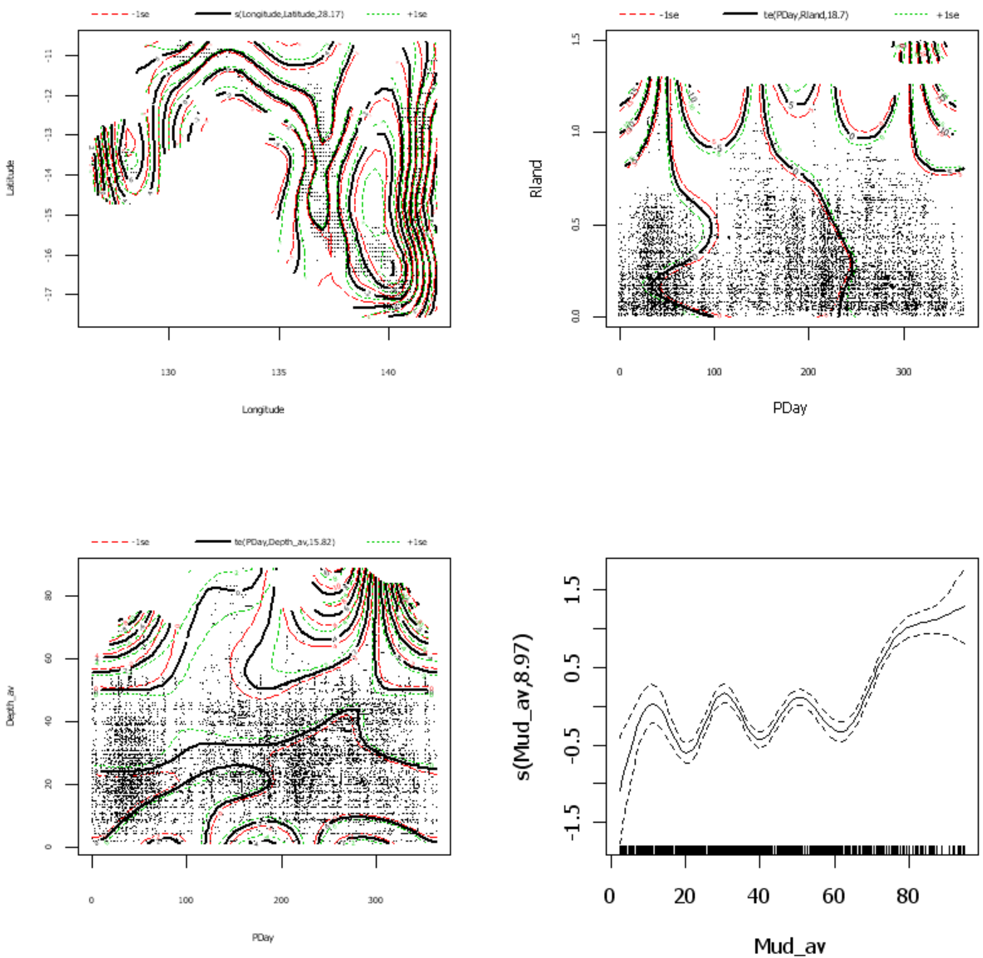


Figure 4.3: Additive components for the endeavour prawn catch allocation model.

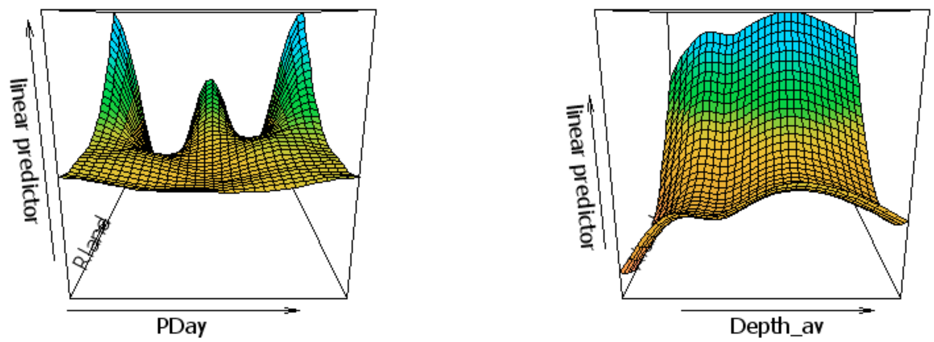


Figure 4.4: Perspective diagrams of the periodic components in the endeavour model.

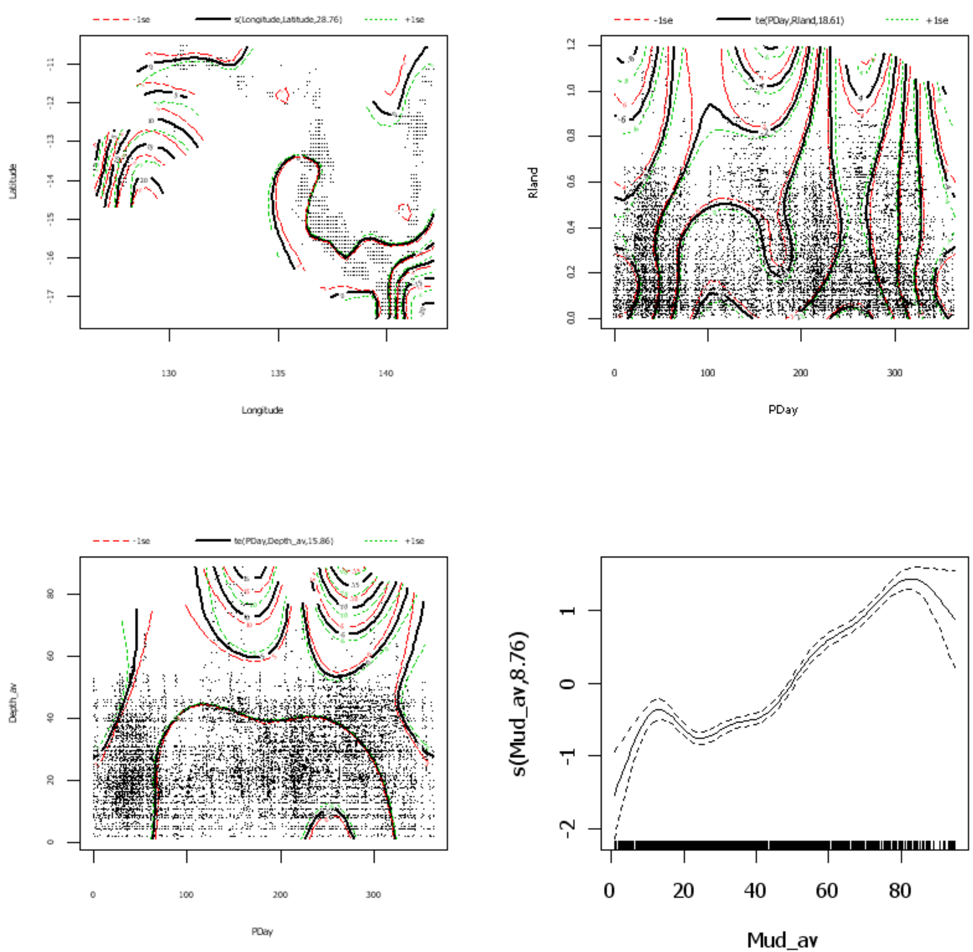


Figure 4.5: Additive components for the tiger prawn catch allocation model**.**

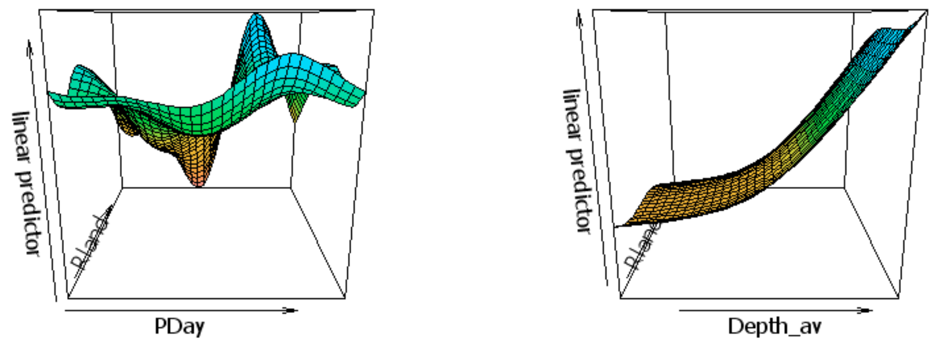


Figure 4.6: Perspective diagrams of the periodic components in the tiger prawn model.

4.4 Effect on catch allocation processes

The updates to the data sets, critical revisions to the historical data sets and the minor modelling changes will have some effect on the outcomes of catch allocation procedures. We propose to gain some insight on the extent and practical consequences of these changes by looking at weighted differences in proportions, old – new, where the weights are determined by the actual catches made in the logbook record. In detail our method is as follows:

1. For the years 1970-2004, estimate the species proportions for each location and date recorded in the logbooks using old and new models, and the difference in proportions, (Species Distribution project, 2006) – (TAC Project, current).
2. Calculated weighted difference for each tiger stock region separately for each year, where the weights are the actual tiger catches for that year and region.
3. Perform the same calculations for the endeavour prawn species using the endeavour prawn estimated proportions, SD - TAC, and similar aggegate endeavour prawn catch as the weights.

In symbols, these weighted differences of proportions will be

$$\delta_{yr} = \frac{\sum_i w_{iyr}\left(\hat{p}_{iyr}^{\mathrm{SD}} - \hat{p}_{iyr}^{\mathrm{TAC}}\right)}{\sum_i w_{iyr}}$$

where y refers to the year, r to the stock region and i to the individual logbook record within the combination of year and stock region. Thus w_{iyr} is the tiger, (respectively endeavour), catch for logbook record i in year y and stock region r.

This procedure is designed to measure the average change between old and new models that pays attention to the spatial and temporal distribution of fishing effort and catch.

These quantities are shown in Addendum 3 in Table 4.4 and Table 4.5. The majority of these are very small, though there are a very few which are quite large. This is particularly the case in regions outside the Gulf of Carpentaria, where sampling has been rather sparse. It is not surprising that recent additions to the data in these areas can radically change our estimate of the species proportions as in the previous model the predictions were largely made by extrapolation from the experience within the Gulf and less on hard data from, for example, the JBG. This is true of both tiger and endeavour prawns.

What these tables do not show is the total catch for the years, seasons and regions for which the weighted averages have been computed. Rather than table these as well, we present this information graphically in Figure 4.7 and Figure 4.8 below. These plot the weighted changes against the total catch, in tonnes, for the year/season/region.

The strong message that both these plots send is that the volatile changes in estimated catch proportions overwhelmingly occur in times and places of low catches, and hence presumably low effort as well. This is somewhat reassuring, as it means that the effect on the assessment will be small, but if these areas attract higher effort and catch in the future, the present species allocation models may be unreliable in those cases.

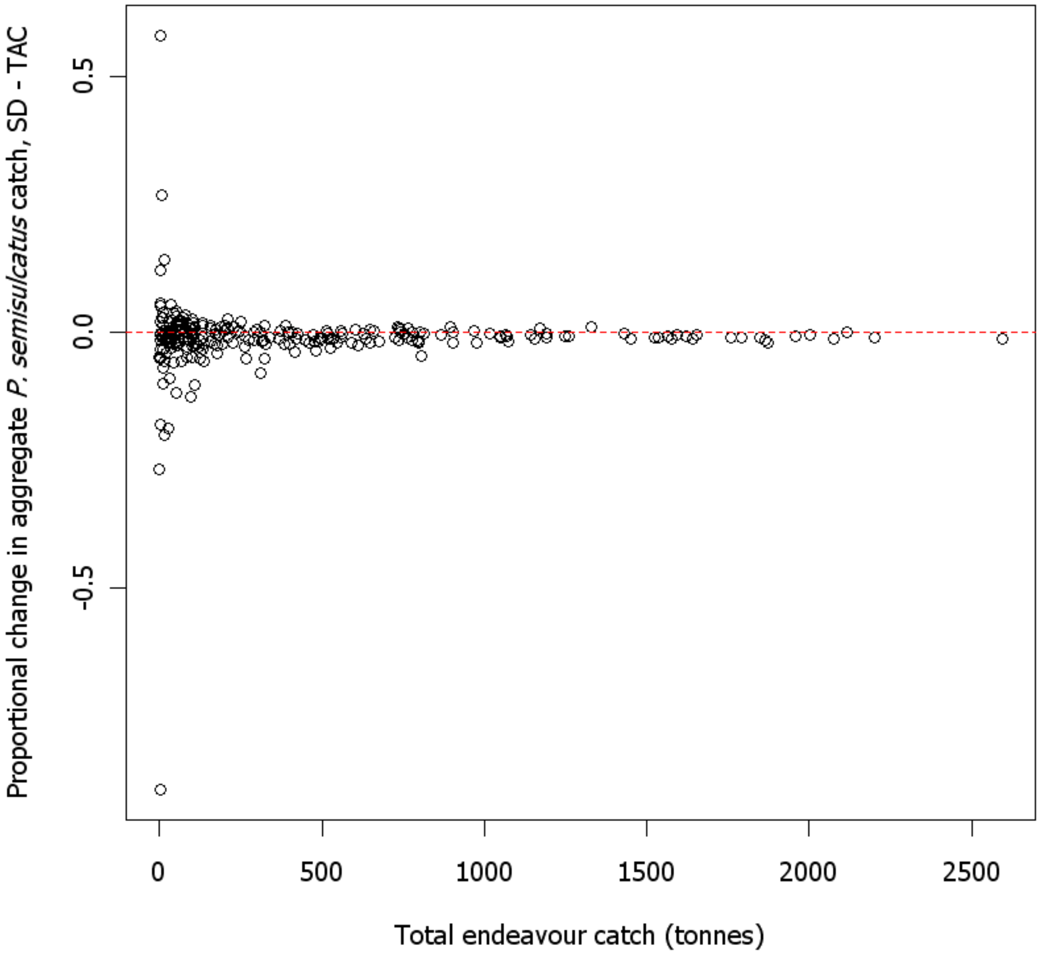


Figure 4.7: Weighted changes in tiger prawn catch proportions against total catch for a year, season and stock region.

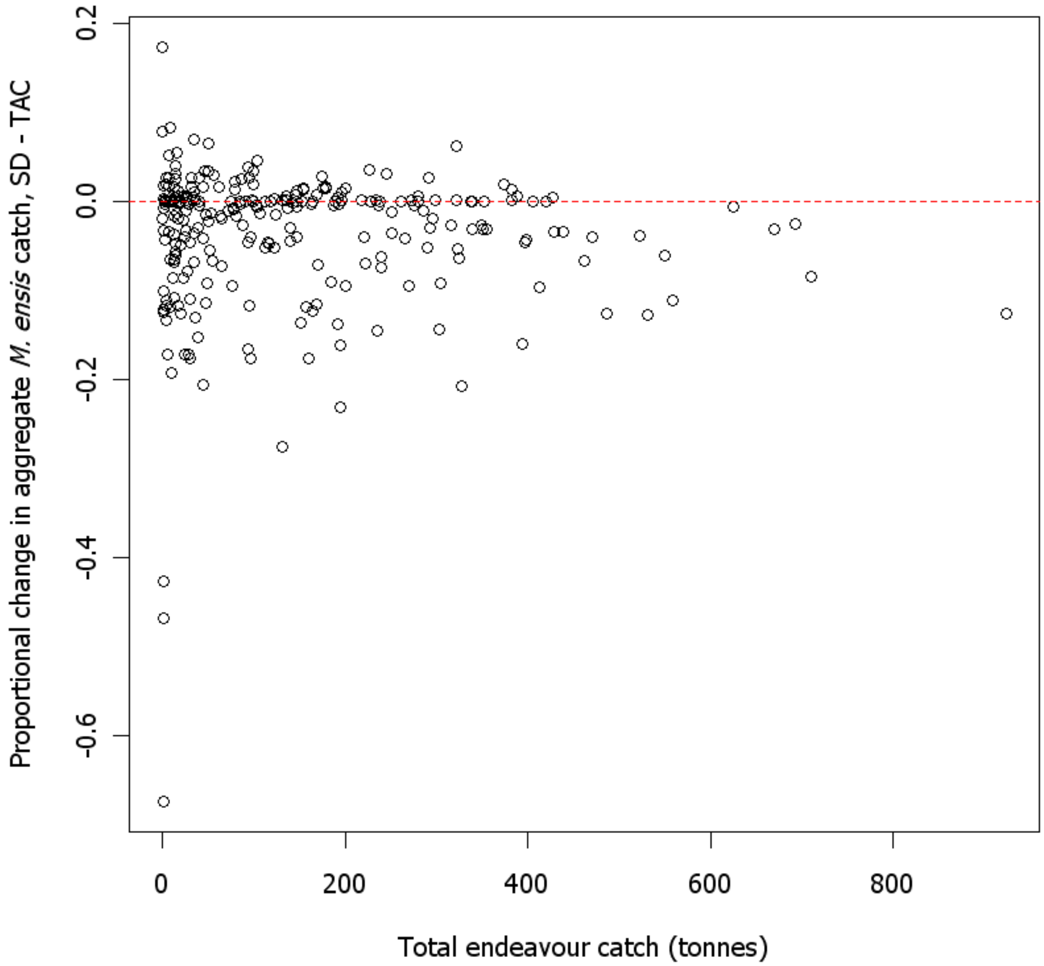


Figure 4.8: Changes in estimated *M. ensis* catch as a proportion of aggregate endeavour catch against aggregate catch for a year and stock region

4.5 Discussion

In the introduction we listed four informal objectives that this component of the TAC project had as its main foci. We now return to these and discuss progress and outcomes to date.

1. *To design a sampling scheme and collect additional in-season data with particular focus on endeavour prawn species.*

This has been effectively achieved, to the extent that the movement of volunteer contributing vessels allowed. A sampling scheme was devised making every effort to concentrate on spatial regions and species for which the historical data record was at best patchy. Some effort was made to secure some samples outside the Gulf of Carpentaria, as this is a region very different to the Gulf, where most sampling has occurred, and hence species split by extrapolation from the Gulf experience is likely to be unreliable. This has been shown to be the case, but as the tiger and endeavour prawn catches for these regions are still relatively small.

2. *To revise the historical data sets and incorporate all new data into a consolidated data set.*

This has also been effectively achieved. The historical data sets have been critically revised and the new data sets, from the present TAC project component and the NPF monitoring surveys have been incorporated. The additional data has been considerable, approximately 2000 shots, as shown by the italicised portion at the bottom of Table 4.3.

3. *To recalibrate the tiger and endeavour species split models with the consolidated data set and provide them for use in tiger and endeavour assessments for the NPF.*

After testing, we have decided to retain essentially the same overall methodology as that used in the Species Distribution report, (Venables, Kenyon *et al.* 2006), for the reasons extensively explored and justified in that report. We have made two minor changes, namely

a. The purely spatial term in Longitude and Latitude is now an isotropic term in both models. In the previous case the term was isotropic for endeavour prawns but a simpler tensor spline term for tiger prawns.

b. The tensor spline terms involving time of year are now constrained to be periodic, ensuring that the temporal influence is smooth across the end of year boundary.

Neither of these changes has had a great influence on the outcome, but from a statistical point of view they make the models more satisfactory and may well use the data a little more efficiently.

The additional data has had an influence on the catch allocation regions, but mainly in regions where actual catches, and hence efforts, have hitherto been low. As most of the in-season sampling also comes from fleet, this result is both reassuring and unsurprising, but it does indicate that the present models have a limited spatial and temporal range in which they can safely extrapolate.

4. *To examine the stability of the models and recommend on future precautionary sampling that may be needed to monitor the stability of the species proportions.*

Non-stationary models were fitted with the explicit aim of checking whether or not there was a long-term shift, or instability, in the overall species proportions for either species group. There is cogent that there are such overall shifts going on, as shown by the long-term components in Figure 4.1 and Figure 4.2, which are statistically very significant. However it is, in relative terms, not a very large effect and rather volatile, suggesting that the irregularity of sampling is affecting the estimates in some way. From a practical point of view there is no strong reason to go to a non-stationary model for catch allocation at the present time, but there is a need to continue with some level of in-season sampling into the future to monitor this more closely. This will become a critical need if fishing effort patterns change in the future, particularly if more tiger and endeavour prawn effort goes outside the Gulf of Carpentaria.

4.5.1 Continuing problems with endeavour prawn species split

Addendum 4 displays the distribution of aggregate catch by distance along the coastline and time of year, firstly in aggregate for the years 1970 – 2007, and then broken down by year. They show, (according to the species split model), that *M. ensis* is generally caught later in the year than *M. endeavouri*. Moreover *M. endeavouri* is largely caught in the southern and western Gulf of Carpentaria and *M. ensis* mainly in Weipa or outside the Gulf. Obtaining in-season data from the times and places where *M. ensis* has been found in the past has been difficult in recent years, in this project in particular, simply because the fleet is now small and largely avoids those regions at those times.

In the scientific survey data *M. endeavouri* is the overwhelmingly dominant species and *M. ensis*, when it occurs at all, only occurs in mixed species samples. The maximum proportion by weight for *M. ensis* in the scientific survey data is only about 0.34. This nevertheless seems to be enough to establish a fairly clear pattern, which is the basis for the species split model. In the historical data there are times and places where, according to this model, the *M. ensis* split proportion is much higher than this, from which we infer that the model is being used to extrapolate widely, and perhaps unsafely in some instances.

In 1997, and to some extent in 1982, there appear to be relatively large catches of *M. ensis* in the JBG and Weipa, late in the season. Since there is very little survey data, particularly recent survey data, that has polled these regions at those times, these apparently higher catches rely on extrapolation from the species split model that has to be considered potentially unsafe.

These considerations point to a continuing need for survey data that covers these critical times and places for *M. ensis*. The need for such data, and the effect of obtaining at least some more than was available in the Species Distribution project is clearly shown in Table 4.5, where essentially all estimates of *M. ensis* catch have been revised down from the Species Distribution model extrapolations. In regions inside the gulf the adjustments are both smaller and more evenly balanced with respect to direction.

As such servery data is going to be difficult to obtain from fleet samples in the near future, and as *M. ensis* is very clearly much less common than *M. endeavouri*, it may be some time before a credible assessment of *M. ensis* is feasible.

4.6 Addendum 1: Tiger prawn stock regions and effort

The following diagram shows the 7 stock regions used for both tiger and endeavour prawns, together with the effort coverage in recent seasons. The grey squares indicate individual 6-minute grids.

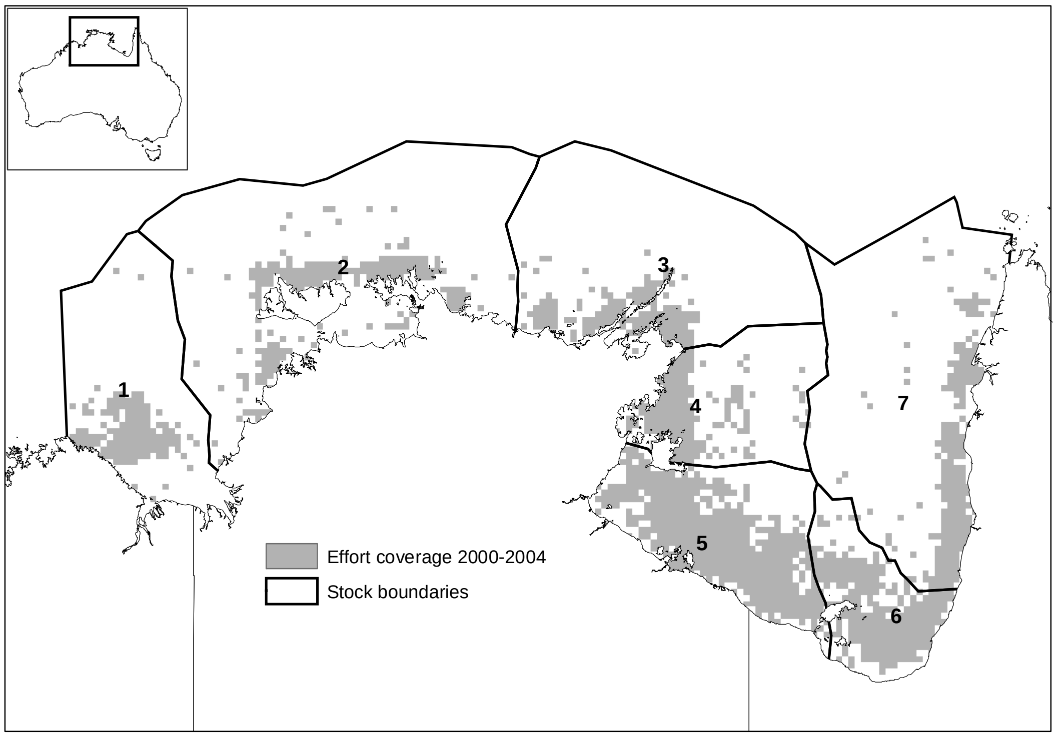


Figure 4.9: The Northern Prawn Fishery showing the 7 stock regions, 1 – JBG (JB), 2 – Coburg-Melville (CM), 3 – Arnhem (AM), 4 – Groote (GE), 5 – Vanderlins (VL), 6 – Karumba (KA), 7 – Weipa (WA), and recent overall effort patterns. (Figure kindly supplied by Roy Deng, CMAR.)

4.7 Addendum 2: Data sets used in the study

In this appendix we give some information on the spatial and temporal distribution of the shots which have been used in the analysis. The studies are identified by a 2-letter acronym, as shown in table 4.1. Table 4.2 and Table 4.3 show the studies, their start and end dates and the spatial distribution of the shots that they contribute to this study.

Table 4.1: Data sets used in this study, 2-letter codes, brief title and number of usable shots.

Code	Study	Shots
AB	Albatross Bay study	2011
BS	Bycatch Sustainability Study 1997	232
BT	Bycatch Sustainability Study 1998	193
CC	Commercial Catch Observer data	2088
CR	Try gear shots (Carolyn Robins)	192
DV	Try gear shots (Dave Vance)	1276
MX	Maxim cruises	1737
NM	NPF Monitoring surveys	3974
RF	Redfield cruises	1604
SD	Species Distribution project	763
TE	Closures Study data (Rik Bukworth)	261
WG	Western Gulf of Carpentaria Study (Rik Bukworth)	411

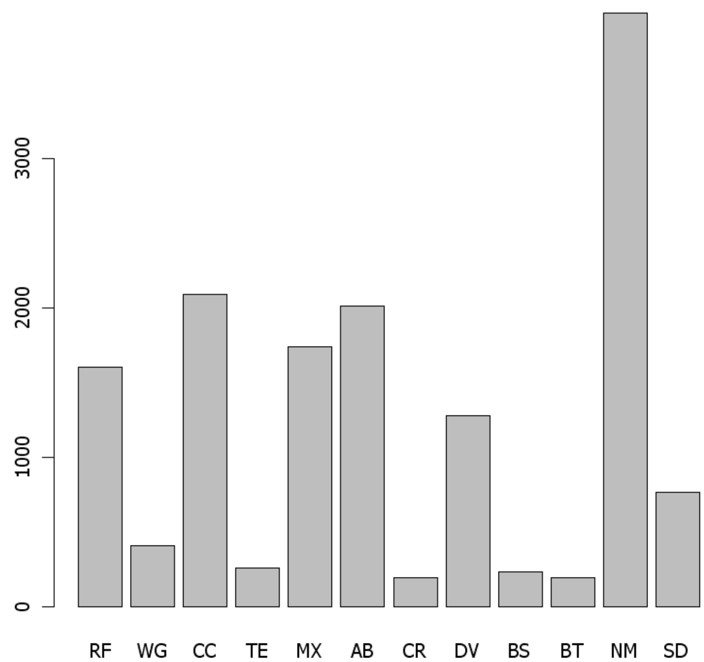


Figure 4.10: Numbers of shots used in the consolidated data set from the component studies. The individual studies are ordered by starting date. The largest study, NM, is entirely pre-season and SD is entirely within-season.

Table 4.2: Studies contributing data to this project showing the start and end data, and the numbers of shots by tiger prawn stock region. Studies are ordered by starting date. The final two studies, NM and SD, are continuing. SD will end sampling in May 2009 and NM will continue for the foreseeable future.

Study	Start	End	JB	CM	AM	GE	VL	KA	WA	Total
RF	1976-06-12	1979-02-16	-	-	-	6	-	732	866	**1604**
WG	1979-02-05	1984-12-04	-	-	-	258	152	1	-	**411**
CC	1979-03-14	1990-11-29	81	212	54	425	1047	236	33	**2088**
TE	1982-01-07	1984-03-03	-	-	-	81	180	-	-	**261**
MX	1983-08-02	1985-03-28	-	-	-	1737	-	-	-	**1737**
AB	1986-03-10	1992-04-01	-	-	-	-	-	-	2011	**2011**
CR	1994-08-01	1994-08-09	-	-	-	-	192	-	-	**192**
DV	1996-05-31	1997-09-28	-	-	-	-	765	429	82	**1276**
BS	1997-10-04	1997-10-31	-	13	-	26	134	35	24	**232**
BT	1998-09-24	1998-10-17	-	-	-	93	100	-	-	**193**
NM	2002-08-16	2009-03-15	-	-	-	593	1556	1318	507	**3974**
SD	2002-09-10	2008-11-12	25	59	33	230	367	42	7	**763**
		Total shots	**106**	**284**	**87**	**3449**	**4493**	**2793**	**3530**	**14742**

Table 4.3: Shots used in the study by year and tiger prawn stock region. Shots shown in italics towards the end of the table are new since the original Species Distribution project.

Year	JB	CM	AM	GE	VL	KA	WA	Total
1976	-	-	-	6	-	9	58	**73**
1977	-	-	-	-	-	300	383	**683**
1978	-	-	-	-	-	416	425	**841**
1979	-	-	-	71	44	7	-	**122**
1980	-	-	-	65	36	-	-	**101**
1981	-	-	-	10	10	-	-	**20**
1982	-	-	-	106	150	1	-	**257**
1983	-	-	-	439	169	-	-	**608**
1984	-	-	-	1212	110	24	-	**1346**
1985	-	-	-	241	11	1	-	**253**
1986	-	-	-	-	-	-	266	**266**
1987	-	-	-	-	1	-	365	**366**
1988	46	126	6	74	219	82	393	**946**
1989	18	76	31	121	307	61	336	**950**
1990	17	10	17	162	322	68	295	**891**
1991	-	-	-	-	-	-	271	**271**
1992	-	-	-	-	-	-	118	**118**
1993	-	-	-	-	-	-	-	**-**
1994	-	-	-	-	192	-	-	**192**
1995	-	-	-	-	-	-	-	**-**
1996	-	-	-	-	216	173	82	**471**
1997	-	13	-	26	683	291	24	**1037**
1998	-	-	-	93	100	-	-	**193**
1999	-	-	-	-	-	-	-	**-**
2000	-	-	-	-	-	-	-	**-**
2001	-	-	-	-	-	-	-	**-**
2002	4	17	5	139	159	48	-	**372**
2003	5	4	4	151	365	303	142	**974**
2004	2	3	4	89	234	269	163	**764**
2005	-	-	-	*82*	*222*	*157*	*40*	***501***
2006	-	-	-	*82*	*217*	*152*	*39*	***490***
2007	*14*	*3*	*5*	*142*	*337*	*164*	*41*	***706***
2008	-	*32*	*18*	*108*	*294*	*176*	*48*	***293***
2009	-	-	-	*41*	*110*	*91*	*41*	
Total	**106**	**284**	**87**	**3449**	**4493**	**2793**	**3530**	**14742**

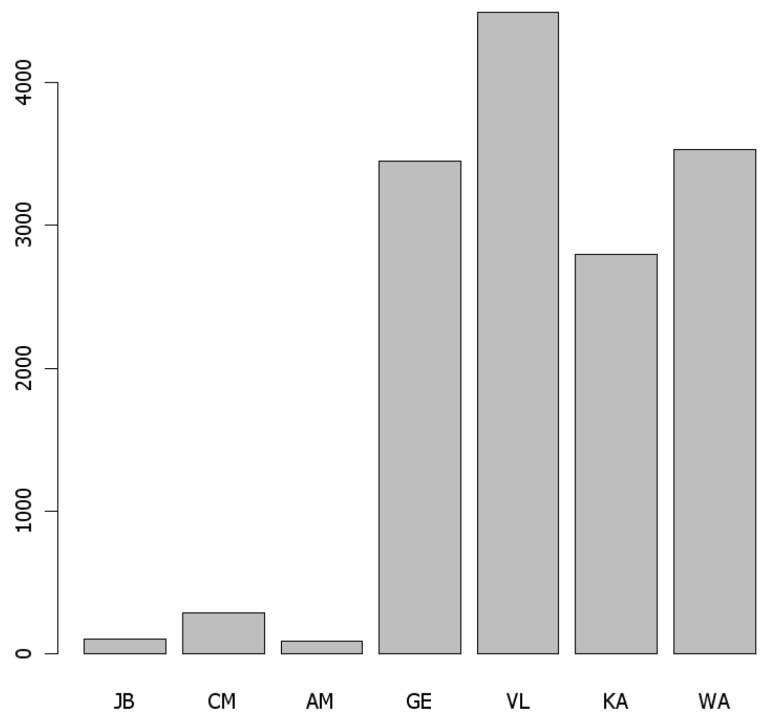


Figure 4.11: Scientific sampling shots by tiger stock region in the NPF.

4.8 Addendum 3: Weighted average differences between catch proportions

The following tables show weighted differences between catch proportions for tiger prawns for the previous and updated species allocation models. The first part is for season 1 and the second for season 2. The models are used for grid squares and times that actually occur in the logbook record and the weights are the tiger catch for that year, season and region.

Table 4.4: Weighted aggregate differences in *P. semisulcatus* catch proportions, SD – TAC, by year and stock region, as a percentage of total tiger catch

	JB	CM	AM	GE	VL	KA	WA
1970		-1.2	-0.3	-0.1	-1.9	-2.5	-0.3
1971		-5.3	3.9	-0.3	-2.3	-4.9	1.2
1972		-4.2	-5.1	-1.3	-1.9	-2.6	2.1
1973		-4.8	-5.0	-1.0	-2.6	-5.6	0.5
1974		-3.4	2.2	1.3	-1.8	-2.0	2.8
1975		-5.6	-1.6	0.0	-2.3	-3.0	1.0
1976		-2.4	5.7	-2.1	-5.2	-1.6	-1.0
1977		-3.8	0.2	-0.8	-2.1	-3.0	-0.4
1978		-8.0	0.4	-0.7	-2.2	-1.7	-0.3
1979	-89.7	-5.2	1.3	-0.6	-0.5	-2.1	0.6
1980	58.1	-3.7	1.7	-1.1	-1.1	-1.5	0.4
1981	-18.0	-4.7	2.1	-1.2	-0.8	-1.5	-0.6
1982	-18.8	-3.8	3.8	-1.1	-1.3	-1.5	-0.6
1983	-20.2	-2.5	0.8	-0.4	-1.3	-2.2	2.1
1984	-6.9	-1.6	1.9	-1.3	-1.7	-2.2	0.2
1985	-4.2	-2.4	2.6	-1.0	-2.1	-2.7	-0.1
1986	-6.0	-0.6	1.7	-0.5	-1.7	-1.5	0.9
1987	-9.0	-1.6	1.7	-0.4	-0.1	-2.1	2.8
1988	1.2	0.4	-2.0	-0.1	-1.4	-2.2	1.1
1989	-1.8	0.8	-2.7	0.1	-1.0	-1.2	1.1
1990	0.9	0.1	-12.8	-0.2	-0.6	-1.0	0.7
1991	-0.3	-0.8	-12.0	0.4	-0.9	-1.8	4.1
1992	-0.9	-1.1	-10.5	0.3	-1.1	-1.3	2.9

1993	-3.3	-0.9	-3.2	0.0	-0.9	-1.9	3.0
1994	-1.7	-3.3	-2.6	-0.1	-0.7	-1.2	2.5
1995	0.2	-2.7	-1.9	0.0	-1.3	-1.0	1.4
1996	1.2	-2.1	-10.0	0.2	-0.9	-1.2	0.4
1997	-1.9	-2.8	-0.6	-0.2	-0.6	-1.5	-1.0
1998	0.0	-2.7	-0.3	1.0	-1.4	-1.3	1.9
1999	-0.5	-1.4	0.3	0.1	-0.7	-1.0	0.2
2000	-4.9	-1.6	2.2	0.6	-0.8	-1.7	1.2
2001	-0.1	-0.3	1.4	0.4	-0.4	-2.3	-0.6
2002	-0.7	-0.3	3.4	0.8	-1.3	-1.0	-5.7
2003	-0.7	-0.2	1.1	0.7	0.9	-1.5	-0.6
2004	5.3	-1.7	0.2	0.5	1.0	-0.9	12.1
2005	14.2	-0.6	1.3	0.3	0.0	-0.1	5.0
2006	-26.8	-3.3	0.8	-0.2	-0.2	-0.1	2.8
2007	26.8	2.1	1.4	0.1	-1.0	0.0	-3.4

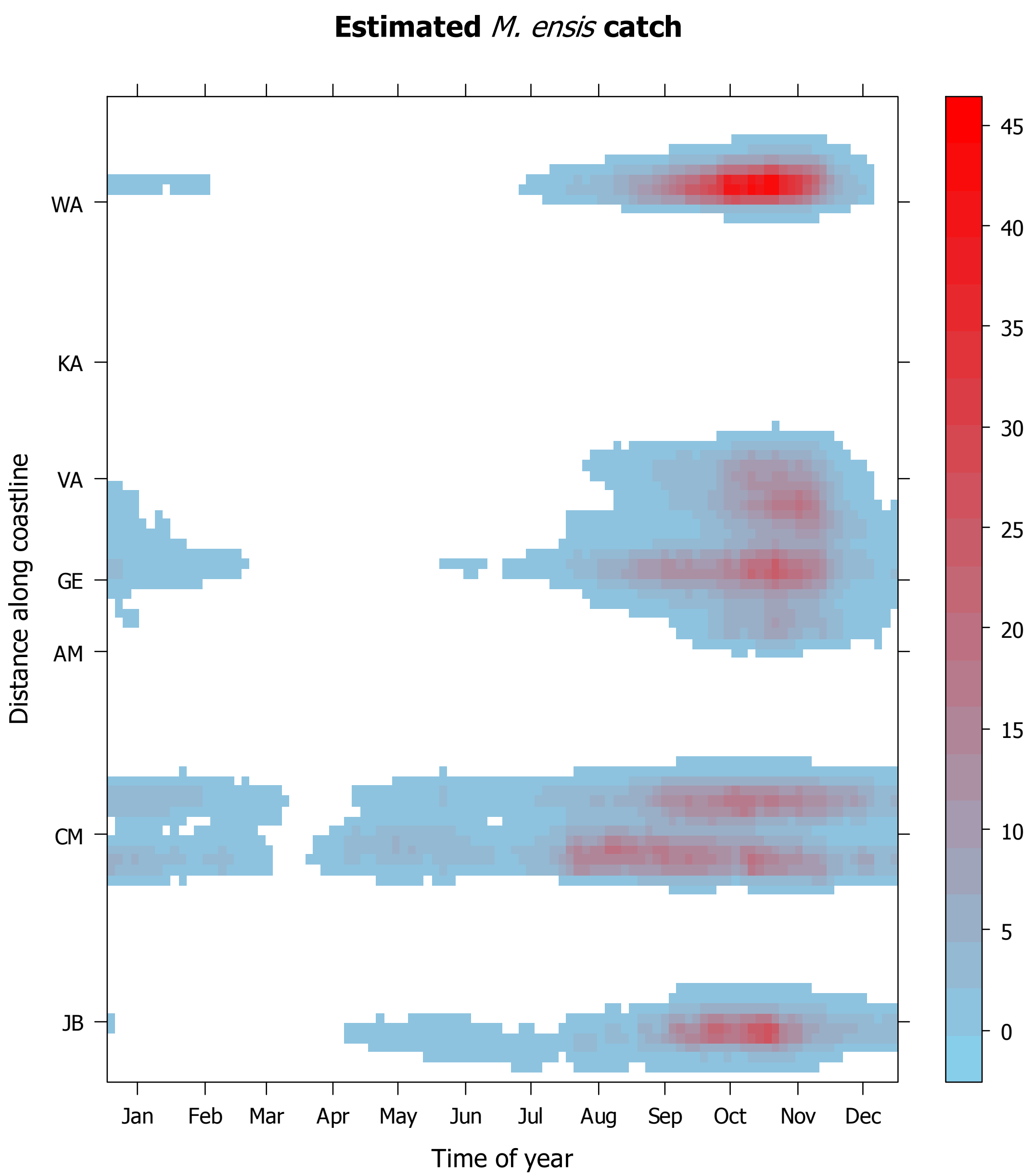
Table 4.5: Weighted aggregate differences in *M. ensis* catch proportions, SD – TAC, by year and stock region, as a percentage of total endeavour catch

	JB	**CM**	**AM**	**GE**	**VL**	**KA**	**WA**
1970	-46.8	-11.8	7.8	0.7	0.0	0.5	2.6
1971		-16.6	-2.0	0.6	-1.0	0.6	1.6
1972		-11.5	-12.2	1.3	-0.7	0.4	-1.3
1973		-17.6		1.0	-0.4	0.6	2.7
1974		-13.8	-42.6	1.4	-0.5	0.4	0.1
1975		-17.6	0.1	0.3	-2.0	0.6	3.4
1976		-16.0	-10.1	1.5	-0.5	0.0	3.4
1977		-23.2	6.6	0.6	-1.2	0.1	1.5
1978		-20.8	5.4	0.2	-0.4	0.1	4.6
1979	-3.3	-14.3	-4.2	0.2	-4.0	0.1	2.7
1980	-67.4	-12.7	-5.5	0.4	-2.5	0.1	2.2
1981	-11.0	-12.6	-1.1	1.3	-3.9	0.1	1.5
1982	-16.2	-11.1	-1.4	-0.4	-3.1	0.0	1.9
1983	-27.6	-6.4	-0.2	-0.4	-3.4	0.1	1.9

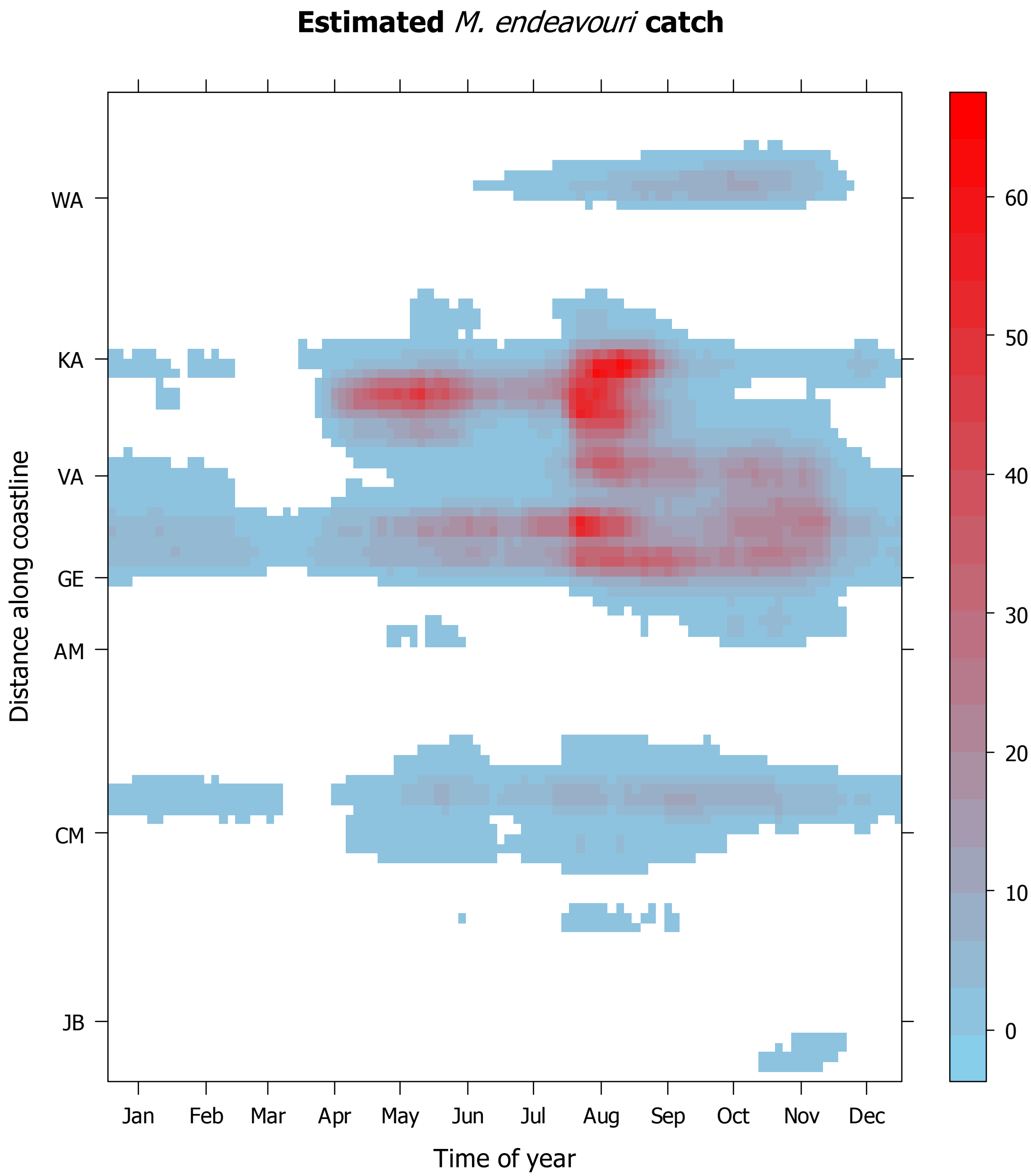
1984	-11.6	-9.1	-2.0	-2.9	-6.2	-0.1	0.7
1985	-17.6	-9.5	0.6	-1.0	-8.4	0.0	3.1
1986	-15.2	-6.9	-4.0	0.1	-3.6	0.1	2.7
1987	-7.3	-9.1	-0.3	-0.8	-6.3	0.1	1.9
1988	-9.3	-1.4	-3.5	0.0	-7.4	-0.1	3.0
1989	-6.7	-4.5	-2.1	-0.8	-5.1	0.0	3.5
1990	-11.4	-5.2	-4.7	-0.3	-4.1	0.0	3.8
1991	-6.1	-11.9	-3.4	-1.0	-3.1	0.0	-0.2
1992	-11.7	-9.4	-0.8	-0.6	-3.1	0.0	0.2
1993	-10.8	-7.9	8.3	-2.7	-4.6	0.0	1.6
1994	-8.6	-3.5	1.2	0.4	-3.2	0.0	3.3
1995	-7.2	-4.7	5.2	-0.2	-5.3	0.0	2.7
1996	-13.0	-6.9	2.7	-3.9	-4.4	0.0	6.2
1997	-0.6	-7.2	4.0	1.4	-2.7	0.0	2.6
1998	-6.6	-4.5	1.0	-2.7	-6.7	0.0	3.1
1999	-2.3	6.9	2.5	0.6	-3.5	0.0	2.7
2000	-5.0	-17.1	-5.6	1.6	-9.6	0.0	1.1
2001	-4.7	-12.3	-1.5	-1.9	-12.6	0.0	1.7
2002	-8.7	-20.6	-6.8	-0.4	-13.6	0.1	1.7
2003	-3.7	-12.6	-1.6	-3.0	-14.5	0.0	1.8
2004	-3.0	-19.3	-6.5	-4.4	-9.4	0.0	17.3
2005	-17.2	-17.2	-11.6	-1.7	-4.0	0.0	0.2
2006	-12.5	-11.1	-3.3	-1.3	-4.0	-0.1	-0.4
2007	-13.4	-4.3	1.8	-1.7	-5.2	0.0	-0.8

4.9 Addendum 4: Spatial and temporal distribution of tiger and endeavour prawn catches

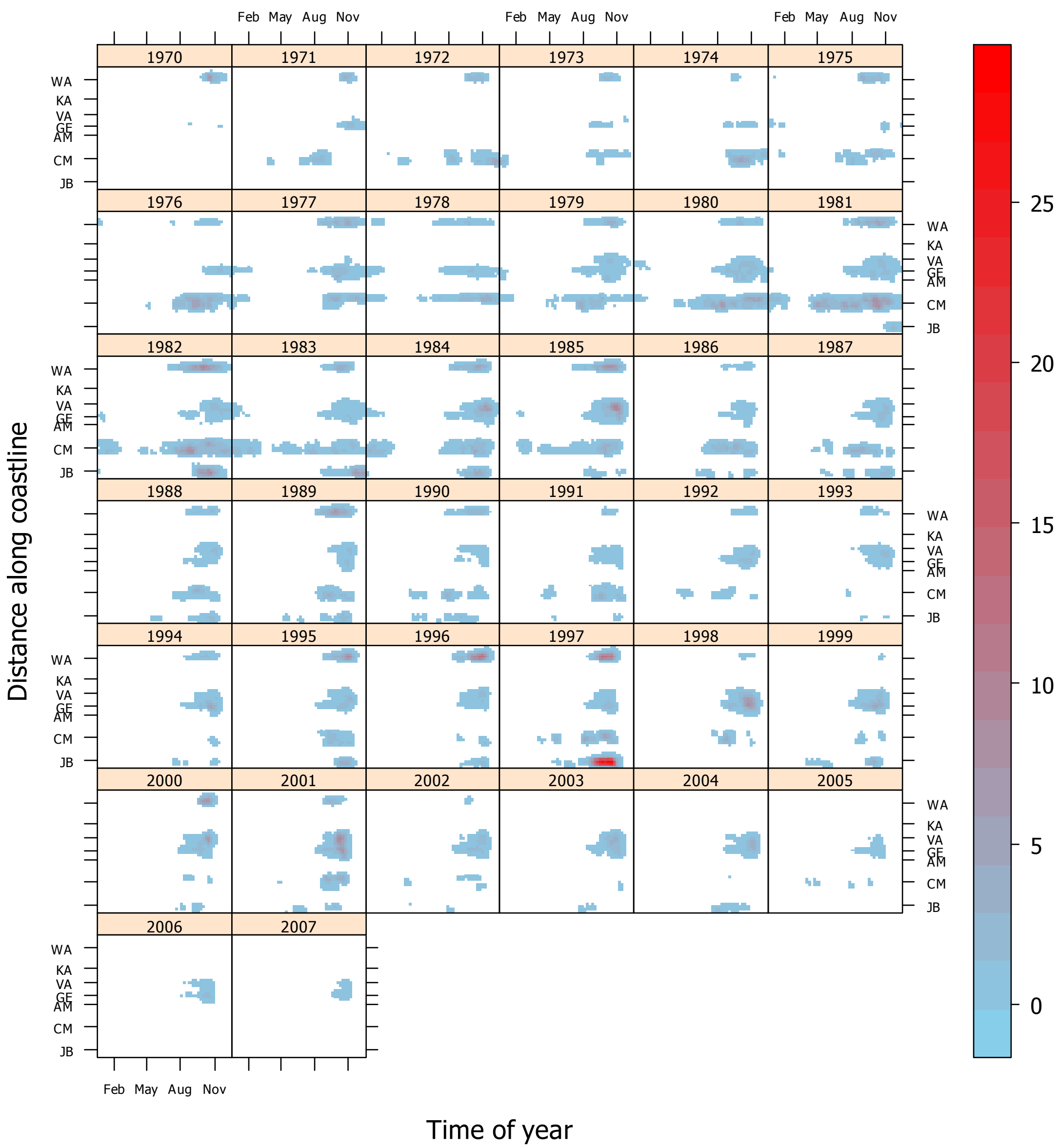
In this addendum we give a graphical display of the spatial and temporal endeavour and tiger prawn catches for the seasons 1970 – 2007. In each graph the y-axis represents distance along the coastline, west to east, with the central point of each stock region indicated. The x-axis shows the time of year, with the 15th of each month shown. The first two displays show the aggregate estimated catches for all seasons, and the second two displays show the annual breakdown. In all cases the catch scale is relative. The graphs are slightly smoothed, and catches less than 1% of the catch range, in each case have been removed to enhance the clarity of the presentation.



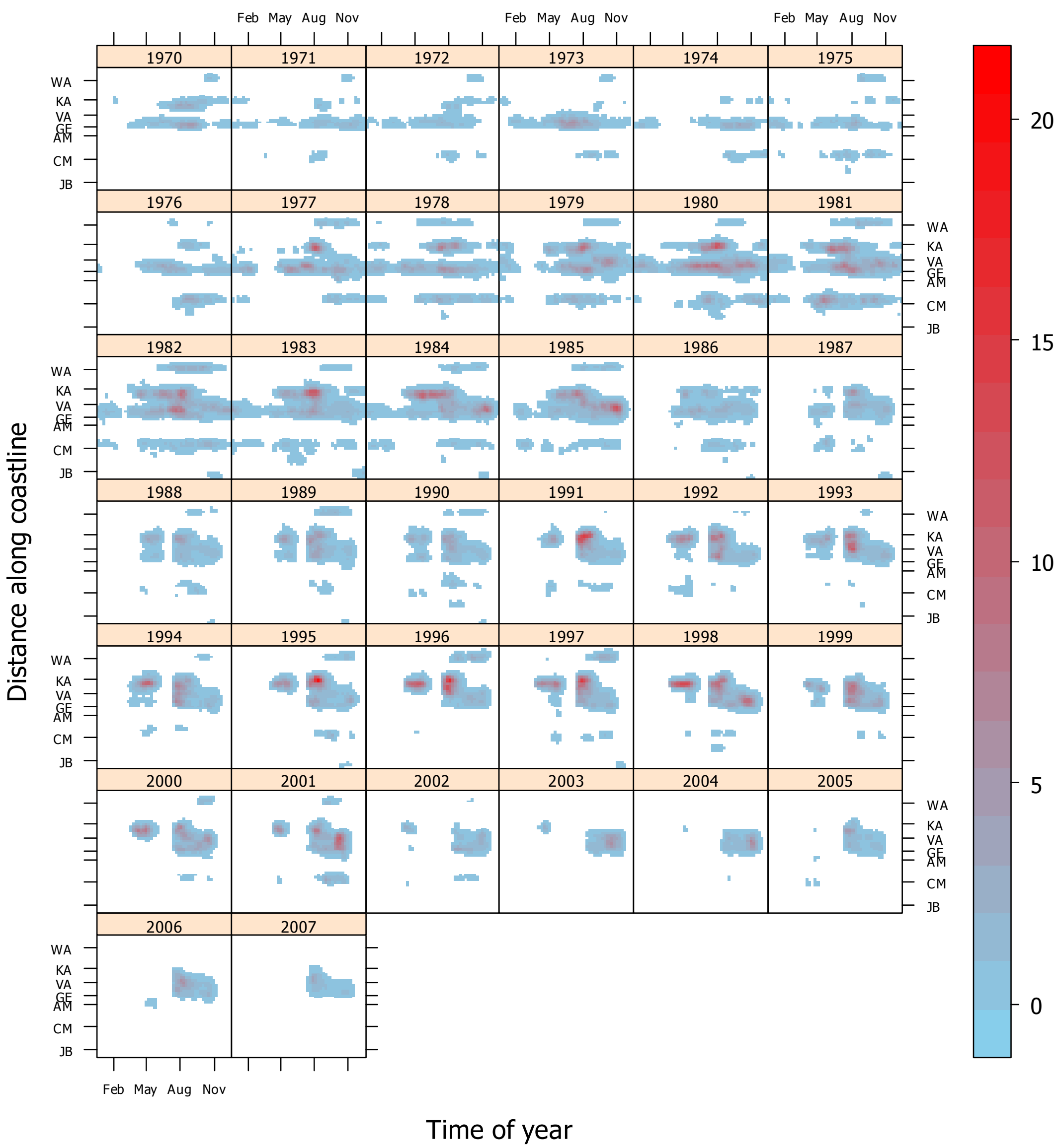
Estimated *M. ensis* catch
Distance along coastline
WA
KA
VA
GE
AM
CM
JB
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Time of year
45
40
35
30
25
20
15
10
5
0

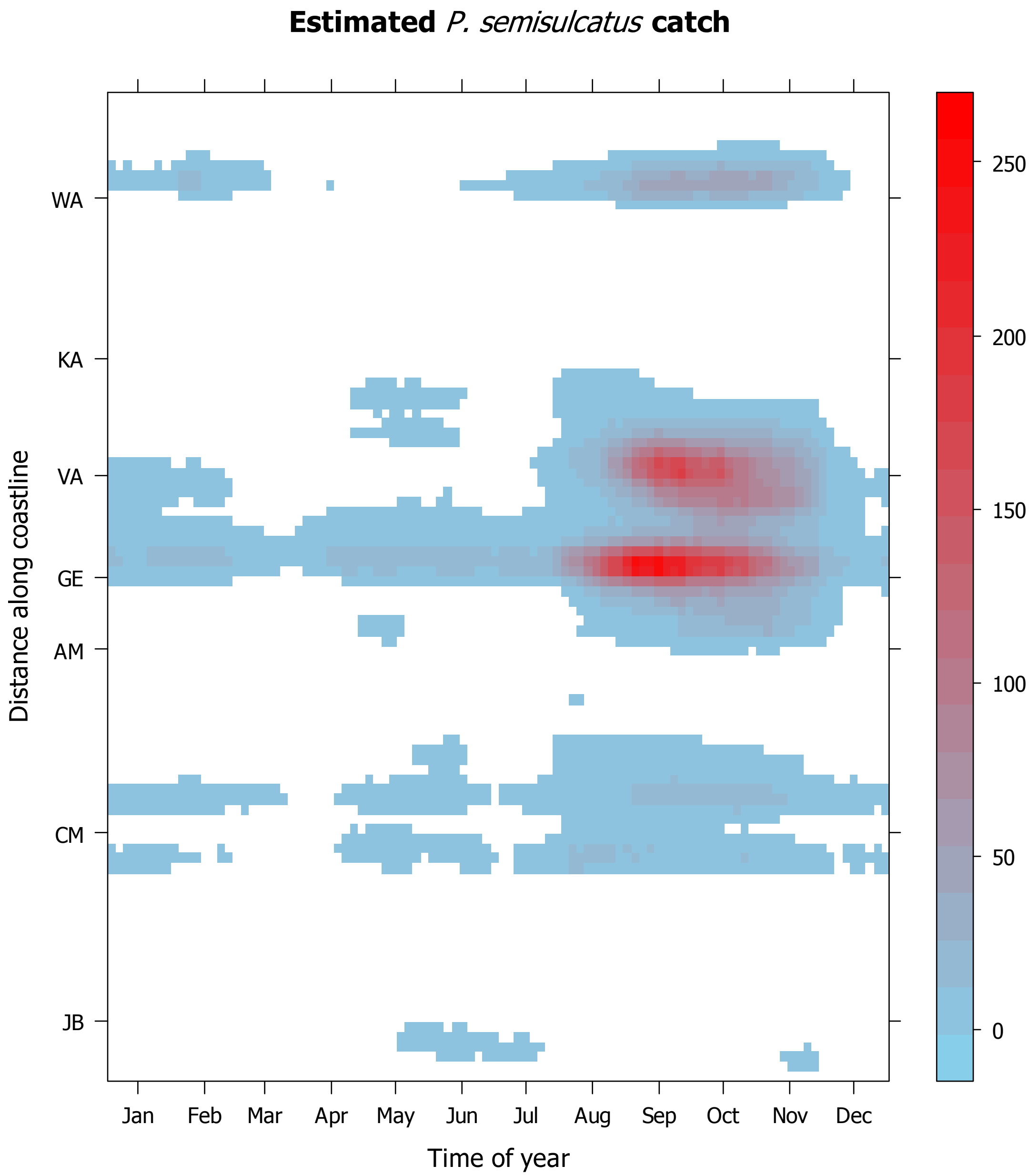

Estimated M. endeavouri catch
Distance along coastline
WA
KA
VA
GE
AM
CM
JB
Time of year
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
60
50
40
30
20
10
0

Estimated *M. ensis* catch

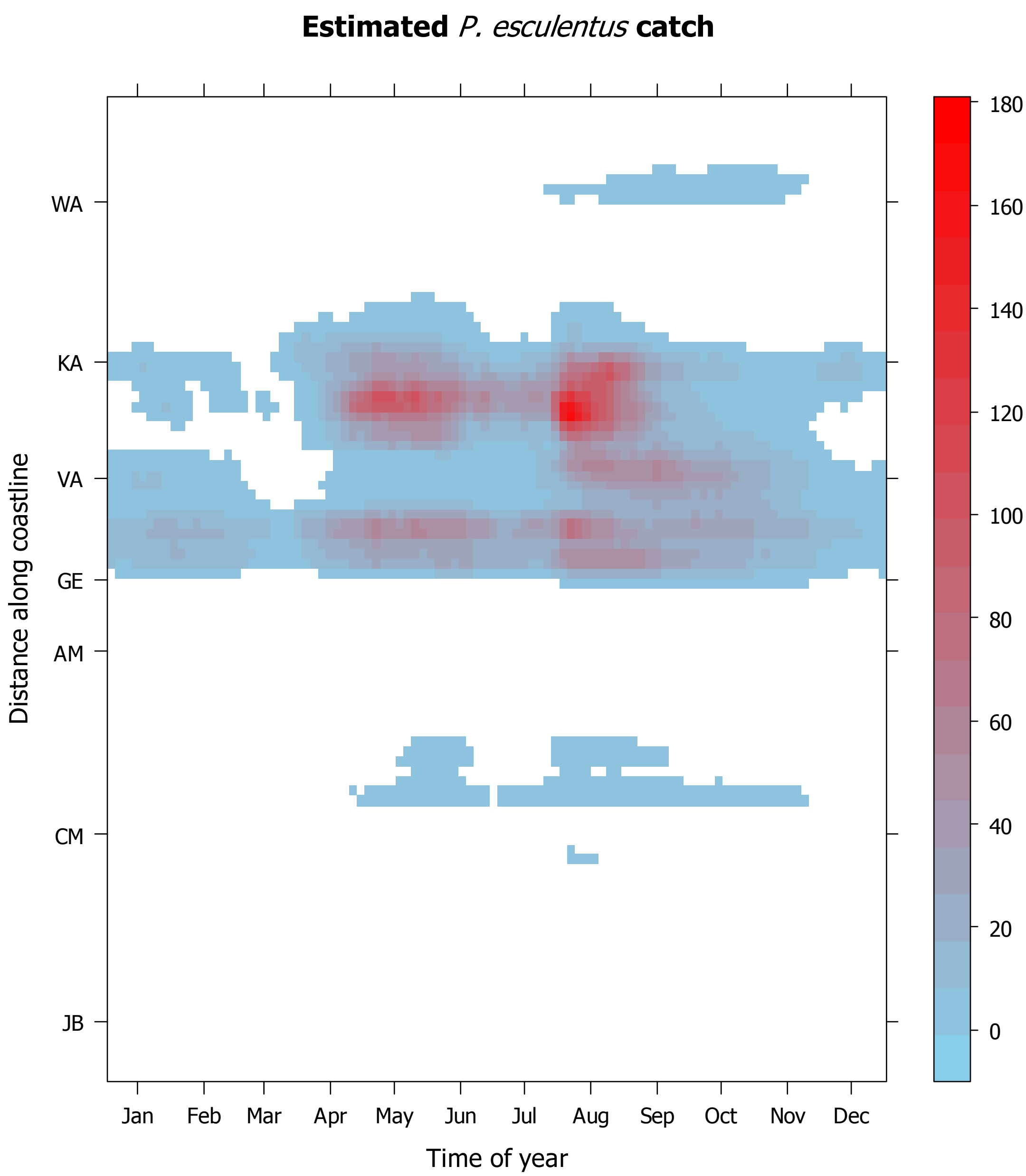


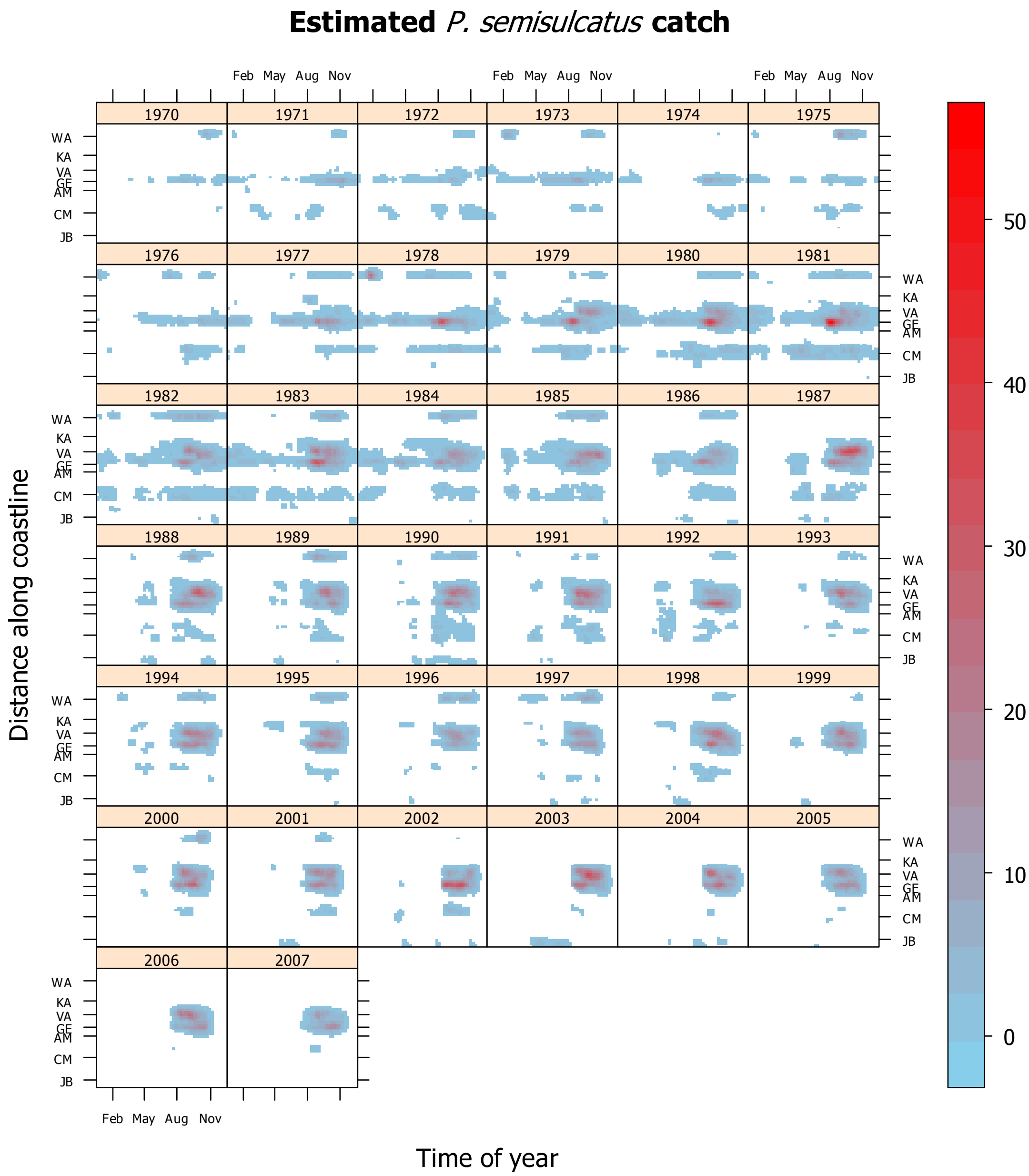
Estimated *M. endeavouri* catch





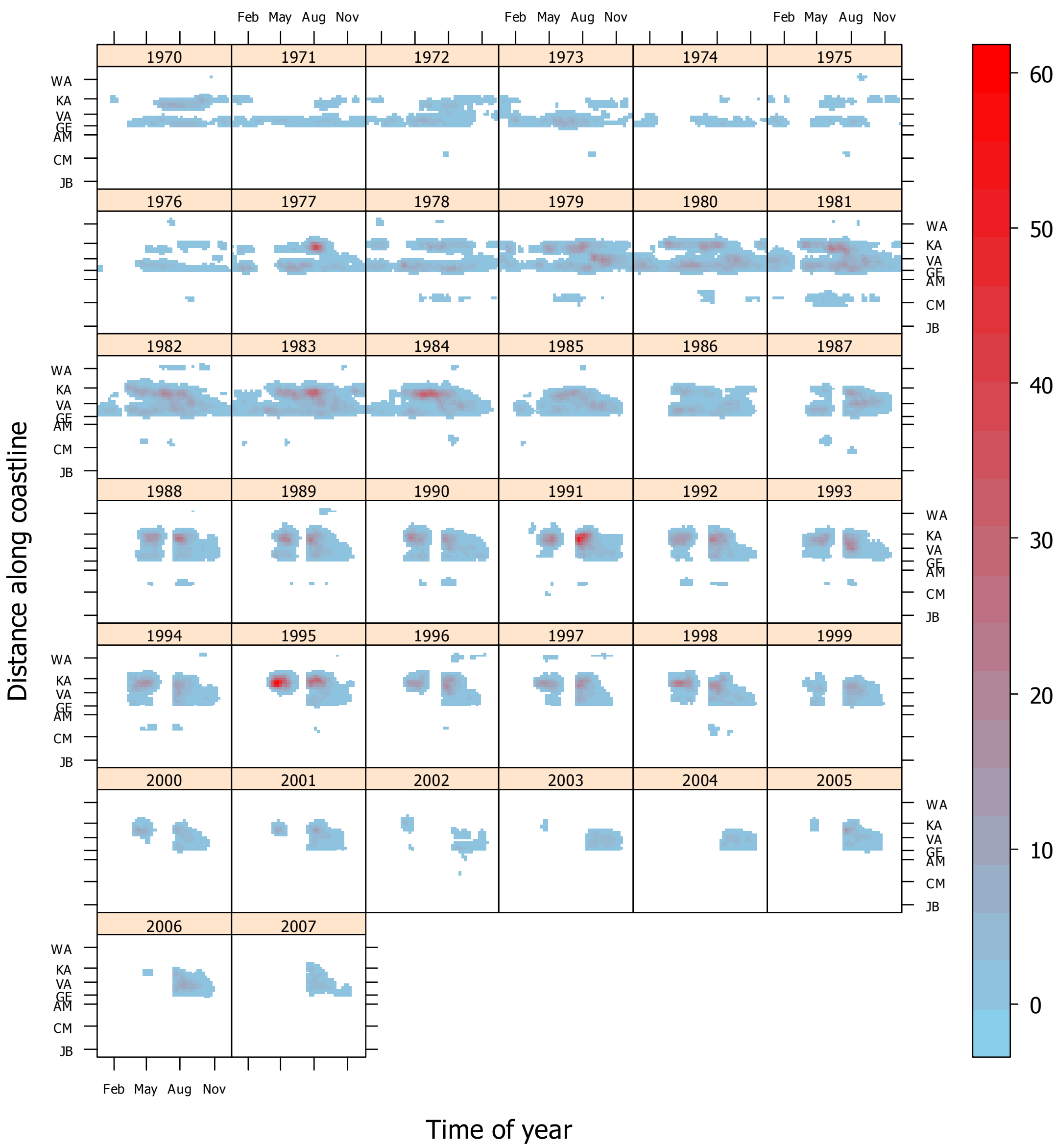
Estimated P. semisulcatus catch
Distance along coastline
WA
KA
VA
GE
AM
CM
JB
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Time of year
250
200
150
100
50
0


Estimated P. esculentus catch
WA
KA
VA
GE
AM
CM
JB
Distance along coastline
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Time of year
180
160
140
120
100
80
60
40
20
0



Estimated *P. semisulcatus* catch
Distance along coastline
Time of year
Feb May Aug Nov
WA
KA
VA
GE
AM
CM
JB
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
0
10
20
30
40
50

Estimated *P. esculentus* catch



4.10 Addendum 5: Notes on the collection and processing of samples

The material of this Addendum has been kindly supplied by Tonya van der Velde.

4.10.1 Collection of samples for scientific processing

Close liaison with both vessel owners and crews (skippers and crew) ensured the cooperation and participation of Industry to provide to date, 297 x 5 kg Endeavour prawn samples and 75 x 5kg tiger prawn samples during the 2007/2008 season. Samples have come from most fishing regions of the NPF, but were numerically dominated by samples from the tiger prawn grounds in the Gulf of Carpentaria.

4.10.2 Source of samples

The distribution (and proportion by location) of the two species of Endeavour prawns were sampled by receiving a 5 kg carton of randomly-selected endeavour prawns from participating vessels. As an ongoing monitoring process some Tiger prawn sample were also collected during the seasons. The samples were then transhipped to Brisbane for scientific measurement. Data sheets, sample labels, prawn cartons and instructions were provided to each participating vessel prior to the season. Samples were instigated by telephone at regular interval throughout each season. To date a total of 297 x 5kg of endeavour prawns and 75 x 5kg of tiger prawn samples were collected (Table 4.6)

Table4.6. Number of participating vessels, and number of samples collected, 2007-2009.

	2007 Season 2	2008 Season 1	2008 Season 2	2009 Season 1
Vessels	18	8	17	~ 19
Samples	197	21	153	in-season

Port-visits at the initiation of the sampling, and at the beginning and end of each fishing season during which we established and maintained good relationships with about 20 Industry vessels. Port visits were conducted in Cairns and Darwin. Close liaison was the key to the success of sample provision by the fleet. We explained the sampling procedures to the skippers and crew of participating vessels prior to each fishing season.

As well, we had to liaise closely with the vessel owners and fleet masters to ensure a clear understanding that the samples were being purchased by the project and that they could expect a financial return for the prawns that they supplied us. Initial contacts were followed up by written communication, detailing the weight and value of the samples provided and inviting the owner to invoice the project for payment.

4.10.3 Samples collected

The current project collected to date 371 samples (5 kg each) (Table 4.1), the prawns from which have been speciated and measured. Most samples came from the two 'tiger prawn seasons' in 2007 and 2008 and one banana season in 2008. Obviously, most vessels fish for tiger prawns during the second season each year and all participating vessels supplied endeavour and tiger samples.

21 samples were collected from the 2008 'banana prawn seasons'. Few vessels fish for Endeavour/tiger prawns during the first season each year, and those that do only do so for a few weeks at the end of the season. Usually about 50% of participating vessels supplied Endeavour/tiger prawn samples from the first season each year.

Samples were collected in most of the fishing regions of the NPF. Most samples originated from the Groote, Vanderlin and Mornington regions of the Gulf of Carpentaria. However, good collection was done around the top end of the NPF in the Kimberly's and Bonaparte regions.

4.10.4 Data collected with each sample

Three sources of data were available to the project (Table 4.2); a 'Bridge Sheet' which was completed by the vessel skipper whilst fishing, a 'sample label' which was completed by the on-deck collector, and the processing/measurement information for each prawn sample (collected in Brisbane)(Table 4.7). The Bridge Sheet was a summary of the duration, environment and catch of the shot from which the sample was taken. The 'sample label' provided similar (but reduced) information to the Bridge Sheet and cross referenced to the Bridge Sheet. Measurement information on each individual prawn was taken during the processing of each sample by CSIRO staff at the Raptis Factory.

Table 4.7: Description of the data provided by NPF vessels on the 'Bridge Sheet' and sample labels, and the data collected during sample processing and measurement.

Bridge Sheet data	Sample Label data	Individual prawn data
		Project sample number
Vessel	Vessel	
Skipper		
Collector	Collector	
Vessel sample number	Vessel sample number	Vessel sample number
Date	Date	Species
Start Time	Start/Finish Time	Length
Start Depth		Weight (sub sample)
Latitude	Latitude	Sex
Longitude	Longitude	Maturity
Endeavour/Tiger prawn weight - sample shot		Parasite (presence of)
Endeavour/Tiger prawn weight - first shot		Moult stage
Endeavour/Tiger prawn weight - second shot		Comments
Endeavour/Tiger prawn weight - third shot		
Endeavour/Tiger prawn weight - fourth shot		
Comments		

4.11 On-shore processing and measurement of samples

4.11.1 Summary

Five kilogram Endeavour / tiger prawn samples collected from the commercial catch were transhipped to Brisbane for processing and measurement by CSIRO staff at A Raptis and Sons factory. Approximately 20 days processing, to date, has been carried out by 3 scientific personnel. Key biological data were measured during the processing of each sample. Upon completion of processing, the prawns were returned to the commercial product line and the project was paid commercial rates for the product. In the first instance, the samples were purchased from the NPF vessels owners at near market rates; the re-imbursement for the processed product offset costs to the ‘Species Distribution Project’.

4.11.2 Scientific measurement of samples

The 5 kg samples were transhipped to the A Raptis and Sons factory at Colmslie, Brisbane where the prawns were classified into species, sexed and measured by CSIRO staff. Following scientific processing the prawns were returned to the commercial product processing within the factory. The project received payment for the product that originated from the project and the level of payment assisted project funds to reimburse vessel owners for the samples that they had generously provided. We attempted to transfer the product in a way that was revenue neutral for all parties, apart from a cost to the project itself. A small number of samples are taken to CMR Cleveland for further processing; to calibrate length-weight relationship curves and for genetic studies.

Similarly to the liaison with Industry to obtain samples, processing them at the Raptis factory also required the establishment of a good working relationship between CSIRO staff and staff at the Raptis factory.

CSIRO staff used the electronic measurement system developed for the FRDC (Figure 4.12) ‘Monitoring’ project to efficiently process the samples. In total, about 2000 kg of prawns were measured at Raptis factory over two years.

The following information was collected on each individual prawn (see also Table 4.7):

- Species, sex, carapace length, presence of parasites, reproductive stage and moult stage.

▪

Figure 4.12: Electronic measurement system used to process the samples at the Raptis factory.

4.11.3 Payment for Commercial Product

Vessel owners were offered a price per kg for the prawns that they supplied the project as a sample. The price offered was usually just above market price, to maintain the cooperation of the Industry.

Following processing at the Raptis factory, the product was on-sold to Raptis at a price negotiated with Raptis staff. This price was the best available, given the quality of the product and the costs of processing at the factory (mainly labour costs assisting with the handling of the samples). A shortfall between the price paid for the samples and the price received after processing was met by the project.

4.12 References

Dichmont, C. M., D. Die, et al. (2001). Risk Analysis and Sustainability Indicators for the Prawn Stocks in the Northern Prawn Fishery. Fisheries Research and Development Corporation. Cleveland, Qld., Fisheries Research and Development Corporation 98/109.

Venables, W. N., R. A. Kenyon, et al. (2006). Species Distribution and Catch Allocation: data and methods for the NPF, 2002-2004, Australian Fisheries Management Authority**:** 190.

Wood, S. N. (2006). Generalized Additive Models: An Introduction with R. London, Chapman and Hall/CRC Press.

APPENDIX 5. FISHING POWER IN THE NORTHERN PRAWN – TIGER PRAWN FISHERY, 1970-2007

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5.1 Summary

This study addresses objective 2 of the TAC Project: Update the fishing power series and develop a pre-ITQ fishing power. The following elements have been completed:

- The 2003 models have been re-fitted and the coefficients re-estimated, using all the latest available data (1970 to 2007)
- The extent and treatment of technology changes since 2002 have been reviewed
- Possible improvements to the fishing power models of 2003 were identified
- We have shown that reducing the fleet size is associated with decreases in expected catch rates
- A model (to be referred to as the 2009 integrated model) has been identified that integrates the features of the 2003 basic and spatial models, and the results of the above-mentioned reviews and investigations (Figure 5.1).

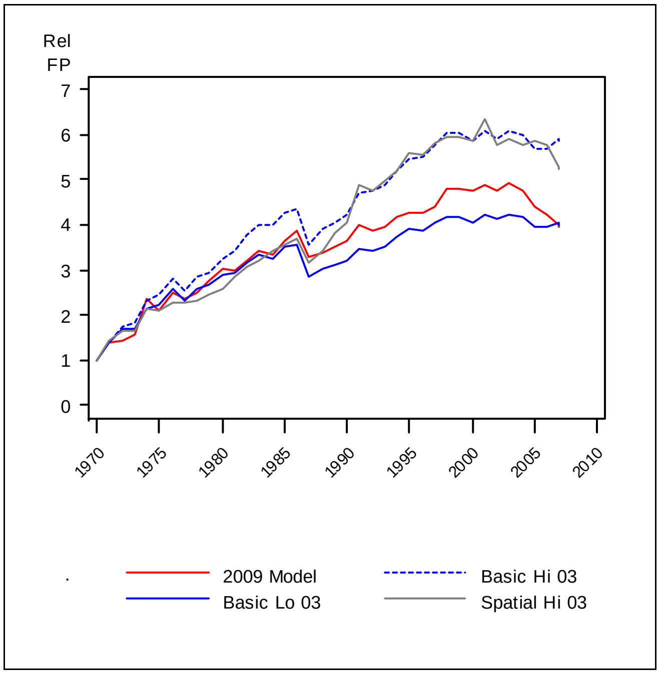

Figure 5.1. Cumulative relative fishing power from 2009 integrated model compared to three series from 2003

5.1.1 Summary of recommendations

1. We recommend the 2009 integrated model to represent the lower bound of trends in relative fishing power in the NPF (as an alternative to the 2003 basic low model). Like the 2003 series, the 2009 integrated model is based on evidence from the data as far as possible, and incorporates expert knowledge and judgement in a manner that is comparable to the 2003 Basic Low model.
2. There is evidence that relative fishing power could be higher, especially in the first season (2009-S1, Figure 5.9, and associated text). We suggest an explicit precautionary allowance for this be made in the stock assessments, as we are unable to recommend a series that is based on the data alone to represent a High boundary. A "middle" series is available, that is an estimate above the "Low" boundary, but not an upper bound of uncertainty. A change in philosophy is implied if the RAG adopts the 2009 mid-high series and abandons the 2003 High series. That is, we are stating that we have no corresponding high for 2009 as a proposal (as compared to the 2003 High series) and the RAG deliberated over the implications of the change in the practice of defining ranges of uncertainty that this represents. The RAG adopted the mid-High model for sensitivity tests of the stock model to fishing power alternatives. They did not require an Upper bound and acknowledged the change in philosophy.
3. Monitoring innovations in fishing technology, the specifications of new vessels and changes in gear due to changes in management regulations are important prerequisites for assessing fishing power changes into the future. We noted the following items for observation: innovations in TED/BRDs particularly their position; net tapers, high strength netting, 3D

plotters, GPS linked to autopilot. Specific recommendations are reported to NPFRAG along with routine stock assessments.

5.2 Introduction

The approach to estimating relative fishing power for the NPF tiger prawn fishery has been to fit a statistical linear model to logbook data, to predict daily catch rates (on a log scale) from a suite of terms that represent abundance, vessels, skippers and technology (Bishop, Venables, Dichmont *et. al*., 2008). This approach is well-known (Maunder and Punt, 2004); however in the prawn fisheries of the NPF the fitting of such models is compromised by severe confounding between vessel terms and prawn abundance.

This confounding is severe due to a confluence of factors: the fishery has been actively managed by input controls which have forced sudden major changes in nets and consequently in swept area capacity. The fleet is a modern industrial one, and adoption of innovations in fishing technology has been rapid (for example see Robins, Wang and Die, 1998). There has been an influx of purpose built vessels. Many of the changes in fishing gear are within-vessel changes, and the vessel refits usually occur during the end of year season closure. Consequently, the modified vessels fish for the first time in a new season on a new cohort of prawns. Since prawns are short-lived animals with a life span of 18 months maximum, the annual abundance is inevitably confounded with the within-vessel changes. Previous work has concluded that the logbook data alone could not fully resolve the fishing power issues, because of this confounding between vessel technology changes, movements of vessels and local abundance (Bishop *et al*,. 2008). In such circumstances there is a high risk that fishing power series will be biased low, and corresponding standardised abundance series will be biased high (Bishop, 2006).

To compensate for this unavoidable deficiency in the data, the fishing power models for the NPF tiger prawn fishery have the feature that some of the coefficients (e.g. for technology that could not be well-estimated from the available data) were fixed (or offset) at values obtained from external evidence including expert knowledge and judgement. So-called “high” models also allowed for a precautionary element, when fixing the coefficients for technology. The “low” and “high” models were intended to provide an envelope of possible fishing power changes from 1970 to 2002, based on all available evidence, and it was considered unlikely that fishing power would be lower than “Low”, and unlikely to be higher than “High”.

These models that have been used for recent annual stock assessments up until 2007 are referred to as “the 2003 models” in the present report. They are the basic low (BLO), basic high (BHI) and spatial high (SPHI) models described in Dichmont, Bishop, Venables *et al.* (2003) and Bishop et *al.* (2008). Each model is of the form:

$$\log(C_{ijkt}) = \alpha_0 + \gamma \log(f_{ijkt}) + \sum_q \alpha_q X_{qjkt} + \sum_p \beta_p \log(V_{pik}) + \sum_h g(i,k,h)\delta_h + \varepsilon$$

(Equation 1)

where

C_{ijkt} denotes the daily catch weight of tiger prawns plus half the endeavour prawns, of vessel *i* fishing in area *j*, year *k* and month *t*;

f_{ijkt} represents effort, hours trawled per day;

X_q are terms to represent abundance and availability: (including year, month, area);

V_p are 1 to *p* continuous vessel, gear and skipper characteristics;

$g(i,k,h)$ functions *g* of categorical vessel, gear and skipper characteristics;

ε an error term assumed independent and homoscedastic;

The basic relative fishing power for the fleet each year was the arithmetic mean of per vessel fishing powers, weighted for the effort of each vessel that year.

$$R_{k,i/s,j} = \frac{\sum_{ik} f_{ik}(\exp(c_{ik} - c_{sk}))}{\sum f_{ik}} \qquad \text{Equation 2}$$

The relative fishing power each year (relative to 1970, $\frac{R_{k,i/s,j}}{R_{1970,i/s,j}}$), and the fishing power each year relative to the previous year $q_{inc} = \frac{R_{k,i/s,j}}{R_{k-1,i/s,j}}$ were calculated.

The 2003 models used data from 1970-2002 for estimation of the coefficients. A vessel dataset with imputed values for some vessel or gear characteristics (to fill data gaps in the 1970s and 1980s) was used for the evaluation of relative fishing power. Imputation methods included cluster analysis, assumptions based on sister ships and adjacent years, and random allocation in the proportions expected fleetwide according to published descriptions (Dichmont *et al.*, 2003). This dataset will be referred to as the "Reconstructed fleet". For annual stock assessment in the years 2003-2007, each new year of vessel configurations was added to the reconstructed fleet dataset for evaluation of changes in relative fishing power; however the fishing power model itself was not re-estimated.

The present study addresses objective 2 of the TAC Project: *Update the fishing power series and develop a pre-ITQ fishing power*. To achieve this objective,

e) The BLO, BHI and SPHI models were re-fitted, and the coefficients re-estimated, using all the latest available data to 2007.

f) The extent and treatment of technology changes since 2002 were reviewed,

g) A major change in the fishery since 2002 has been a reduction in fleet size (from 97 vessels in 2003 to 51 vessels in 2007). We investigated whether reducing the fleet size has had any impact on the fishing power of the fleet.

h) Possible improvements to the fishing power models were also investigated.

i) A new fishing power model was identified (to be referred to as the 2009 integrated model). This model integrates the features of the 2003 models, and the results of the above-mentioned reviews and investigations. It is a new “Low” series. A new “High” series could not be identified. However, a mid-high series is available for sensitivity tests of stock assessments.

5.3 Methods

5.3.1 Re-fit the 2003 models using the latest available data

The 2003 models were re-fitted using all the latest available data, (1970 to 2007, n=635,770) and the coefficients were re-estimated. The fishing power series from the newly re-fitted models were compared to the projections for 2003-7 (not re-estimated) that had been used in recent stock assessments.

5.3.2 Review the extent and treatment of technology changes since 2002

Three methods of review were:

1. Informal discussions with industry members to determine significant innovations in technology since 2002, with a view to identifying items for which data should be collected, whether for current or future fishing power assessments.

2. Analytical Hierarchy Process (AHP)

In the 2003 models, coefficients for technology that could not be well-estimated from the available data were fixed (or offset) at values obtained from external evidence including expert knowledge and judgement. A criticism of the 2003 models is that no formal or data driven process had been applied to the process of setting values for the offsets. The present study investigated the application of the AHP (Saaty, 1980) to these decisions. AHP is a technique that decomposes a decision-making process into a hierarchy of criteria, and alternatives. Experts are asked to make numerous of pairwise comparisons, which are arranged into matrices and eigenvectors calculated to achieve ranking of alternatives.

Four sources of information for this AHP were:

(a) coefficients from the statistical analyses of commercial logbook records (described in this report);
(b) other published information about the impact of technology on fishing power;
(c) skippers’ rankings of technology with respect to their contribution to fishing power, obtained by questionnaire in 1998-99 (Bishop and Sterling, 1999), and
(d) scientists rankings of the information value of different data sources.

3. Analysis of coefficients from structured series of models

Items of technology that were only partially adopted in the NPF in 2003 were reassessed with the new years of data (2003-2007).

Older technology were assessed for instability that might indicate the presence of confounding. The findings were used to suggest improvements to the models. Analysis of coefficients for each technology item that were estimated by each of 62 model variants that were investigated (These models are described in a later section). For each technology item a dataset was built that contained 62 records, one from each of the 62 modelling runs (32 from the computational experiment, plus 30 from the further “candidate models” series). If the technology item was coded to three levels (presence, absence, unknown) then the coefficient for “presence” relative to “absence” was the one selected to take part in the analysis. For each technology item that was re-assessed, the coefficients were investigated by a linear regression where the dependent variable was the coefficient for a single technology item, and the independent predictors were the factors to be investigated by the sensitivity experiment and further candidate models. Factors that proved statistically significant were taken to be confounded with the technology item; conversely, the mean value for a coefficient with small standard error and no significant predictors was interpreted to indicate stable and converging evidence for the importance of that technology for fishing power.

5.3.3 A new variable to represent navigational accuracy

An immediate outcome of the three review processes was an alternative treatment of electronic aids to navigation, that makes use of external information about navigational accuracy. Accuracy of position fixed by electronic navigation aids can be affected by the number of satellites above the horizon and their height, the distance to a base station, ionospheric conditions which vary during a day, errors in satellite ephemera and clocks, and the hardware and software and the datum setting of the receiver unit (Geoscience Australia, 2005; Seynat, Kealy and Zhang, 2005).

In the 1990s one of the greatest limitations in accuracy of GPS for civilian users was due to deliberate degrading of the broadcast GPS signal by the US Department of Defense, for homeland security reasons (“selective availability). Additional infrastructure was used with the differential concept (where range errors were determined at a known location and transmitted to users; differential GPS or DGPS), to improve the level of accuracy. In 2000 selective availability was turned off, thus instantly improving the accuracy of both GPS and DGPS.

Given all the possible sources of error, and uncertainty about these from day to day, Table 5.1 gives an indicative schedule (compiled from external sources) of navigational accuracy that may have applied on fishing vessels in the NPF. The navigational accuracy potential of each vessel each year was determined as precision (in metres) according to the information in Table 5.1. If technology status for a vessel was unknown, NavAccuracy = (best accuracy at the time)*(probability of presence in unknown vessels that year), based on historical fleet aggregate data described in Dichmont *et al.* 2003

Navigational accuracy was fitted in the fishing power models in two alternative forms: (1) The natural logarithm(accuracy, m) as a linear term; (2) as categories of accuracy (because this allowed for non-linearity including thresholds to be detected).

Table 5.1. Schedule of navigational accuracy (Approximate history of accuracy on Australia's northern coastline)

Aid to navigation	Accuracy*: metres radius
Radar in the Gulf of Carpentaria – flat featureless coastline, and long trips often many days out of sight of land (GB Ministry of Defence, 1987)	10,000
Satnav (Transit satnav accuracy depended tremendously on the frequency of position updates which only occurs once for each satellite that passes by- every few hours or so. Location relied on dead reckoning (logging speed and gearing) between fixes) (Logsdon, 1995)	500
GPS with selective availability turned on (Navstar; allowing for number of satellites above the horizon and remoteness of NPF from base stations; 1989-1999) Geoscience Australia, 2005	120
GPS with selective availability turned off (2000 +) Geoscience Australia, 2005	20
D_GPS with selective availability turned on (~1996-1999) Geoscience Australia, 2005	20
D_GPS with selective availability turned off (2000+) Seynat 2004, furuno.com.au GP 37	5

If technology status for a vessel was unknown, NavAccuracy = (best accuracy at the time)(probability of presence in unknown vessels that year), based on historical fleet aggregate data described in Dichmont *et al*. 2003

5.3.4 Does reducing the fleet size affect relative fishing power?

There has been a reduction in fleet size over recent years, from 97 vessels in 2003 to 51 vessels in 2007). In order to investigate the relationship of reductions in fleet size (and search potential) and catch rates, a moving sum of effort within about 10 mile radius each week was calculated, which we refer to as Local Tiger Effort. Local Tiger Effort was the sum of effort in the 6-nautical-mile square grid and eight neighbouring grids, for the week centred on the current day. This effort was fitted in the fishing power models, in two alternative forms, namely as spline terms and as categories of Tiger Local Effort.

5.3.5 Investigate possible improvements to the fishing power models of 2003

The model specifications of the Basic Low and High and the Spatial models of 2003 were reviewed with the aim of identifying possible improvements to the models. The sensitivity of relative fishing power to a number of modelling decisions or alternatives was then investigated.

In order to identify possible improvements to the 2003 models, the sensitivity of relative fishing power to modelling decisions or alternatives was investigated in the following ways. A computational experiment was conducted, to assess various combinations of 12 binary factors, in a fractional factorial design, that jointly specified characteristics of models all of the same form as Equation 1. This computational experiment was similar to those described in Bishop *et al.*, 2008. The factors that were investigated are listed in Table 5.2. A second series of models (referred to as "candidate models") was also fit to compare results from some additional decisions including linear, random effects and robust regression. All these modelling decisions were assessed with respect to their impact on cumulative fishing power, and annual increments in fishing power q_{inc}.

In summary, there were 62 modelling runs (32 From the computational experiment plus 30 from the further "candidate models" series). Each model run produced a series with 38 rows (one for each year) and with 2 outcome variants for each model run (basic and spatial relative fishing power). A dataset was built that contained all these outputs (n=4788 records with columns for relative fishing power and Qinc and all the factors and their levels). The analysis was to fit a linear mixed model, where the dependent variable was log(q_{inc}.), fixed effects were the 12 binary factors of the experimental design, and year was included as a random effect.

Table 5.2. Modelling decisions or alternatives that were systematically investigated by means of computational experiment, candidate model series and alternative definitions of relative fishing power.

	Topic
Factors assessed by computational experiment	
1	Catch records aggregated to month-grid vs. daily, unaggregated
2	Include or exclude hours: log(hours fished per day)
3	Include or exclude lightly fished grids (< 3 days per month)
4	Treatment of unknown technology status: present/absent/unknown category or continuous variable ranging from 0 to 1 with unknown status represented by the proportion expected in the unknown fleet.
5	Navigation accuracy schedule or "NAV3" hierarchy of navigation aids, plotters and plotter software, or all as separate categorical variables.
6	Skipper and company terms
7	Spatial term: tiger prawn stock region (as in previous models) and sub region (based on banana prawn regions
8	bspline(day) vs month as categorical term
9	bspline(depth) vs quadratic depth
10	Include or omit terms for moon phase and interactions
11	Include or omit three way interaction terms
12	Include or omit terms for habitat at fine spatial scale (Mud, Untrawlable ground, fine scale effort term based on effort of 1996-2000, with interactions)

Some candidate models

13 The models were fitted by robust regression to limit the influence of outliers (fitted by M estimation; Huber, 1973) and linear mixed models with either random Year, random Vessel, or random Year.Vessel (Venables and Dichmont, 2004) in addition to the usual linear model with fixed effects.

14 Include or omit local effort (nearest 6nm grids per week)

Fishing power outcomes that were investigated as factors in the sensitivity analysis

15 Alternative definitions of relative fishing power : see Table Footnote #15

1. **Basic**: Sum of linear predictors for vessel terms (∑V) with YAM constant, M reflects Season 2
2. **Spatial-year**: ∑VAM with Y constant;
3. **Spatial-season**: ∑VA with YM constant, M reflects Season 1
4. As for #3 above, and M reflects Season 2

16 Relative fishing power for reconstructed fleet data compared to relative fishing power for estimation dataset

17 For spatial relative fishing power: Survey denominator compared to commercial denominator

18 Subset of similar vessels vs entire fleet, and "indirect fishing power" see Table Footnote #18

Table Footnote #15

Two classes of fishing power definitions were implemented in the 2003 models: the **Basic** and the **Spatial,** in future to be referred to as the **Spatial-year**. A third definition, the **Spatial-season**, was implemented in the current project.

The **Basic** fishing power is a per-fleet measure, defined as the mean of the per-vessel powers for season 1 or season 2 each year. The per-vessel relative fishing power (per year) is defined as the sum of the linear predictors for the vessel component. The basic definition of fishing power does not reflect any change in spatial or temporal patterns of fishing and therefore lacks accounting for improvements in targeting, and loss of fishable areas due to closures. (By convention, the 2003 Basic relative fishing powers adopted Basic-season-2 outputs, Table 3.2).

The **spatial-year** fishing power incorporates additional components to reflect changes in spatio-temporal fishing patterns relative to the most favourable times and places. The **spatial-year** definition of fishing power captures improvements in targeting, and loss of fishable areas due to spatial and season closures and accounts for these as changes in fishing power. However, by accounting for season closures, the **spatial-year** fishing power captures some of the within-year availability changes as fishing power, which is undesirable because availability is already accounted for in the stock model.

The new **spatial-season** definition of fishing power is part-way between the **Basic** and the **Spatial-year** definitions. It is intended to account for improvements in spatial targeting as fishing power, while avoiding double-accounting of availability changes by fixing month to minimise the contribution to fishing power of any season closures.

Table 5.3: Differences among the definitions of fishing power. V is terms to represent vessels and technology, Y is year, A is Area or Region, M is Month, D is Depth, H is Habitat variables, L is Lunar phase.

	Basic	**Spatial-year** (also known as **Spatial**)	**Spatial-season**
Fishing power is sum of linear predictors for these terms	∑V	∑VAMDHL	∑VAD
Terms held constant	YAMDHL	Y	YM

Value of constant month term	May (Season 1) Sep (Season 2)	--	May (Season 1) Sep (Season 2)
Conventional Usage	2003 Basic Low and Basic High , and current study (with month fixed at September to represent Season 2)	2003 Spatial High, and current study	Current study

Table Footnote #18

The standardised cpue was the mean daily catch rate, in kg/ standard night with 12 hours trawling covering 209 hectares, according to the exponent of the linear predictor, with a correction for bias, for a hypothetical standard vessel in depth strata for each region, month and year, at new moon

$$U_{j,k,t} = \exp(C_{s,j,t} + \tfrac{1}{2}\sigma^2)$$

From these results for each month and stratum, an appropriate weighted (for stratum area) index of relative abundance was constructed to represent the entire fishery, each year.

An alternative definition of fishing power was developed as follows. “Indirect fishing power” was defined as the ration of nominal cpue for the year to the standardised abundance for the year (an index in relative units then standardised to unity in a baseline year):

$$CPUE_y \big/ U_y$$

The hope is that indirect fishing power may prove accurate and reliable, not only when obtained from the entire fleet but also when obtained from a subset of similar vessels, say from one company, because this would reduce the extent of data required on vessel and gear characteristics.

Model diagnostics including AIC, BIC and R^2 were not utilised because these have not proved useful in previous analyses of the NPF tiger fishery logbook data (Bishop *et al.*, 2008). One reason is that because of the large number of records, the available degrees of freedom can overwhelm the change due to adding or removing a few parameters. Another reason is because information criteria including AIC and BIC are not relevant when the dataset does not contain the information that is sought, for example when it has not been collected for the purpose of the model, as is the case with fisheries commercial logbook data. Instead, the criteria for choosing between models included parsimony, degree of separation of cumulative relative fishing power from relative abundance, and stability of results (avoiding indications of possible confounding).

We wanted to identify the source of variability in the data that remained after fitting the preferred model. Analysis of variance components was used to investigate the relative contribution of random effects of vessels, years, and seasons to the variance of the residuals of the preferred model. The model was fitted by the minimum variance quadratic unbiased estimation method (MIVQUE0; Hartley, Rao and LMotte; 1978).

5.3.6 Integrated model of fishing power

A model was specified to incorporate the findings from all the preceding topics of investigation (the new years of data, the review of technology terms, the impact of reducing fleet size, and the review of modelling decisions and fishing power definitions). This model is of the same form as the 2003 models (given in Equation 1) and is a "Low" model. We term the model the 2009 integrated model. A summary of differences between the 2009 and the 2003 models appears in (Table 5.4). The main features are as follows:

- The spatial scale is slightly finer, being stock sub_regions rather than stock regions. This should improve the model's ability to correctly reflect declines in abundance such as the North Mornington decline in brown tiger prawns.
- Electronic aids to navigation (Satnav, GPS/Plotter, DGPS) were replaced by a single variable for navigational accuracy, and plotter included as a separate item.
- A variable to reflect the number of vessels fishing in the local area at the same time was added, thereby giving the model the ability to capture loss in fishing power when the number of vessels in the fleet dropped very low.
- The definition of fishing power was "spatial season 2" a lower result than the "spatial all-year" that was the convention in the 2003 SPLO model, but higher than the "basic" that was the convention in the 2003 BLO and BHI models.
- A number of terms (including moon phase, habitat variables, some technology items and skipper and company terms) were omitted. These were terms had been thought necessary to enable the spatial model to work, or to capture the suite of technology impacts on fishing power, but could now be dropped given the other changes in the models.

The detailed specifications of the 2009 Low model are compared to those for the 2003 models in Table 3.5 and Table 3.6.

A mid-high model (a "middle series") was also proposed, similar to the 2009 integrated model. The 2009 mid-High model differs from the 2009 Low by a) fixing trygear and plotter coefficients at higher levels by offsets and b) using the spatial-year definition of fishing power instead of the spatial-season 2.

Table 5.4. Summary of changes from 2003 model to 2009 Integrated Low Model*

Changes
Spatial term stock_sub-region instead of stock region.
Moon terms omitted
Fine scale spatial terms omitted (historical effort 1996-00, mud%, untrawlable ground)

Electronic aids to navigation as categories of navigational accuracy, and plotter included as a separate item
Plotter software omitted
Colour echo sounder omitted
Sonar omitted
Satellite phone omitted
Skipper terms omitted
Size of company omitted
Local effort (fleet size in the local area) added
Definition of relative fishing power: Spatial for September-October

* Justifications for all but the last of these changes are found in Table 7.

Table 5.5. Structure of fishing power models – summary of differences among models. Shading indicates topics with differences

	Models of 2003			2009 Integrated model
	Basic Low	Basic High	Spatial High	Low
Intercept	Include	Include	Include	Include
Abundance (Y=Year, A=Area, M=Month, c=bspline(calendar day)	Y A M YA YM AM	Y A M YA YM AM	Y A M YA YM AM	Y A c YA Yc Ac
Moon Phase and interactions	Include	Include	Include	Omit
Spatial – habitat attributes				
Spatial term (Area)	Tiger stock region	Tiger stock region	Tiger stock region	Stock sub-region
Fine scale spatial effort history and interactions	Omit	Omit	Include	Omit
Depth	Quadratic	Quadratic	Quadratic	Quadratic
Mud, Untrawlable ground	Omit	Omit	Include	Omit
Availability depth-month from survey data	Omit	Omit	Include	Omit
Vessel				

Hull age and construction group	Include	Include	Include	Include
Swept area				
Log(Swept area rate) from PTPM	Offset	Offset	Offset	Offset
Log(hours fished)	Offset	Offset	Offset	Offset
Catching efficiency of gear				
TED/BRD	Offset	Offset	Offset	Offset
Navigation accuracy				
Radar	Offset	Offset	Offset	Offset
SatNav, GPS, D_GPS	Categories with or without plotter and plotter software	Offsets with or without plotter and plotter software	Offsets with or without plotter and plotter software	Categories for navigational accuracy with probabilistic treatment of unknown
Imaging				
B&W Echosounder	Offset	Offset	Offset	Offset
Colour echo-sounder	Include	Offset	Offset	Omit
Sonar	Include	Offset	Offset	Omit
Sampling				
Trygear	Include	Offset	Offset	Include
Information storage				
Plotter	Include both with navigation, see above	Include both with navigation, see above	Include both with navigation, see above	Include
Plotter software				Omit
Communications				
PC_Satellite	Include	Offset	Offset	Include
Satellite phone	Include	Offset	Offset	Omit
Skippers				
Years of experience as skipper in NPF, Year first worked as skipper in NPF	Include	Include	Include	Omit
Size of company	Include	Include	Include	Omit
Catch handling				
Autopilot	Offset	Offset	Offset	Offset
Local Effort (fleet size effect)	Omit	Omit	Omit	Include
Precaution	None	In tech offset values	In tech offset values	None
Definition of fishing power	Basic – season 2	Spatial	Spatial	Spatial – season 2
Sum over year of linear predictor for these terms	$\sum$V	$\sum$VAM	$\sum$VAM	$\sum$VA
Terms held constant	YAM	Y	Y	Yc

Table 5.6. Assumptions of fishing power models – summary of differences among models

	Models of 2003			2009
	Basic Low	Basic High	Spatial High	Low and mid-High
Definition of target effort	Tiger+endeav> banana	Tiger+endeav> banana	Tiger+endeav> banana	Species Dist 2 (model) And Tiger+Endeav>0
Logbook data inclusions	"Augmented", 2003 method 5 tiger prawn stock regions Months 3-5,8-11	"Augmented", 2003 method 5 tiger prawn stock regions Months 3-5,8-11	"Augmented", 2003 method 5 tiger prawn stock regions Months 3-5,8-11	"Augmented", 2003 method 5 tiger prawn stock regions Months 3-5,8-11
Treatment of missing hours	Imputed (2003 method)	Imputed (2003 method)	Imputed (2003 method)	Imputed (2003 method)
Vessel Codes	Pre-review	Pre-review	Pre-review	Post-review
Basis of relative fishing power	Reconstructed fleet, 2003 method	Reconstructed fleet, 2003 method	Reconstructed fleet, 2003 method	Reconstructed fleet, 2003 method

5.4 Results

5.4.1 Re-fit the 2003 models using the latest available data

The 2003 models have been re-fitted using all the latest available data, (1970 to 2007) and the coefficients were re-estimated. The newly re-fitted models were compared to results from the 2003 model and its projections for 2003-7 (these projections had been used as inputs to stock assessments each year for 2003 to 2007)(Figure5.2). While the effects of re-fitting are not large in the case of the basic models, there is an effect in the case of the spatial model.

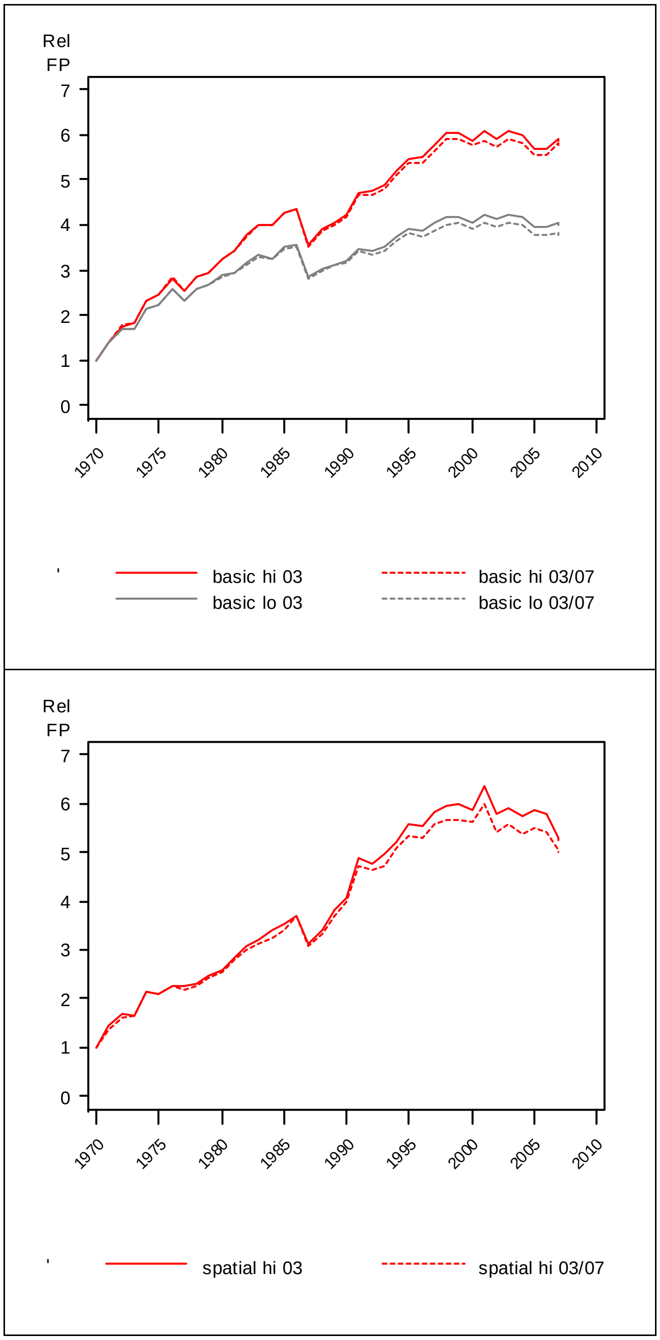

Figure 5.2. Cumulative relative fishing power from 2003 models re-estimated from latest available data (data to 2007, labelled 03/07. These are the new results), compared to "old" results, from the 2003 models projected forwards from 2003 to 2007 series. Top: Basic models. Bottom: Spatial model.

5.4.2 Review the extent and treatment of technology changes since 2002

Harvesting

Changing management regulations, including a series of cuts in allowed headline length, had imposed significant changes in gear since 2003. The impacts of changes since 2002 in headline length, boards, engines and propulsion on swept area performance rate (SAR) were captured by an engineering model, the Prawn Trawl Performance Model (PTPM, Sterling, 2005). These changes and impacts have been separately reported to the NPF RAG (Bishop, 2008). An important feature was the change from the traditional shape of nets that had occurred when nets were cut down in size in response to the cuts in allowed headline. The modified nets were draggier than traditional nets, and the PTPM was modified to adjust for this. The resultant swept area rates have been incorporated into all the fishing power models.

There has been no known change in the catch efficiency of TED/BRDs since 2003. The allowance for loss of catch due to TED/BRDs, (-3% in recent years; Brewer, Heales, Milton et al., 2006) have been incorporated into all the fishing power models.

We recommend that innovations in TEDs/BRDs should be monitored, particularly their position in nets.

Navigation

Increased navigational accuracy allows precise positioning of the trawl, which allows new targeting strategies such as trawling very close to untrawlable ground, or repeatedly trawling the same trawl track ("trawling the line"). GPS appeared in the NPF or 1989 and was fully taken up by the fleet by 1992. Differential GPS (DGPS) appeared in 1997, and by 2002 was on board roughly half the fleet. However, whether DGPS had any impact on fishing over and above the impact of GPS was difficult to assess due to changes in accuracy of GPS and D_GPS, and possibly some confounding among innovations that appeared concurrently --GPS, differential GPS, plotters, and plotter software.

The esimates of the impact of categorised navigational accuracy on catching power were stable and internally consistent (Figure 5.3, Figure 5.4). The impact of satnav compared to no navigation equipment at all was to increase catch rates by 8%. When GPS had an accuracy of 120 metres radius (1988-99), the impact on catch rates compared to no navigation equipment at all was to increase catch rates by 10% on average. When accuracy increased to 20 metres (whether by GPS when selective availability was turned off in 2000, or by differential GPS), catch rates increased by another 4%. The coefficient for log (navigational accuracy) was -0.024.

Equipment that links GPS output to autopilot is an innovation with potential to improve fishing power and the uptake of this technology should be monitored in future.

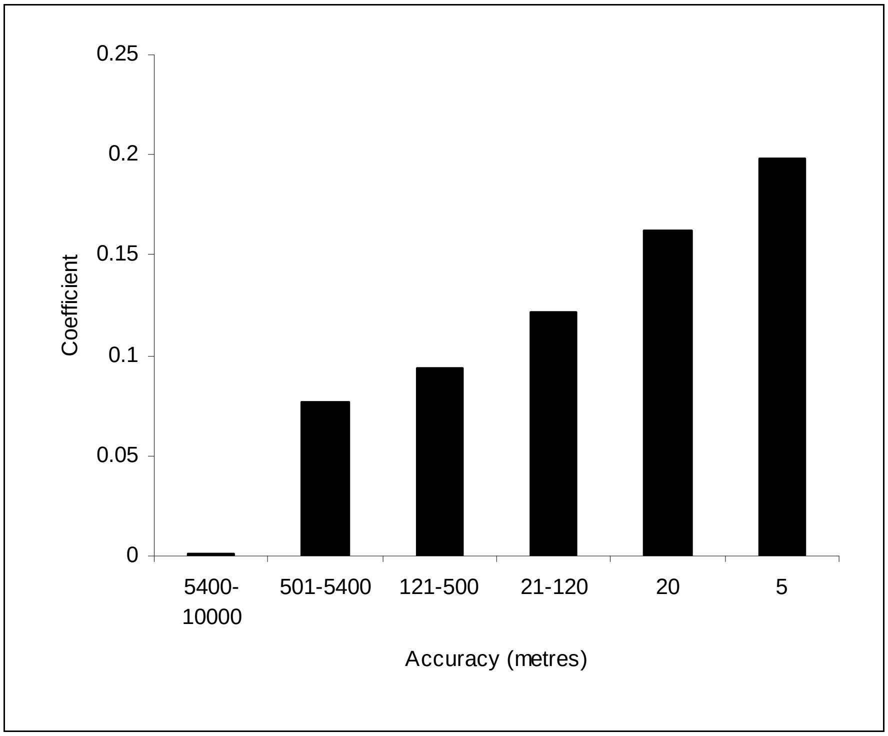

Figure 5.3. Coefficients for impact of navigational accuracy on log(catch kg/day)

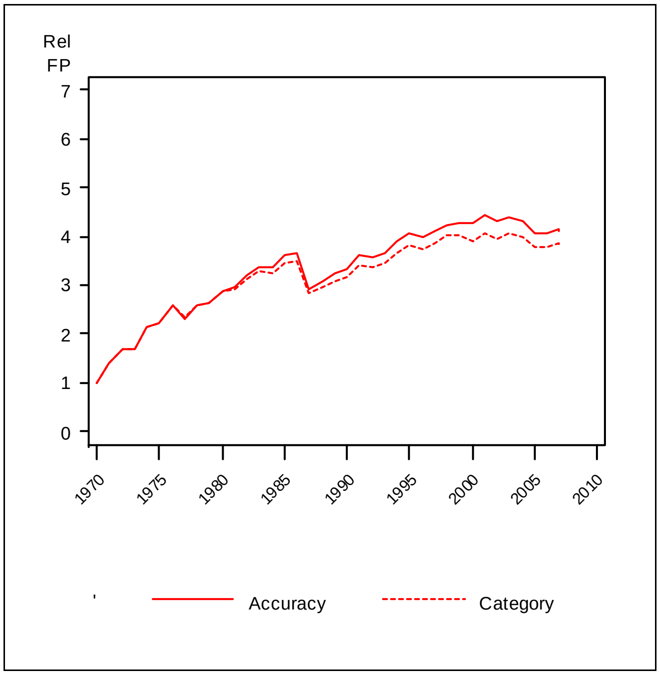

Figure 5.4. Cumulative relative fishing power with alternative representations of electronic aids for navigation: categories (to represent presence absence or unknown status), or navigational accuracy.

Imaging

Colour echosounders appeared in the fleet in 1982 and were fully taken up by 1987. The assessment of colour echo-sounder has tended to be unstable in previous analyses. The analysis of coefficients from the sensitivity experiment and the candidate models produced no clear evidence that the impact of colour echo-sounder differed from zero.

Sonar appeared in the NPF fleet in 1982, and by 2007 had reached 14%. The highest prevalence of 25% occurred in 1998. The fact that prevalence of sonar never reached even 50% in the fleet suggests that its real benefit may be small. Recent years of data are all years with contrast in the data. When investigated with the new years of data, sonar was not associated with any important impact on fishing power (Figure 5.5).

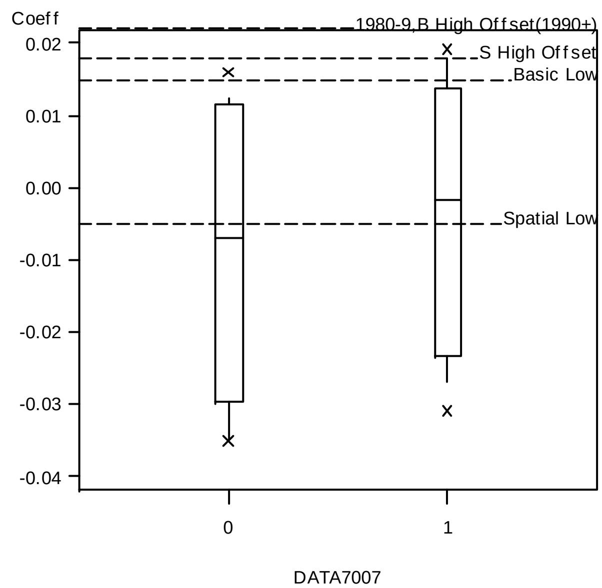

Figure 5.5. Coefficients for sonar from sensitivity experiment

Information management

Plotters allow storing and sharing of information about trawling hazards, and favourable trawl lines. Plotter software makes it easier to manage the stored information, possibly making it more concise and useful. The data for presence and absence of plotters is almost identical to the data for presence and absence of GPS, therefore the results for these items have been difficult to separate in previous models. With the navigation accuracy variable in the model replacing GPS, the impact of plotters was estimated to be important, at around 0.043. This result was quite stable.

Plotter software appeared in 1997 and prevalence in the fleet reached 97% by 2007. Plotter software had only 23% uptake at the time of the previous project, therefore the new years of data (and contrast within years) potentially added important evidence for the assessment of plotter software usefulness. However, in the new years of data, the presence of Plotter Software is completely confounded with the variable that represents having a computer on board that is connected to satellite email (PC_SAT). When investigated with the new years of data, Plotter Software was not associated with any important impact on fishing power (Figure 5.6).

The 3D seabed mapping plotters appeared in 2005, but are not common enough in the fleet yet to assess any impact on fishing power from logbook data.

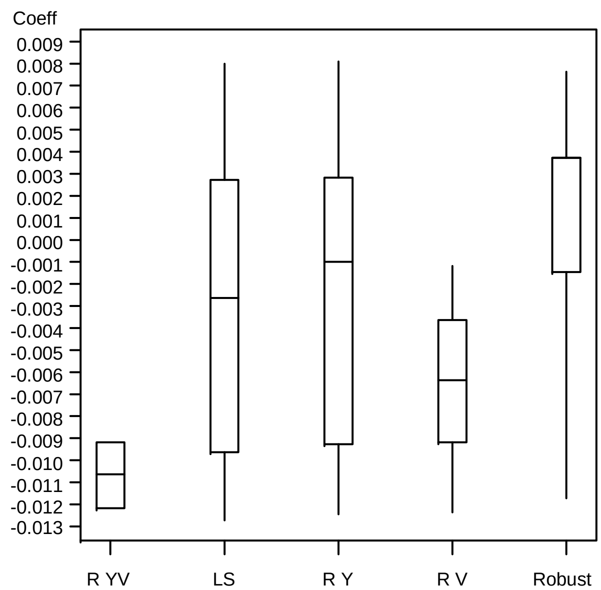

Figure 5.6. Coefficient for plotter software from some candidate models: YV=Random Year+ Vcode; LS=Least Squares; Y=Random Year; V=Random Vcode; Robust=Robust regression

Communications

Communications technology aids skippers decisions about how long to stay in a given fishing ground, and in which direction and how far to steam. Does communication technology aid decisions about targeting shots within a given grid? If no, then the impact of communication could be entirely captured by the spatial and temporal terms in the model, given the spatial definition of fishing power.

Satellite phone appeared in 1996 and reached full uptake in 1998. There was no evidence that satellite phone added anything to fishing power (estimates were consistently less than zero).

Computer on board connected to email facilities appeared in the fleet in 1997. In 1998 Satellite Vessel Management System (VMS) was introduced so technically 100% of vessels had access to email. Since then the coding of computer on board has continued, (in later years the variable is suspected to be unreliable), however nature and extent of any use of the computer with email facilities is unknown. Therefore the variable no longer captures the intended concept of the email form of communication. In spite of these limitations, the impact of PC_SAT on fishing power was consistent, stable and important (about 0.025 to 0.029) when fitted with the new years of data.

5.4.3 Does reducing the fleet size affect relative fishing power?

Expected catch declined slowly in association with declining local effort (Figure 5.7). There was a small effect on fishing power when the local effort term was included in the models (Figure 5.8).

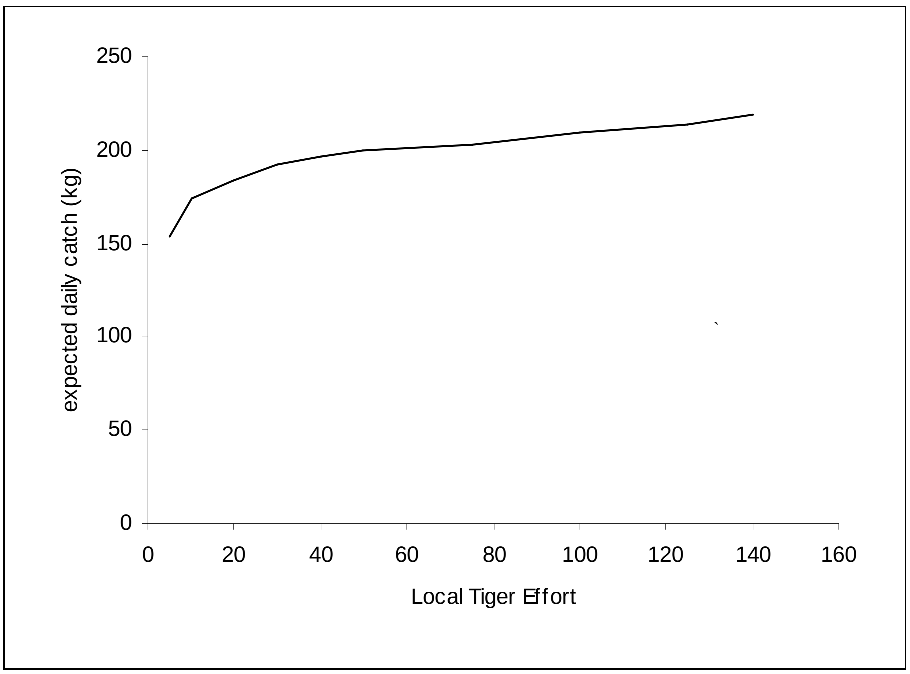

Figure 5.7. Impact on expected catch of local effort directed to tiger prawns (within moving 8 neighbouring grids and week, centred on current grid and day)

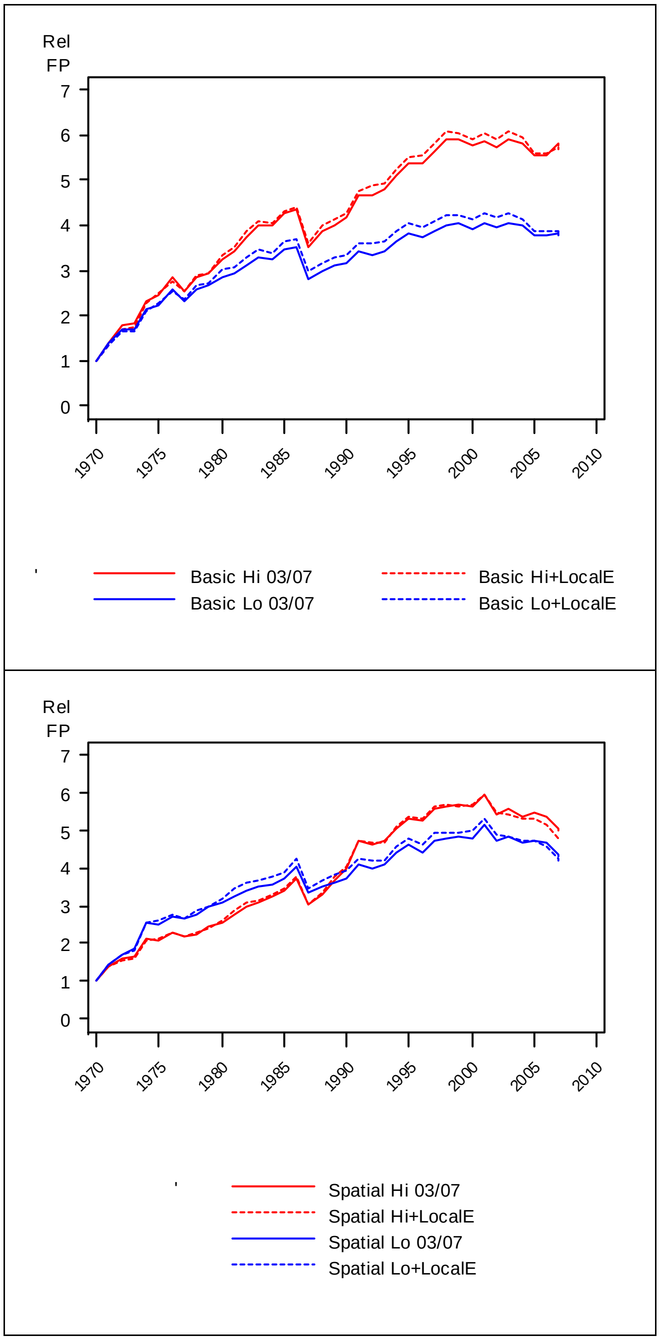

Figure 5.8. Cumulative relative fishing power when changes in local effort were accounted for, compared to similar models without such accounting (the 2003 models fitted with 1970-2007 data.). Top: Basic low and high. Bottom: Spatial low and high.

5.4.4 Investigate possible improvements to the fishing power models of 2003

Among the topics that were investigated, the definitions of fishing power proved to be influential, and for clarity this topic is considered first, in section 3.3.1. The results of the other investigations into the sensitivity of model outputs to modelling decisions are outlined in section 3.3.2.

Definitions of relative fishing power

The fishing power outcomes were sensitive to the definitions of fishing power (Figure 5.9). The **Spatial** series are all higher than the **Basic** fishing power, which indicates that spatial targeting has occurred in the NPF and that an increment for this can be captured by the **spatial** definitions of fishing power. The differences between the **spatial-season** series constitute weak evidence that fishing power could be higher in season one than in season two. Fishing power is inherently more difficult to assess in season 1 than in season 2 due to the influence of variable abundance of banana prawns as an alternative target, and a smaller sample size (due to lower effort on tiger prawns). The variability in the **spatial-season-one** series suggests that some component of abundance has been incorporated into fishing power. Any difference between fishing power in the two seasons has important implications given that the target tiger prawn species differ between the two seasons.

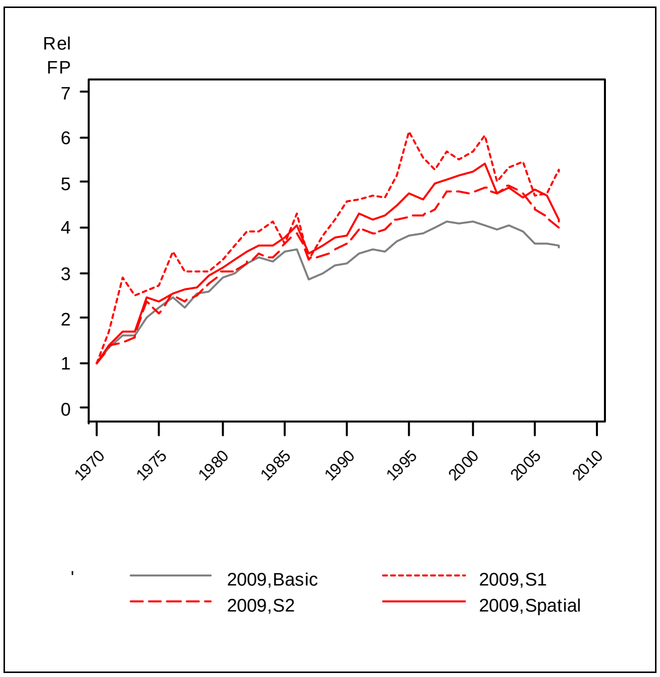

Figure 5.9. Basic, Spatial (Spatial-Year), and Spatial-season definitions of relative fishing power. S1 is season 1 (represented by May), S2 is season 2 (represented by September).

We recommend the use of the **spatial-year** fishing power (2009, Spatial in Figure 3.9), or the **spatial-season-two** series (2009), but we consider that the **spatial-season-one** series is not robust enough to be used in the stock assessments.

Sensitivity of relative fishing power to alternative modelling decisions

Table 5.7 presents a summary of the results from the series of computational experiments made and, on the basis of these results, the conclusions.

The fishing power models were found to be relatively robust in some respects. Some terms could be dropped from both abundance and vessel components with little impact on the outcome of cumulative fishing power.

On the other hand, relative fishing power was sensitive to the degree to which the catch data was aggregated, the geographical extent of the fishing grounds on which the model was fitted, the inclusion of hours fished per day, and the treatment of unknown technology status. These features of the 2004 fishing power models were retained with no change.

Table 5.7. Sensitivity of relative fishing power to the modelling decisions or alternatives (Y is year, A is area, M is month, V is vessel)

	Topic	Result	Conclusion
1	Catch records aggregated to month-grid vs. daily, unaggregated	Sensitive	Prefer unaggregated
2	Include or exclude hours: log(hours fished per day)	Sensitive	Include log(hours)
3	Include or exclude lightly fished grids (< 3 days per month)	Sensitive	Include all grids
4	The models were fitted by robust regression and general linear mixed models (random Year, random Vessel and random Year Vessel) in addition to the usual linear model with fixed effects	Sensitive	linear model with fixed effects
5	Alternative definitions of relative fishing power were reviewed: 5. **Basic**: Sum of linear predictors for vessel terms ($\sum$V) with YAM constant, M reflects Season 2 6. **Spatial-year**: $\sum$VAM with Y constant; with survey denominator. 7. As for #2 above, with commercial denominator 8. **Spatial-season**: $\sum$VA with YM constant, M reflects Season 1 9. As for #4 above, and M reflects Season 2	Sensitive	Use **spatial-year**, or **Spatial-season-2** **Spatial-season** results suggested that fishing power in season 1 may be higher, but spatial-season-1 result is too variable to rely on for ongoing use Denominator makes little difference in practice, but “survey” denominator preferred (details are in final report).
6	Relative fishing power for reconstructed	Sensitive	Use reconstructed fleet

	fleet data compared to relative fishing power for estimation dataset		
7	Treatment of unknown technology status: present/absent/unknown category or continuous variable ranging from 0 to 1 with unknown status represented by the proportion expected in the unknown fleet.	Sensitive	Prefer unknown category
8	Navigation accuracy schedule or "NAV3" hierarchy of navigation aids, plotters and plotter software, or all as separate categorical variables.	Some effect	Consider as alternative
9	Include or omit local effort (nearest 6nm grids per week)	Small effect	Include
10	Skipper and company terms	Small effect	Consider replacement with alternative allowance
11	Spatial term: tiger prawn stock region (as in previous models) and sub region (based on banana prawn regions	Robust	Use tiger stock sub_region to allow sensitivity to fluctuations in productivity of adjacent nursery grounds.
12	bspline(day) vs month as categorical term	Robust	Spline(day) appears to be more robust for years with short seasons
13	bspline(depth) vs quadratic depth	Robust	Use quadratic depth
14	Include or omit terms for moon phase and interactions	Robust	Omit
15	Include or omit fine scale effort term based on effort of 1996-2000, with interactions	Robust	Omit
16	Include or omit three way interaction terms	Robust	Omit
17	Include or omit terms for habitat at fine spatial scale (Mud, Untrawlable ground)	Robust	Omit

Analysis of residuals: Variance components

Analysis of variation in the residuals (when the effects were fitted as random terms) showed that Year*VCODE was associated with the greatest amount of residual variance (15%)(Table 5.8). This provides evidence that fishing power in the NPF is higher than the series captured by the models to date.

Table 5.8. Variance Component on residuals of the Integrated 2009 Low model

Source	Variance	Variance as % of total error
Var(YEAR)	-0.0001	-0.09
Var(TSTOCKAREA)	0.0000	-0.02
Var(Month)	0.0000	-0.002
Var(VCODE)	0.0053	3.62
Var(YEAR*VCODE)	0.0225	15.27
Var(TSTOCKAREA*VCODE)	0.0033	2.24
Var(YEAR*TSTOCKAREA)	-0.0004	-0.25
Var(Error)	0.1470	100.0

5.4.5 Integrated model of fishing power

The 2009 integrated Low model (Figure 5.1) integrates the features of the 2003 basic and spatial models, and the results of all the above-mentioned reviews and investigations. Mid-high model was also proposed (a "middle series"). Figure 5.10 depicts results from the 2009 integrated Low and mid-high model compared to those from the re-estimated 2003 models.

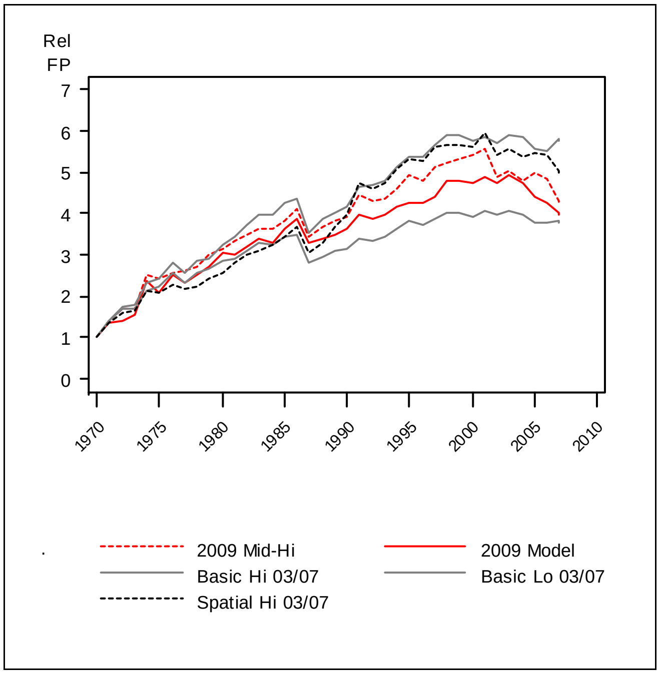

Figure 5.10. Cumulative relative fishing power from 2009 integrated model (a revised low series of fishing power, and a mid-high option), compared to three series from 2003.

5.5 Discussion and conclusions

The 2009 model is more parsimonious than all of the 2003 models, due to the navigational accuracy treatment, and omission of terms for moon, habitat, fine scale effort history, skipper and some technology terms. Omitting plotter software and sonar was based on new evidence obtained by analysing the extra years of data which had contrast for these items. Having fewer variables improves the efficiency of the fishing power analyses.

The 2009 model accounts for changes in fleet size, as presented in Section 5.6 where a term for local effort was introduced into the model.

Furthermore, the 2009 model is at a spatial and temporal scale that allows slightly more flexibility in modelling abundance fluctuations; so it should be better at detecting local declines, compared to the 2003 models. The old spatial models enforce a highly stable abundance pattern due to the larger spatial scale and the use of the effort 1996-2000 variable to model hotspots that were assumed to be large, stable and consistent over the years.

We recommend the 2009 integrated model as an alternative to the 2003 Basic Low model as a representation of the lower bound of trends in relative fishing power in the NPF. The 2009 integrated model is based on evidence from the data as far as possible, and expert knowledge and judgement, and is comparable to the 2003 low series.

When comparing the 2009 model to the 2003 models, we consider it important to review the rationale for developing low and high series. The 2003 low and high series of fishing power were developed to provide an envelope within which the true fishing power series is most likely to occur. In the context of the low and high series of 2003, the 2009 integrated model represents a revised “Low” boundary to the values of relative fishing power, which is supported by analysis of the available data combined with some expert knowledge and judgement. The 2009 model is a higher series than the 2003 Low, and in that respect it narrows the envelope of possible fishing powers an therefore decreases the uncertainty of the fishing power inputs to the stock model.

Although there is evidence that fishing power could be higher than that indicated by the 2009 integrated model, we were unable to identify a suitably robust model along the same lines as the Basic High to represent the high (upper) limit of possible fishing power changes. Instead, a Mid-high model was proposed (a “middle series”).

We wish to emphasise that choosing this “middle series” model as a new, less-precautionary “mid-high” means that there could be a potential fishing power series higher than this, whereas the 2003 Basic Low and 2003 High was seen as the lower and upper bounds of the uncertainty, respectively. In other words, boundaries that reflect the range of estimates taking into account the various uncertainties. While the new 2009 integrated model represents directly a lower bound on the uncertainty (as was the 2003 Basic Low); we do not have a corresponding model (and series) to the 2003 High that we can propose on the basis of the analyses presented herein. There is no new 2009 High series for fishing power. We only have a “middle series”, which while precautionary to a degree, does not represent an upper bound. This needs to be acknowledged and we request that the RAG deliberate over the implications of the change in the practice of defining ranges of uncertainty that this represents

In summary,

a) We recommend the 2009 integrated model as an alternative to the 2003 Basic Low model as a representation of the lower bound of trends in relative fishing power in the NPF.

b) We were unable to identify a suitably robust model along the same lines as the Basic High to represent the high (upper) limit of possible fishing power changes. A mid-high model is available.

5.6 References

Bishop, J. and Sterling, D 1999. Survey of technology utilised in the Northern Prawn Fishery 1999. Australian Fisheries Management Authority. Canberra. pp. 50.

Bishop, J. 2006. Standardizing fishery-dependent catch and effort in a complex fishery where technology changed. Rev. Fish. Biol. Fisheries 16:21-38.

Bishop, J. 2008 Relative fishing power: Northern Prawn Fishery when targeting tiger prawns in 2007. Report to NPF RAG, April, 2008

Bishop, J., Venables, W.N., Dichmont, C.M., Sterling, D.J. 2008. Standardizing catch rates: is logbook information by itself enough? ICES Journal of Marine Science 65: 255–266

Brewer, D., Heales, D., Milton, D., Dell, Q., Fry, G., Venables, W., and Jones, P. 2006. The impact of Turtle Excluder Devices and Bycatch Reduction Devices on diverse tropical marine communities in Australia's Northern Prawn Trawl Fishery. Fisheries Research. 81:176-188.

Dichmont, C.M., Bishop, J., Venables, W.N., Sterling, D.J., Eayrs, S. and Rawlinson N. 2003. A new approach to fishing power analysis and its application in the Northern Prawn Fishery. CSIRO R99/1494, Cleveland, Australia

GB Ministry of Defence 1987 Admiralty manual of navigation, Volume 1 Volume 45 of BR Series BR ; 45. 697 pp.

Geoscience Australia 2005 Global Positioning System (GPS) & GLONASS http://www.ga.gov.au/geodesy/gps/gpsoverview.jsp viewed 15/05/2010

Hartley, H. O., Rao, J. N. K., and LaMotte, L. 1978 A Simple Synthesis-Based Method of Variance Component Estimation. Biometrics, 34: 233–244

Huber, P.J. 1973 Robust Regression: Asymptotics, Conjectures and Monte Carlo. Ann. Stat., 1: 799–821

Logsdon, T. 1995 Understanding the Navstar. Springer 2nd ed. 350 pp.

Maunder, M.M., and Punt, A.E. 2004 Standardizing catch and effort data: a review of recent approaches. Fisheries Research, 70: 141-159

Robins, C.M., Wang, Y.-G. & Die D. 1998. The impact of Global Positioning Systems and plotters on fishing power in the Northern Prawn Fishery, Australia. Can. J. Fish. Aquat. Sci., 55, 1645-1651.

Saaty T. L., 1980 The analytic hierarchy process: planning, priority setting and resource allocation. McGraw-Hill, New York. 287pp.

Seynat, C., Kealy, A. and Zhang, K. 2005 A Performance Analysis of Future Global Navigation Satellite Systems. J Global Positioning Systems (2004) 3: 232-241.

Sterling, D. 2005 Modelling the physics of prawn trawling for fisheries management. PhD thesis, School of Applied Physics, Curtin University of Technology, Perth. 270 pp.

Venables, W.N., Dichmont, C.M., 2004. GLMs, GAMs, GLMMs: an overview of theory for applications in fisheries research. Fish. Res. 70, 315–333.

APPENDIX 6. PARTITIONING THE NPF BANANA PRAWN FISHERY INTO EASTERN AND WESTERN REGIONS FOR SEPARATE TAC ALLOCATION

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6.1 Introduction

The banana prawn catch in the NPF consists of two biological species, namely *Penaeus merguiensis* (common banana prawns) and *P. indicus* (red-legged banana prawns), which are undifferentiated in the catch. Common banana prawns are caught throughout the NPF, often in aggregations close to the surface and in relatively shallow water. By contrast red-legged banana prawns are confined to a number of discrete regions in the West of the NPF and are caught in relatively deep water by trawl methods more reminiscent of tiger prawn trawling.

Ideally, to manage both biological species a separate TAC would be set for both. Since the catch is undifferentiated, however, for practical purposes the best approximation to this situation is for the banana prawn component of the NPF fishery to be partitioned spatially into two regions and a separate banana prawn TAC be set for each.

6.2 Criteria for the partition

Three evident criteria for a spatial partitioning of the TAC regions are, possibly in increasing order of importance:

The interface between the two spatial regions should be clear and precise and as well separated as possible from the normal operation of the fishery,

The interface should be simple to specify, making compliance simple for the industry and easy to ensure by the management authority

The western partition should contain as much of the red-legged banana catch, and as little of the common banana catch, as possible.

Figure 6.1 following shows the total nominal effort pattern for the NPF, 1970-2008, as recorded in the logbooks, in boat-days. Two possible dividing lines between an Eastern and Western region which satisfy the criterion of minimal interference with the activity of the fleet are immediately apparent, and conveniently these are both North-south lines, and hence also satisfy the second criterion of simple specification and hence easy compliance. These are:

- A line in the Eastern part of the Joseph Bonaparte Gulf (JBG) extending north from Pearce Point (14.4246^{0}S, 129.3567^{0}E) along the same longitude to the northern extreme of the fishery, and
- A line extending from the Arnhem Land coast at (11.8762^{0}S, 134.0000^{0}E) north along the same longitude to the northern extreme of the fishery.

We will refer to these two possible partitioning lines as the *JBG* and *Arnhem green lines* respectively.

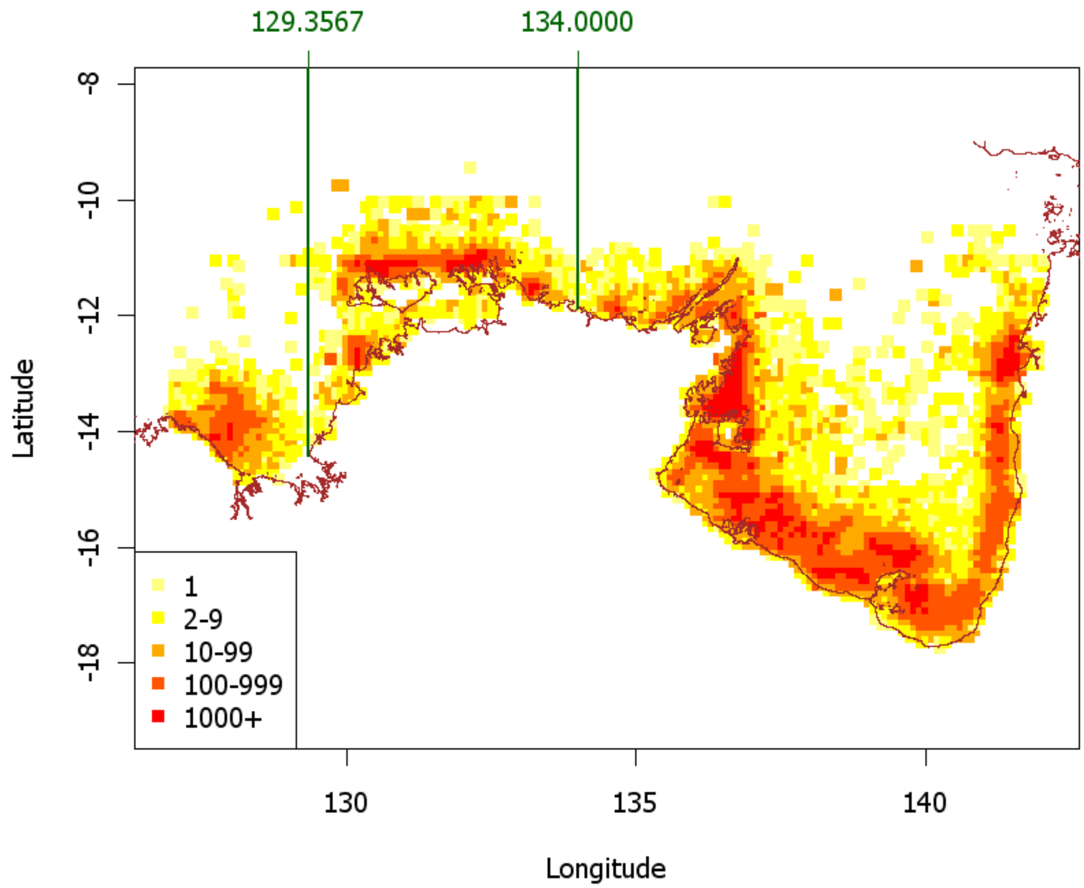

Figure 6.1: Total nominal effort levels for the 6 minute grid squares of the NPF, 1970-2008. The two green lines show possible separation lines for an Eastern and Western banana prawn TAC area for the NPF.

A second view of the effort levels is given in Figure 6.2, which shows the total nominal effort levels in the NPF, 1970-2008, grouped by longitude in 0.5 degree bins. This makes it clear that if the NPF is to be partitioned into an Eastern and Western region by a line of longitude, than the two possible lines we identify above interfere very little with the operations of the fishery, and may be nearly optimal in this sense.

As lines of longitude are easy for both fleet to comply, and management authority to ensure compliance, such a partitioning line would satisfy the second criterion identified above as well.

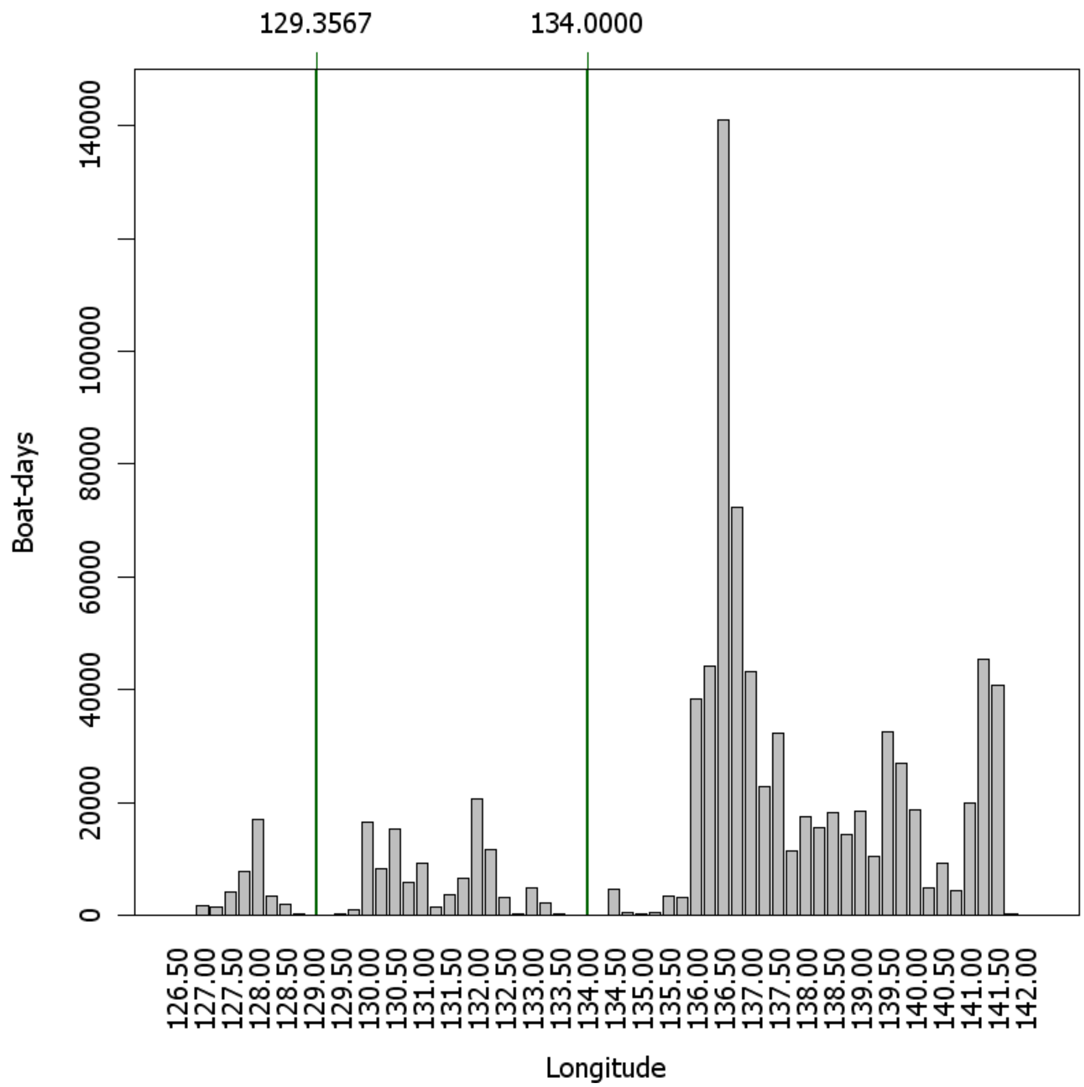

Figure 6.2: Effort levels in the NPF, 1970-2008, grouped in bins of 0.5 degrees of longitude.

The third criterion, possibly the most important, is that the partition into two regions should isolate the catch of the two banana prawn species as much as possible.

Table 6.1: Percentage of the total banana prawn catch, 1970-2008, by species, caught to the West of either possible green line.

Green line	JBG	Arnhem
P. merguiensis	0.93	15.99
P. indicus	64.74	100.00

Some information on this is shown in Table 6.1 above. The JBG green line isolates a negligible proportion of the common banana prawn catch to the West but only about 65% of the red-legged banana catch. The Arnhem green line isolates the entire red-legged banana prawn catch to the West, but about 16% of the common banana prawn catch. These critical percentages are also illustrated by the cumulative proportion of catch curges shown in Figure 6.3 below.

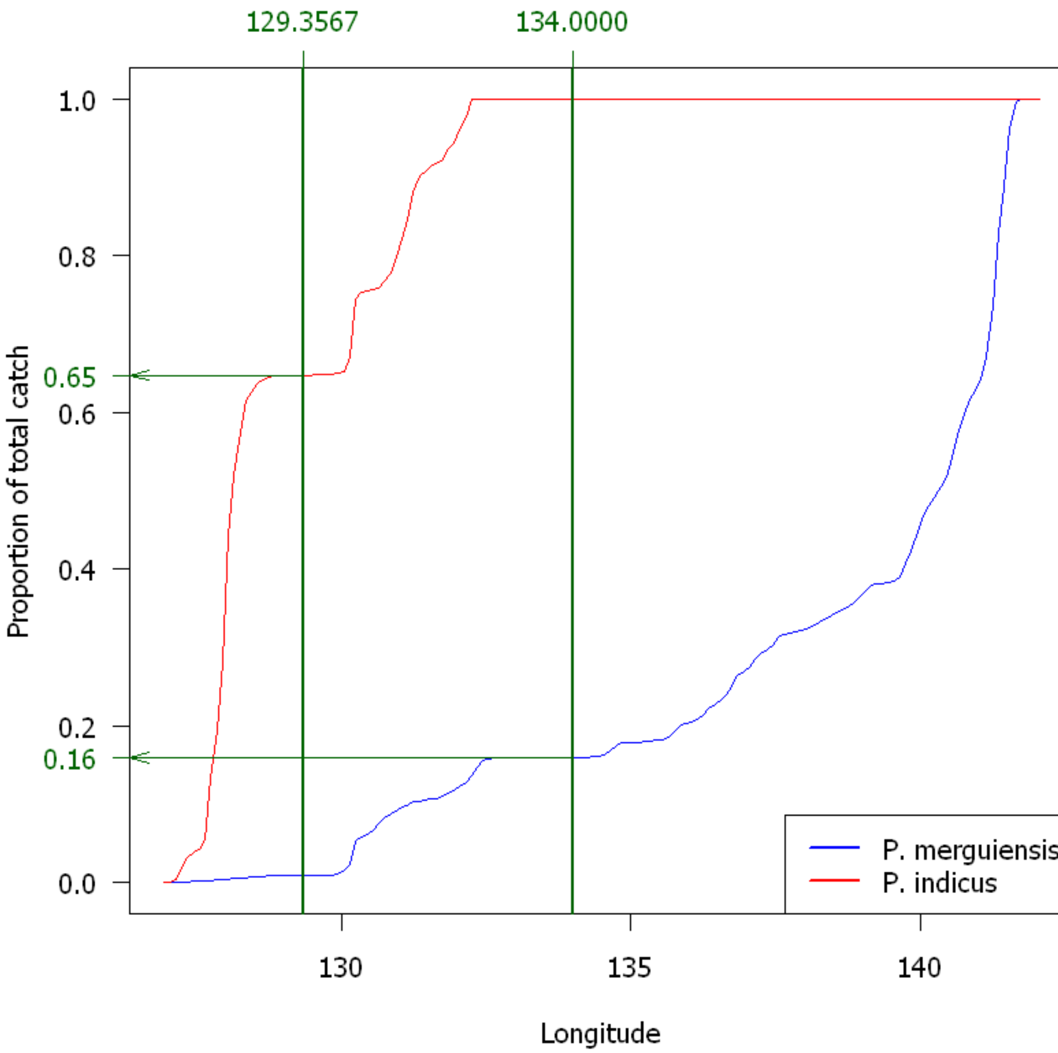

Figure 6.3: Cumulative catch proportions of both banana prawns, 1970-2009.

Since the TAC will be set annually, a further consideration is the variability of these catch proportions to the West of each green line, by year. These variabilities are illustrated in Figure 6.4, Figure 6.5 and Figure 6.6 below. The proportion of the red-legged banana catch to the West of the Arnhem green line is always 100%, so this diagram is not show.

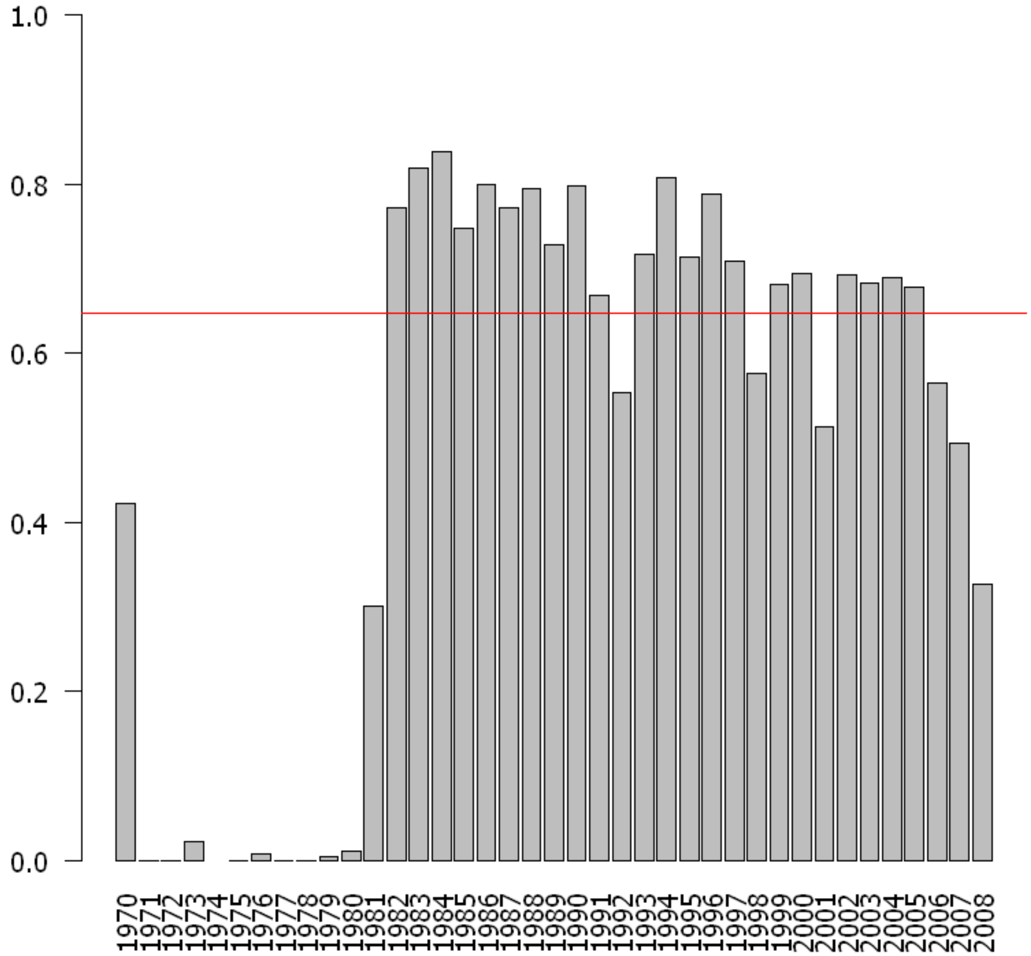

Figure 6.4: Proportions of *P. indicus* caught West of the JBG green line, by year. The horizontal red line shows the overall proportion, namely 0.647.

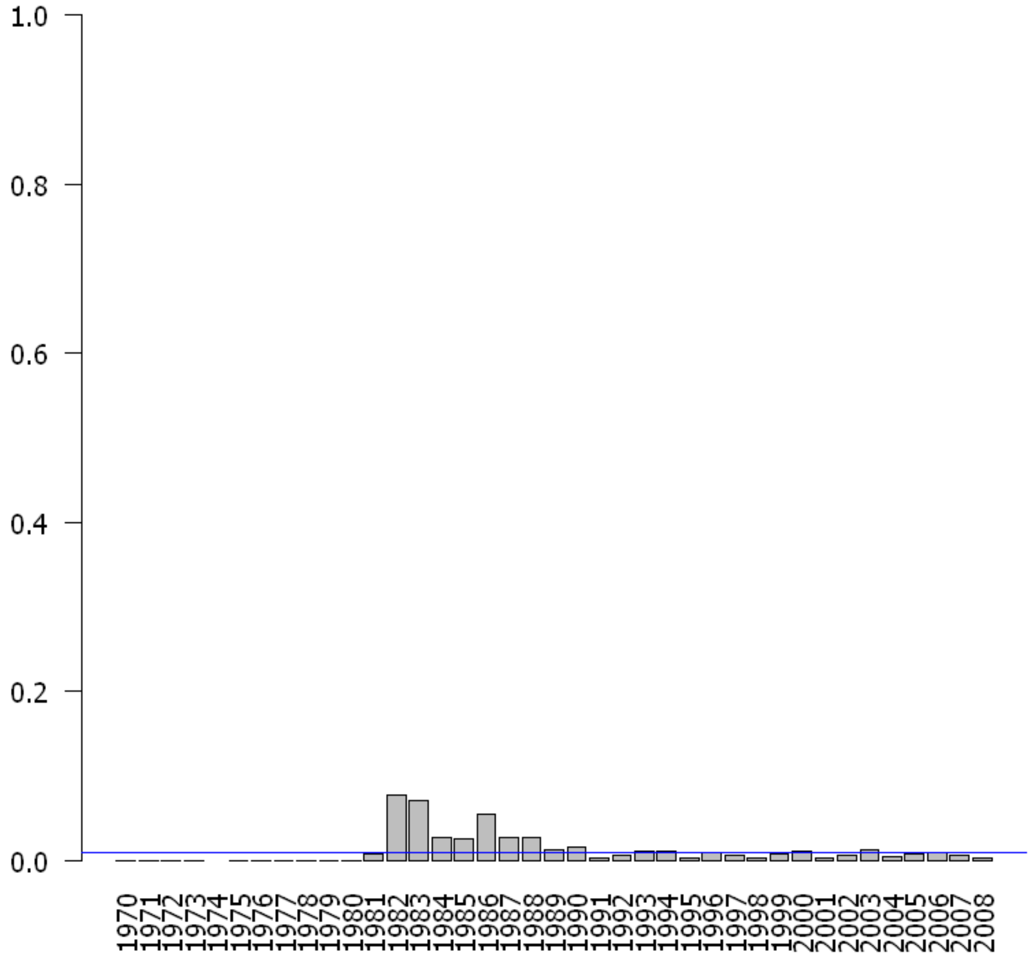

Figure 6.5: Proportions of *P. mergueinsis* caught West of the JBG green line, by year. The horizontal blue line shows the overall proportion, namely 0.009.

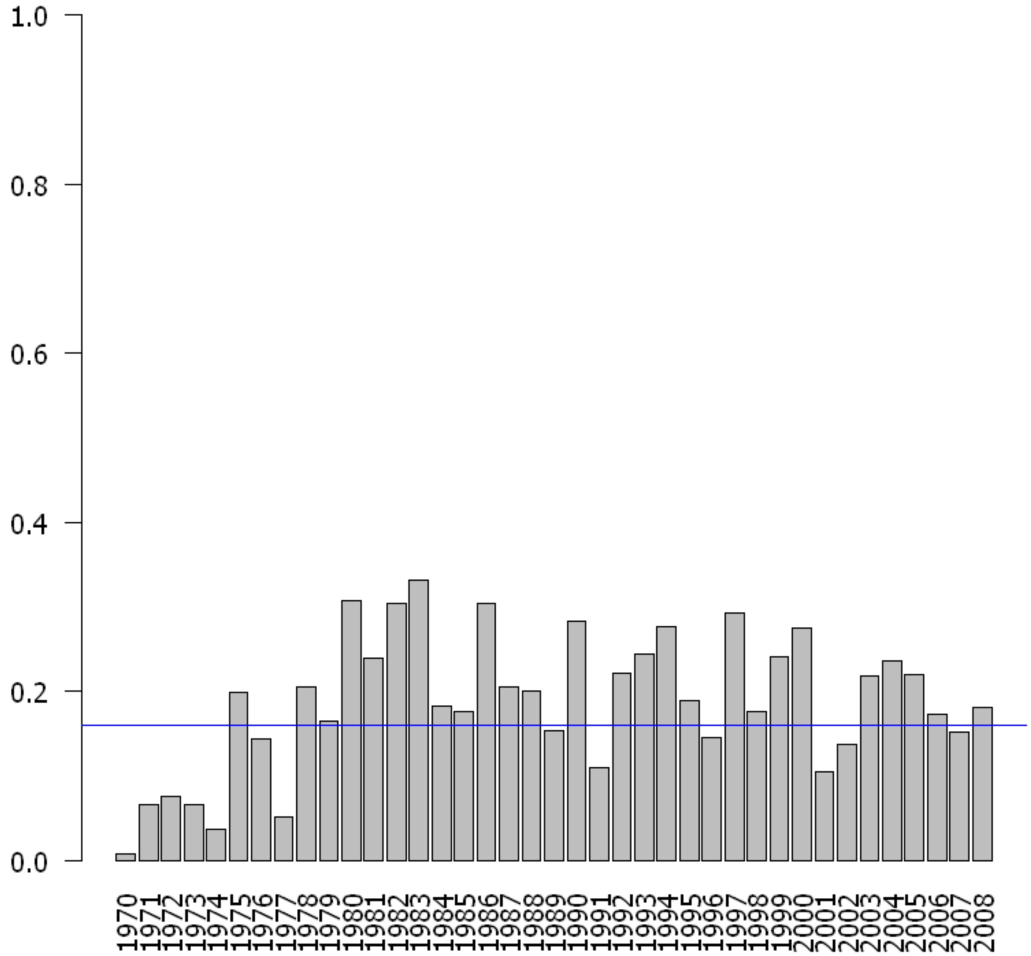

Figure 6.6: Proportions of *P. mergueinsis* caught West of the Arnhem green line, by year. The horizontal blue line shows the overall proportion, namely 0.1599.

6.3 Discussion

The main conclusions of this document are as follows:

- The nominal effort patterns in the NPF, 1970-2008, show that natural breaks occur at two lines of longitude, namely at 129.3567^0E and at 134.0000^0E. If the NPF banana prawn fishery is to be partitioned into a Western and an Eastern region for banana prawn TAC purposes in a way that interferes as little as possible with the commercial operations of the fleet, either of these dividing lines could be considered.
- The more Westerly dividing line, at 129.3567^0E ("The JBG green line") contains a negligible proportion of the *P. merguiensis* catch, but only about 65% of the *P. indicus*

catch, historically. This proportion can vary quite widely, even in recent historical times. It can go over 80% in some years and in 2008 fell to about 32% (Figure 6.4). This relatively low proportion of the *P. indicus* catch, with relatively high variability, seems to argue against setting the JBG green line as the partitioning line.

- The more Easterly dividing line, at 134.0000^0E, isolates 100% of the *P. indicus* catch to the West, but also has, on average, about 16% of the *P. merguiensis* catch. This proportion also varies to some extent, going over 30% in some years, but is relatively consistent (Figure 6.6).
- The Arnhem green line would seem to provide the most practical and effective dividing line of the NPF banana prawn fishery. It will require, however, some developmental work in order for the procedure to set the TAC in both regions to achieve the aim of protecting both biological species.

APPENDIX 7. INTEGRATING SIZE-STRUCTURED ASSESSMENT AND BIO-ECONOMIC MANAGEMENT ADVICE IN AUSTRALIA'S NORTHERN PRAWN FISHERY

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7.1 Abstract

Three species in Australia's Northern Prawn Fishery (*Peneaus semisulcatus*, *P. esculentus*, and *Metapenaeus endeavouri*) are assessed using a size-structured population dynamics model which operates on a weekly time-step. The parameters of this multi-species population dynamics model, which include annual recruitment, fishery and survey selection patterns, parameters which define the size-transition matrix, and recruitment patterns, are estimated using data on catches, catch-rates, length-frequency data from surveys and the fishery, and tag release-recapture data. The model allows for the technical interaction among the three species a result of bycatch when targeting one or the other species. The results from the multi-species stock assessment form part of the basis for evaluating the time-series of catches (by species) and levels of fishing effort (by fishing strategy) which maximize net present value. The bio-economic model takes into account costs which are proportional to catches, and those which are proportional to fishing effort, as well as fixed costs. The sensitivity of the results is examined by changing the assumptions regarding the values for the economic parameters of the bio-economic model as well as those on which the assessment are based. The results suggest that fishing effort needs to be reduced in the short-term to achieve economic goals even though most stocks are estimated to currently be above the stock size corresponding to MSY. Short-term catches and effort levels are sensitive to model assumptions, in particular, trends in prices and costs.

Keywords: Australia, bio-economic assessment, prawns, stock assessment, size-structure, technological interactions

7.2 Introduction

Fisheries for tropical prawn species are generally characterised as being data-poor and are typically managed using effort controls selected primarily to maximize yield (Gillett, 2008). In contrast, the fisheries management actions for Australian's Northern Prawn Fishery (NPF), a multi-species, multi-stock prawn fishery in the tropical region of northern Australia (Fig. 7.1), are selected with the aim of achieving Maximum Economic Yield (MEY) for the fishery.

The NPF is one of Australia's most valuable Federally-managed commercial fisheries and historically has regularly returned a profit (Rose and Kompas, 2004). In more recent years, however, increased supply of aquaculture-farmed prawns to both domestic and international markets, the appreciation of the Australian dollar, and increasing fuel prices have meant that the fishery has been less profitable. The fishery targets several species groups of prawns (banana, tiger, endeavour, and king) as well as other species of invertebrates, including species known locally as "bugs" (*Thenus indicus* and *Thenus orientalis*), and various squid species, although the bulk of the revenue from the fishery is obtained from harvesting common banana prawns (*Penaeus merguiensis*), grooved tiger prawns (*P. semisulcatus*) and brown tiger prawns (*P. esculentus*). The fishery has generally operated from April to November with a mid-season closure from roughly June to August (the exact dates for the length of the whole season and the dates separating the first and second sub-seasons depend on the assessed status of spawning stocks or in-season catch rates). After several industry and government funded buy-back schemes, there are now 52 vessels and 19 operators in the fishery.

The management decisions for this fishery are made by the Board of the Australian Fisheries Management Authority (AFMA) who are advised by a Management Advisory Committee (MAC) and a Resource Assessment Group (RAG). The fishery is currently managed using effort-controls, including limitations on season length, number of vessels, and most recently total gear length. Gear has been transferable among vessels since 2000, implying that fishers have rights in the form of Individual Transferable Effort (ITE) units. Before 2008, the objective of management was to move the spawning stock size of the two tiger prawn species to that at which Maximum Sustainable Yield (MSY) is achieved on average. However, since 2008, the management objective has been to manage the fishery to achieve MEY (Dichmont *et al.*, 2008), consistent with Australian government policy for Federally-managed fisheries (DAFF, 2007). The fishery is also currently transitioning to management based on Individual Transferable Quotas (ITQs).

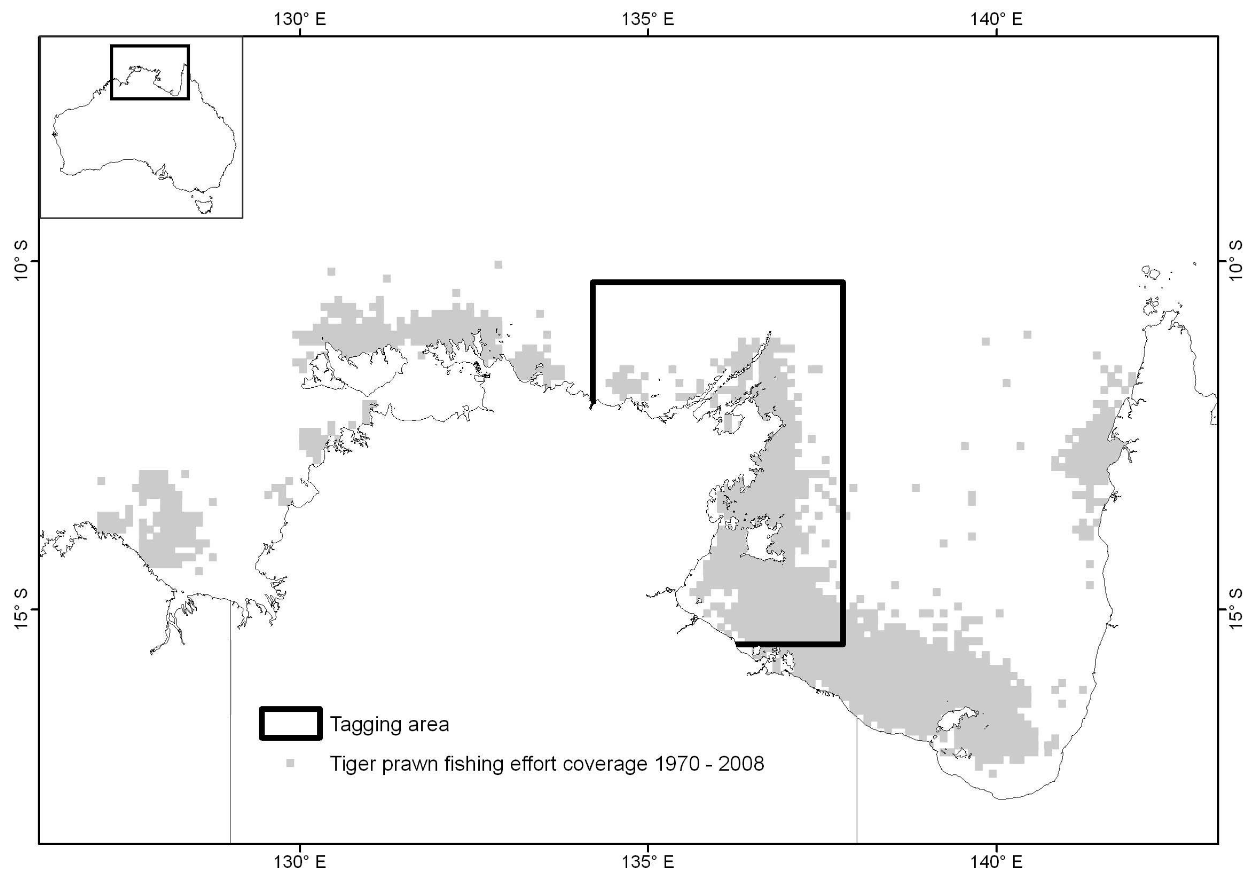

Figure 7.1. Northern Australia, the location of the shots which have caught tiger prawns at least five times, and the northwestern Gulf of Carpentaria where the tagging studies took place.

Although the NPF has a long history of basing management decisions on the results from quantitative stock assessments (e.g. Somers, 1990; Wang and Die, 1996; Dichmont *et al*., 2003), the recent (and anticipated future) changes in the fishery have led to new challenges for the provision of scientific management advice. Specifically, scientific advice needs to be provided for the fishing strategies which target the two tiger prawn species, at present in the form of limits on effort and in the near future in terms of Total Allowable Catches (TACs). Separate TACs may be set for the two tiger prawn species, as well as for one of the key bycatch species of the fishery for tiger prawns, the blue endeavour prawn, *M. endeavouri*. While the provision of scientific advice in multi-species fisheries is difficult under any circumstances, doing so in the NPF is especially difficult because: (a) management advice needs to be based on a management objective of achieving MEY (interpreted as selecting management actions so as to maximise net present value) rather than MSY, necessitating consideration of economic as well as biological factors, (b) prawns cannot be aged which means that age-based methods of stock assessment cannot be applied, and (c) the longevity of prawns (a maximum age of approximately 18 months) implies the need for advice on TACs to be based on forecasts of stock size. In contrast, management advice in recent years has been based on the results of the application of a weekly delay-difference model (Dichmont *et al*., 2003) to catch and effort data.

This paper outlines an approach which integrates a multi-species weekly sex- and size-structured population dynamics model with an economics model which calculates profit given assumptions about future effort levels, and changes over time in costs and prices. This approach generalizes previous stock assessment methods for the fishery (Dichmont *et al*., 2003), and methods for integrating biological and economic information (Dichmont *et al*., 2008) which were based on population dynamics models which ignored size- and sex-structure. This paper is therefore the first attempt to fully integrate the biological and economic data sets for this fishery. The analyses focus only on the tiger prawn fishery rather than on that which targets banana prawns owing to a complete lack of understanding of the dynamics of banana prawns, in particular, a lack of data to monitor changes in abundance. The tiger and banana fisheries are largely separated temporally, making it possible to consider management regulations separately for these two fisheries.

Basing management advice on a bio-economic model requires more assumptions and inputs than conventional harvest control rules. The paper therefore summarizes the sensitivity of the key outputs from the bio-economic model (time-trajectories of effort levels and catches, the latter effectively potential TAC levels), to both biological and economic assumptions.

7.3 Methods

7.3.1 Biological monitoring information

The data available for stock assessment purposes are catch and effort by week and species since 1970 (the start of the fishery), catch size-composition data, tag-recapture data, and survey indices of abundance and the associated size-composition information (Milton *et al*., 2008). Although catches are recorded in logbooks by species group (e.g. both tiger species combined), research data on the split of the species groups to individual species allows catches to be split fairly accurately to species (Venables and Dichmont, 2004). The effort data are also divided into two fishing strategies, one which targets *P. semisulcatus* and another which targets *P. esculentus*, although there are technical interactions between the two strategies in that effort targeted at *P. semisulcatus* will also catch *P. esculentus*, and *vice versa* (Dichmont *et al*., 2003).

Although the fishery has collected information on the size composition of the catches for several decades, these data were by broad “grade category”. Unfortunately, while grades are relevant for understanding the revenue of the fishery (prices are by grade), the small number of grade categories and lack of consistency in grading amongst companies means that these data are of limited use for stock assessment purposes. More recent data from onboard sampling has been used to construct catch size-compositions and these data are used in the analyses in this paper.

Tag-recapture data are available from experiments conducted in the northwestern Gulf of Carpentaria (Fig. 7.1) in 1983 and 1984 (Somers and Kirkwood, 1991; Buckworth, 1992). In common with Somers and Kirkwood (1991) and Wang *et al*. (1995), the data used in the analyses were restricted to animals that were at liberty for at least two weeks and which were not infected (at release or recapture) by the bopyrid parasite *Epipenaeon ingens*. Only prawns for which species, sex, length-at-release, length-at-recapture and time-at-liberty are known, were included in the analyses.

Surveys of the NPF have been conducted biannually since August 2002. The surveys early in the year (the "recruitment" surveys) are designed to more fully sample the smaller prawns (recruits) while those later in the year (the "spawning surveys") are designed to sample larger prawns (Dichmont *et al*., 2002). The data available from each survey include the index of abundance and the associated size-composition data. "Effective" sample sizes for the length-frequency data from the catches and the surveys are computed using the approach of Folmer and Pennington (2000).

7.3.2 Size-structured population dynamics model

In common with previous stock assessments of the tiger and endeavour prawns (e.g. Dichmont *et al*., 2003), the population dynamics model operates on a weekly time-step:

$$\underline{N}_{k,y,w+1,s} = \mathbf{X}_{k,s}\mathbf{H}_{k,y,w,s}\underline{N}_{k,y,w,s} + 0.5\underline{R}_{k,y,w+1} \qquad (1)$$

where $N_{k,y,w,s,l}$ is the number of prawns of species *k* and sex *s* in length-class *l* (1mm length-classes between lengths of 15 and 55 mm) alive at the start of week *w* of year *y* ($\underline{N}_{k,y,w,s}$ denotes the vector of numbers by length), $\mathbf{H}_{k,y,w,s}$ is the survival matrix for species *k* and sex *s* during week *w* of year *y* (a diagonal matrix with $e^{-Z_{k,y,w,l}}$ on the diagonal), $\mathbf{X}_{k,s}$ is the growth matrix (the probability of an animal of species *k* and sex *s* in size-class *i* growing into size-class *j*) during a week, $\underline{R}_{k,y,w}$ is the recruitment of species *k* to the population during week *w* of year *y*:

$$R_{k,y,w,l} = \begin{cases} \alpha_{k,w} R_{k,\tilde{y}(y,w)} & \text{if } l = 15\,\text{mm} \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

$\alpha_{k,w}$ is the expected fraction of the annual recruitment for species *k* that occurs during week *w*, $R_{k,\tilde{y}}$ is the recruitment of species *k* during 'biological year' $\tilde{y}$, and $\tilde{y}(y,w)$ is the 'biological year' corresponding to week *w* of year *y*:

$$\tilde{y}(y,w) = \begin{cases} y & w < 40 \\ y+1 & \text{otherwise} \end{cases} \qquad (3)$$

Total mortality, $Z_{k,y,w,l}$, on animals of species *k* in length-class *l* during week *w* of year *y* is given by:

$$Z_{k,y,w,l} = M_k + F_{k,y,w,l} \qquad (4)$$

where M_k is the average (over week) weekly instantaneous rate of natural mortality (assumed to be independent of sex, length and time), and $F_{k,y,w,l}$ is the fishing mortality on animals of species *k* in length-class *l* during week *w* of year *y*.

Equation (3) implies that the 'biological year' ranges from week 40 (roughly the start of October) until week 39 (roughly the end of September) while Equation (2) implies that recruitment contributes only to first length-class considered in the model. Growth is assumed to be time-invariant (seasonally and annually) and the annual recruitment pattern (defined by $\alpha_{k,w}$) is assumed to be the same each year in the absence of data to parameterize seasonal growth and time-dependent recruitment patterns.

The spawner stock size index for species *k* and calendar year *y*, $\tilde{S}_{k,y}$, is computed using the equation:

$$\tilde{S}_{k,y} = \sum_{w} \beta_{k,w} \sum_{l} \omega_{k,l} \frac{1-e^{-Z_{k,y,w,l}}}{Z_{k,y,w,l}} N_{k,y,w,\text{fem},l} \qquad (5)$$

where $\beta_{k,w}$ is a relative measure of the amount of spawning by species *k* during week *w*, and $\omega_{k,l}$ is the proportion of females of species *k* in length-class *l* which are mature.

For the purposes of this study, it is assumed that the probability that an animal in size-class *i* grows into size-class *j* during each time-step is governed by a normal distribution, i.e. for each species *k*:

$$X_{k,s,i,j} = \int_{L_j}^{L_{j+1}} \frac{1}{\sqrt{2\pi}\sigma^I_{k,s}} \exp\left(-\frac{\{L+0.5-(L_i+I_{k,s,i})\}^2}{2(\sigma^I_{k,s})^2} \right) dL \qquad (6)$$

where $\sigma^I_{k,s}$ determines the variability in the growth increment for animals of species *k* and sex *s*, $L_{i/j}$ is the lower limit of size-classes *i* / *j*, and $I_{k,s,i}$ is the growth increment for animals of species *k* and sex *s* in size-class *i*, determined according to a von Bertalanffy growth curve parameterized in terms of $\kappa_{k,s}$ and $\ell_{\infty,k,s}$, i.e.:

$$I_{k,s,i} = (\ell_{\infty,k,s} - L_i)(1-e^{-\kappa_{k,s}}) \qquad (7)$$

Annual recruitments for the years for which information on catches and survey indices of recruitment is available (1970-2008) are treated as estimable parameters while those for (future) years are assumed to be related to $\tilde{S}_{k,y}$ according to a Ricker stock-recruitment relationship:

$$\hat{R}_{k,y+1} = \tilde{\alpha}_k \tilde{S}_{k,y}\, e^{-\tilde{\beta}_k \tilde{S}_{k,y}} \qquad (8)$$

where $\hat{R}_{k,y}$ is the conditional mean for the recruitment during biological year *y* (i.e. the recruitment from October of year *y*-1 to September of year *y*) based on the stock-recruitment relationship, and $\tilde{\alpha}_k$ and $\tilde{\beta}_k$ are the parameters of the stock-recruitment relationship.

The relationship between the actual recruitment for future year *y* and the conditional mean based on the stock-recruitment relationship is given by:

$$R_{k,y} = \hat{R}_{k,y}\, e^{\eta_{k,y}} \qquad \eta_{k,y+1} = \rho_{r,k}\eta_{k,y} + \sqrt{1-\rho^2_{r,k}}\,\xi_{k,y+1} \qquad \xi_{k,y+1} \sim N(0;\sigma^2_{r,k}) \qquad (9)$$

where $\rho_{r,k}$ is the environmentally-driven temporal correlation in recruitment (account needs to taken of the possibility of environmentally-driven temporal correlation because the residuals about the fit of Equation 9 exhibit auto-correlation), and $\sigma_{r,k}$ is the (environmental) variability in recruitment about the stock-recruitment relationship.

7.3.3 Fishing mortality and catch

Catch in the model is a function of weekly stock size, the level of fishing effort expended each week, the relative fishing power of the fleet in that year,[15] the relative availability of each species in each week, the size selectivity of the fishing gear, and the catchability of the species. The fishing mortality on animals in length-class *l* during week *w* of year *y*, $F_{k,y,w,l}$, is given by:

$$F_{k,y,w,l} = A_{k,w}\,\gamma_{y,w}\,S^F_{k,l}\,(q^G_k E^G_{y,w} + q^B_k\,E^B_{y,w}) \tag{10}$$

where $E^{G/B}_{y,w}$ is the effort during week *w* of year *y* 'targeted' towards *P. semisulcatus* (G) and *P. esculentus* (B), $q^{G/B}_k$ is the catchability coefficient for the fishing strategies targeting *P. semisulcatus* (G) and *P. esculentus* (B), $A_{k,w}$ is the relative availability of animals of species *k* during week *w*, $\gamma_{y,w}$ is the relative efficiency of the two fishing strategies during week *w* of year *y*, and $S^F_{k,l}$ is the selectivity of the fishery on animals of species *k* in length-class *l* (assumed to be a logistic function of length).

The catch (kg) of prawns of species *k* of size class *l* during week *w* of year *y* ($Y_{k,y,w,l}$) is given by:

$$Y_{k,y,w,l} = \sum_s w_{k,s,l}\,\tilde{Y}_{k,y,w,s,l} \tag{11}$$

where $w_{k,s,l}$ is the mass of animals of species *k* and sex *s* in length-class *l*, and

$$\tilde{Y}_{k,y,w,s,l} = \tfrac{F_{k,y,w,l}}{Z_{k,y,w,l}} N_{k,y,w,s,l}(1-e^{-Z_{k,y,w,l}}) \qquad 12)$$

Total mortality as a function of length does not depend on sex as both fishery selectivity and natural mortality are assumed to be independent of sex. However, dimorphic growth means that mortality due to the fishery is sex-specific.

7.3.4 Economic model

The economic model estimates the flow of costs and revenues from fishing over time. It differs from the previous bioeconomic model (Dichmont *et al*., 2008) in that it incorporates fixed as well as variable costs, and allows for prices to depend on prawn size. The objective function involves the maximisation of the net present value (NPV) of the flow of profits over time, from

[15] Fishing power is a measure to capture relative changes in productivity of the fleet over time. It converts nominal effort (measured in units such as days fished) into effective effort, allowing for the effects of changes in fishing practices, technology and other vessel characteristics to be captured in the model (Bishop *et al*., 2008).

the first year (taken to be 2008 in this study) to the terminal year of the simulation (taken to be 2050), given by:

$$NPV = \sum_{y=1}^{T-1} \pi_y \Big/ (1+i)^{y-1} + \left[\pi_T / i\right] \Big/ (1+i)^{T-1} \tag{13}$$

where i is the rate of interest (the discount rate, assumed to be 5% per annum in this study), π_y is the profit during year y, and π_T is the level of profit during the terminal year. Profits were assumed to continue at the level π_T indefinitely on the basis that the system is in equilibrium.

The level of profits in each year (including the terminal year) are given by:

$$\pi_y = \sum_w \left\{ \sum_k \sum_l v_{k,y,w,l} Y_{k,y,w,l} - VC_{y,w} \right\} - \Omega_y V_y \tag{14}$$

where $v_{k,y,w,l}$ is the average price per kilogram for animals of species k in length-class l during week w of year y, $VC_{y,w}$ is the total variable costs during week w of year y, Ω_y is the average annual fixed costs associated with a vessel operating during year y and V_y is the number of vessels operating during year y. The model assumes that all of the catch ($Y_{k,y,w,l}$) is landed, which is not unreasonable since the fishery is currently managed using input controls and therefore no incentives exist to high grade or otherwise discard any of the catch. The combined term $v_{k,y,w,l} Y_{k,y,w,l}$ represents the revenue each week associated with each species and length class.

Variable costs include labour, fuel (and oil) costs, and other material costs. Maintenance and repair costs are also assumed to be variable (i.e. relate to the amount of fishing effort) for the purposes of the model. Crew are currently paid a share of the revenue, while other material costs are proportional to the size of the catch in weight. Variable costs, therefore, are given by:

$$VC_{y,w} = \sum_k \sum_l \left[(c_L v_{k,y,w,l} + c_M \right] Y_{k,y,w,l} + (c_k + c_F) E_{y,w} \tag{15}$$

where c_L is the share cost of labour, c_M is cost of packaging and gear maintenance (assumed to be proportional to the fishery catch in weight), c_K is the cost of repairs and maintenance per unit of effort, $c_{F,y}$ is the cost of fuel and oil per unit of effort during (future) year y, and $E_{y,w}$ is the total effort ($E_{y,w} = E^G_{y,w} + E^B_{y,w}$).

Fixed costs (Ω_y) include a measure of the opportunity cost of capital, depreciation, and other annual vessel costs (i.e. those not related to the level of fishing effort) such that:

$$\Omega_y = W_y + (o + d) K_y \tag{16}$$

W_y is the annual vessel costs, o is the opportunity cost of capital (equal to the interest rate $o=i$), d is the economic depreciation rate, and K_y is the average value of capital (vessel plus gear) in year y.

The key choice variable in the model is fishing effort by fishing strategy, week and year. Effort for the first seven years of the projection period is selected to maximize Equation (13), with effort for the seventh and all future years set to that for the seventh year (Dichmont *et al*., 2008). A key reason for only estimating a subset of the possible time-series of effort levels is that effort converges to a constant value when the dynamics are deterministic and because the results of the model are only used to set effort levels for the two years following the year for which the most recent data are available. Further, the reliability of forecasts of economic parameters (input and output prices) decreases with length of forecast, so attempting to use the model to determine optimal effort levels over anything other than the relatively short term would be unrealistic. Maximization of Equation (13) is subject to the constraints that annual profit is non-zero, i.e. $\pi_y \geq 0$ (ensuring that the model does not "close" the fishery or reduce effort to a level that would result in short term losses in order to obtain longer term gains)[16], and that effort for each fishing strategy cannot drop below half of that for 2007 (2777 days).

7.4 Parameter estimation

7.4.1 Population dynamics model

The values for most of the parameters of the population dynamics model are assumed to be known, while the estimable parameters are those which define selectivity, growth and annual recruitment (Table 7.1). The recruitment in the first year (1969) is assumed to be same as that in the second year (1970) and the population is assumed to be at the unfished equilibrium corresponding to that recruitment at the start of 1970. The former assumption is made because there are no catches for 1969, so the 1969 recruitment is essentially non-estimable. The values for the estimable parameters of the model are determined by minimizing a negative log-likelihood function that involves data on catches (in weight), survey indices of relative abundance, tag-recapture data, survey size-composition, and catch size-composition data. The summations in Equations 17, 18 and 20 are restricted to the years and weeks for which data are available (e.g. those in which the catch is non-zero for Equation 17).

Table 7.1: The parameters of the population dynamics model for each species.

Parameter	Treatment
Recruitment and spawning	
Annual recruitment, R_y	Estimated
Relative weekly recruitment, α_w	Estimated (by month)
Relative weekly spawning, β_w	Based on auxiliary analyses (see Figure 7.2a)
Maturity-at-length, κ_l	Based on auxiliary analyses (see Figure 7.2b)

[16] The rationale for this constraint is that vessels in the fishery do not have a viable alternative use. Under such circumstances – unless the stocks are severely depleted – it is not optimal to close down the fishery (Clark *et al*., 1979). As a corollary to this, from the fisher perspective, it is not desirable to impose short term losses on the fishery if these can be avoided.

Stock-recruitment relationship parameters, $\tilde{\alpha}$, $\tilde{\beta}$	Estimated
Temporal correlation in recruitment, ρ_r	Estimated
Variance in recruitment, σ_r	Estimated
Effort – fishing mortality related	
Catchability – *P. semisulcatus* strategy, q^G (x10^{-5})	8.8; 0.792; 8.320*
Catchability – *P. esculentus* strategy, q^B (x10^{-5})	1.0648; 8.8; 20.4996*
Relative weekly availability, A_w	Based on auxiliary analyses (see Figure 7.2c)
Relative efficiency, $\gamma_{y,w}$	Based on auxiliary analyses (see Figure 7.2d)
Biological parameters	
Von Bertalanffy growth curve parameters, $\ell_\infty, \kappa, \sigma^I$	Estimated
Length-weight regression	Based on auxiliary analyses (see Figure 7.2e/7.2f)
Natural mortality, *M*	0.045 wk^{-1}
Selectivity	
Fishery	Estimated (logistic function of length)
“recruitment” survey	Estimated (logistic function of length)
“spawning survey”	Estimated (logistic function of length)
The observation model	
Additional survey variance, σ_k^E	Estimated
Catch-rate observation error variance, σ_k^C	Estimated
Survey catchability, q_k^S	Estimated
Extent of overdispersion, ϕ	“Tuned”

* *P. semisulcatus, P. esculentus, M. endeavouri*

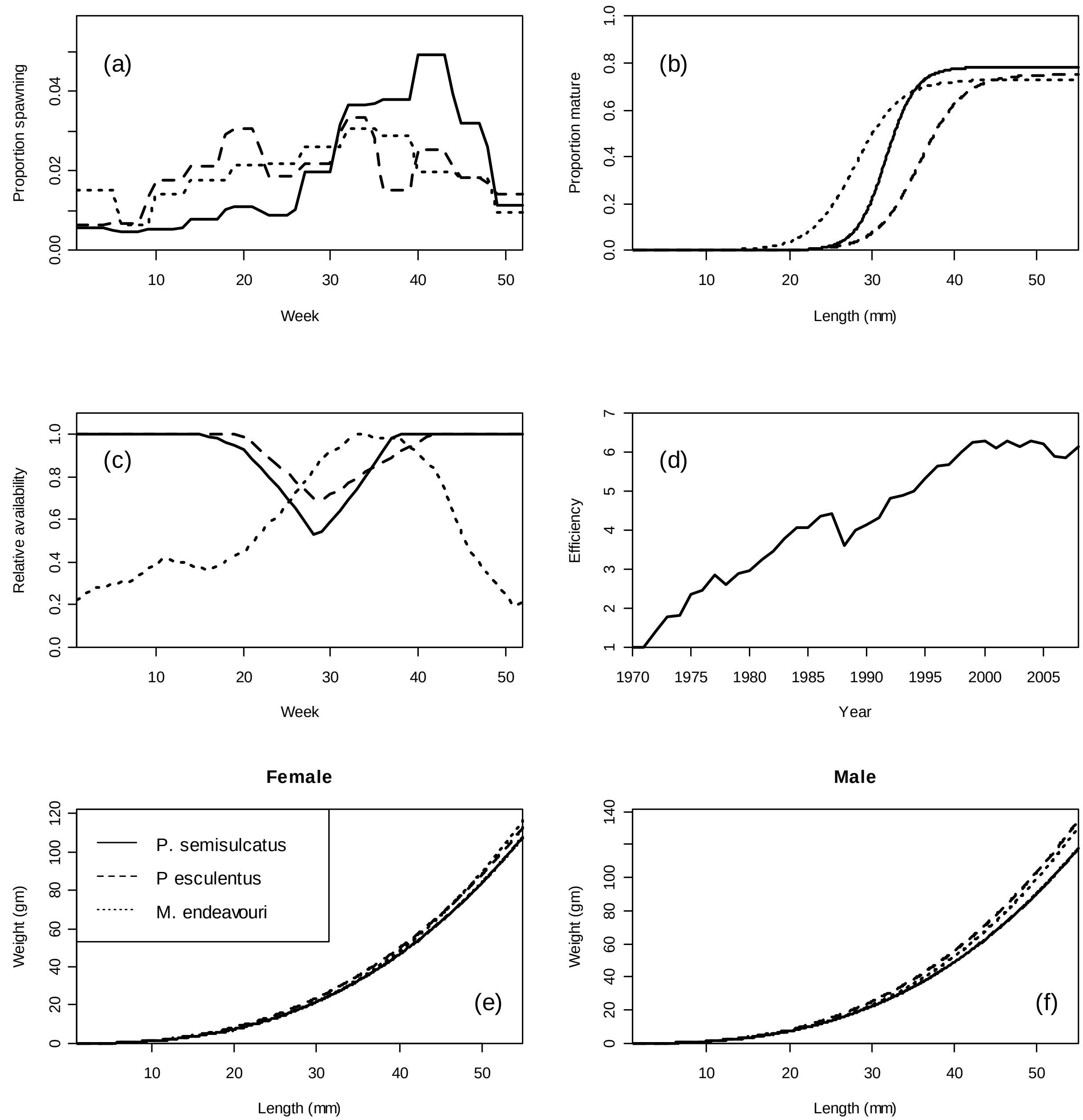

Figure 7.2. Pre-specified parameters of the population dynamics model (by species where appropriate): (a) proportion spawning by week, (b) proportion mature by length, (c) relative availability, (d) changes over time in fishing efficiency, and (e-f) weight as a function of length.

Assuming that the square root of the observed catch is normally distributed (Dichmont *et al.*, 2003), the contribution of the catch in weight data to the likelihood function is:

$$L_1 = \sum_k \sum_y \sum_w \{\log \sigma_k^C + \frac{1}{2(\sigma_k^C)^2}[\sqrt{Y_{k,y,w}^{\text{obs}}} - \sqrt{Y_{k,y,w}}]^2\} \qquad (17)$$

where σ_k^C is the residual standard deviation for species *k*, $Y_{k,y,w}^{\rm obs}$ is the observed catch (in weight) of prawns of species *k* during week *w* of year *y*, and $Y_{k,y,w}$ is the model-estimate of the catch of species *k* during week *w* of year *y*:

$$Y_{k,y,w} = \sum_l Y_{k,y,w,l}$$

The contribution of the data for each of the two surveys ("recruitment" and "spawning") to the negative of the log-likelihood function is given by:

$$L_2 = \sum_k \sum_y \left\{ \log \tilde{\sigma}_{k,y}^S + \tfrac{1}{2(\tilde{\sigma}_{k,y}^S)^2} [\log I_{k,y}^S - \log \hat{I}_{k,y}^S]^2 \right\} \tag{18}$$

where $I_{k,y}^S$ is the survey index for species *k* during year *y*, $\tilde{\sigma}_{k,y}^S$ is the standard error of the logarithm of $I_{k,y}^S$:

$$\tilde{\sigma}_{k,y}^2 = (\sigma_k^E)^2 + (\sigma_{k,y}^S)^2$$

$\sigma_{k,y}^S$ is the standard error of the logarithm of $I_{k,y}^S$ due to sampling error, σ_k^E is a measure of the variation caused by sources other than sampling for species *k*, $\hat{I}_{k,y}^S$ is the model estimate corresponding to $I_{k,y}^S$ (for a survey conducting during week *w* of year *y*):

$$I_{k,y}^S = q_k^S \sum_s \sum_l w_{k,s,l} S_{k,l}^S \frac{1 - e^{-Z_{k,y,w,l}}}{Z_{k,y,w,l}} N_{k,y,w,s,l} \tag{19}$$

q_k^S is survey catchability for species *k*, and $S_{k,l}^S$ is the selectivity of the survey gear on prawns of species *k* in length-class *l*.

The size composition data (fishery and survey) are assumed to be multinomially distributed (although account is taken of overdispersion), e.g., for the fishery catch size-composition data:

$$L_3 = -\phi \sum_k \sum_y \sum_w \sum_s \tilde{N}_{k,y,w,s} \sum_l p_{k,y,w,s,l}^C \log(\hat{p}_{k,y,w,s,l}^C) \tag{20}$$

where $p_{k,y,w,s,l}^C$ is the proportion of the catch of prawns of species *k* and sex *s* during week *w* of year *y* that were in length-class *l*, $\tilde{N}_{k,y,w,s}$ is the effective sample size for catch size-composition data for prawns of species *k* and sex *s* during week *w* of year *y*, and $\hat{p}_{k,y,w,s,l}^C$ is the model-estimate of $p_{k,y,w,s,l}^C$:

$$\hat{p}_{k,y,w,s,l}^C = \tilde{Y}_{k,y,w,s,l} / \sum_{l'} \tilde{Y}_{k,y,w,s,l'} \tag{21}$$

and ϕ is a parameter which determines the extent of overdispersion (estimated separately for the catch and survey size-composition data).

After grouping the data to the width of each size-class and week, the tag-recapture data can be summarized by sets of triplets (l_1, *t* and l_2, where l_1 is the length-at-release, *t* is the time-at-liberty, and l_2 is the length-at-recapture). The contribution of the tag-recapture data to the likelihood function is then the product over animals of the probability of observing that a prawn tagged at length l_1, and at liberty for *t* time-steps was recaptured at length l_2 (McGarvey and Freenstra, 2001; Punt *et al.*, 2009). This probability is the (l_1, l_2) entry of the matrix $\mathbf{X}_k^t$.

Estimation of the four parameters of the stock-recruitment relationship ($\tilde{\alpha}_k$, $\tilde{\beta}_k$, $\rho_{r,k}$ and $\sigma_{r,k}$) involves minimising an objective function, which includes the temporal correlation among recruitments due to environmental fluctuations and the uncertainty associated with the estimates of each annual recruitment (see Dichmont *et al*. (2003) for further details).

The recruitment pattern is assumed to depend on month (with the monthly recruitment allocated equally to weeks within a month), resulting in eleven parameters to define the weekly recruitment pattern for each species. The maximum likelihood estimates for the monthly recruitment patterns can vary substantially (and unrealistically) among months if these parameters are unconstrained. A smoothness penalty based on the 2nd derivative of the recruitment pattern is therefore imposed on the monthly recruitment proportions (c.f. Maunder and Watters, 2003).

7.4.2 Economic parameters

The key parameters of the profit equation are prices, and variable and fixed costs. Prawn and fuel prices are assumed to change over time, whereas all other costs are assumed to remain constant in real terms. All values in the model (including historical values) are real values in 2007-08 prices.[17] All prices and costs used in the analysis are financial, although with the assumption of properly operating markets, these prices should reflect their true economic values. The analysis also requires projections of prices and costs (in real terms) as these influence the optimal trajectory and also the final estimate of MEY.

The key cost parameters in the economic component of the model (Table 7.2a) were derived from an ABARE economic survey of 34 boats in the fishery during 2006-07 and 30 boats during 2007-08, representing 44% and 54% of the fleet each year respectively (Vieira and Perks 2009)[18]. The ABARE economic survey does not divide the NPF into the tiger prawn and the banana prawn fisheries. Therefore, average revenue and costs per vessel were computed from the NPF sample as a whole (Dichmont *et al*., 2008). The key variable cost components in the model are crew cost, packaging and marketing costs, fuel costs and repairs and maintenance. Crew are paid a share of the revenue (c_L). The unit packaging and marketing costs (c_M) were estimated by dividing the reported costs by the total catch to give a cost per kilogram. Average repairs and maintenance costs per day (c_K) were estimated by dividing the total reported costs by the number of days fished over the whole year.

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[17] Real values were derived using the consumer price index produced by the Australian Bureau of Statistics and available from www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6401.0Jun%202009?OpenDocument

[18] An estimate of the parameter values for the 2007 calendar year was derived from these data by ABARE (S. Vieira, pers comm.).

Table 7.2: The parameters of the profit equation.

(a) Cost variables

Parameter	Value
Unit cost of labour, c_L	0.23
Unit cost of other costs, c_M	0.98 (A$ / kg)
Unit cost of repairs and maintenance, c_K	497 (A$ / day)
Base unit cost of fuel and oil, c_F	1,824 (A$ / day)
Annual vessel costs, W_y	56,116 (A$ / vessel)
Opportunity cost of capital, o	0.05
Economic depreciation rate, d	0.037
Average value of capital, K_y	727,184 (A$ / vessel)

(b) Prices (A$/kg)

Species Group	All sizes	< 40 mm	40-45 mm	45-50 mm	50-55 mm	> 55 mm
Tiger	19.85	16.17	21.05	22.01	28.74	28.35
Endeavour	12.80	10.43	13.57	14.20	18.53	18.28

Fuel costs per day ($c_{F,y}$) were estimated similarly to repair costs, although account was taken also of the different number of hours fished per day in the banana and tiger fisheries. The model included fuel price projections that altered the average fuel cost per day. Fuel prices in the NPF are assumed to follow a pattern similar to the Australian Farm Fuel Price index (see ABARE (2007)), which is based on forecasts drawn from a number of sources, including time series data from Ampol, Caltex Australia, Fueltrac and Shell Australia. The price of fuel is expected to fall by 16 per cent from its current high value (for an indexed value of 100 in 2008) over the next seven years and to remain constant in real terms after 2013 (Figure 7.3a).

Fixed costs are independent of the level of fishing activity. However, given that the model represents only part of the fishing activity of the vessels (i.e. excludes the banana fishery), it is not appropriate to attribute the full fixed costs to the tiger prawn fishery. Fixed costs, and also total capital, were allocated to the tiger prawn fishery based on its contribution (61%) to total revenue. The opportunity cost of capital (equivalent to the discount rate) was assumed to be 5%. The depreciation rate was based on ABARE survey estimates (Vieira and Parks, 2009).

Current prawn prices by grade ($v_{k,y,w,l}$) are given in Table 7.2b, and the projections of price used in the analyses are given in Figure 7.3b. The major market for NPF prawns is Asia (especially Japan), and the price received is largely dependent on the Yen-AUD exchange rate as well as the total supplies to this market. Price forecasts for prawns over the period 2008-2014 were based on an otherwise standard ARIMA (autoregressive moving average) model, where the main drivers were the exchange rate (itself forecasted by ABARE (2007)) and projected increases in world output (including aquaculture supplies in Asia). On this basis, the price of tiger prawns is expected to increase over the next seven years in real terms by 12%, due largely to a projected ‘softening’ of the Australian dollar from its current high values. Prices after 2014 are assumed to remain constant in real terms.

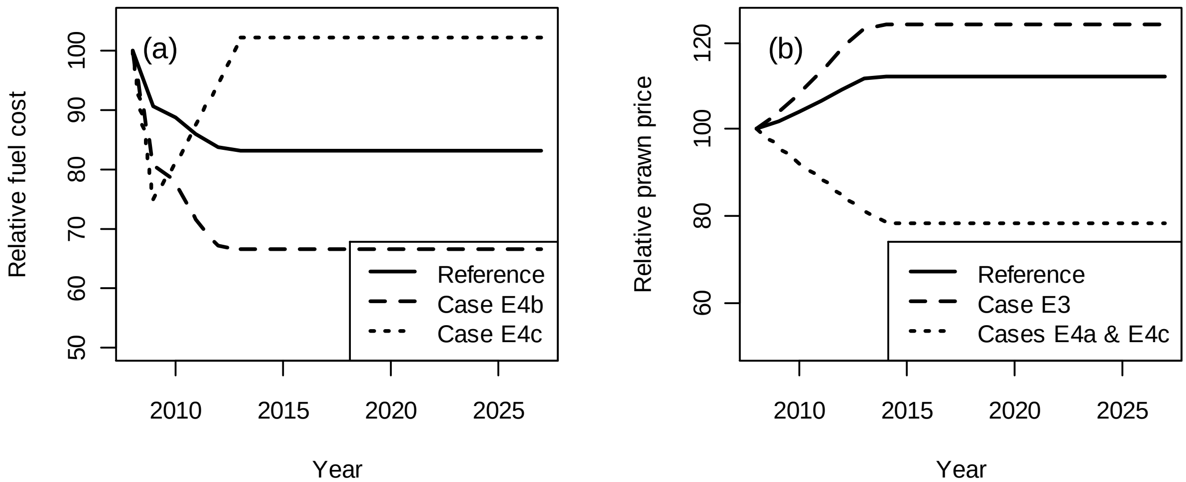

Figure 7.3. Relative trends in (a) fuel price and (b) prawn prices for the reference case analysis and the sensitivity tests which modify the trends in prices and costs.

7.4.3 Scenarios and representing uncertainty

The results from the model relate to the current status of the population relative to biological reference points and the short- and long-term predictions from the economics model. The current biological status of the three species is summarized using the following statistics (by species): $S_{2007} / S_{\mathrm{MSY}}$ and $S_{2007} / S_{\mathrm{MEY}}$ where S_{MSY} and S_{MEY} are respectively the spawning stock sizes at which MSY and MEY are achieved[19]. The results of the economics model are summarized by the expected catch for 2008, C_{2008}, the long-term catch under an MEY strategy, C_{MEY}, the number of fishing days for 2008, E_{2008}, the number of fishing days in 2014 and later under an MEY strategy, E_{MEY}, the ratio of S_{MEY} to S_{MSY} for each species, and the relative profit. The first two of these quantities are reported by species, and the second two are reported for the fishing strategy which targets *P. semisulcatus* and for that which targets *P. esculentus*. The relative profit is the profit for z scenario relative to that of a reference case scenario.

Although the bulk of the parameters of the economics and population dynamics models are either based on the results of auxiliary studies or by fitting the population model to the available data, there are key assumptions as well as specifications to which the key model outcomes may be sensitive (Table 7.3). The sensitivity tests are variants of a "reference case" analysis. This analysis is typical of the model configurations on which management advice using the model

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[19] MSY is defined here as the catch by species when fishing effort for the two fishing strategies is selected to maximize the sum of the catches by species (in mass). S_{MSY} therefore accounts for technical interactions and is hence it is not the same as the spawning stock size at which yield is maximized if each species could be perfectly targeted.

will be based. The model configurations in Table 7.3 explore the sensitivity of the results to assumptions about prices, the discount rate, and in particular, how future effort will be expended over time and by week. The reference case assumption is that the effort distribution by week will mimic that for the last five years (2003-2007) while the sensitivity tests explore two more dynamic approaches: (a) effort is optimally allocated to week (but static over time), and (b) the proportion of the effort by week is related dynamically to the effort expended according to a system which mimics roughly how the Management Advisory Committee has modified the fishing season in the past (Figure 7.4). The fleet currently consists of 52 vessels and this assumption forms part of the specifications of the reference case analysis. Sensitivity is, however, explored to the alternative assumption that each vessel fishes an average of 135 days each year and the changes in effort are a consequence of the entry and exit of vessels.

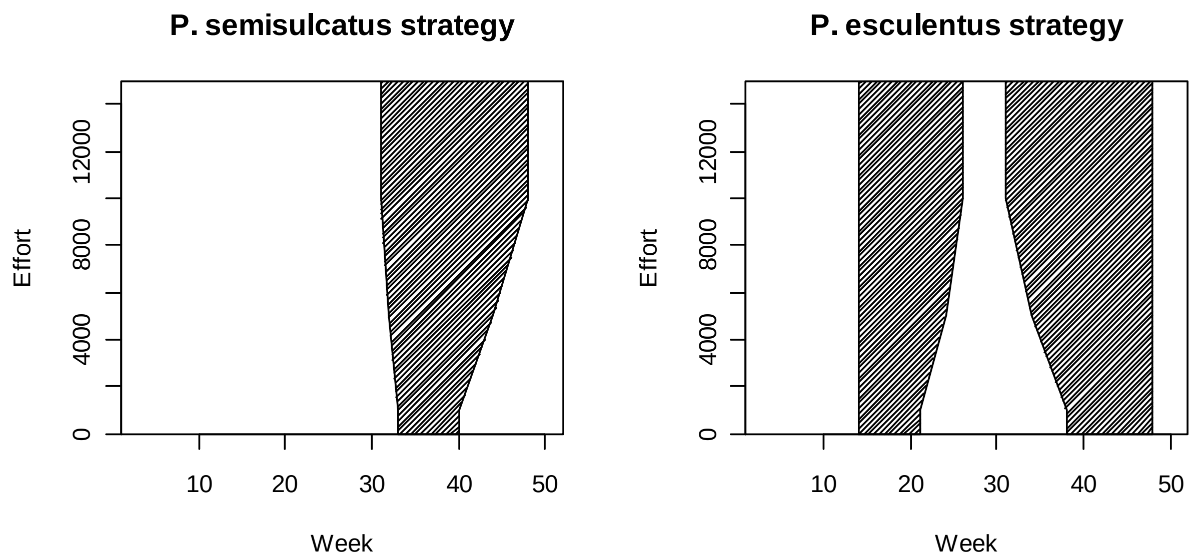


Figure 7.4. Weeks which are open to fishing as a function of the effort (fishing days) by fishing strategy.

Table 7.3: The specifications of the sensitivity tests. The reference case analysis is based on the size-structured population dynamics model, uses all of the available data, uses grade-specific prices, assumes that effort is distributed across the season as in 2003-7, and assumes a fixed fleet of 52 vessels. Unless specified otherwise, the configuration of the population dynamics and economics models for each sensitivity test match those for the reference case.

Case No	Description
R	Reference case
P1	No survey data
P2	Delay-difference population dynamics model (prices are independent of grade)
E1	Discount rate = 4%
E2	Discount rate = 6%
E3	Prices increase by twice the reference case forecast rate (Fig. 7.3b)
E4a	Prices decrease at the historic rate of increase (4% pa) until 2015 (Fig. 7.3b)
E4b	Rate of change in fuel cost is twice that for the reference case (Fig. 7.3a)
E4c	Prices decrease at the historic rate of increase (4% pa) and the fuel cost crashes in 2009 and then recovers at 8% p.a. (Fig. 7.3)
E5	Weekly distribution of effort is estimated (1 July – 31 December for the *P. semisulcatus* fishing strategy; 1 April – 31 December for the *P. esculentus* fishing strategy). Effort is constrained not to exceed seven days per week per vessel.
E6	The weekly distribution of effort depends on the effort expended (linearly interpolated between three levels; see Fig. 7.4)
E7	Prices are independent of grade
E8	Free entry and exit of vessels (each vessel is allowed to fish for 135 days[a])

a – the average number of days fished per vessel over the period 2003-2007

The bulk of the analyses ignore future recruitment variability (for consistency with previous approaches to providing management advice and because this reduces the computational demands of the calculations) and also base the application of the economic model on the maximum likelihood estimates for the parameters of the population dynamics model. The impact of parameter uncertainty is, however, explored using a bootstrap-like approach (Patterson *et al.*, 2001) for the reference case analysis. This involves sampling recruitments from the asymptotic variance-covariance matrix for the parameters and then computing the maximum likelihood estimates for the parameters of stock-recruitment relationship and hence the key outputs from the bio-economic model. This approach is preferred to a true bootstrap procedure involving resampling residuals because the residuals are not independent.

7.5 Results and discussion

7.5.1 Stock status and size-structured stock assessment

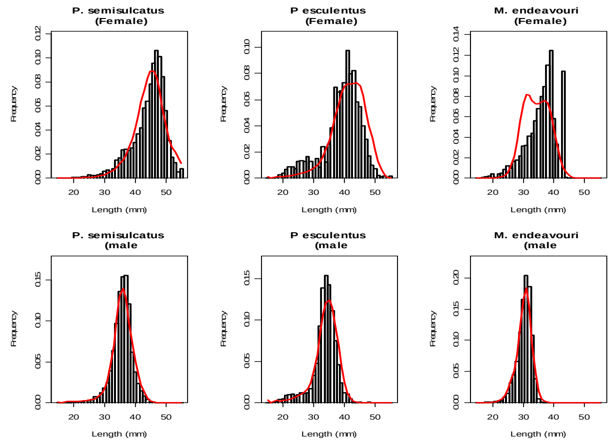
The fits of the size-structured population dynamics model to the available data are summarized in Figures 7.5 and 7.6. The fits to the length-frequency data (aggregated over year; Figure 7.5) indicate that the model is capable of capturing the broad features of the catch and survey length-frequency data adequately. The notable misfits occur for: (a) the catch length-frequency data for female *P. esculentus* (Fig. 7.5a, upper centre panel), (b) the catch length-frequency data for female *M. endeavouri* (Fig. 7.5a, upper right panel), and (c) the length-frequency data from the recruitment surveys for female *P. esculentus* (Figure 7.5c, upper centre panel). The poor fits for the catch length data for female *P. esculentus* occur because sample sizes are relatively small and there are occasional catches of small female *P. esculentus*. The model is able to follow the survey indices fairly well (Figure 7.6), although the extent of additional variation (i.e. variation beyond that expected given sampling errors), is relatively high (an additional CV ranging from 0.11 to 0.40, with these CVs being largest for *M. endeavouri*).

There are a large number of catch-rate data points (38 years x 52 weeks x 2 fishing strategies x 3 species) so the fits to these data are not shown. The residuals are approximately normally distributed for all three species and there is no obvious evidence for systematic patterns in the residuals when the data are grouped by year and week.

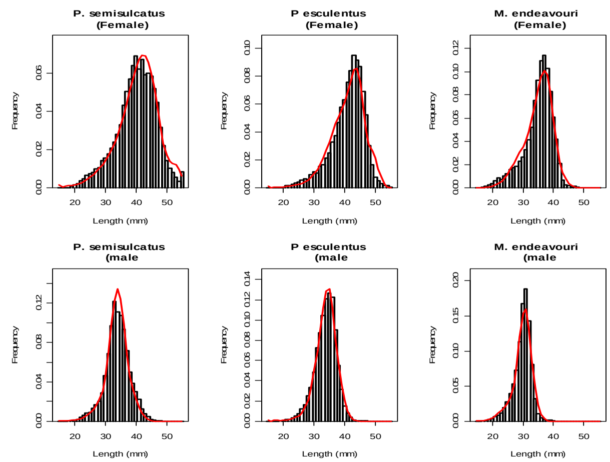
The selectivity patterns for the two surveys (Figures 7.7b, c) behave as expected, with selectivity for smaller prawns being higher in the recruitment survey than in the spawning survey. The selectivity patterns for the three species differ quite markedly. In particular, *P. semisulcatus* is estimated to be more selected to the survey gear than the other species, but less so to the fishery (Figure 7.7d). This can be attributed to differences in spatial distribution of the fishery and the survey.

The key output from the stock assessment is the time-trajectory of spawning stock size (Figure 7.8). The qualitative trends in the estimates of these quantities for the historical period (1970-2007) are insensitive to the form of the population dynamics model and the inclusion (or otherwise) of the survey data. However, the absolute values for some of the model outputs are quite sensitive to these specifications. This is most evident for the first and last years of the assessment period for *P. esculentus*, with the delay-difference model suggesting a decline in abundance in the last year while the size-structured model suggests an increase. This difference is primarily due to different treatments of the recruitment indices (which are treated as indices of recruitment biomass in the delay-difference model, but as a measure of selected biomass in the size-structured model).

(a) Catch length-frequency



(b) “Spawning” survey length-frequency



(c) “Recruitment” survey length-frequency

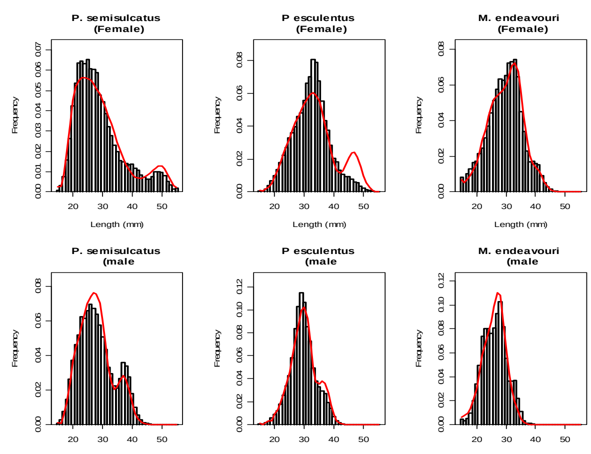


Figure 7.5. Observed length-frequencies (bars) and model-predictions from the base-case size-structured population dynamics model (line). The values shown are averages over the years for which data are available (with weights proportional to effective sample sizes).

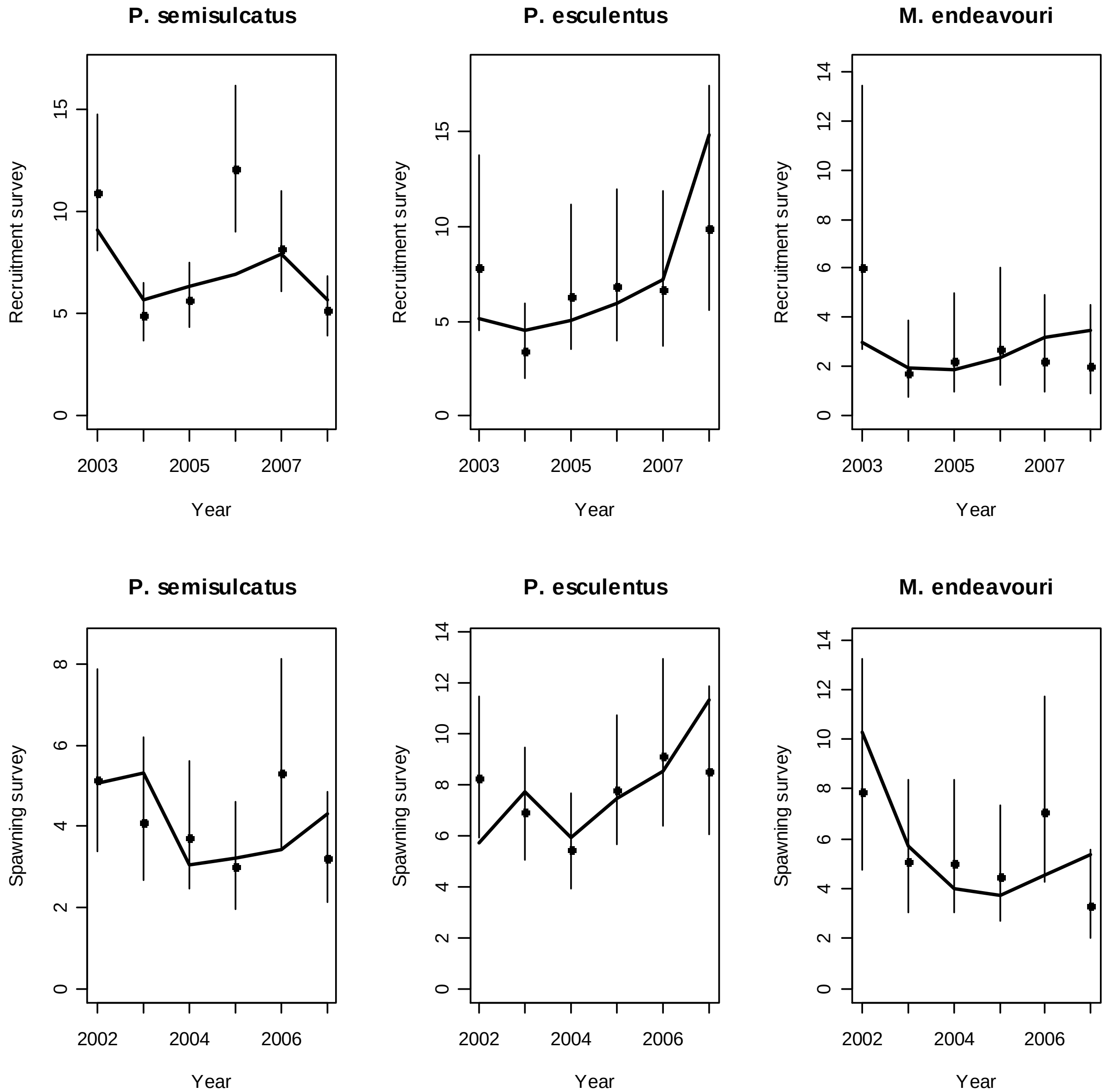


Figure 7.6. Observed survey indices (dots) and model-predictions from the base-case size-structured population dynamics model (lines) for the “recruitment” and “spawning” surveys (upper and lower panels respectively). The vertical lines are 95% confidence intervals based on the sampling error and the maximum likelihood estimate for the extent of additional variation.

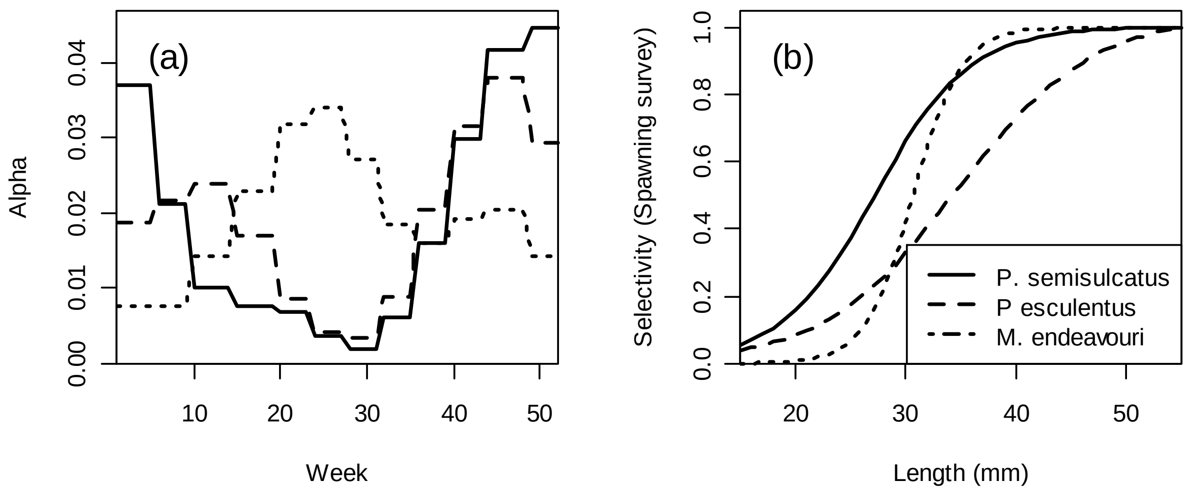


Figure 7.7. Estimates of biological and fishery parameters for the base-case size-structured population dynamics model: (a) monthly recruitment pattern, (b) selectivity to the spawning survey, (c) selectivity to the recruitment survey, and (d) selectivity to the fishery.

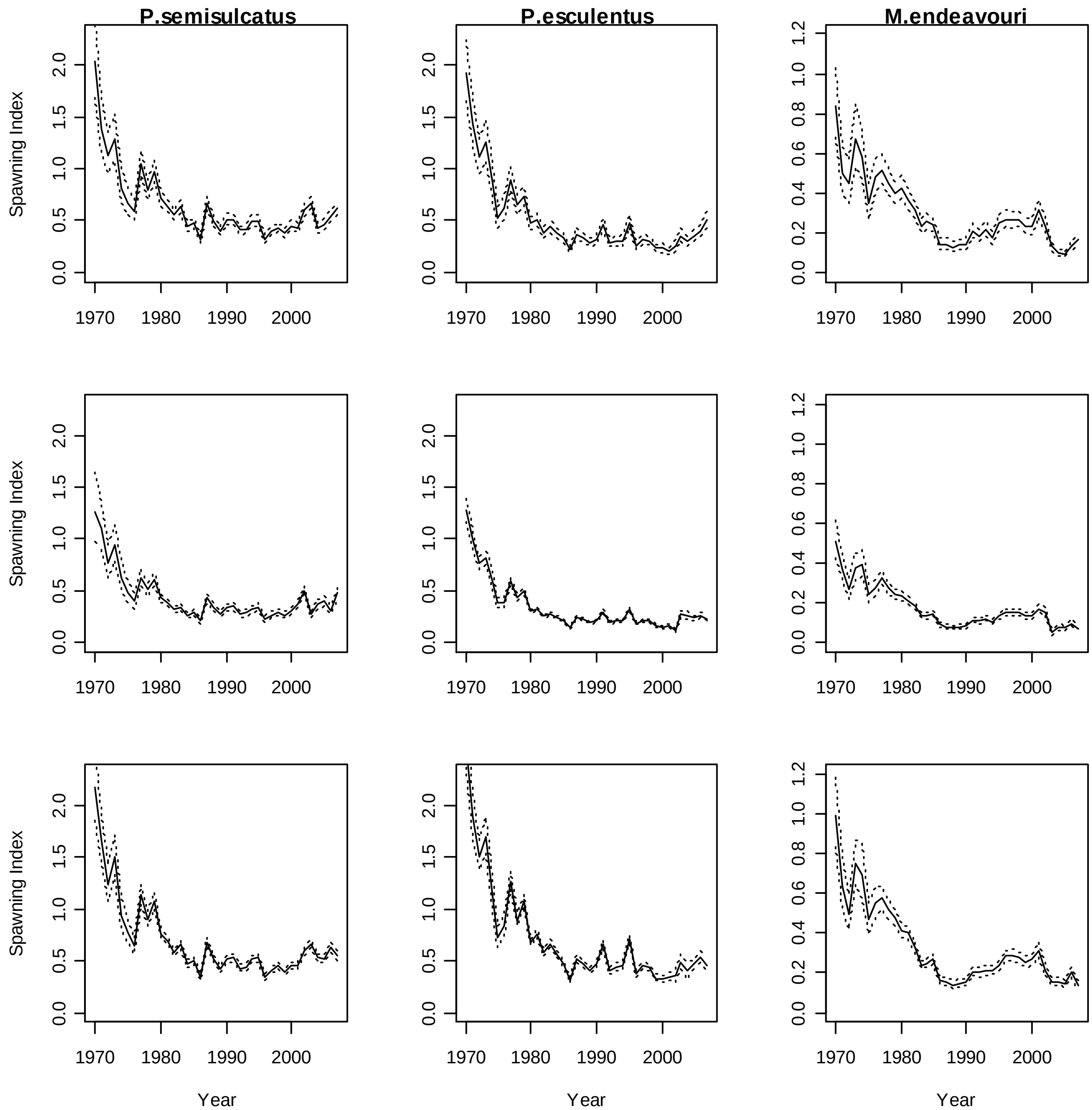


Figure 7.8. Time-trajectories of spawning stock size from the base-case size-structured population dynamics model (upper panels), a variant of this model in which the survey data are ignored (centre panels) and the delay-difference model (lower panels). The dotted lines indicate 90% confidence intervals.

7.5.2 Estimating Maximum Economic Yield

The reference case analysis (see Table 7.4) suggests that two of the three species (*P. semisulcatus* and *P. esculentus*) were above the spawning stock size at which MSY is achieved, S_{MSY}, in 2007 and also above the spawning stock size corresponding to MEY, S_{MEY}. In contrast, the third species *M. endeavouri* was estimated to be below S_{MSY} and S_{MEY}, the latter by quite a considerable extent. This pattern is robust among the various sensitivity tests (note that

S_{2007}/S_{MSY} is the same for all of the sensitivity tests which vary the assumptions of the economic model because S_{MSY} is only impacted by assumptions related to the biological characteristics of the stocks). However, ignoring the survey data or basing the assessment on the delay-difference model suggests that both *P. esculentus* and *M. endeavouri* are currently below S_{MSY}.

As expected, S_{MEY} is larger than S_{MSY}. However, the extent to which this is the case depends on species, the method of assessment, and the values for the parameters of bio-economic model. The average (across cases in Table 7.4) values for S_{MEY}/S_{MSY} are 1.33, 1.16, and 1.22 for *P. semisulcatus*, *P. esculentus*, and *M. endeavouri* respectively.

The effort for each fishing strategy for 2008 in the reference case analysis (and the two sensitivity tests which vary the formulation of the assessment model) is less than that in recent years, but increases rapidly thereafter (Figure 7.9). There are several reasons for effort being low in 2008, one of which is that the recruitment for 2008, which determines a large proportion of the catch for 2008, is estimated to be relatively poor based on the stock assessment. Given the low discount rates applied (relative to the growth rate of the stock), there are economic reasons also why effort is lower for 2008. Fundamentally, the future gains in profits as a result of the higher stock level exceeded the short term reduction in profit.

There is a fairly considerable variation among the sensitivity tests in all of the output quantities and the extent of among-sensitivity test variation exceeds that attributable to parameter uncertainty (Table 7.4; Figure 7.9). Some quantities are, however, much less sensitive to the assumptions of the bio-economic model than others. For example, the profit, relative to that for the reference case analysis, has a coefficient of variation of 30% among the sensitivity tests. In contrast, the coefficient of variation for the total catch over species at MEY (average across sensitivity tests of 3331t) is only 7.5%. The among-sensitivity test variation in the total catch over species for 2008 is higher than the variation among sensitivity tests in the catch at MEY (14.6% vs. 7.5%). This result is perhaps not unexpected because, while both the catch for 2008 and the catch at MEY depend on the values for the biological parameters of the stock assessment, as well as the assumptions and parameter values for the bio-economic model, the catch for 2008 also depends on the estimate of recruitment for the forthcoming year. This uncertainty is also reflected in the 95% confidence intervals for the catch for 2008 compared to the catch at MEY (Figure 7.9). The impact of the biological model (and the data used to estimate its parameters) consequently can have a substantial impact on the key outputs of the bio-economic model.

The net present value is notably higher than that for the reference case analysis for sensitivity tests E1 (lower discount rate), E3 (prices increase by twice the reference case forecast rate), and E4b (rate of change in fuel cost is twice that for the reference case). These sensitivity tests were expected to have led to higher profits as they involved either higher prices or lower costs. Although these sensitivity tests differ in terms of expected profit from the reference case analysis, the time-trajectories of catch, and profit do not differ notably among these cases (Figure 7.10). The sensitivity tests which lead to notably lower net present values than the reference case analysis are E2 (high discount rate), E4a (Prices decrease at the historic rate of increase), and E4c (prices decrease at the historic rate of increase and the fuel cost crashes in 2009 and then recovers at 8% p.a.). Again, these results are expected as they involve lower prices and/or higher costs. In contrast to Figure 7.10, the time-trajectories of catch and profit for sensitivity tests E4a and E4c differ quite markedly from those for the reference case analysis. In particular, profits decline markedly over time for the two sensitivity tests in which prices decline in the future, as would be expected.

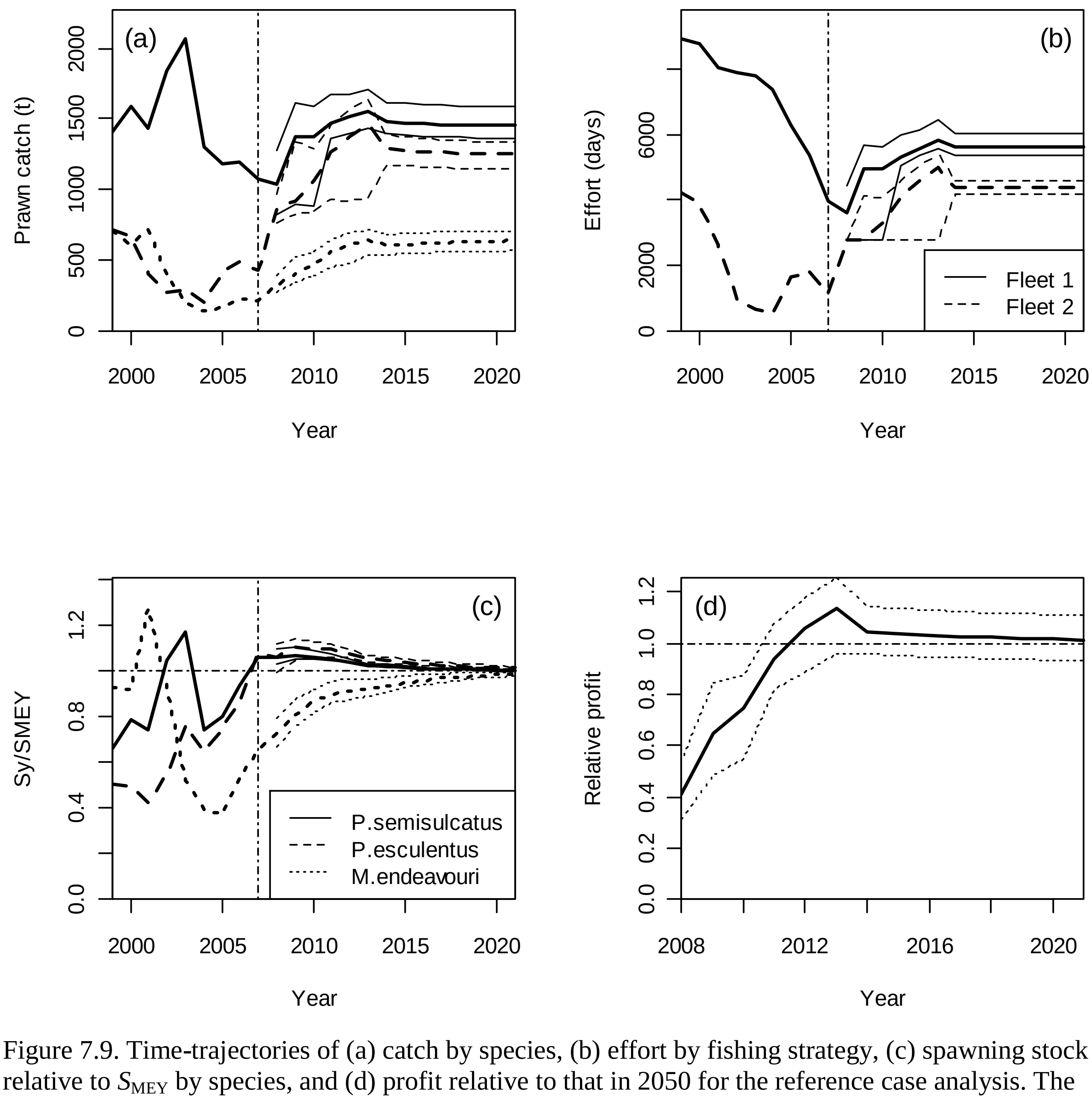


Figure 7.9. Time-trajectories of (a) catch by species, (b) effort by fishing strategy, (c) spawning stock size relative to S_{MEY} by species, and (d) profit relative to that in 2050 for the reference case analysis. The vertical lines denote the first year of the projection period and the dotted lines denote 90% confidence intervals.

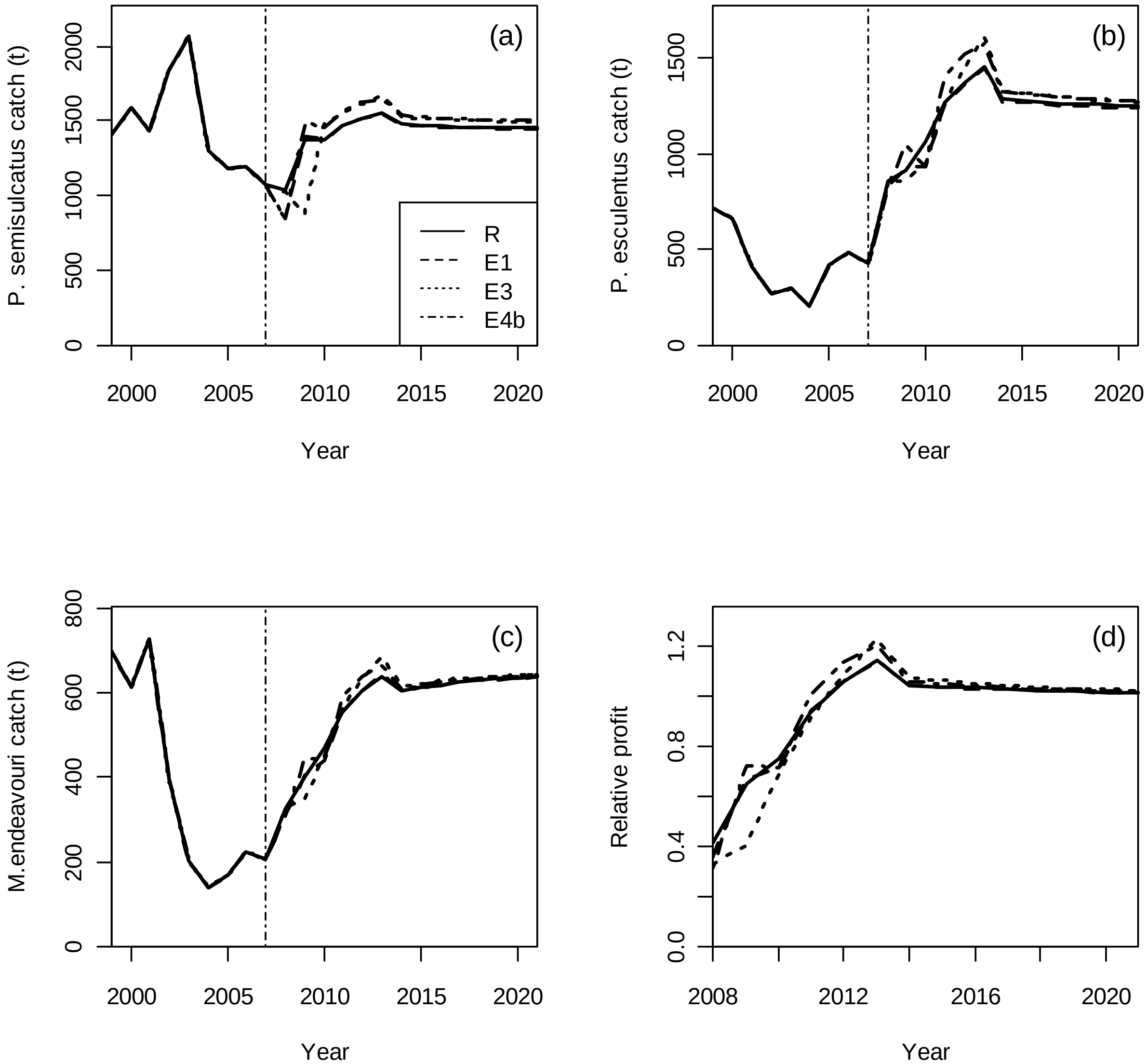


Figure 7.10. Time-trajectories of catch by species (a-c) and profit relative to that in 2050 (d) for the reference case analysis and three sensitivity tests that lead to high profits.

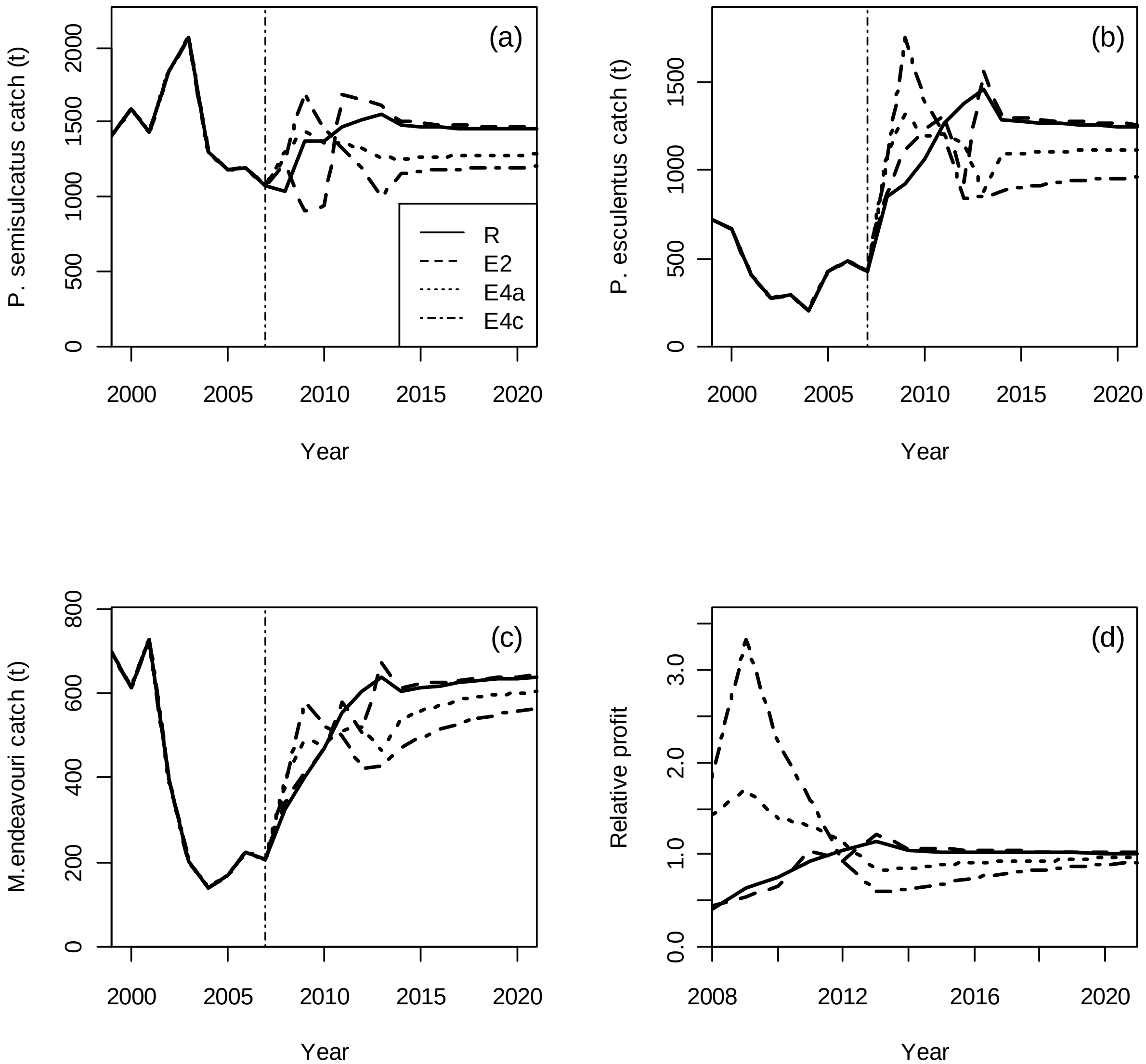


Figure 7.11. Time-trajectories of catch by species (a-c) and profit relative to that in 2050 (d) for the reference case analysis and three sensitivity tests that lead to low profits.

Table 7.4. Summary of the outcomes of the integrated economics model. The values in a parentheses for the reference case denote 90% confidence intervals.

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Reference								
P. semisulcatus	1039	1447	1.331	1.414	1.063	3587	5602	100
	(839-1253)	(1386-1536)	(1.309-1.356)	(1.339-1.499)	(1.008-1.118)	(2777-4217)	(5422-5896)	(93-108)
P. esculentus	852	1231	1.164	1.250	1.073	2777	4370	
	(783-927)	(1148-1303)	(1.134-1.203)	(1.166-1.362)	(1.002-1.161)	(2777-2777)	(4197-4542)	
M. endeavouri	325	646	1.218	0.796	0.653			
	(278-372)	(593-699)	(1.191-1.259)	(0.724-0.888)	(0.587-0.727)			
P1								
P. semisulcatus	860	1500	1.293	1.428	1.104	2828	5812	92
P. esculentus	719	1284	1.090	0.712	0.653	2777	3592	
M. endeavouri	192	649	1.296	0.544	0.420			
P2								
P. semisulcatus	824	1608	1.239	0.964	0.779	2777	5392	115
P. esculentus	695	1313	1.081	0.705	0.652	2777	3861	
M. endeavouri	311	691	1.190	0.555	0.467			
E1								
P. semisulcatus	852	1439	1.340	1.414	1.056	2777	5526	127
P. esculentus	833	1222	1.181	1.250	1.058	2777	4264	
M. endeavouri	307	644	1.233	0.796	0.645			
E2								
P. semisulcatus	1213	1456	1.321	1.414	1.071	4406	5688	82
P. esculentus	871	1240	1.147	1.250	1.090	2777	4482	

M. endeavouri	343	647	1.201	0.796	0.662			
E3								
P. semisulcatus	1025	1478	1.297	1.414	1.091	3526	5938	122
P. esculentus	851	1247	1.131	1.250	1.104	2777	4562	
M. endeavouri	324	649	1.183	0.796	0.672			
E4a								
P. semisulcatus	1298	1290	1.470	1.414	0.962	4729	4327	42
P. esculentus	1094	1131	1.305	1.250	0.957	3687	3562	
M. endeavouri	394	618	1.370	0.796	0.581			

(Table 7.4 Continued)

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
E5								
P. semisulcatus	1189	1396	1.486	1.414	0.952	4314	4858	101
P. esculentus	917	1200	1.167	1.250	1.071	2777	3994	
M. endeavouri	297	602	1.408	0.796	0.565			
E6								
P. semisulcatus	1002	1363	1.390	1.528	1.099	3522	5394	96
P. esculentus	928	1210	1.130	1.280	1.132	2777	4078	
M. endeavouri	295	626	1.207	0.723	0.599			
E7								
P. semisulcatus	1027	1447	1.330	1.414	1.063	3534	5579	98
P. esculentus	851	1246	1.133	1.250	1.103	2777	4583	
M. endeavouri	324	648	1.195	0.796	0.666			
E8								
P. semisulcatus	1062	1447	1.332	1.414	1.063	3840	5601	100
P. esculentus	504	1231	1.164	1.250	1.073	1395	4371	
M. endeavouri	247	646	1.218	0.796	0.653			
E4b								
P. semisulcatus	852	1491	1.280	1.414	1.105	2777	6097	113
P. esculentus	833	1253	1.118	1.250	1.118	2777	4640	
M. endeavouri	307	650	1.170	0.796	0.681			
E4c								
P. semisulcatus	1263	1211	1.529	1.414	0.924	4574	3889	34

P. esculentus	1041	997	1.437	1.250	0.869	3471	2777
M. endeavouri	381	578	1.500	0.796	0.531		

7.6 General discussion

This paper has outlined a way to incorporate more data (catch and survey length-frequency data as well as tagging data) into assessments of prawn species in Australia's Northern Prawn Fishery than has been possible in the past. As a result, the size-structured population dynamics model has fewer pre-specified parameters than the delay-difference model on which management advice has previously been based [although it should be noted that the delay-difference model of this paper estimated the recruitment pattern unlike the version published by Dichmont *et al.* (2003) because this leads to improved residual patterns]. The size-structured population dynamics model also allows grade-specific prices to be considered unlike the delay-difference model which is forced to assume that price is independent of size. This is potentially important when season dates may be varied, or fishers may choose to fish only at peak times of the year (for example, under an ITQ system as is proposed for the fishery). For this particular case, however, the time-trajectories of catch and effort which maximize net present value are not very sensitive to whether prices depend on grade or not (contrast the results for the reference case and sensitivity test E7 in Table 7.4). Unlike the delay-difference model, the size-structured population dynamics model allows selectivity to be estimated using the available data. Figure 7.7 suggests that knife-edged recruitment, the assumption on which the delay-differencedelay-difference model is based, is a relatively poor assumption for the three species examined.

The base-case analysis of this paper includes the survey data when estimating the values for the model parameters (delay-difference and size-structured assessments). One reason for doing this is that the data from the most recent "recruitment" survey (in this case the 2008 recruitment survey) are available when assessments are conducted (generally April of the year for which management advice is needed) and these data provide a means of estimating the recruitment for the upcoming year. Given the population dynamics of prawn species, this should provide an improved means of forecasting biomass and hence estimating catch and effort levels in the short-term. However, this needs to be confirmed, e.g. using simulation analyses.

Several fisheries management jurisdictions are now using size-structured population dynamics models as the basis for fisheries management advice (e.g. Johnston and Butterworth, 2005; Haist *et al*., 2009; Hobday and Punt, 2001; Zheng *et al*., 1995). The assessment of this paper is unusual (but not unique, see Haist *et al*. (2009)) in that the parameters which determine the size-transition matrix **H** are estimated along with the other parameters of the model. In contrast, most size-structured stock assessments estimate the size-transition matrix using auxiliary information and assume this to be known. The approach of this paper allows all of the sources of data to inform the parameters of the size-transition matrix rather than just the tag release-recapture data and also allows the uncertainty associated with the size-transition matrix to be reflected in the measures of uncertainty.

It should be noted that the size-structured method of assessment is not without problems. In particular, the size-structured stock assessment method is much more computationally demanding than the delay-difference approach. This makes quantification of uncertainty using, for example, bootstrapping, very time-consuming and simulation evaluation of any management strategies based on the size-structured assessment very difficult (if not prohibitive). Similarly, calculating effort levels which maximize net present value is computationally very challenging (a reason only limited results based on bootstrapping are shown in this paper).

The estimates of the ratio $S_{\mathrm{MEY}}/S_{\mathrm{MSY}}$ all exceed 1 (and the 90% confidence intervals for $S_{\mathrm{MEY}}/S_{\mathrm{MSY}}$ for the reference case do not include 1). This confirms the expectation that maximization of net present value leads to higher target stock sizes (and lower target levels of catch and effort). However, the extent to which the spawning stock size corresponding to MEY exceeds that corresponding to MSY differs among species (generally highest for *P. semisulcatus* and lowest for *M. endeavouri*) which suggests that a single value for this ratio (as envisaged in DAFF (2007) who suggest a default for $S_{\mathrm{MEY}}/S_{\mathrm{MSY}}$ of 1.2 as a proxy to estimate S_{MEY}) is not appropriate, and that this ratio will be case-specific.

Unsurprisingly, the catches and levels of effort which lead to maximization of net present value are lower than those which maximize yield in mass. Implementation of a strategy of selecting catches and effort levels to maximize net present value should lead to lower impacts not only on the target stocks but also on the broader ecosystem (Dichmont *et al*., 2008).

The bio-economic model of this paper builds on over 30 years of bio-economic modelling in the fishery (e.g. Clark and Kirkwood, 1979; Haynes and Pascoe, 1988; Somers and Wang, 1997; Dichmont *et al.*, 2008; Kompas *et al*. 2008), although only recently have such models (and variants thereof) formed the basis for management advice for the tiger prawn fishery in the NPF. Further, it is one of the very few instances where such models have formed the direct basis for fisheries management by implicitly defining a harvest control rule which includes economics. In contrast, many jurisdictions (e.g. the U.S.) use a biological harvest control rule to provide one piece of information on allowable levels of catch and efforts and “adjust” these allowable catches and efforts taking account of economic, social and ecological factors. Similarly, in the European Union, economic implications for selected fleets of TACs based on biological considerations only are undertaken and feed into the TAC setting process (Daw and Gray, 2005; Frost and Andersen, 2006).[1] Alternative TACs are not proposed taking economic factors into consideration, instead only economic consequences of biologically-based proposals are evaluated. Thus, the biological and economic consequences are considered separately, and without feedback, and the final TAC is determined in a political process by the Council of Ministers (Daw and Gray, 2005). In contrast, the approach used in this study integrates the biological and economic systems from the start, allowing for dynamic optimization and full feedback between the systems. The use of a bio-economic model for management advice in the NPF is, however, a direct consequence of the decision by the Australian

[1] Initial TACs are proposed by ICES based on biological considerations only (Stokke and Coffey, 2004). Economic implications (in terms of short term impacts on vessel profitability) of these proposed TACs are evaluated by the Scientific, Technical and Economic Committee for Fisheries (STECF) for a selection of key fleets and stocks (Frost and Andersen, 2006).

government to have limit reference points for spawning stock size based on biological considerations, but target reference points which reflect economic considerations (DAFF, 2007).

Although the use of bio-economic harvest control rules is essentially mandated by Australia's national fisheries policy, it is clear from Table 7.4 that accounting for economic considerations adds additional uncertainty to the management advice. This is reflected by for example, the higher between sensitivity-test variation in $S_{2007}/S_{\mathrm{MEY}}$ compared to $S_{2007}/S_{\mathrm{MSY}}$. Dichmont *et al*. (2008) compared management strategies based on achieving MEY with those based on F_{MSY}-like control rules and found that the former performed better. However, Dichmont *et al*. (2008) did not consider uncertainty in costs and prices. Uncertainty regarding future costs and prices is one reason why the parameters of the economics model need to be updated regularly and it is planned that management advice based on the bio-economic model will be updated every 2nd year.

In principle, the bio-economic analyses could be conducted for more species (e.g. including king prawns in the analyses). However, assessments for such species could not be undertaken using a delay-difference model (let alone a size-structured model) and future work needs to examine how it might be possible to link, for example, a production model-based assessment for a data-limited species with the current size-structured bio-economic model. Zhou *et al*. (2010 - in press)(Appendix 8) provide an approach to conducting assessments using a spatially-structured biomass dynamics model, and, in principle, results from that approach could be linked to the size-structured (or delay-difference) model.

7.7 Acknowledgements

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7.8 References

ABARE (Australian Bureau of Agricultural and Resource Economics). 2007. Australian Commodity Statistics 2006. Canberra.73 pp.

Bishop, J., Venables, W. N., Sterling, D. J., and Dichmont. C. M. 2008. Standardising catch rates – is logbook data by itself enough? ICES Journal of Marine Science 6: 255–266.

Buckworth, R. C. 1992. Movements and growth of tagged blue endeavour prawns *Metapenaeus endeavouri* (Schmitt 1926) in the western Gulf of Carpentaria, Australia. Australian Journal of Marine and Freshwater Research 43: 1283–1299.

Clark C. W., Clarke F. H., and Gordon R. M. 1979. The optimal exploitation of renewable resource stocks: problems of irreversible investment. Econometrica 47: 25–47.

Clark, C. W., and Kirkwood. G. 1979. Bioeconomic model of the Gulf of Carpentaria prawn fishery. Journal of the Fisheries Research Board of Canada. 36: 1304–1312.

Daw, T., and Gray, T. 2005. Fisheries science and sustainability in international policy: a study of failure in the European Union's Common Fisheries Policy. Marine Policy 29: 189–197.

DAFF (Department of Agriculture, Fisheries and Forestry). 2007. Australian Fisheries Harvest Policy: Policy and Guidelines. 55 pp.

Dichmont, C. M., Burridge, C., Deng, A., Jones, P., Taranto, T., Toscas, P., Vance, D., and Venables, W. 2002. Designing an integrated monitoring program for the NPF optimising costs and benefits. Australian Fisheries Management Authority report Number R01/1144. 101 pp.

Dichmont, C. M., Punt, A. E., Deng, A., Dell, Q., and Venables, W. 2003. Application of a weekly delay-difference model to commercial catch and effort data in Australia's Northern Prawn Fishery. Fisheries Research 65: 335–350.

Dichmont, C. M., Deng, A., Punt, A. E., Ellis, N., Venables, W. N., Kompas, T., Zhou, S., and Bishop, J. 2008. Beyond biological performance measures in management strategy evaluation: Bringing economics and the effects of trawling on the benthos. Fisheries Research 94: 238–250.

Folmer, O., and Pennington, M. 2000. A statistical evaluation of the design and precision of the shrimp trawl survey off West Greenland. Fisheries Research 49: 165–178.

Frost, H., and Andersen, P. 2006. The Common Fisheries Policy of the European Union and fisheries economics. Marine Policy 30: 737–746.

Gillett, R. 2008. Global study of shrimp fisheries. FAO Fisheries Technical Paper. 475: 1–331.

Haist, V., Breen, P. A., and Starr, P. J. 2009. A multi-stock, length-based assessment model for New Zealand rock lobster (*Jasus edwardsii*). New Zealand Journal of Marine and Freshwater Research 43: 355–371.

Haynes, J., and Pascoe, S. 1988. A Policy Model of the Northern Prawn Fishery, Australian Bureau of Agricultural and Resource Economics Occasional Paper 103, AGPS, Canberra. 49 pp.

Hobday, D., and Punt, A. E. 2001. Size-structured population modelling and risk assessment of the Victorian southern rock lobster, *Jasus edwardsii*, fishery. Marine and Freshwater Research 52: 1495–1507.

Johnston, S. J., and Butterworth, D. S. 2005. Evolution of operational management procedures for the South African west coast rock lobster (*Jasus Ialandii*) fishery. New Zealand Journal of Marine and Freshwater Research 39: 687–702.

Kompas, T., Che, N., and Grafton, R. Q. 2008, Fisheries instrument choice under uncertainty. Land Economics 84: 652–666.

Maunder, M. N., and Watters, G. M. 2003. A-SCALA: an age-structured statistical catch-at-length analysis for assessing tuna stocks in the eastern Pacific Ocean. Bulletin of the Inter-American Tropical Tuna Commission 22: 433–582.

McGarvey, R., and Feenstra, J. E. 2001. Estimating length-transition probabilities as polynomial functions of premoult length. Marine and Freshwater Research 52: 1517–1526.

Milton, D. A., Kenyon, R. A., Burridge, C., Zhu, M., Pendrey, R., van der Velde, T., Donovan, A., and Kienzle, M. 2008. An integrated monitoring program for the fishery for the Northern Prawn Fishery 2006/8. Australian Fisheries Management Authority R05/1024. 245 pp.

Patterson, K., Cook, R., Darby, C., Gavaris, S., Kell, L., Lewy, P., Mesnil, B., Punt, A., Restrepo, V., Skagen, D. W., and Stefansson, G. 2001. Estimating uncertainty in fish stock assessment and forecasting. Fish and Fisheries. 2: 125–157.

Punt, A. E., Buckworth, R. C., Dichmont, C. M., and Ye, Y. 2009. Performance of methods for estimating size transition matrices using tag-recapture data. Marine and Freshwater Research 60: 168–182.

Rose, R., and Kompas, T. 2004, T. Management Options for the Australian Northern Prawn Fishery. Australian Bureau of Agricultural and Resource Economics, Commonwealth of Australia, Canberra. 47 pp.

Somers, I. 1990. Manipulation of fishing effort in Australia's penaeid prawn fisheries. Australian Journal of Marine and Freshwater Research 41: 1–12.

Somers, I. F., and Kirkwood, G. P. 1991. Population ecology of the grooved tiger prawn, *Paneaus semisulcatus*, in the north-western Gulf of Carpentaria, Australia: Growth, movement, age structure and infestation by the bopyrid parasite *Epipenaeon ingens*. Australian Journal of Marine and Freshwater Research 42: 349–267.

Somers I., and Wang Y-G. 1997. A simulation model for evaluating seasonal closures in Australia's multispecies northern prawn fishery. North American Journal of Fisheries Management 17: 114–130.

Stokke, O. S., and Coffey, C. 2004. Precaution, ICES and the common fisheries policy: a study of regime interplay. Marine Policy 28:117–126.

Venables, W. N., and Dichmont, C. M. 2004. A generalized linear model for catch allocation: an example from Australia's Northern Prawn Fishery. Fisheries Research 70: 409–426.

Vieira, S., and Perks, C. 2009, Australian fisheries surveys report 2009: Survey results for selected fisheries, 2006-07 and 2007-08, preliminary estimates for 2008-09. Australian Bureau of Agricultural and Resource Economics, Commonwealth of Australia, Canberra. 53 pp.

Wang, Y-G., and Die, D. 1996. Stock-recruitment relationships of the tiger prawns (*Penaeus esculentus* and *Penaeus Semisulcatus*) in the Australian Northern Prawn Fishery. Marine and Freshwater Research 47: 87–95.

Wang, Y-G., Thomas, M. R., and Somers, I. F. 1995. A maximum likelihood approach for estimating growth from tag-recapture data. Canadian Journal of Fisheries and Aquatic Sciences 52: 252–259.

Zheng, J., Murphy, M. C., and Kruse, G. H. 1995. A length-based population model and stock-recruitment relationships for red king crab, *Paralithodes camtschatiucus*, in Bristol Bay, Alaska. Canadian Journal of fisheries and Aquatic Sciences 52: 1229–1246.

Zhou, S., Punt, A. E., Deng, R., Dichmont, C. M., Ye, Y., and Bishop, J. 2010 (in press). Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Marine and Freshwater Research 00: 00–00.

APPENDIX 8. MODIFIED HIERARCHICAL BAYESIAN BIOMASS DYNAMICS MODELS FOR ASSESSMENT OF SHORT-LIVED INVERTEBRATES: A COMPARISON FOR TROPICAL TIGER PRAWNS

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8.1 Abstract

Conventional biomass dynamics models express next year's biomass as this year's biomass plus surplus production less catch. These models are typically applied to species with several age-classes but it is unclear how well they perform for short-lived species with low survival and high recruitment variation. Two alternative versions of the standard biomass dynamics model (Standard) were constructed for short-lived species by ignoring the "old biomass" term (Annual), and assuming that the biomass at the start of the next year depends on density-dependent processes that are a function of that biomass (Stock-recruit). These models were fitted to catch and effort data for the grooved tiger prawn *Penaeus semisulcatus* using a hierarchical Bayesian technique. The results from the biomass dynamics models were compared to those from more complicated weekly delay-difference models. The analyses show that: the Standard model is flexible for short-lived species; the Stock-recruit model provides the most parsimonious fit; simple biomass dynamics models can provide virtually identical results to data-demanding models; and spatial variability in key population dynamics parameters exists for *P. semisulactus*. The method outlined in this paper provides a means to conduct quantitative population assessments for data-limited short-lived species.

Keywords: surplus production, process error, observation error, squid, state-space, maximum likelihood

8.2 Introduction

Biomass dynamics (or production) models remain one of the most popular tools for analysing both finfish and shellfish population dynamics (Smith and Addison 2003). They are typically used when information on the age-structure of the catch is unavailable and hence when more sophisticated methods of stock assessment such as Virtual Population Analysis or statistical catch-at-age analysis cannot be applied, and when information on the size of the biomass of the population alone is adequate for management purposes. Biomass dynamics models use difference equations in which new biomass equals old biomass plus growth less catch, and 'growth' includes recruitment, somatic growth, and natural mortality (Punt 2003; Chaloupka and Balazs 2007).

A variety of formulations of the biomass dynamics model have been developed and examined (review in Quinn and Deriso 1999). An implicit assumption of most biomass dynamics models is that natural mortality is not very high so that a fairly large proportion of the biomass at the start of the next (annual) time-step consists of the biomass at the start of the current time-step. However, the suitability of these models and their assumptions have rarely been examined for short-lived species such as tropical prawns and squids that exhibit high annual recruitment variation and for which the catch comprises only a single age class. Rather, researchers have used alternative approaches for assessment of short-lived species. For example, Roel and Butterworth (2000) and Isoda *et al*. (2005) adopted different recruitment functions for different stock sizes when assessing short-lived squids using biomass dynamics models. Bellido *et al.* (2001) used generalized additive models for modelling variation in abundance of squid rather than applying population dynamics models.

A single-stock, single-fleet biomass dynamics model based on the assumption that the dynamics are deterministic has been applied to species-aggregated data for two tiger prawn species (*Penaeus semisulcatus* and *P. esculentus*) in Australia's Northern Prawn Fishery (NPF), but the results were unrealistic (Dichmont *et al*. 2005). It is not clear whether this was because a biomass dynamics model is not suitable for a short-lived species or because the method used to fit the model was inappropriate. The assumption that all of the error is in the observation process and that the dynamics are deterministic (the assumptions of an observation-error only estimator) is standard when applying biomass dynamics models (Punt and Hilborn 1996; Mueter and Megrey 2006). This assumption is often made because simulation studies have shown this method of fitting biomass dynamics models is more robust than the conventional alternative of assuming that the observations are made without error, but the dynamics are stochastic (Polacheck *et al.* 1993). In contrast, the dynamics of short-lived species are subject to considerable process error (annual recruitment constitutes a large proportion of future biomass) as well as observation error.

The concerns with the use of an observation-error estimator may be overcome using a Bayesian state-space formulation of the biomass dynamics model (Meyer and Millar 1999). Moreover, concern that it is inappropriate to apply a standard biomass dynamics model to short-lived species may be resolved by reformulating the biomass dynamics model. This paper therefore outlines two alternative formulations of the standard biomass dynamics model which better account for the high rate of natural mortality for short-lived species and applies it to the grooved tiger prawn (*P. semisulcatus*). These formulations account for the multi-species nature of the fishery for *P. semisulcatus* by fitting the model to catch-rate data from a fleet which targets *P. semisulcatus* and from another fleet which targets another prawn species in the Australia's NPF, *P. esculentus,* and has a by-catch of *P. semisulcatus*.

There is evidence that tiger prawns in the NPF constitute multiple "stocks" (Dichmont *et al.* 2005). The analyses of this paper therefore analyse the data for *P. semisulcatus* using a hierarchical formulation of the Bayesian state-space method and hence imposes priors on the between-stock variation in some key population dynamic parameters. This avoids the need to specify prior distributions for the parameters of the model using (non-existent) auxiliary information and imposes the assumption that the values for the parameters should not differ markedly among stock areas. Finally, the results from the alternative models are compared to those from two other models that have been applied to data for *P. semisulcatus*: (1) a model that aggregates data spatially and assumes a single fleet and estimates parameter values using an observation-error estimator (Dichmont *et al*. 2005; also see this fishery used as an example in Haddon 2000); and (2) a weekly delay-difference model that incorporates additional parameters such as recruitment pattern, catchability, availability, growth, natural mortality, and estimates annual recruitment (Dichmont *et al*. 2003).

8.3 Methods

8.3.1 Alternative biomass dynamics models

In this section, the population dynamics models are assumed to be deterministic and any dependence on "stock" is omitted for ease of presentation. The standard (or conventional) formulation of the biomass dynamics model is (Polacheck *et al.* 1993; Punt and Hilborn 1996):

$$B_y = B_{y-1} + rB_{y-1}\left(1 - \frac{B_{y-1}}{K}\right) - C_{y-1}, \qquad (1)$$

where B_y is the biomass at the start of year *y*, *r* is the intrinsic growth rate, *K* is the carrying capacity, and C_y is the total catch during year *y*. For short-lived species whose catchable biomass is made up entirely of new recruitment, last year's biomass contributes little to the biomass this year so Eqn 1 can be simplified to:

$$B_y = rB_{y-1}\left(1 - \frac{B_{y-1}}{K}\right) - C_{y-1}. \qquad (2)$$

Eqn 2 is the popular logistic model for annual terrestrial organisms such as insects and plants (Gillman and Hails 1997) when the catch term C_y is omitted. Eqn 2 can be extended further with two alternative assumptions: (1) most of the catch occurs before spawning, and (2) density-dependence is more likely to depend on this year's biomass (B_y) rather than last year's biomass (B_{y-1}), i.e.:

$$B_y = r\left(B_{y-1} - C_{y-1}\right)\left(1 - \frac{B_y}{K}\right). \qquad (3)$$

Rearranging Eqn 3 leads to:

$$B_y = \frac{r\left(B_{y-1} - C_{y-1}\right)}{1 + \frac{r}{K}\left(B_{y-1} - C_{y-1}\right)}. \qquad (4)$$

Eqn 4 has the appearance of a classical Beverton-Holt stock-recruitment model when the mean weight is the same over time. The biomass remaining after fishing $\left(B_{y-1} - C_{y-1}\right)$ represents the spawning biomass in the Beverton-Holt model, and *r* is the maximum recruits-per-spawner at low stock size. The parameter *K* in Equations 2 and 4 cannot be interpreted as carrying capacity (unlike in Eqn 1). Here, we defined the carrying capacity B_∞ as the equilibrium population size in the absence of fishing. Table 8.1 lists the equations for B_∞, the population growth rate λ (slope at origin), the biomass at which *MSY* is achieved, and the *MSY* for each of models 1, 2 and 4. Table 8.1 also lists the relationships between the parameters *r* and *K* for each model. Eqn 1 will be referred to as the 'Standard' model, Eqn 2 as the 'Annual' model, and Eqn 4 as the 'Stock-recruit' model. These three models can be extended to consider multiple stocks by substituting r_s for *r*, K_s for *K*, and $B_{s,y}$ for B_y where *s* denotes stock.

Table 8.1. Three alternative biomass dynamics models, the relationship between the parameters r and K for each model, and the equations defining the population growth rate λ, carrying capacity B_∞, B_{MSY} and MSY.

	Standard	Annual	Stock-recruit
Model	$B_y = B_{y-1} + r^{Std} B_{y-1}\left(1-\frac{B_{y-1}}{K^{Std}}\right) - C_{y-1}$	$B_y = r^{Anl} B_{y-1}\left(1-\frac{B_{y-1}}{K^{Anl}}\right) - C_y$	$B_y = \frac{r^{SR}\left(B_{y-1}-C_{y-1}\right)}{1+\frac{r^{SR}}{K^{SR}}\left(B_{y-1}-C_{y-1}\right)}$
r relationship	r^{Std}	$r^{Anl} = 1 + r^{Std}$	$r^{SR} = \left(\frac{2}{2-r^{Std}}\right)^2$
K relationship	K^{Std}	$K^{Anl} = \frac{(1+r^{Std})K^{Std}}{r^{Std}}$	$K^{SR} = \frac{K^{Std}}{r^{Std}}$
λ	$1+r^{Std}$	r^{Anl}	r^{SR}
B_∞	K^{Std}	$\frac{(r^{Anl}-1)K^{Anl}}{r^{Anl}}$	$\frac{(r^{SR}-1)K^{SR}}{r^{SR}}$
B_{MSY}	$0.5K^{Std}$	$\frac{(r^{Anl}-1)K^{Anl}}{2r^{Anl}}$	$K^{SR}\left(1-\frac{1}{\sqrt{r^{SR}}}\right)$
MSY	$\frac{r^{Std}K^{Std}}{4}$	$\frac{\left(r^{Anl}-1\right)^2 K^{Anl}}{4r^{Anl}}$	$K^{SR}\left(1-\frac{1}{\sqrt{r^{SR}}}\right)^2$

Note: the relationships between $r^{\mathrm{Std}} \sim r^{\mathrm{SR}}$, and $K^{\mathrm{Std}} \sim K^{\mathrm{SR}}$ are true only when $B_{MSY}^{Std} = B_{MSY}^{SR}$.

8.3.2 Parameter estimation

The values for the parameters of the three models were estimated by fitting them to data on catch-per-unit-effort (CPUE). For a multi-stock, multi-fleet fishery where some fleets target the species of interest, and other fleets take it as by-catch, the model-estimate corresponding to the catch-rate for stock *s*, fleet *f*, and year *y*, $\hat{U}_{s,f,y}$ is:

$$\hat{U}_{s,f,y} = q_{s,f} P_y B_{s,y}, \qquad (5)$$

where $q_{s,f}$ is the catchability coefficient for stock *s* and fleet *f*, and P_y is the relative fishing power during year *y*. The observed catch-rate was assumed to be log-normally distributed about its expected value in common with most applications of biomass dynamics models (Polacheck et al. 1993; Meyer and Millar 1999):

$$U_{s,f,y} \sim \text{log-normal}\{\ell\text{n}(\text{E}[\hat{U}_{s,f,y}], \tau_{U,s,f})\} \qquad (6)$$

where $\tau_{U,s,f}$ is the precision (the inverse of the variance) of the observation error for the catch-rate data for stocks *s* and fleet *f*. $\tau_{U,s,f}$ is allowed to differ among fleets because it would not be expected that fleets that target a species and which take it as by-catch would lead to indices of abundance with the same precision.

Equations 1, 2 and 4 are deterministic. However, it is necessary to hypothesize how realised biomass relates to the expectation based on Eqns 1, 2 and 4 to account for process error in the population dynamics (and hence formulate the biomass dynamics models as state-space models). For the purposes of this paper, we assumed that deviations about the expected biomass are log-normally distributed (Meyer and Millar 1999; Chaloupka and Balazs 2007), i.e.:

$$B_{s,y} \sim \log-\text{normal}\{\ell n(E[B_{s,y}]), \tau_{B,s}\} \qquad (7)$$

where $\tau_{B,s}$ is the precision of the process error for stock *s*. The prior for the biomass at the start of the first year of the modelled period is assumed to be the same as for the carrying capacity for stock *s*.

It is necessary to specify prior distributions for all of the parameters of the model to implement each of the three state-space models within a hierarchical Bayesian framework. Under the assumption that the key parameters are unlikely to differ substantially among areas, it was assumed that *r*, *K* and *q* were log-normally distributed about a common mean, i.e., *r*, *K* and *q* for each stock are random effects about a common mean, and:

$$\begin{aligned} K_s &\sim \text{log-normal}(\mu_K, \tau_K) \\ r_s &\sim \text{log-normal}(\mu_r, \tau_r) \qquad (8) \\ q_{s,f} &\sim \text{log-normal}(\mu_{q,f}, \tau_{q,f}) \end{aligned}$$

where μ_K, μ_r, and $\mu_{q,f}$ are the prior means for *K*, *r* and fleet-specific catchability, respectively, and τ_K, τ_r, and $\tau_{q,f}$ are the corresponding prior precisions. Collectively, these parameters are known as hyper-parameters (Harley and Myers 2001; Su *et al*. 2001). We assumed a normal distribution, N(M_θ, T_θ), for μ_θ, where θ is either *K*, *r*, or *q*. Bayesian hierarchical models have the advantages that there is no need to set the values for the parameters of the priors, but only those of the hyper-parameters, and that the results of models are less sensitive to the values for the parameters of the hyper-prior than those of the prior. We specified values for the means (M_θ) of these hyper-priors (McAllister *et al*. 2004; Askey *et al* 2007) by considering results of other studies and set the values for T_θ to large values so that the hyper-priors were relatively non-informative, but still proper (Gelman 2006). We tested a wide range of values for M_θ and found that the results were not sensitive to them. For example, setting M_K = 8.2 or 9.6 had little impact on the results. Two alternative approaches for setting the values for the hyper-parameter T_θ were considered: (a) set so that the CV (coefficient of variation) of the hyper-prior is 150% and so that the hyper-prior is relatively non-informative (McAllister et al. 2004), and (b) a half–Cauchy distribution. The Cauchy distribution was obtained as the ratio of a normal and the square root of a chi-square distribution with one degree of freedom (Dongen 2006; Gelman 2006). The results for the two methods for setting T_θ were similar so results are only shown for the half-Cauchy hyper-prior.

The hyper-priors for the τ_θ, as well as the priors for the observation precisions, $\tau_{U,s,f}$, and the process precisions, $\tau_{B,s}$, were set to proper, but reasonably non-informative gamma distributions with mean 1 and variance 1000, i.e., $gamma(0.001, 0.001)$.

In summary, the hierarchical structure of the alternative biomass dynamics models contains the following levels:

Hyper-priors: $\mu_\theta \sim$ N(M_θ, T_θ), $\tau_\theta \sim$ G(0.001, 0.001);

Hyper-parameters: μ_K, μ_r, $\mu_{q,f}$, τ_K, τ_r, $\tau_{q,f}$;

Priors: log(K_s)~N(μ_K, τ_K), log($B_{s,1}$)~N(μ_K, τ_K), log(r_s)~N(μ_r, τ_r), log($q_{s,f}$)~N($\mu_{q,f}, \tau_{q,f}$), $\tau_{U,s,f}$~G(0.001, 0.001), $\tau_{B,s}$~G(0.001, 0.001);

Parameters: K_s, r_s, $q_{s,f}$, $B_{s,1}$, $\tau_{U,s,f}$ $\tau_{B,s}$;

Data: $U_{s,f,y}$.

Given the assumptions regarding the nature of the state-space model, the priors for the parameters and those for hyper-priors, the posterior distribution is proportional to:

$$\begin{aligned}
&p(\mu_K)p(\tau_K)p(\mu_r)p(\tau_r)p(\underline{\mu}_{q,f})p(\underline{\tau}_{q,f})\\
&p(\underline{K}_s \mid \mu_K,\tau_K)p(\underline{B}_{1970,s} \mid \mu_K,\tau_K)p(\underline{r}_s \mid \mu_r,\tau_r)p(\underline{q}_{s,f} \mid \underline{\mu}_{q,f},\underline{\tau}_{q,f})p(\underline{\tau}_{B,s})p(\underline{\tau}_{U,s,f}) \qquad (9)\\
&\prod_{s,y}\left(p(B_{s,y} \mid B_{s,y-1},K_s r_s,C_y,\tau_{B,s})\prod_f p(U_{s,f,y} \mid B_{s,y},q_{s,f},P_y,\tau_{U,s,f})\right)
\end{aligned}$$

where the underlined parameters denote a vector or matrix over stock *s*, fleet *f*, and/or year *y*.

The Gibbs sampler, a Markov chain Monte Carlo (MCMC) technique, implemented using the WinBUGS package (http://www.mrc-bsu.cam.ac.uk/bugs) was used to sample parameter vectors from the posterior distribution (Eqn 9). Three Markov chains were constructed based on dispersed initial values, and the results of the first 4,000 cycles of each chain were taken as the burn-in period. The results of an additional 60,000 cycles from the three chains were saved, which formed the basis for further analysis. Whether the burn-in period was sufficient and the MCMC algorithm converged adequately to the posterior were evaluated by visually examining the three chains for each parameter in Eqn 9 and using the CODA package (Best *et al.* 1996).

8.3.3 Model diagnostics and selection

The fit of the model to the data was evaluated using the following criteria: (1) graphical assessment of the 95% prediction credibility intervals, (2) χ^2 goodness-of-fit statistics, (3) posterior predictive *p* values, and (4) Kolmogorov-Smirnov (KS) two-sample tests (Sheskin 1997). We calculated these statistics from posterior predictive distributions for the time-series of catch-per-unit-effort. For each observed catch-rate, this distribution was obtained by sampling parameters from the posterior distribution (Eqn 9) and then, conditional on those samples, sampling catch-rates from the log-normal distribution assumed to capture observation error (Eqn 6). The posterior predictive distribution of catch rate for each fleet, stock and year, $u_{s,f,y}^{pred}$ is:

$$P\left(u_{s,f,y}^{pred}\middle|\mathbf{U}\right)=\int P\left(u_{s,f,y}^{pred}\middle|\underline{\theta}\right)P\left(\underline{\theta}\middle|\mathbf{U}\right)d\underline{\theta}. \qquad (10)$$

In this equation, $\underline{\theta}$ denotes all parameters, including model parameters and hyper-parameters. The 2.5th, 50th and 97.5th percentiles from the posterior predictive distribution were plotted together with the observed catch-rates $U_{s,f,y}$.

The second criterion for model checking based on the posterior predictive distribution involved comparing the realized discrepancy χ^2_{rel} (between the observed catch rates and the posterior expected catch rates) and the posterior predictive χ^2_{pred} discrepancy (between catch rates from the posterior predictive distribution and the posterior expected catch rate) (Gelman et al. 1996). That is, for each fleet *f*, this χ^2 discrepancy was:

$$\chi^2_f\left(u_f\mid\underline{\theta}\right)=\sum_s\sum_y\left[\ln(u_{s,f,y})-\ln(\hat{U}_{s,f,y})\right]^2\tau_{U,s,f}, \qquad (11)$$

where u_f is either the observed CPUE or the predicted CPUE from Eqn 10 for fleet *f*.

We also calculated the posterior predictive *p*-value for the χ^2 discrepancy as:

$$p\left(u_f^{pred}\right)=\int P[\chi^2_n\geq\chi^2_{pred,f}(u_f^{pred}\mid\underline{\theta})]P(\underline{\theta}\mid\mathbf{U})d\underline{\theta}, \qquad (12)$$

where χ^2_n is the standard chi-square distribution, and *n* is the number of data points for each fleet.

The nonparametric Kolmogorov-Smirnov two-sample test was used to test the hypothesis that the predicted catch rates for each replicated sample and the observed catch rates were from the same distribution. The *p*-value of this test is displayed using histograms. Furthermore, the proportion of replicates in which the null hypothesis is rejected at $\alpha = 0.05$ is defined as the overall KS *p*-value:

$$p_f^{KS} = \frac{1}{n} \sum_s \sum_y I(p_{s,y,f} < 0.05), \qquad (13)$$

where *n* is the total number of data points for fleet *f*, *I* is the indicator function that takes the value of 1 when its argument is true and zero otherwise, and $p_{s,y,f}$ is the probability value from the Kolmogorov-Smirnov for each species, year and fleet.

We used two criteria to compare alternative models: the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002), and the mean square predictive error loss function (MSPE) on the log-scale (Ghosh and Norris 2005; Webster et al. 2008). The latter was defined as:

$$MSPE = \frac{1}{n} \sum_s \sum_f \sum_y \left[\ln(u_{s,f,y}^{pred}) - \ln(U_{s,f,y}) \right]^2 \qquad (14)$$

where $u_{f,s,y}^{pred}$ is sampled from Eqn 10. These equations were coded directly in the WinBUGS program, except for the Kolmogorov-Smirnov test and Eqn 13 which were implemented using R. The best model was the one that had the smallest values for E[MSPE] and DIC.

8.3.4 Application to *P. semisulcatus*

The grooved tiger prawn *P. semisulcatus* is a tropical species with a typical life span of less than 18 months and an assumed natural mortality rate of 0.045 week^{-1} (Dichmont *et al.* 2003). Sex-specific length frequency data from scientific surveys show that the catch just before the start of fishing season is largely composed of a single cohort (Ye *et al*. 2007). Given the high mortality typically associated with prawns, this implies that few animals will survive an entire year. Catch-rate data for each stock were available for two “fleets”: one that targets *P. semisulcatus* and another that catches this species as by-catch when targeting another commercially-valuable prawn species, *P. esculentus*. Fishing power in Eqn 5 is expressed relative to that at the start of 1993 (Dichmont *et al.* 2003) so $q_{s,f}$ is the catchability coefficient at the start of 1993. There is a need to model changes over time in fishing power because of improvements in technology and fishing skill in the NPF (Bishop 2006).

Compulsory commercial logbook data form the primary basis for the assessment of prawn species in the NPF, including that for *P. semisulcatus*. These data can be divided into fishing days which targeted one of the two tiger prawns or other species (in particular, the common banana prawn, *P. merguiensis*) based on the probability for each fishing day of catching banana or tiger prawns (Venables *et al*. 2006). In addition, although catch and effort data are recorded by species group rather than species (e.g. *P. semisulcatus* and *P. esculentus* combined rather than individually), information on, for example, the date and location of shots can be used to split the species-combined catches to those of individual species (Venables and Dichmont 2004; Dichmont *et al*. 2005). Furthermore, the catches of tiger prawns by day are assigned to one of the two “fleets” based on whichever tiger species had the highest relative probability of being caught on that day given where the fishing occurred (Venables and Dichmont 2004).

The two species of tiger prawns in the NPF have each been divided into seven putative "stocks" based on geographic and biological information. These have been combined into four stocks for assessment purposes (Fig. 8.1) primarily because the abundance in some of these putative stocks is so low that data are uninformative, precluding the application of assessment models (Dichmont *et al.* 2005). For simplicity, we refer to these four stocks as follows: Outside Gulf of Carpentaria - Stock 1, Groote - Stock 2, Vanderlins - Stock 3, and Weipa - Stock 4. The application to *P. semisulcatus* is based on 291 catch-rate data points (i.e., 2 fleets, 4 stocks, and 38 years with a few 0-effort data points).

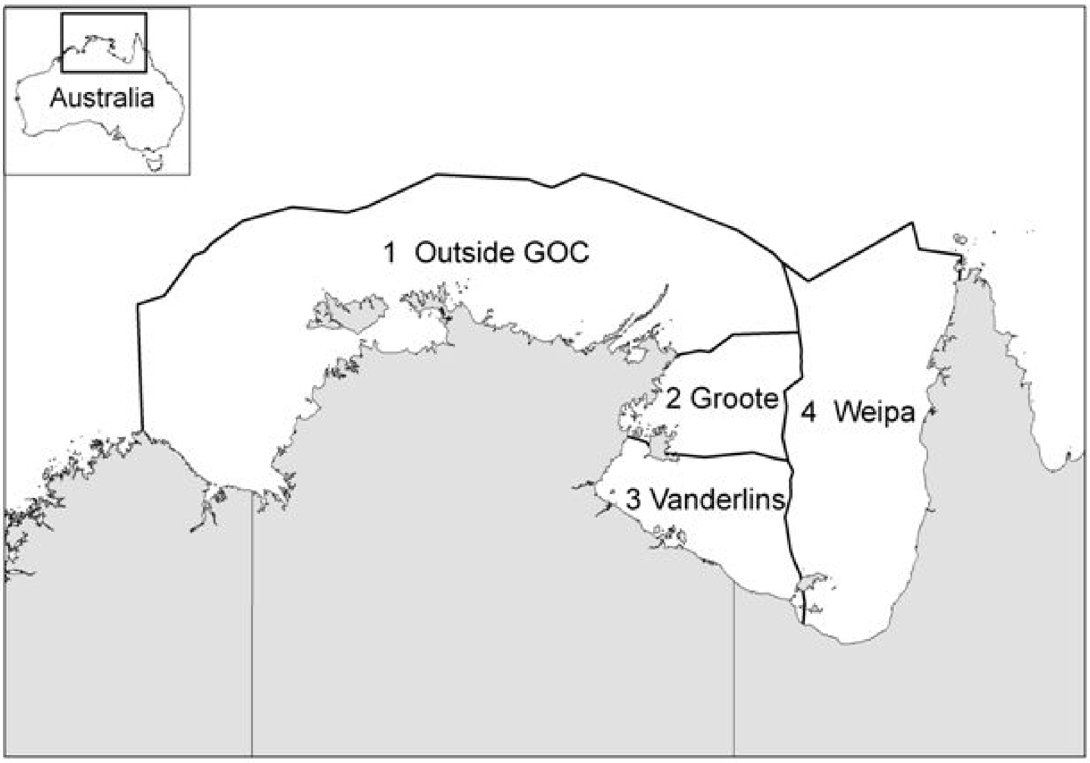


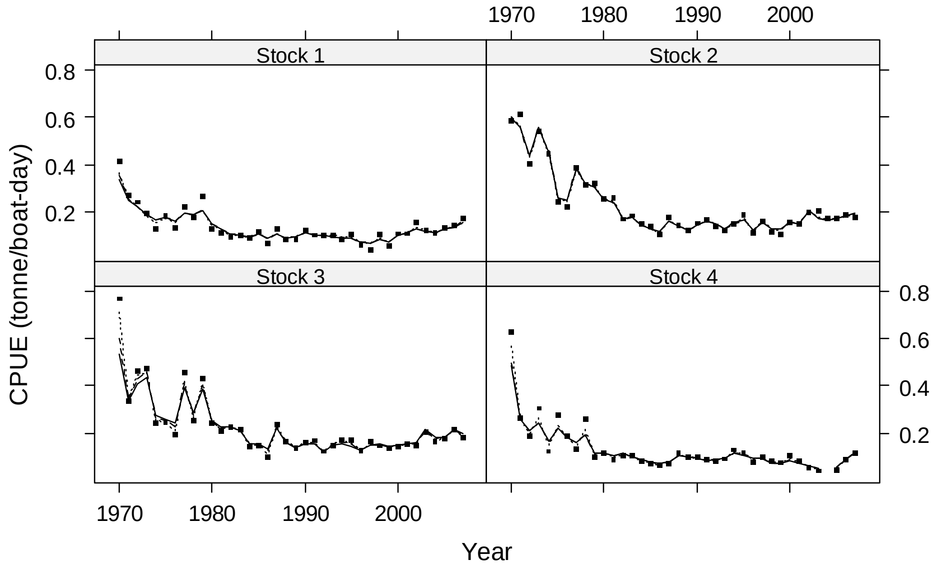
Fig. 8.1. The four stock regions in the Northern Prawn Fishery for *P. semisulcatus*.

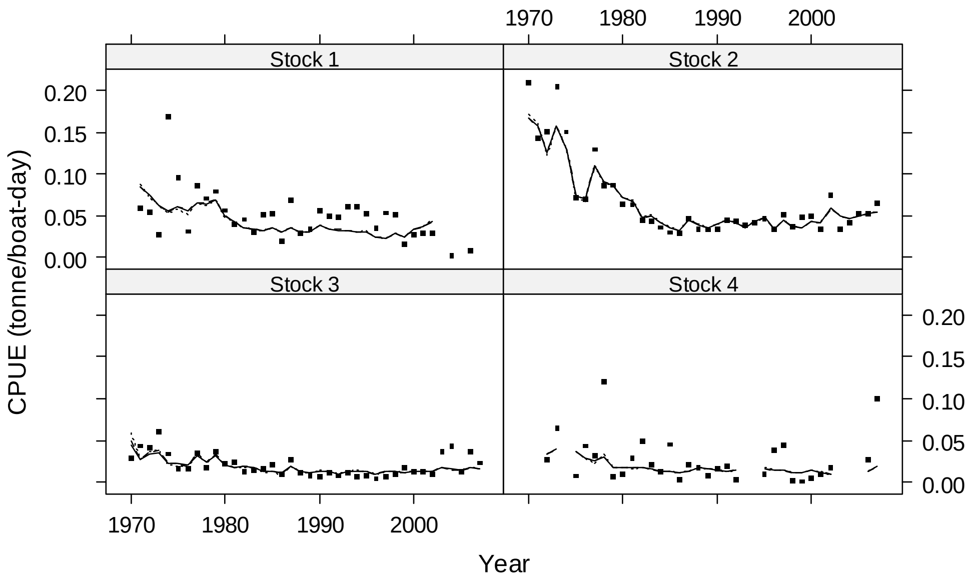
8.4 Results

8.4.1 Model diagnostics and selection

The convergence diagnostics generally do not exhibit evidence for non-convergence after about 2,000 cycles of the MCMC algorithm (e.g. a value for Gelman-Rubin statistic around 1.0), suggesting that the length of the burn-in and the number of subsequent cycles is sufficient for the results to form the basis for inference. The fits of the three models to the catch-rate data are visually very similar, and suggest that the models mimic the data well apart from the catch-rates for the by-catch fleet for the Outside GoC and Weipa stocks (Stocks 1 and 4; Fig 8.2). Consequently, detailed results are only shown for one of these models (Stock-recruit) for the model diagnostics.

(A)



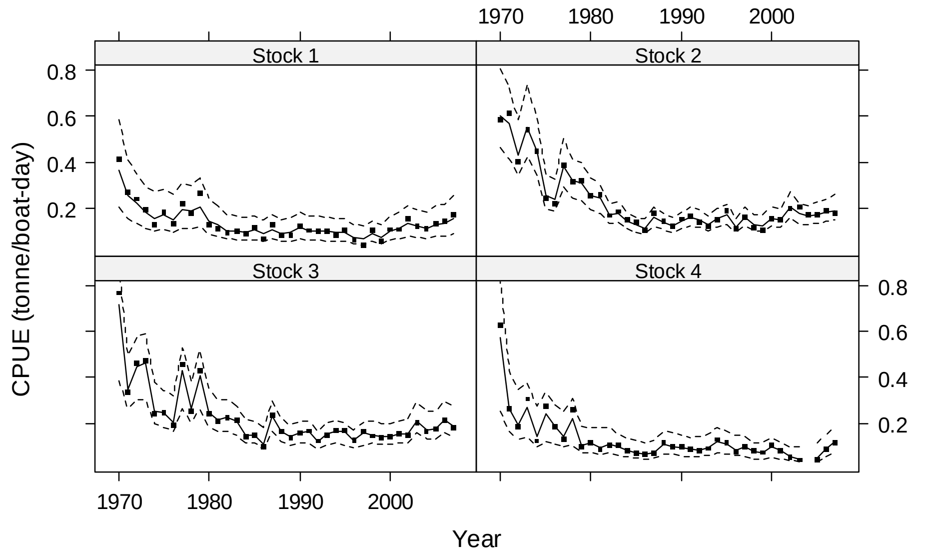


B)

Fig. 8.2. Observed catch-rates for the targeted (A) and by-catch (B) fleets (dots), and the posterior median time-trajectories of predicted catch-rate from three alternative models. Solid line = Standard, dashed line = Annual, dotted line = Stock-recruit. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

The posterior predictive distributions for the catch-rates for the target fleet mimic the observed catch rate data and are relatively narrow (e.g., Fig. 8.3 panel A). In contrast, and as expected from Fig. 8.2, the posterior predictive distributions for catch-rates for the bycatch fleet are much broader, especially for Stock 1 (Outside GoC) and Stock 4 (Weipa) (Fig. 8.3 panel B).

(A)



(B)

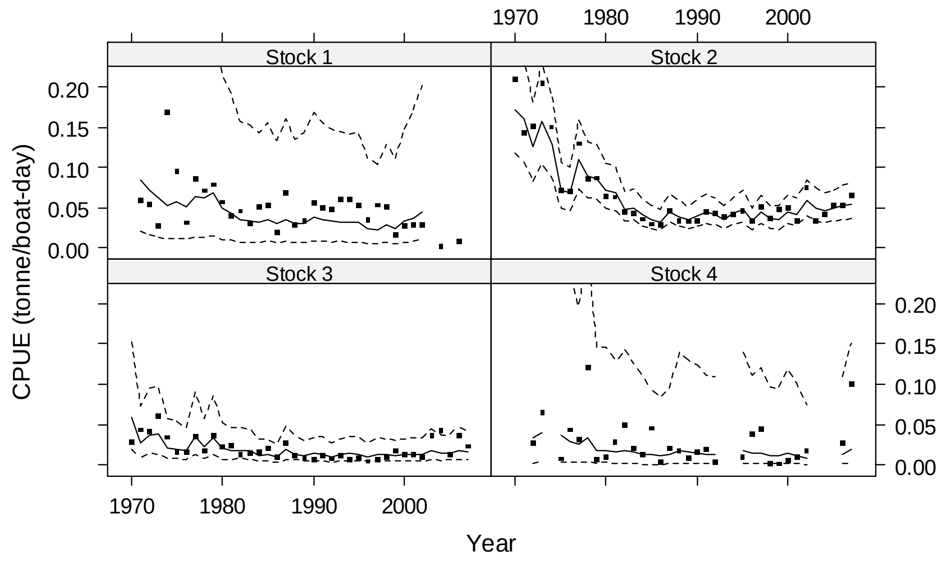


Fig. 8.3. Observed catch-rates (dots) for the targeted (A) and by-catch (B) fleets, and the posterior predictive distributions (medians and 95% credibility intervals) for catch-rate based on the Stock-recruit model.

The realized discrepancy χ^2_{rel} and the predictive discrepancy χ^2_{pred} do not indicate problems of model fit. For example, the proportion of points above the 45^o line, which is the *p*-value for this χ^2-test, is close to 0.5. The predictive *p*-values are similar between models and fleets: 0.533, 0.481, and 0.518 for the target fleet for the Standard, Annual, and Stock-recruit models, and 0.515, 0.523, and 0.507 for the bycatch fleet for these three models, respectively.

The results of the Kolmogorov-Smirnov two-sample test are somewhat different from those of the χ^2 goodness-of-fit test. Although the target fleet has high KS *p*-values (the overall *p*-value = 1), the distribution of *p*-values for the bycatch fleet is relatively uniform (Fig. 8.4). The overall *p*-value (Eqn 13) is 0.969, meaning that the null hypothesis that the predicted and the observed data are from the same distribution was rejected for nearly 3% of the replicates. This KS test indicates that the model fits the catch rate data for the target fleet better than the catch rate data for the bycatch fleet. It also indicates that the KS test is more sensitive than the overall chi-square test.

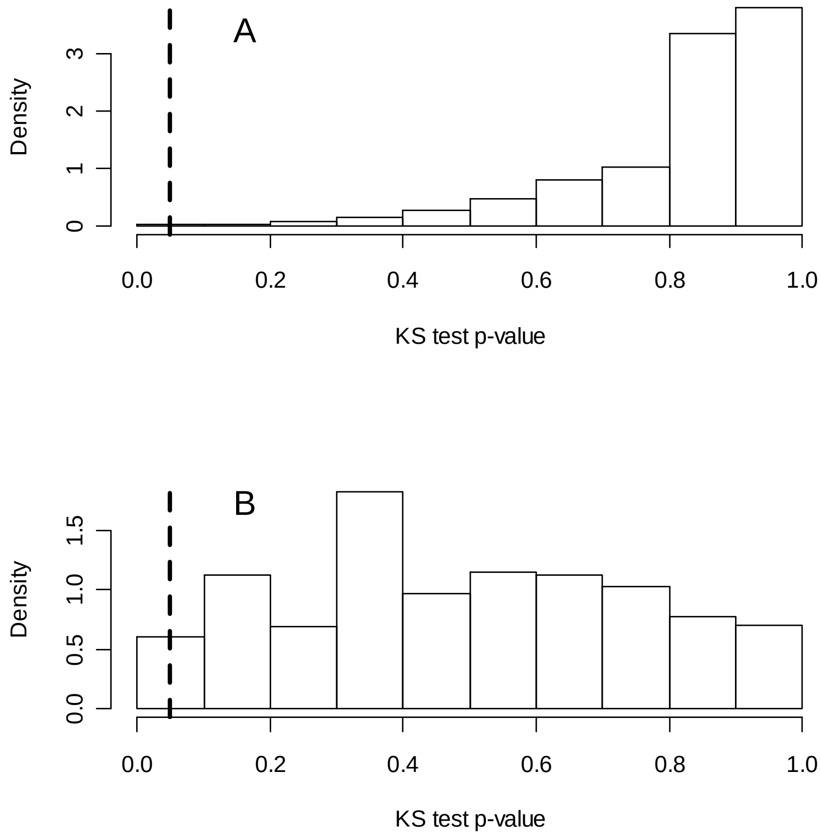


Fig. 8.4. Distribution of Kolmogorov-Smirnov (KS) test *p*-value comparing posterior predictive CPUE from Stock-recruit model and the observed CPUE. The vertical dashed line is where $p = 0.05$. A: target fleet, B: bycatch fleet.

The model selection method based on DIC and the mean square predicted loss selected the Stock-recruit model as “best”, and the Standard model as “worst”. The Standard and Annual models had respectively DICs 56.85 and 47.59 greater than that for the Stock-recruit model. The extent of difference in DIC between the Stock-recruit models and other two models is “definitive” (DIC difference > 10; Spiegelhalter et al. 2002), while the difference between the Annual and Standard models is “substantial” (DIC difference between 5 and 10). The mean MSPEs were consistent with the inferences based on DIC; 0.425, 0.422, and 0.419 for the Standard, Annual, and Stock-recruit models, respectively.

8.4.2 Quantities of management interest

The posterior distributions for B_{MSY} and *MSY* do not differ substantially among models. The posterior medians for *MSY* (summed across stocks) were 1,927, 1,921, and 2,001 tonnes for the Standard, Annual, and Stock-recruit models, respectively. These values are slightly higher than the estimate of *MSY* from the weekly delay-difference model currently used to provide management advice (Dichmont et al. 2003) ($\widehat{MSY}$ = 1,768t), but fall within the 95% confidence intervals for this estimate (1,517-2,043t).

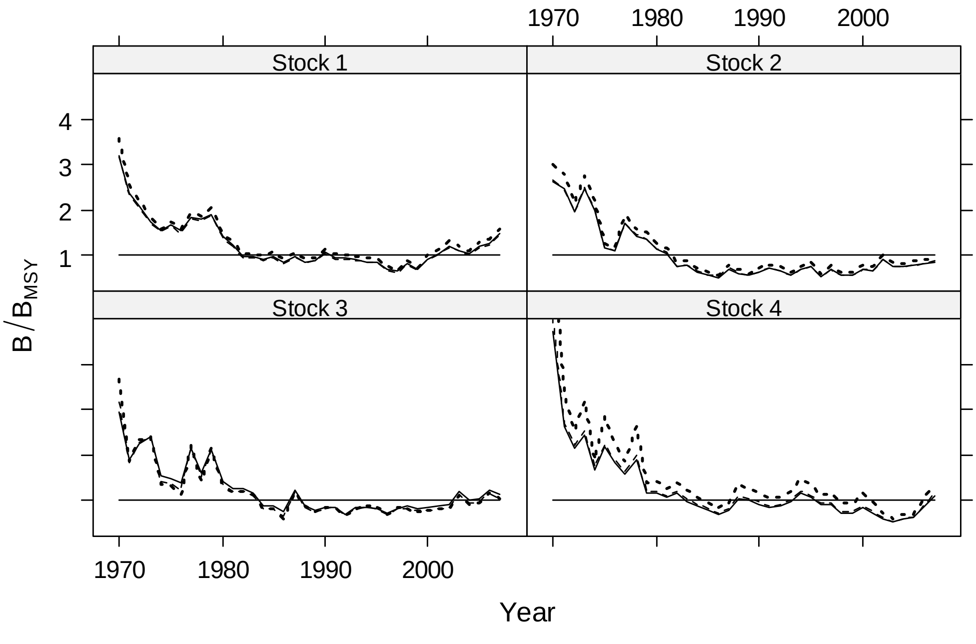


Fig. 8.5. Posterior median time-trajectories for B/B_{MSY} by stock and model. Solid line = Standard, dashed line = Annual, thick dotted line = Stock-recruit. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

The time-trajectories of biomass relative to B_{MSY} (a key management indicator for the NPF) from the three biomass dynamics models are similar for each individual stock (Fig. 8.5) and when the data for all stocks are aggregated (Fig. 8.6), although the Stock-recruit model tends to produce a higher estimates of B/B_{MSY} than the other two models. All of the analyses suggest that the stocks have been reduced in abundance since the start of fishing in 1970, dropped below B_{MSY} during early the 1980s, and increased in abundance in recent years. The posterior median values for B_{2007}/B_{MSY} exceeded 1 for three of the four stocks. The exception is the Groote stock (Stock 2), for which the posterior median for B_{2007}/B_{MSY} is 0.86, 0.87, and 0.95 for the Standard, Annual, and Stock-recruit models, respectively.

When aggregated over stocks, the ratio of current biomass to B_{MSY} exceeds 1 and the time-trajectory of B/B_{MSY} is remarkably similar to that from the weekly delay-differencedelay-difference model even though the latter is substantially more complicated than a biomass dynamics model (Fig. 8.6). In contrast, the results from a Schaefer biomass dynamics model implemented as a maximum-likelihood observation-error estimator and fitted by means of maximum likelihood (Dichmont *et al.* 2005) differ markedly from those of the Bayesian state-space models and the weekly delay-difference model even though it uses the same basic data and makes the same assumptions about changes over time in fishing power as the other biomass dynamics model (Fig. 8.6).

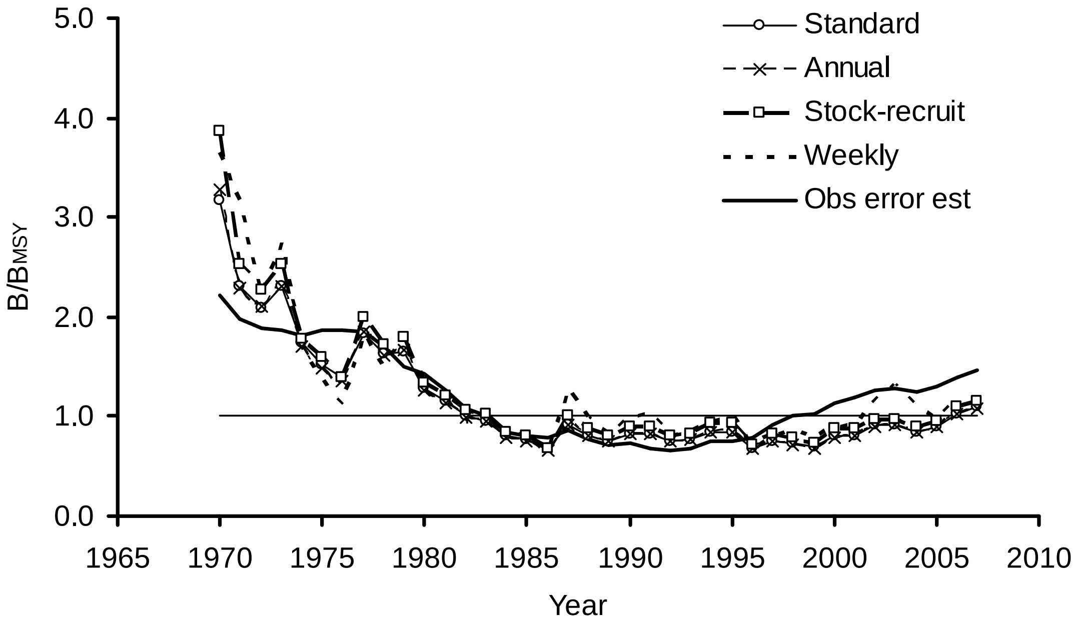


Fig. 8.6. Posterior median time-trajectories for B/B_{MSY} for the three alternative biomass dynamics models aggregated over stock, the weekly delay-difference model, and a maximum likelihood observation-error estimator.

The posterior distribution provides a convenient way to examine parameter uncertainty. The coefficients of variation for K, B_{MSY}, *MSY*, and growth rate r are fairly small (generally below 20% for each stock and when results are aggregated spatially). Catchability q for the target fleet is also precise: a CV of 18%, 15%, and 15% for the Standard, Annual, and Stock-recruit models, respectively. However, the CV of q for the bycatch fleet is high: 52%, 55%, and 54% for the Standard, Annual, and Stock-recruit models, respectively. The posteriors for the catchability of the target fleet are similar among stocks but those for the catchability of the bycatch fleet vary among stocks (Fig. 8.7). The process and observation error variances are similar among the three models. However, the observation error variances differ substantially between the target and bycatch fleets. The observation error variances for the bycatch fleet also differ substantially among the four stocks.

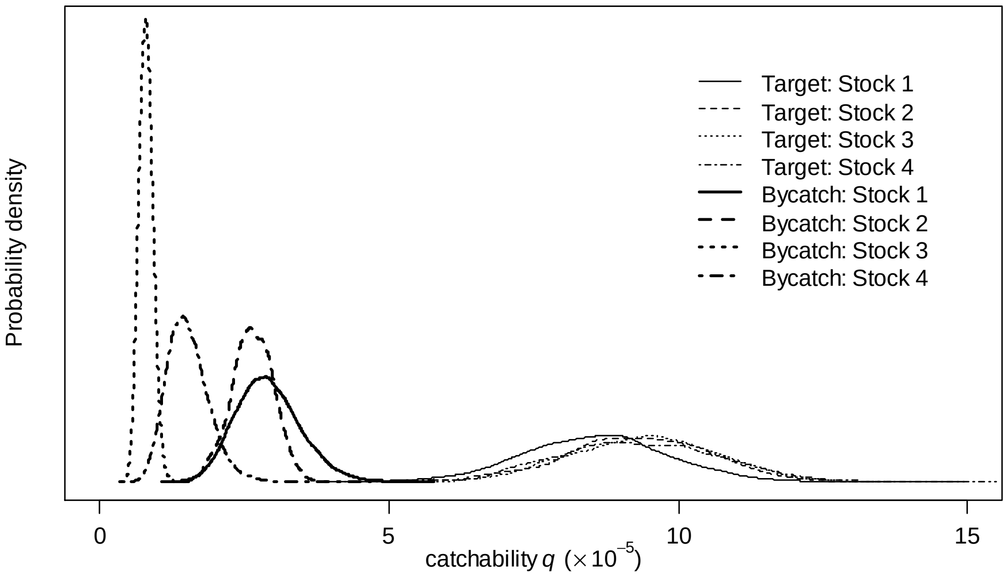


Fig. 8.7. Posterior distributions for catchability q ($\times 10^{-5}$) by fleet (target and bycatch) and stock from Stock-recruit model.

8.5 Discussion

This study demonstrates that biomass dynamics models are appropriate for short-lived species when both process and observation error are taken into account. The biomass dynamics model that assumes that density-dependence is governed by current year biomass (the Stock-recruit model) appears to be particularly effective for short-lived species. While the methods developed in this paper have clear advantages, some caveats should be taken into consideration.

8.5.1 Advantages of hierarchical Bayesian state-space models

Comparisons between hierarchical Bayesian biomass dynamics models, the weekly delay-difference model and a standard observation-error estimator indicate the former has clear advantages. The estimates of the ratio of biomass to B_{MSY} from the hierarchical Bayesian biomass dynamics models are virtually identical to those from a more sophisticated weekly delay-difference model. In contrast, the estimates of this ratio from the standard observation-error estimator are markedly different. This can be attributed to making allowance for process error and hence capturing the dynamics of the resource better.

Past attempts to assess even data-rich prawn species by stock have led to unreliable or unrealistic results (Dichmont *et al*. 2005). The use of a Bayesian estimation framework which imposes hyper-priors on the key parameters of the model clearly improved the stability of the model by allowing the assessment for the more data-poor stocks to 'borrow strength' from those for the more data-rich stocks. The benefits of a hierarchical Bayesian techniques in this respect has been identified for several applications in the past (Rivot and Prevost 2002; McAllister *et al.* 2004).

The results of a stock-specific assessment reveal spatial differences in both parameters and stock status (although perhaps less than would have been the case had the assessment not imposed priors on the parameters). In particular, although biomass of *P. semisulcatus* is assessed to be above B_{MSY} when results are aggregated over stocks in the NPF, the stock-specific results indicate that at least one stock (Groote) has not recovered to the extent that the other stocks have and remains below $B_{MSY.}$

8.5.2 Potential violation of model assumptions

The Stock-recruit model is selected as "best" using DIC and the mean square predicted loss even though the fits to the data were visually very similar to those of the other models. This model assumes that very few prawns survive a year, and that the density-dependence is a function of current rather than past biomass. However, these assumptions will be violated to some extent for *P. semisulcatus* because at least some animals survive an entire year. Moreover, spawning occurs over an extensive period indicating that a discrete formulation for the biomass dynamics will always be an approximation irrespective of assumptions regarding density-dependence and survival.

8.5.3 Effects of observation error between target and bycatch fleets

We presented results for the three alternative biomass dynamics models where the precision parameter $\tau_{U,s,f}$ (the inverse of the variance) of the observation error for the catch-rate data varies among stocks and fleets. We compared two alternative assumptions regarding the variance of the observation error: (1) it is the same across stocks and fleets; and (2) it differs among stocks, but is the same for each fleet. The time-trajectories of B/B_{MSY} from these models are much smoother than those shown in Figs 8.5 and 8.6. However, the models fit the data poorly. For example, ΔDIC is 513 for the variant of the Stock-recruit model in which it is assumed that the observation error variance is the same among stocks and fleets, and 201 when the observation error variance varies among stocks, but not between fleets.

The results of poor fits to the bycatch fleet data for two stocks (Outside GoC and Weipa) also suggest that assuming a constant observation error variance across stocks and fleets is inappropriate. These poor fits are mainly due to very limited catch and effort data. For example, only 2% and less than 1% of total effort by the bycatch fleet occurred on the Outside GoC and Weipa stocks, respectively.

8.5.4 Application of the method to other short-lived invertebrates

The hierarchical Bayesian biomass dynamics models developed in this paper could be applied to other short-lived invertebrate species for which only catch and effort data are available. The data for *P. semisulcatus* are adequate to apply fairly complicated stock assessment methods. However, this is not the case generally for species in the NPF for which information on stock status is needed. These species lack information on recruitment pattern, catchability, availability, growth and natural mortality, which precludes application of, for example, the method of Dichmont et al. (2003) to the data for these species. The similarity of results between the biomass dynamics models implemented in the state-space framework and those of the weekly delay-differencedelay-difference models provides some confidence that the biomass dynamics models outlined in this paper may be applied to data for species such as blue and red endeavour prawns (*Metapenaeus endeavouri* and *M. ensis*), red-legged banana prawns (*Fenneropenaeus indicus* -formerly *Penaeus indicus*), and king prawns (*Melicertus latisulcatus* and *M. longistylus*) which are of commercial value and for which data on catch and effort are available, but for which data on biological parameters such as growth and natural mortality are either absent or considered unreliable. Of course, model diagnostics and examination are needed when one applies this method to other species because *P. semisulcatus* is perhaps unusual among tropical prawns because recruitment appears to be functionally related to spawning stock size and among-year fluctuations in recruitment are relatively small.

8.6 Acknowledgements

Drs You-Gan Wang (CSIRO Mathematics and Statistics), Wayne Rochester, Malcolm Haddon and two anonymous reviewers are thanked for their comments on an earlier version of this paper. This work was supported by the Australian Fisheries Research and Development Corporation.

8.7 References

Askey, P.J., Post, J.R., Parkinson, E.A., Rivot, E., Paul, A.J., et al. (2007). Estimation of gillnet efficiency and selectivity across multiple sampling units: a hierarchical Bayesian analysis using mark-recapture data. *Fisheries Research* 83, 162-174.

Bellido, J.M., Pierce, G.J., and Wang, J. (2001). Modelling intra-annual variation in abundance of squid *Loligo forbesi* in Scottish waters using generalised additive models. *Fisheries Research* 52, 23-39.

Best, N., Cowles, M.K., and Vines, K. (1996). ‘CODA Convergence Diagnosis and Output Analysis Software for Gibbs Sampling Output.’ (MRC Biostatistics Unit: Cambridge.)

Bishop, J. 2006. Standardizing fishery-dependent catch and effort in a complex fishery where technology changed. *Review in Fish Biology and Fishery* 16, 21-38.

Chaloupka, M. and Balazs, G. (2007). Using Bayesian state-space modelling to assess the recovery and harvest potential of the Hawaiian green sea turtle stock. *Ecological Modelling* 205, 93-109.

Dichmont, C.M., Punt, A.E., Deng, A., Dell, Q., and Venables, W. (2003). Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australian's Northern Prawn Fishery. *Fisheries Research* 65, 333-350.

Dichmont, C.M., Deng, A.R., Venables, W.N., Punt, A.E., Haddon, M. et al. (2005). A new approach to assessment in the NPF: spatial models in a management strategy environment that includes uncertainty. Fisheries Research and Development Corporation Report 2001/002, Australia.

Dongen, S.V. (2006). Prior specification in Bayesian statistics: three cautionary tales. *Journal of Theoretical Biology* 242, 90-100.

Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis* 1, 515-534.

Gelman, A., Meng, X., and Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica* 6, 733-807.

Gillman, M., and Hails, R. (1997). 'An Introduction to Ecological Modelling—Putting Practice into Theory' (Blackwell Science: Oxford.)

Ghosh, S.K., and Norris, J.L. (2005). Bayesian capture-recapture analysis and model selection allowing for heterogeneity and behavioural effects. *Journal of Agriculture, Biological and Environmental Statistics* 10, 35-49.

Haddon, M. (2001). 'Modelling and Quantitative Methods in Fisheries' (Chapman and Hall/CRC: Boca Raton.)

Harley, S.J., and Myers, R.A. (2001). Hierarchical Bayesian models of length-specific catchability of research trawl surveys. *Canadian Journal of Fisheries and Aquatic Sciences* 58, 1569-1584.

Isoda, Y., Bower, J.R., and Hasegawa, S. (2005). Assessing environmental effects on recruitment of Japanese common squid (*Todarodes pacificus*) in the Japan Sea using a biomass dynamics model. *Bulletin of Fisheries Science Hokkaido University* 56, 19-31.

McAllister, M.K., Hill, S.L., Agnew, D.J., Kirkwood, G.P., and Beddington, J.R., (2004). A Bayesian hierarchical formulation of the DeLury stock assessment model for abundance estimation of Falkland Islands' squid (*Loligo gahi*). *Canadian Journal of Fisheries and Aquatic Sciences* 61, 1048-1059.

Meyer, R., and Millar, R.B. (1999). BUGS in Bayesian stock assessments. *Canadian Journal of Fisheries and Aquatic Sciences* 56, 1078-1086.

Mueter, F.J., and Megrey, B.A. (2006). Using multi-species surplus production models to estimate ecosystem-level maximum sustainable yields. *Fisheries Research* 81, 189-201.

Polacheck, T., Hilborn, R., and Punt, A.E. (1993). Fitting surplus production models: comparing methods and measuring uncertainty. *Canadian Journal of Fisheries and Aquatic Sciences* 50, 2597-2607.

Punt, A.E. (2003). Extending production models to include process error in the population dynamics. *Canadian Journal of Fisheries and Aquatic Sciences* 60, 1217-1228.

Punt, A.E. and Hilborn, R. (1996). 'Biomass Dynamic Models. User's manual.' FAO Computerized Information Series (Fisheries). (Rome: FAO.)

Quinn, T.J., and Deriso, R.B. (1999). 'Quantitative Fish Dynamics.' (Oxford University Press: New York.)

Rivot, E., and Prevost, E. (2002). Hierarchical Bayesian analysis of capture-mark-recapture data. *Canadian Journal of Fisheries and Aquatic Sciences* 59, 1768-1784.

Roel, B.A. and Butterworth, D.S. (2000). Assessing of the South African chokka squid *Loligo vulgaris reynaudii*: Is disturbance of aggregations by the recent jig fishery having a negative impact on recruitment? *Fisheries Research* 48, 213-228.

Sheskin, D. (1997). 'Handbook of Parametric and Nonparametric Statistical Procedures.' (CRC Press: Boca Raton, Florida.)

Smith, M.T., and Addison, J.T. (2003). Method for stock assessment of crustacean fisheries. *Fisheries Research* 65, 231-256.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P., and Van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of Royal Statistical Society Series B* 64, 583-616.

Su, Z., Adkison, M.D., and van Alen, B.W. (2001). A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. *Canadian Journal of Fisheries and Aquatic Sciences* 58, 1648-1662.

Venables, W. and Dichmont, C.M. (2004). A generalized linear model for catch allocation: an example from Australia's Northern Prawn Fishery. *Fisheries Research* 70, 405-422.

Venables, W.N., Kenyon, R.A., Bishop J.F.B., Dichmont, C.M., et al. (2006). Species distribution and catch allocation: data and methods for the NPF, 2002-2004. Final report. AFMA Project No. R01/1149 Canberra: Australian Fisheries Management Authority.

Webster, R.A., Pollock, K.H., Ghosh, S.K., and Hankin, D.G. (2008). Bayesian spatial modelling of data from unit-count surveys of fish in streams. *Transactions of the American Fisheries Society* 137, 438-453.

Ye, Y., Kenyon, R.A., Burridge, C., Dichmont, C.M., Pendrey, R. et al. (2007). An integrated monitoring program for the Northern Prawn Fishery 2005/06. Project Australian Fisheries Management Authority R05/0599, Australia.

APPENDIX 9. STOCK ASSESSMENT OF BROWN TIGER PRAWNS USING MULTI-STOCK AND MULTI-FLEET BAYESIAN HIERARCHICAL BIOMASS DYNAMICS MODELS

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9.1 Introduction

Quantitative stock assessment has been conducted several times for the brown tiger prawns *Penaeus esculentus* along with the grooved tiger *P. semisulcatus* (Wang and Die 1996; Dichmont et al. 2003; Dichmont et al. 2005). However, input data for brown tiger are poorer than that for the grooved tiger. For example, catchability coefficient has not been estimated for the brown tiger but borrowed from the values estimated for the grooved tiger.

We implemented biomass dynamics model in the hierarch Bayesian state-space framework for brown tiger prawns. The method is similar to that developed and tested for the grooved tiger prawns (Zhou *et al.* in review; Appendix 8).

9.2 Methods

9.2.1 Data

The previous research divided the NPF area into seven stock regions for both tiger prawns. However, catch and effort in some region are low. We combined seven stocks into four as did in the current annual stock assessment (Figure 9.1).

The two tiger prawn fleets catch the majority of brown tiger while the two banana prawn fleets catch smaller quantities (Figure 9.2). We included four fleets by-catching brown tiger in four stock regions for biomass estimation but only used the tiger fleets data for model fitting. We used commercial logbooks from 1970 to 2007 as the primary data source. The previous research has split the raw catch and effort data in the logbook into single species and fleet by a statistical method (Dichmont et al. 2005). We refer the four fleets as: semi fleet targeting on *P. semisulcatus*, escu fleet targeting on *P. esculentus*, indi fleet targeting on *P. indicus*, and merg fleet targeting on *P. merguiensis*.

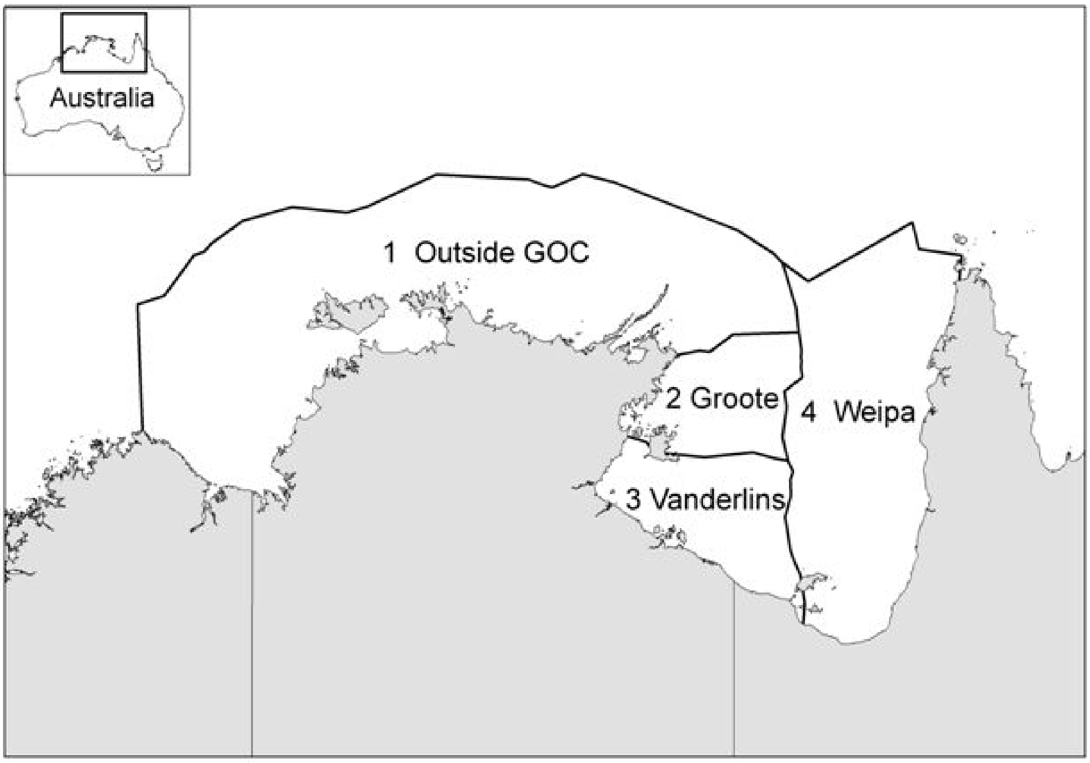

Figure 9.1. Four aggregated brown tiger stock regions used in the analysis.

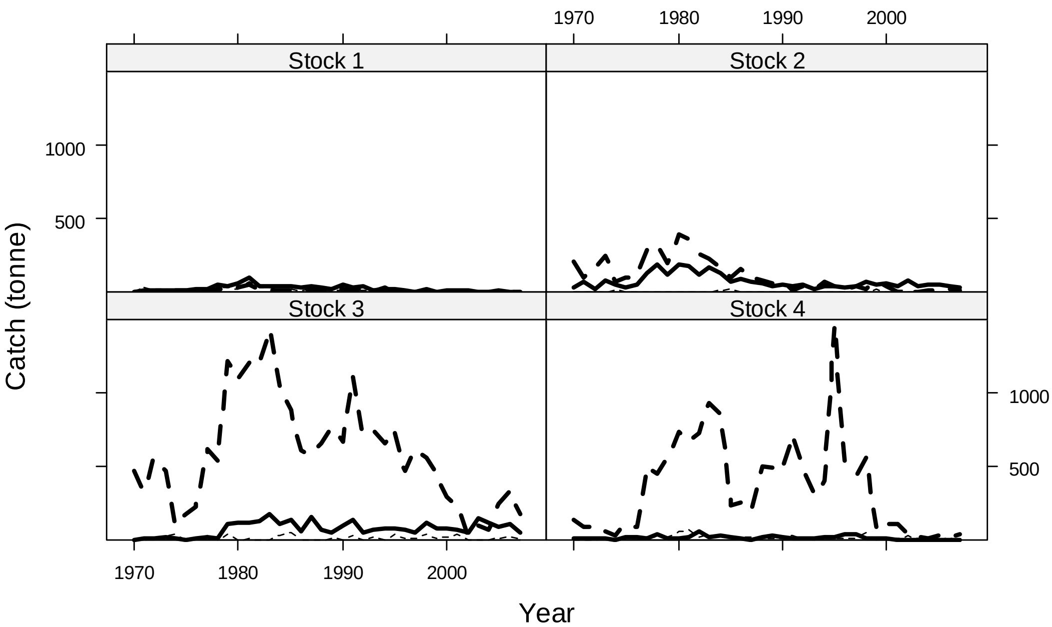

Figure 9.2. Catch of brown tiger prawn by four fleets in four stock regions from 1970 to 2007. Thick solid = P. semi fleet, thick broken = P. escu fleet, thin solid = P. indi fleet, thin broken = P. merg fleet.

9.2.2 Multi-stock and multi-fleet biomass dynamics models

As the catch-effort data are the main reliable information we have for brown tiger prawns, biomass dynamics models seem to be the most appropriate tool for stock assessment. A Bayesian hierarchical biomass dynamics model has been successful developed and tested for the grooved tiger prawn (Zhou et al., in review, Appendix 8). We adopt the similar approach for the brown tiger here. In this method, we assume brown tiger prawns in each stock region is biologically independent of prawns in other stock regions, i.e., there is no spawner or larvae migration among the four stock regions. For stock region *s*, the deterministic version of the biomass dynamics model can be written as:

$$B_{s,y} = B_{s,y-1} + r_s B_{s,y-1}\left(1-\frac{B_{s,y-1}}{K_s}\right) - \sum_{f=1}^{4} C_{s,f,y-1} , \qquad (1)$$

where *B* is biomass (in ton), *r* is the intrinsic growth rate, *K* is the carrying capacity, *C* is the catch. The subscript *y* is year, *s* is stock, and *f* is fleet.

The values for the parameters in equation 1 were estimated by fitting them to data on catch-per-unit-effort (CPUE). For a multi-stock, multi-fleet fishery the model-estimate corresponding to the catch-rate for stock *s*, fleet *f*, and year *y*, $\hat{U}_{s,f,y}$ is:

$$\hat{U}_{s,f,y} = q_{s,f} P_y B_{s,y} , \qquad (2)$$

where $q_{s,f}$ is the catchability coefficient for stock *s* and fleet *f*, and P_y is the relative fishing power during year *y*. The observed catch-rate was assumed to be log-normally distributed about its expected value in common with most applications of biomass dynamics models (Polacheck et al. 1993; Meyer and Millar 1999):

$$U_{s,f,y} \sim \text{log-normal}\{\ell\text{n}(\text{E}[\hat{U}_{s,f,y}], \tau_{U,s,f})\} \qquad (3)$$

where $\tau_{U,s,f}$ is the precision (the inverse of the variance) of the observation error for the catch-rate data for fleet *f*. $\tau_{U,s,f}$ is allowed to differ among fleets because it would not be expected that fleets that target a species and which take it as by-catch would lead to indices of abundance with the same extent of precision as would be the case for a target fleet.

We assumed that deviations about the expected biomass are log-normally distributed (Meyer and Millar 1999; Chaloupka and Balazs 2007), i.e.:

$$B_{s,y} \sim \log-\text{normal}\{\ell n(E[B_{s,y}]), \tau_{B,s}\} \qquad (4)$$

where $\tau_{B,s}$ is the precision of the process error for stock *s*. The prior for the biomass at the start of the first year of the modelled period is assumed to be the same as for the carrying capacity for stock *s*.

It is necessary to specify prior distributions for all of the parameters of the model to implement each of the three state-space models within a hierarchical Bayesian framework. Under the assumption that the population growth parameter and catchability are unlikely to differ substantially among stocks, it was assumed that *r*, *K* and *q* for each stock and fleet were log-normally distributed about a common mean, i.e. these parameters for each stock are random effects about a common mean, i.e.

$$\begin{aligned} r_s &\sim \text{log-normal}(\mu_r, \tau_r) \\ K_s &\sim \text{log-normal}(\mu_K, \tau_K) \\ q_{s,f} &\sim \text{log-normal}(\mu_{q,f}, \tau_{q,f}) \end{aligned} \qquad (5)$$

Where μ_r and $\mu_{q,f}$ are the prior means for *r* and fleet-specific catchability, τ_r and $\tau_{q,f}$ are the corresponding prior precisions, and *a* and *b* are the lower and upper limit of the uniform distribution. Collectively, these parameters are known as hyper-parameters (Harley and Myers 2001; Su et al. 2001). We assumed a normal distribution, N(M_θ, T_θ), for μ_θ, where θ is either *r* or *q*. Bayesian hierarchical models have the advantages that there is no need to specify the values for the parameters of the priors, but rather those of the hyper-parameters, and that the results of models are less sensitive to the values for parameters of the hyper-prior than those of the prior. We specified values for the means (M_θ) of these hyper-priors (McAllister et al. 2004; Askey et al 2007) by considering results from non-hierarchical Bayesian models and set the values for T_θ to large values so that the hyper-priors were relatively non-informative, but still proper (Gelman 2006). The values for the precision hyper-parameter T_θ were set using a half–Cauchy distribution (Gelman 2006).

The hyper-priors for the τ_θ, as well as the priors for the observation precisions, $\tau_{U,s,f}$, and the process precisions, $\tau_{B,s}$, were set to proper, but reasonably non-informative gamma distributions with mean 1 and variance 1000, i.e., $gamma(0.001, 0.001)$.

In summary, the hierarchical structure of the alternative biomass dynamics models contain the following levels:

Hyper-priors: M_θ assigned, T_θ half-Cauchy distribution;

Hyper-priors: $\mu_\theta \sim$ N(M_θ, T_θ), $\tau_\theta \sim$ G(0.001, 0.001);

Hyper-parameters: μ_K, μ_r, $\mu_{q,f}$, τ_K, τ_r, $\tau_{q,f}$;

Priors: log(K_s)~N(μ_K, τ_K), log($B_{s,y}$)~N(log(E[$B_{s,y}$], $\tau_{B,s}$), log(r_s)~N(μ_r, τ_r), log($q_{s,f}$)~N($\mu_{q,f}, \tau_{q,f}$), $\tau_{U,s,f}$~G(0.001, 0.001), $\tau_{B,s}$~G(0.001, 0.001);

Parameters: K_s, r_s, $q_{s,f}$, $B_{s,1970}$, $\tau_{U,s,f}$ $\tau_{B,s}$;

Data: $U_{s,f,y}$.

Given the assumptions regarding the nature of the state-space model, the priors for the parameters and those for hyper-priors, the posterior distribution is proportional to:

$$p(\mu_K)p(\tau_K)p(\mu_r)p(\tau_r)p(\underline{\mu}_{q,f})p(\underline{\tau}_{q,f})$$
$$p(\underline{K}_s \mid \mu_K,\tau_K)p(\underline{B}_{1970,s} \mid \mu_K,\tau_K)p(\underline{r}_s \mid \mu_r,\tau_r)p(\underline{q}_{s,f} \mid \underline{\mu}_{q,f},\underline{\tau}_{q,f})p(\underline{\tau}_{B,s})p(\underline{\tau}_{U,s,f}) \qquad (6)$$
$$\prod_{s,y}\left(p(B_{s,y} \mid B_{s,y-1},K_s,r_s,C_y,\tau_{B,s})\prod_f p(U_{s,f,y} \mid B_{s,y},q_{s,f},P_y,\tau_{U,s,f})\right)$$

where the underlined parameters denote a vector or matrix over stock *s*, fleet *f*, and/or year *y*.

The Gibbs sampler, a Markov chain Monte Carlo (MCMC) technique, implemented using the WinBUGS package (http://www.mrc-bsu.cam.ac.uk/bugs) was used to sample parameter vectors from the posterior distribution (Eqn 6). Three Markov chains were conducted based on dispersed initial values, and the results of the first 4,000 cycles of each chain taken as the burn-in period. The results of an additional 60,000 cycles from the three chains were saved, which formed the basis for further analysis. Whether the MCMC algorithm converged adequately to the posterior was evaluated by visually examining the three chains for each parameter in Eqn 6 and using the Gelman-Rubin diagnostic statistic (Best et al. 1996). From these estimated parameters, we derive the management parameter, the maximum sustainable yield MSY for stock *s*:

$$MSY_s = \frac{r_s K_s}{4}. \qquad (7)$$

9.3 Results

The hierarchical Bayesian biomass dynamics model fits the target fleet (P. escu fleet) CPUE data fairly well (Figures 9.3). However, for the bycatch fleet (P. semi fleet) the model tends to underestimate CPUE in the early part of the time series (before 1985), especially in Stocks 2 and 3 (Figure 9.4). The semi fleet has higher observation errors (low precision utau) for all stocks, while the escu fleet has low observation error only for Stocks 1 (Table 9.1).

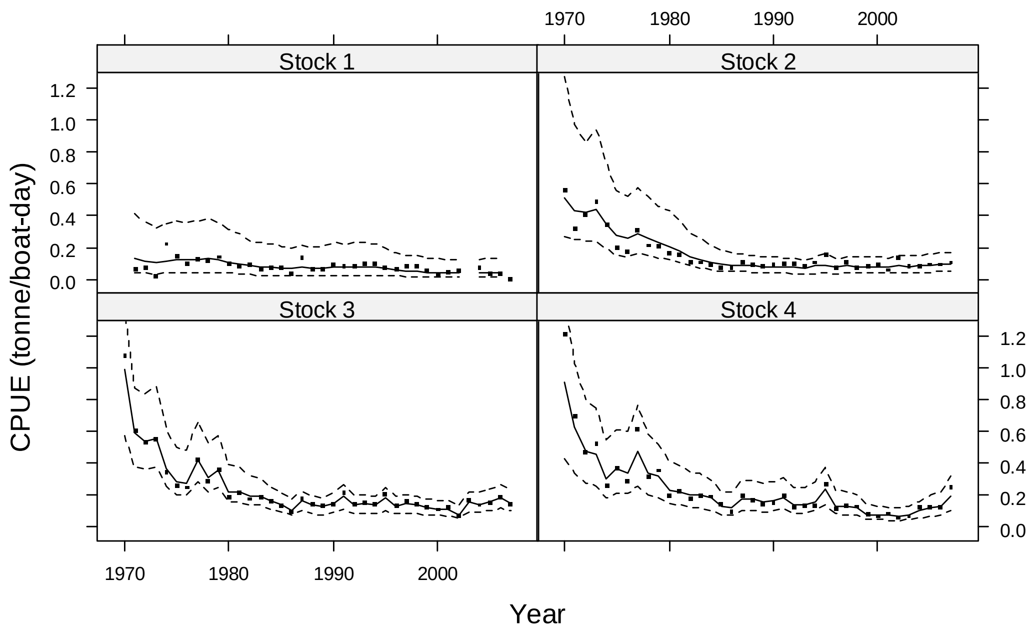

Figure 9.3. Observed catch-rates (dots) and the posterior median time-trajectories of predicted catch-rate (solid lines) with 95% credible intervals for the target fleet (P. escu fleet). Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

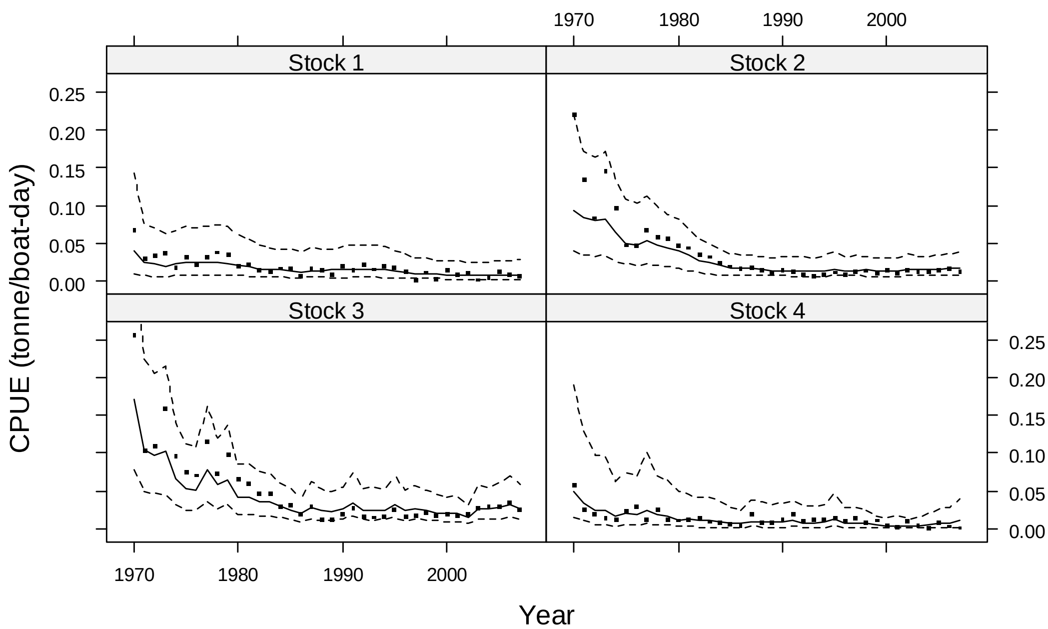

Figure 9.4. Observed catch-rates (dots) and the posterior median time-trajectories of predicted catch-rates (solid lines) with 95% credible intervals for the bycatch fleet (P. semi fleet). Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

Estimated biomass has declined since the beginning of the fishery (Figure 9.5). The results indicate that since mid 1990s, biomass has been below the B_{msy} level of all stocks.

The median intrinsic growth rate r ranges from 0.12 to 0.45 for the four stocks (Table 9.1). The median carrying capacity K ranges from 2014 t to 6908 t for the four stocks. However, the variances for K are very large (Table 9.2), indicating potential problem of the data or the method. The total MSY is estimated close to 1500 t, but uncertainty is also large (Table 9.1).

The fleet targeting *P. esculentus* has a higher catchability (mean q_2 = 7.9E-5) than the fleet targeting P. semisculentus (mean q_1 = 1.2E-5).

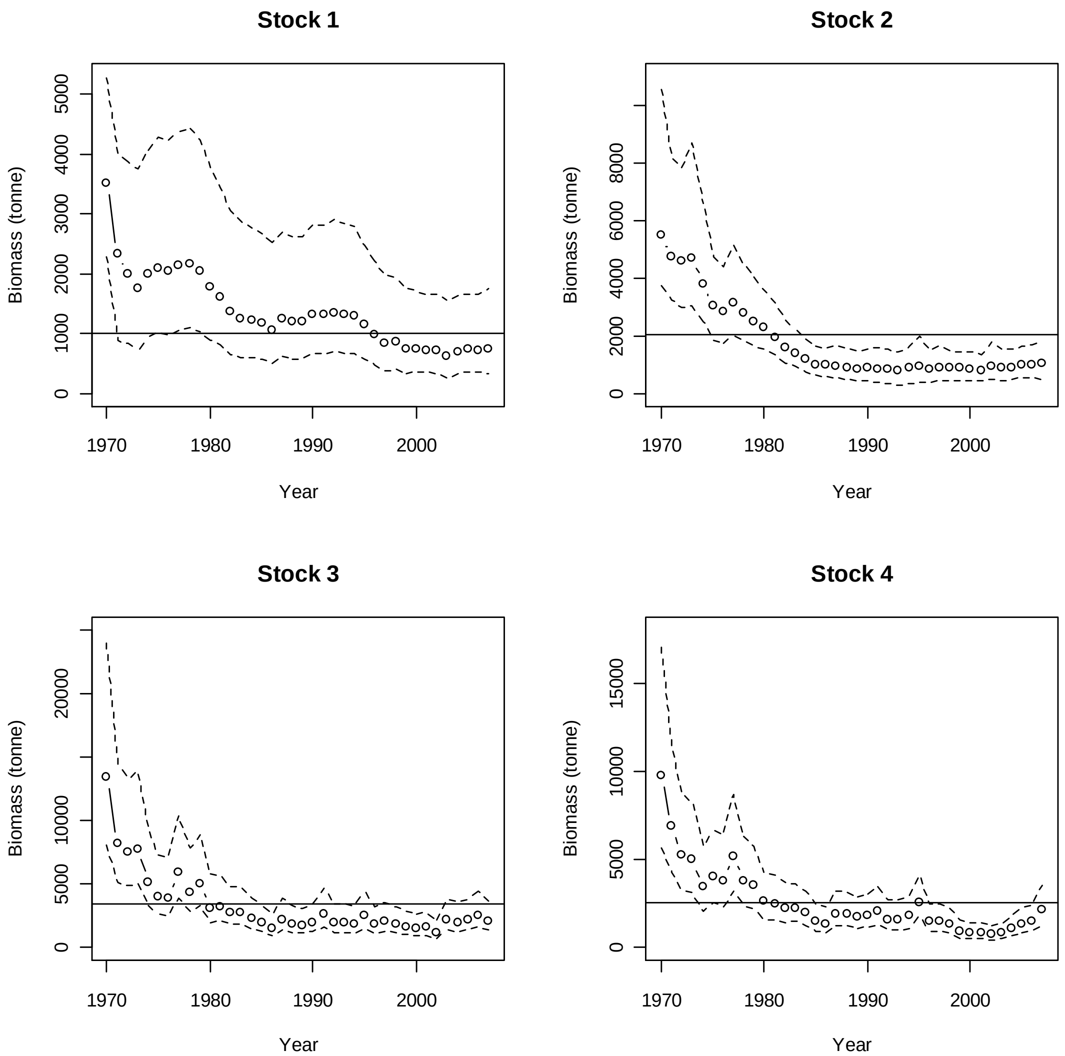

Figure 9.5. Posterior median biomass and 95% credible intervals of brown tiger prawns from 1970 to 2007. The horizontal line is the median B_{msy}.

Table 9.1. Posterior distribution for key parameters. Fleet 1 = semi, Fleet 2 = escu.

Para	mean	2.50%	median	97.50%
K[1]	3,969	856	2,014	9,588
K[2]	5,507	2,507	4,067	9,442
K[3]	8,198	4,956	6,908	12,680
K[4]	6,259	3,633	5,142	9,419
Total	23,933	11,952	18,131	41,129
r[1]	0.13	0.00	0.12	0.35
r[2]	0.17	0.04	0.16	0.31
r[3]	0.45	0.18	0.45	0.73
r[4]	0.35	0.16	0.34	0.55
Mean	0.27	0.09	0.27	0.49
MSY[1]	67	0	56	187
MSY[2]	187	50	172	326
MSY[3]	836	313	810	1274
MSY[4]	483	209	451	753
Total	1,572	572	1,489	2,540
q[1,1]	1.22E-05	5.74E-06	1.18E-05	2.12E-05
q[1,2]	1.73E-05	1.03E-05	1.67E-05	2.81E-05
q[1,3]	1.31E-05	7.65E-06	1.30E-05	1.90E-05
q[1,4]	5.04E-06	3.13E-06	4.92E-06	7.64E-06
Mean	0.000012	0.000007	0.000012	0.000019
q[2,1]	6.36E-05	2.89E-05	6.23E-05	1.07E-04
q[2,2]	9.51E-05	5.77E-05	9.17E-05	1.54E-04
q[2,3]	7.24E-05	4.27E-05	7.23E-05	1.03E-04
q[2,4]	9.12E-05	5.98E-05	8.98E-05	1.31E-04
Mean	0.000081	0.000047	0.000079	0.000124
utau[1,1]	4.0	2.1	3.8	6.6
utau[1,2]	19.3	3.8	7.8	79.2
utau[1,3]	9.5	4.5	8.1	19.1
utau[1,4]	2.6	1.5	2.5	4.1
utau[2,1]	4.4	2.3	4.2	7.7
utau[2,2]	21.1	4.6	15.3	63.1
utau[2,3]	165.3	11.2	55.3	1091.0
utau[2,4]	50.4	9.1	24.3	270.3

Table 9.2. Estimated carrying capacity parameter K for brown tiger prawns and comparison with grooved tiger and endeavour prawns.

Stock	mean	sd	2.50%	median	97.50%	cv
		Brown tiger				
K[1]	3,969	32,440	856	2,014	9,588	170%
K[2]						91%

	5,507	33,950	2,507	4,067	9,442	
K[3]	8,198	40,570	4,956	6,908	12,680	64%
K[4]	6,259	42,600	3,633	5,142	9,419	69%
		Grooved tiger				
K[1]	2,660	553	1,936	2,555	3,927	29%
K[2]	4,774	775	3,535	4,692	6,519	19%
K[3]	3,672	538	2,795	3,611	4,871	18%
K[4]	2,269	600	1,545	2,137	3,693	36%
		Blue endeavouri				
K[1]	1,757	788	1,050	1,673	2,888	32%
K[2]	1,715	982	1,101	1,642	2,677	30%
K[3]	1,941	708	1,308	1,879	2,886	26%
K[4]	1,735	401	1,211	1,676	2,584	27%

9.4 Discussion

The assessment results of brown tiger prawns cause some concerns about the input data or the method. After exploring the data we believe the data may be problematic.

Figure 9.6 shows that catch increases linearly as effort increases. There is no sign of decline in catch even at historically highest fishing effort. Figure 9.7 shows CPUE initially declined within the first decade of NPF history. However, it stays at a constant level even at high fishing effort. These plots indicate that brown tiger prawn may have not been fully exploited. Data collected during a fishery's development period are insufficient to allow reliable estimation of the carrying capacity and the potential yield. The large uncertainty around the estimated *K* and *MSY* also supports this argument.

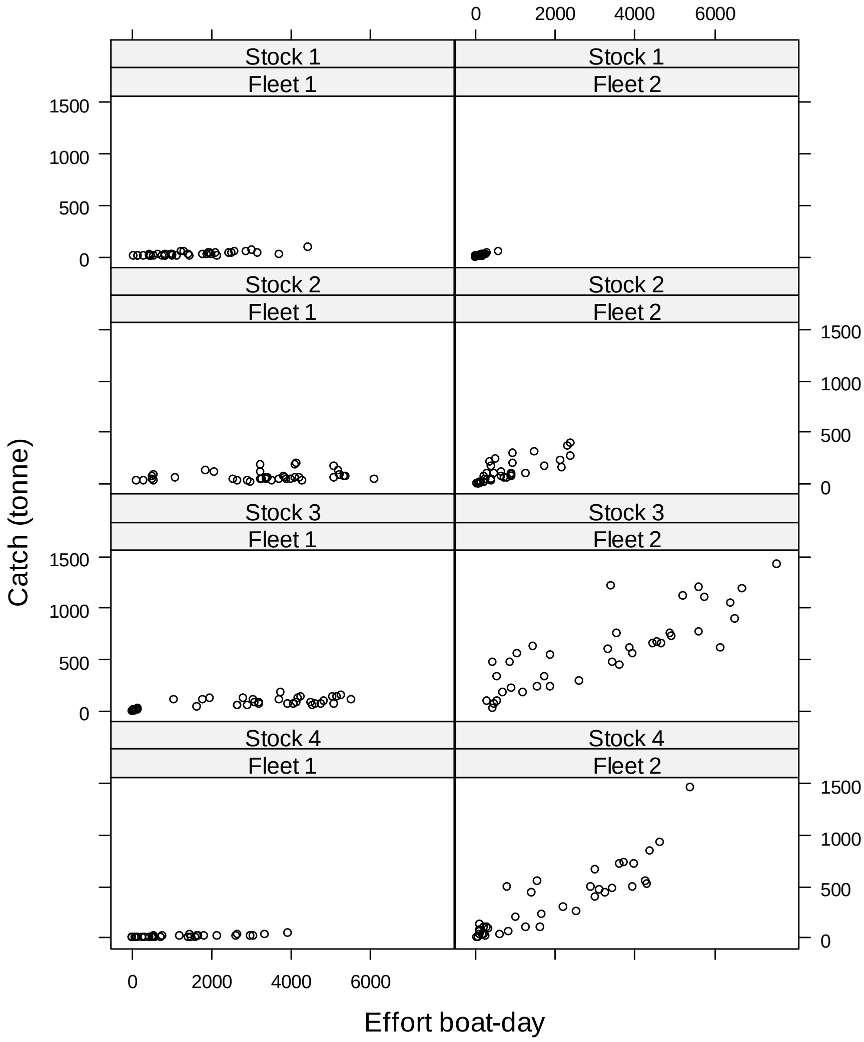

Figure 9.6. Scatter plot of catch and effort standardized by fishing power (base case high) for the brown tiger prawns. Fleet 1 = bycatch fleet (P. semi), Fleet 2 = target fleet (P. escu).

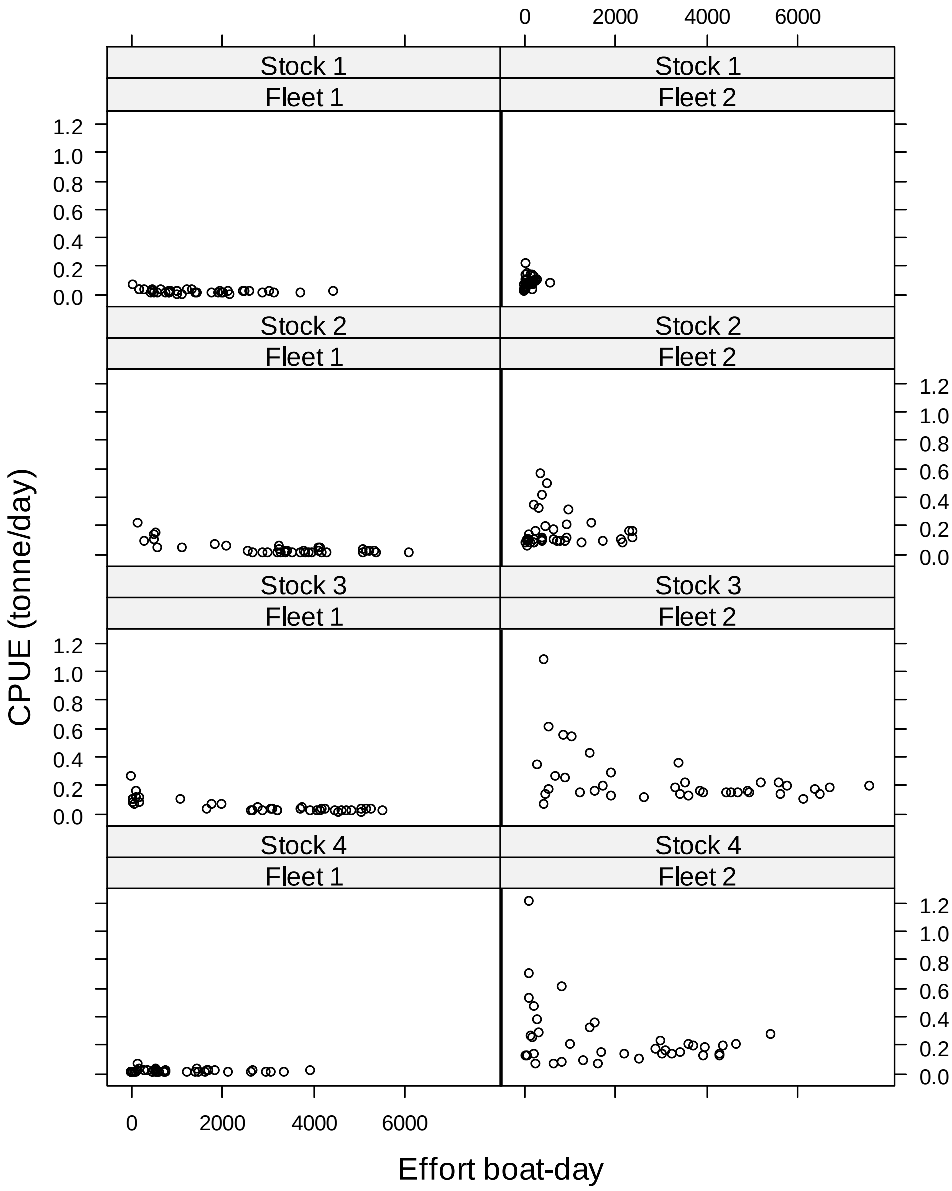

Figure 9.7. Scatter plot of CPUE over effort standardized by fishing power (base case high) for the brown tiger prawns. Fleet 1 = bycatch fleet (P. semi), Fleet 2 = target fleet (P. escu).

9.5 References

Chaloupka, M. and G. Balazs (2007). Using Bayesian state-space modelling to assess the recovery and harvest potential of the Hawaiian green sea turtle stock. Ecological Modelling 205: 93-109.

Dichmont, C.M., Punt, A.E., Deng, A., and Venables, W. 2003. Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery. Fish. Res. 65, 335–350.

Dichmont, C.M., Deng, A.R., Venables, W.N., Punt, A.E., Haddon, M., and Tattersall, K. 2005. A new approach to assessment in the NPF: spatial models in a management strategy environment that includes uncertainty. FRDC Report 2001/002.

Harley, S.J., Myers, R.A., 2001. Hierarchical Bayesian models of length-specific catchability of research trawl surveys. Can. J. Fish. Aquat. Sci. 58, 1569-1584.

McAllister, M.K., Hill, S.L., Agnew, D.J., Kirkwood, G.P., Beddington, J.R., 2004. A Bayesian hierarchical formulation of the DeLury stock assessment model for abundance estimation of Falkland Islands' squid (Loligo gahi). Can. J. Fish. Aquat. Sci. 61, 1048-1059.

Meyer, R., Millar, R.B. (1999). BUGS in Bayesian stock assessments. Canadian Journal of Fisheries and Aquatic Sciences 56, 1078-1086.

Polacheck, T., Hilborn, R., and Punt, A.E. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. Can. J. Fish. Aquat. Sci. 50: 2597-2607.

Su, Z., Adkison, M.D., van Alen, B.W., 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. Can. J. Fish. Aquat. Sci. 58, 1648-1662.

Wang, Y-G., Die, D. 1996. Stock-recruitment relationships of the tiger prawns (Penaeus esculentus and Penaeus Semisulcatus) in the Australian Northern Prawn Fishery. Mar. Freshw. Res. 47, 87–95.

Zhou, S., Punt, A.E., Deng, R., Dichmont, C.M., Ye, Y. and J. Bishop. In review. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Marine and freshwater Research.

APPENDIX 10. STOCK ASSESSMENT OF BLUE ENDEAVOUR PRAWNS USING MULTI-STOCK AND MULTI-FLEET BAYESIAN HIERARCHICAL BIOMASS DYNAMICS MODELS

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10.1 Introduction

The Northern Prawn Fishery (NPF) is a multi-species trawl fishery catching nine species of prawn within an area of about 800,000 square kilometres in northern Australia. These nine commercial species of prawns are white banana (*Penaeus merguiensis*), red-legged banana (*P. indicus*), brown tiger (*Penaeus esculentus*), grooved tiger (*P. semisulcatus*), blue endeavour (*Metapenaeus endeavouri*), red endeavour (*M. ensis*), western king prawn (*P. latisulcatus*), red spot king prawn (*P. longistylus*), and giant tiger prawn (*P. monodon*). White banana prawns and the two species of tiger prawns ((*P. esculentus* and *P. semisulcatus*) make up approximately 80% of catches. The remainder is primarily endeavour and red-legged banana prawns (Raudzens 2007).

The fishery has changed over time as a result of management interventions. From 1970 to 1985 there were no specific controls over fishing seasons. Since 1986 the fishery has been split into two seasons. The banana prawn season starts in late March or early April and ends in mid-May or early June; the tiger prawn season is generally from early August to mid-November. While the fishery targets on banana or tiger prawns during the two seasons, it also catches other species of prawns.

Quantitative stock assessment has been carried out several times for two tiger prawns (Wang and Die 1996; Dichmont et al. 2003; Dichmont et al. 2005). However, credible stock assessments on other prawn species are either lacking or preliminary.

Park (1999) carried out a stock assessment on two endeavour prawn species in Albatross Bay area in the Gulf of Carpentaria (approximately stock region 7 in this paper) using a delay-difference model on commercial catch data from 1980 to 1997. He adopted the natural mortality of tiger prawns for the two endeavour prawn species and assumed two alternative annual fishing power increments at 3% or 5%. The analysis indicated that if the annual increase in fishing power was 3% blue endeavour prawns in Albatross Bay area were underfished. However, if annual increase in fishing power was 5% blue endeavour population was severely overfished. In contrast, the fishing effort during that time was close to the optimal level for the red endeavour prawns for both assumptions of annual fishing power increments.

Up to date, there is essential no quantitative stock assessment on the remaining four prawn species (red-legged banana, western king prawn, red spot king prawn, and giant tiger prawn).

The NPF has been regarded as "data rich" fishery in Australian standard because of its long history of commercial catch and effort data with relatively high quality. However, biological and fishery-independent data are scarce or lacking, especially for non-target species. For example, spawner abundance, recruitment abundance, recruitment patterns, natural mortality, growth rate, catchability, etc. are not well known for most prawn species. For such species, biomass dynamics model becomes the first choice for a quantitative stock assessment since only a time series of catch and effort data are needed to estimate the model parameters two important management quantities, the maximum sustainable yield (MSY) and the optimal fishing effort to achieve MSY. It has been shown that in some situations biomass dynamics model may provide more accurate estimates of management quantities than more complex models (Ludwig and Walters 1985).

Three methods have traditionally been used to fit biomass dynamics models to fishery data: equilibrium model, process-error model, and observation-error model. Polacheck *et al.* (1993) compared these approaches and found that the observation-error estimator is the least biased and the most precise. Recent development in nonlinear non-Gaussian state-space models has a capability to simultaneously consider both process error and observation error. This new powerful approach has become more popular in fishery stock assessment (Meyer and Miller 1999a; Meyer and Miller 1999b; Rivot *et al.* 2004; Chaloupka and Balazs 2007). The general Bayesian models require a modeller specifying prior information. In this paper we go one step further to develop hierarchical Bayesian models (HBM). The HBM shares information among stock regions and avoid the necessity of providing prior at parameter level. Instead, a HBM only requires prior at hyper-parameter level, which could be non-informative. HBMs have been successful applied in many fishery researches (Liermann and Hilborn 1997; Adkison and Su 2001; Harley and Myers 2001; Su *et al*. 2001; Rivot and Prevost 2002; McAllister et al. 2004).

We implemented biomass dynamics model in the hierarch Bayesian state-space framework for blue endeavour prawns. The method is similar to that developed and tested for the tiger prawns (Zhou *et al.* in review; Appendix 8). Fishers in the NPF generally do not target on this prawn species; rather they catch blue endeavour as by-product when targeting banana and tiger prawns. We take such non-target catch into account in our modelling.

10.2 Methods

10.2.1 Data

There are two major prawn fisheries in the Northern Prawn Fishery (NPF): a banana prawn fishery targeting on two banana prawn species (*Penaeus merguiensis* and *P. indicus*) during April to June and a tiger prawn fishery targeting on two species (the grooved tiger *P. semisulcatus* and the brown tiger *P. esculentus*) from August to the end of the year. The previous research divided the NPF area into seven stock regions for both tiger prawns and the blue endeavour prawns (Figure 10.1). However, catch and effort in some region are low. We combined seven stocks into four as did for the tiger prawn. The way we merge the blue endeavour stock is the same as for the brawn tiger prawn since these two species are believed to be associated each other.

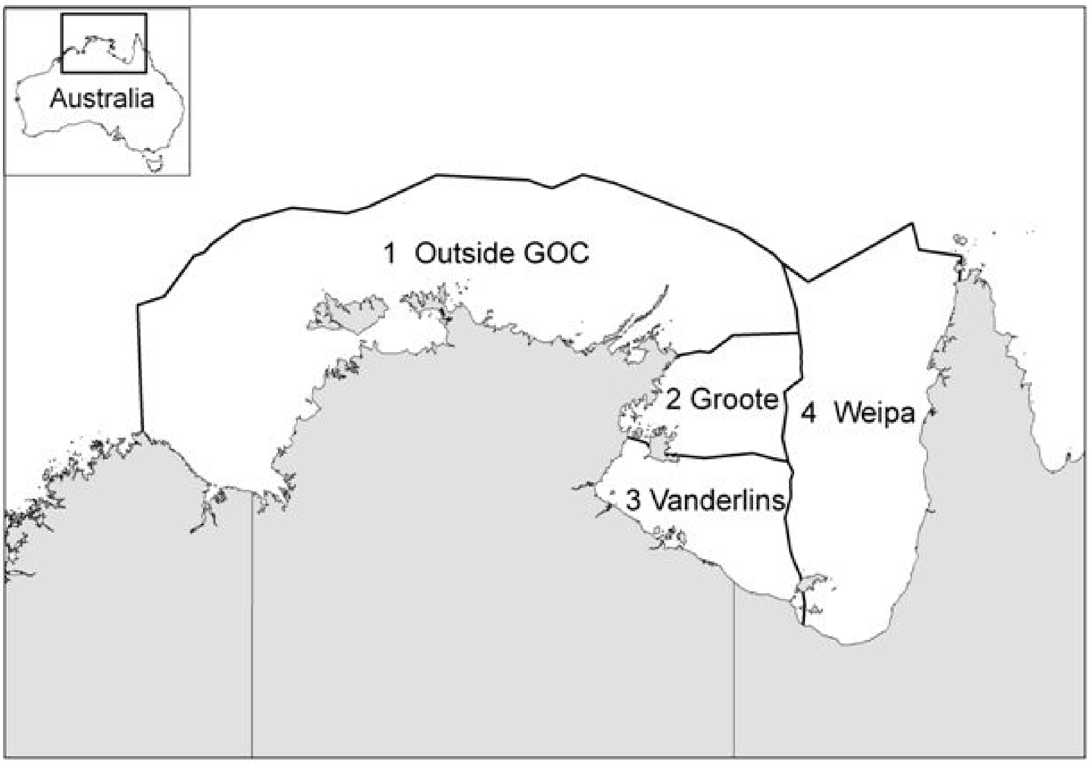


Figure 10.1. Four aggregated endeavour stock regions used in the analysis. These boundaries are the same as for brawn tiger prawn.

The two tiger prawn fleets catch the majority of blue endeavour while the two banana prawn fleets catch smaller quantities (Figure 10.2). We included four fleets by-catching blue endeavour in four stock regions for biomass estimation but only used the tiger fleet data for model fitting. We used commercial logbooks from 1970 to

2007 as the primary data source. The previous research has split the raw catch and effort data in the logbook into single species and fleet by a statistical method (Dichmont et al. 2005). We refer the four fleets as: semi fleet targeting on *P. semisulcatus*, escu fleet targeting on *P. esculentus*, indi fleet targeting on *P. indicus*, and merg fleet targeting on *P. merguiensis*. Generally, no direct effort targeting on endeavour prawns has been considered. In this report we focus on the assessment of blue endeavour prawn (*M. endeavouri*). This species is main by-product of the tiger fishery, and largely caught by the escu fleet in region 2 to 4 (Figure 10.2). The two banana prawn fleets catch a small quantity of blue endeavour in some area but have not caught any in other area (Figure 10.2).

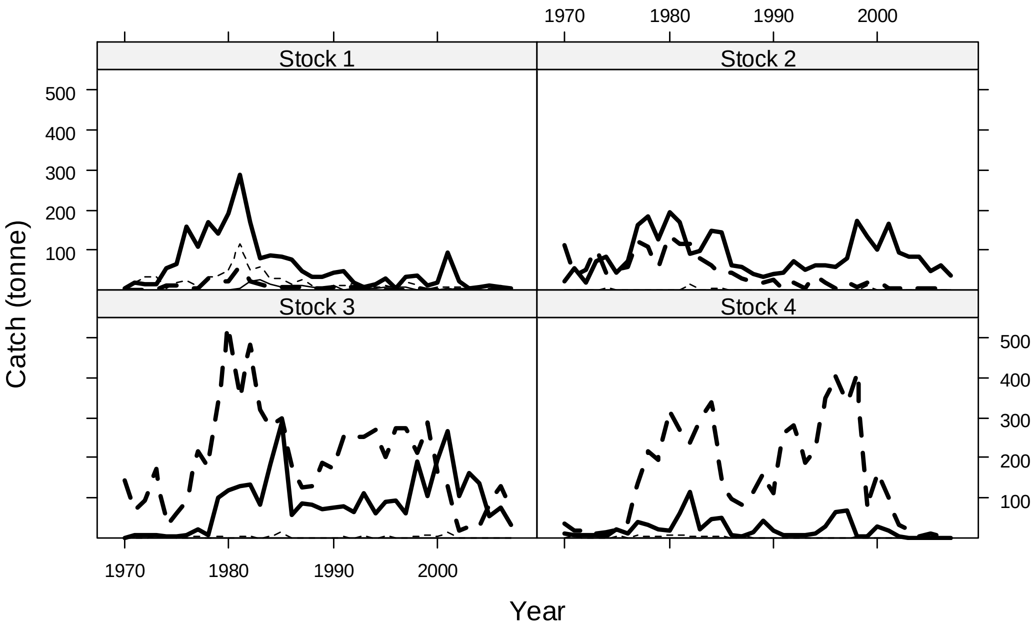


Figure 10.2. Catch of blue endeavour prawn by four fleets in four stock regions from 1970 to 2007. Thick solid = P. semi fleet, thick broken = P. escu fleet, thin solid = P. indi fleet, thin broken = P. merg fleet.

10.2.2 Multi-stock and multi-fleet biomass dynamics models

As the catch-effort data are the only reliable information we have for blue endeavour prawns, biomass dynamics models become our primary choice for stock assessment. A Bayesian hierarchical biomass dynamics model has been successful developed and tested for the grooved tiger prawn (Zhou *et al*., in review, Appendix 8). We adopt the similar approach for the blue endeavour here. In this method, we assume blue endeavour prawns in each stock region is biologically independent of prawns in other stock regions, i.e., there is no spawner or larvae migration among the four stock regions. For stock region *s*, the deterministic version of the biomass dynamics model can be written as:

$$B_{s,y} = B_{s,y-1} + r_s B_{s,y-1}\left(1 - \frac{B_{s,y-1}}{K_s}\right) - \sum_{f=1}^{4} C_{s,f,y-1}\ , \qquad (1)$$

where *B* is biomass (in ton), *r* is the intrinsic growth rate, *K* is the carrying capacity, *C* is the catch. The subscript *y* is year, *s* is stock, and *f* is fleet.

The values for the parameters in equation 1 were estimated by fitting them to data on catch-per-unit-effort (CPUE). For a multi-stock, multi-fleet fishery the model-estimate corresponding to the catch-rate for stock *s*, fleet *f*, and year *y*, $\hat{U}_{s,f,y}$ is:

$$\hat{U}_{s,f,y} = q_{s,f} P_y B_{s,y}\ , \qquad (2)$$

where $q_{s,f}$ is the catchability coefficient for stock *s* and fleet *f*, and P_y is the relative fishing power during year *y*. The observed catch-rate was assumed to be log-normally distributed about its expected value in common with most applications of biomass dynamics models (Polacheck et al. 1993; Meyer and Millar 1999):

$$U_{s,f,y} \sim \text{log-normal}\{\ell\text{n}(\text{E}[\hat{U}_{s,f,y}], \tau_{U,s,f})\} \qquad (3)$$

where $\tau_{U,s,f}$ is the precision (the inverse of the variance) of the observation error for the catch-rate data for fleet *f*. $\tau_{U,s,f}$ is allowed to differ among fleets because it would not be expected that fleets that target a species and which take it as by-catch would lead to indices of abundance with the same extent of precision as would be the case for a target fleet.

We assumed that deviations about the expected biomass are log-normally distributed (Meyer and Millar 1999; Chaloupka and Balazs 2007), i.e.:

$$B_{s,y} \sim \text{log}-\text{normal}\{\ell n(E[B_{s,y}]), \tau_{B,s}\} \qquad (4)$$

where $\tau_{B,s}$ is the precision of the process error for stock *s*. The prior for the biomass at the start of the first year of the modelled period is assumed to be the same as for the carrying capacity for stock *s*.

It is necessary to specify prior distributions for all of the parameters of the model to implement each of the three state-space models within a hierarchical Bayesian framework. Under the assumption that the population growth parameter and catchability are unlikely to differ substantially among stocks, it was assumed that *r*, *K* and *q* for each stock and fleet were log-normally distributed about a common mean, i.e. these parameters for each stock are random effects about a common mean, i.e.

$$\begin{aligned} r_s &\sim \text{log-normal}(\mu_r, \tau_r) \\ K_s &\sim \text{log-normal}(\mu_K, \tau_K) \\ q_{s,f} &\sim \text{log-normal}(\mu_{q,f}, \tau_{q,f}) \end{aligned} \qquad (5)$$

Where μ_r and $\mu_{q,f}$ are the prior means for *r* and fleet-specific catchability, τ_r and $\tau_{q,f}$ are the corresponding prior precisions, and *a* and *b* are the lower and upper limit of the uniform distribution. Collectively, these parameters are known as hyper-parameters (Harley and Myers 2001; Su *et al.* 2001). We assumed a normal distribution, N(M_θ, T_θ), for μ_θ, where θ is either r or q. Bayesian hierarchical models have the advantages that there is no need to specify the values for the parameters of the priors, but rather those of the hyper-parameters, and that the results of models are less sensitive to the values for parameters of the hyper-prior than those of the prior. We specified values for the means (M_θ) of these hyper-priors (McAllister *et al.* 2004; Askey et al 2007) by considering results from non-hierarchical Bayesian models and set the values for T_θ to large values so that the hyper-priors were relatively non-informative, but still proper (Gelman 2006). The values for the precision hyper-parameter T_θ were set using a half–Cauchy distribution (Gelman 2006).

The hyper-priors for the τ_θ, as well as the priors for the observation precisions, $\tau_{U,s,f}$, and the process precisions, $\tau_{B,s}$, were set to proper, but reasonably non-informative gamma distributions with mean 1 and variance 1000, i.e., $gamma(0.001, 0.001)$.

In summary, the hierarchical structure of the alternative biomass dynamics models contain the following levels:

Hyper-priors: M_θ assigned, T_θ half-Cauchy distribution;

Hyper-priors: $\mu_\theta \sim$ N(M_θ, T_θ), $\tau_\theta \sim$ G(0.001, 0.001);

Hyper-parameters: μ_K, μ_r, $\mu_{q,f}$, τ_K, τ_r, $\tau_{q,f}$;

Priors: log(K_s)~N(μ_K, τ_K), log($B_{s,y}$)~N(log(E[$B_{s,y}$], $\tau_{B,s}$), log(r_s)~N(μ_r, τ_r), log($q_{s,f}$)~N($\mu_{q,f}, \tau_{q,f}$), $\tau_{U,s,f}$~G(0.001, 0.001), $\tau_{B,s}$~G(0.001, 0.001);

Parameters: K_s, r_s, $q_{s,f}$, $B_{s,1970}$, $\tau_{U,s,f}$ $\tau_{B,s}$;

Data: $U_{s,f,y}$.

Given the assumptions regarding the nature of the state-space model, the priors for the parameters and those for hyper-priors, the posterior distribution is proportional to:

$$p(\mu_K)p(\tau_K)p(\mu_r)p(\tau_r)p(\underline{\mu}_{q,f})p(\underline{\tau}_{q,f})$$
$$p(\underline{K}_s \mid \mu_K, \tau_K)p(\underline{B}_{1970,s} \mid \mu_K, \tau_K)p(\underline{r}_s \mid \mu_r, \tau_r)p(\underline{q}_{s,f} \mid \underline{\mu}_{q,f}, \underline{\tau}_{q,f})p(\underline{\tau}_{B,s})p(\underline{\tau}_{U,s,f}) \qquad (6)$$
$$\prod_{s,y}\left(p(B_{s,y} \mid B_{s,y-1}, K_s, r_s, C_y, \tau_{B,s}) \prod_f p(U_{s,f,y} \mid B_{s,y}, q_{s,f}, P_y, \tau_{U,s,f}) \right)$$

where the underlined parameters denote a vector or matrix over stock *s*, fleet *f*, and/or year *y*.

The Gibbs sampler, a Markov chain Monte Carlo (MCMC) technique, implemented using the WinBUGS package (http://www.mrc-bsu.cam.ac.uk/bugs) was used to sample parameter vectors from the posterior distribution (Eqn 6). Three Markov chains were conducted based on dispersed initial values, and the results of the first 4,000 cycles of each chain taken as the burn-in period. The results of an additional 60,000 cycles from the three chains were saved, which formed the basis for further analysis. Whether the MCMC algorithm converged adequately to the posterior was evaluated by visually examining the three chains for each parameter in Eqn 6 and using the Gelman-Rubin diagnostic statistic (Best *et al.* 1996).

From these estimated parameters, we derive the management parameter, the maximum sustainable yield MSY for stock *s*:

$$MSY_s = \frac{r_s K_s}{4}. \tag{7}$$

Besides the standard biomass dynamics model (1), we applied three alternative model for blue endeavour prawns. The second model is the Pella-Tomlinson model

$$B_{s,y} = B_{s,y-1} + r_s B_{s,y-1}\left(1 - \left(\frac{B_{s,y-1}}{K_s}\right)^{p_s}\right) - \sum_{f=1}^{4} C_{s,f,y-1}, \tag{8}$$

Where P_s is stock-specific shape parameter. The third model is a recruitment model in similar to the form of Beverton-Holt stock-recruitment model:

$$B_{s,y} = \frac{r_s\left(B_{s,y-1} - \sum_{f=1}^{4} C_{s,f,y-1}\right)}{1 + \frac{r_s}{K_s}\left(B_{s,y-1} - \sum_{f=1}^{4} C_{s,f,y-1}\right)} \tag{9}$$

Because endeavour prawns are non-target species, we considered that catch data may be messy and have many outlies. Therefore, we tested the fourth model using robust assessment approach when the observation error is assumed to follow t-distribution. This should allow for more flexible account for potential outlies:

$$ln(U_{s,f,y}) \sim t\{ln(\mathrm{E}[\hat{U}_{s,f,y}], \tau_{U,s,f}, k_{s,f})\}$$

Where $k_{s,f}$ is degree of freedom for stock *s* and fleet *f*.

10.3 Results

The hierarchical Bayesian biomass dynamics model fits the CPUE data of the two tiger prawn fleets fairly well (Figures 10.3, 10.4, 10.5). However, the model performs better for some stocks and the pattern appears to differ between the two fleets (Figures 10.3 and 10.4, and 10.5 and Table 10.1). The semi fleet has a lower observation error for Stocks 1 and 2, while the escu fleet has a lower observation error for Stocks 3 and 4. These results are in line with commercial catch data in these regions (Figure 10.2). Key parameters are summarized in Table 10.1.

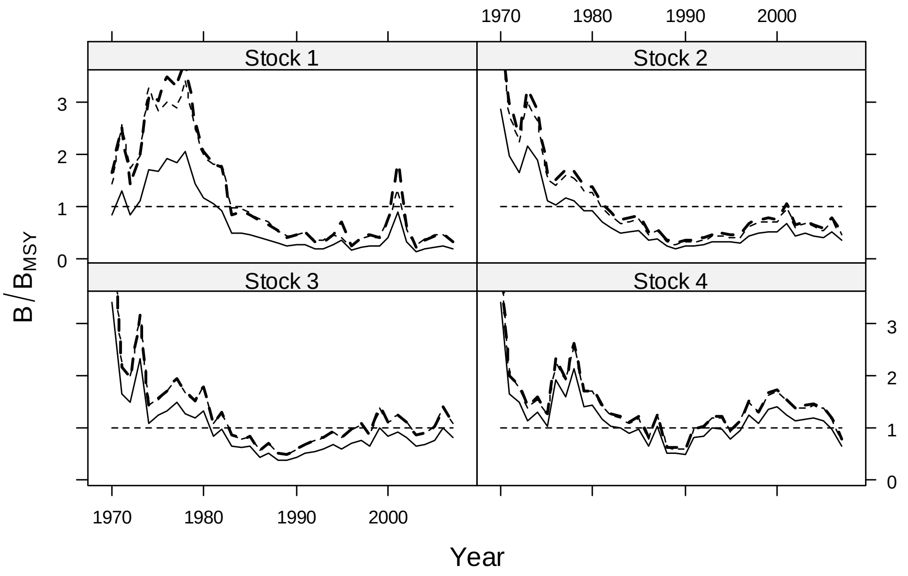
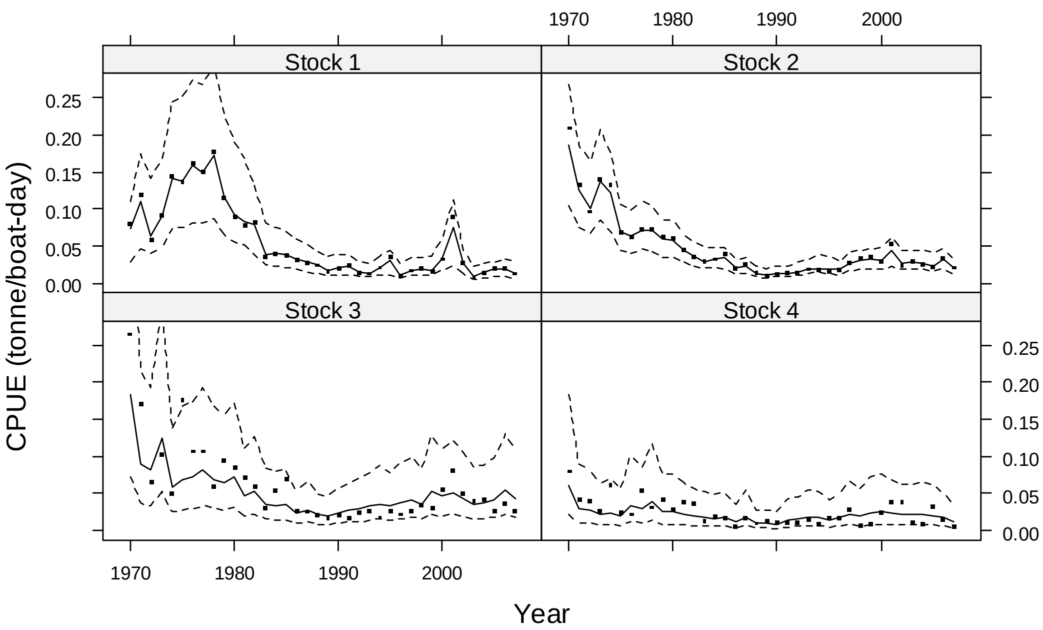


Figure 10.3. Comparison of posterior median B/B_{MSY} from three models: solid line = Standard biomass dynamics model, thick dashed line = Recruitment model with lognormal observation error, thin dashed line = Recruitment model assuming observation error has a log – t-distribution.

Table 10.1. Model selection comparison.

Model	DIC	Δ DIC
Standard BD model	82.03	29.90
Pella-Tomlinson model	100.47	48.34
SR model	55.84	3.71
Robust SR model	52.13	0.00

(A)



(B)

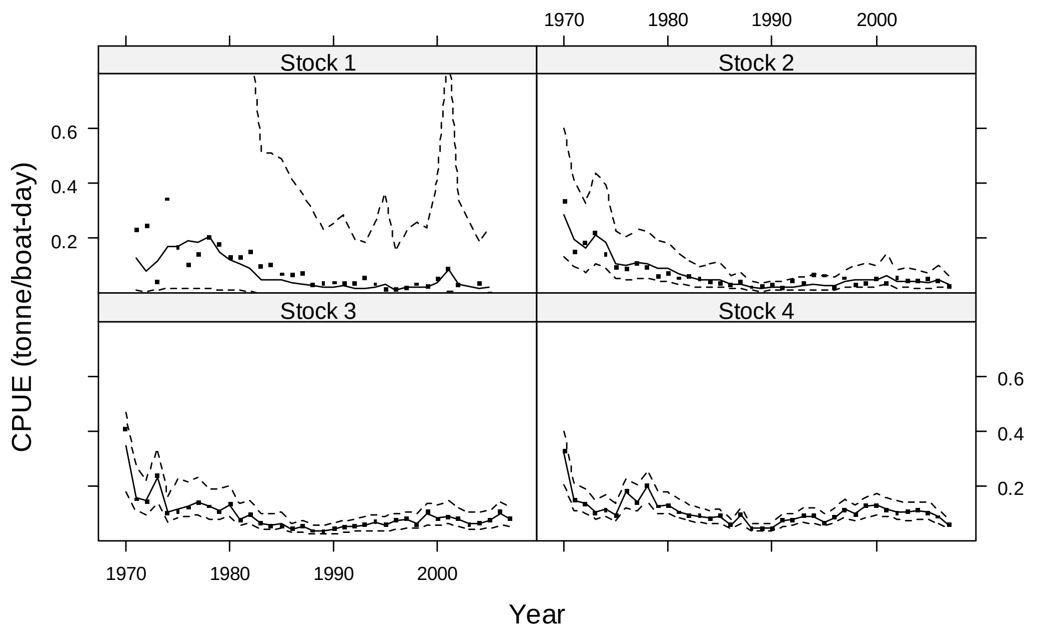
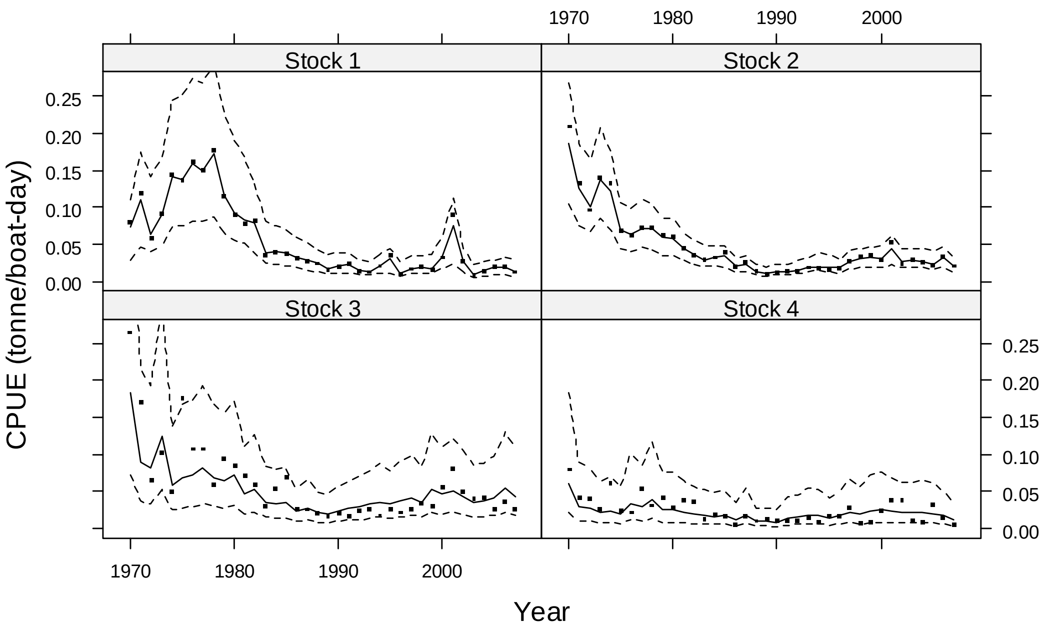


Figure 10.4a. Standard biomass dynamics model estimation of endeavouri catch by P.s grooved fleet (A) and Standard biomass dynamics model estimation of endeavouri catch by P.e brown fleet (B)

(A)



(B)

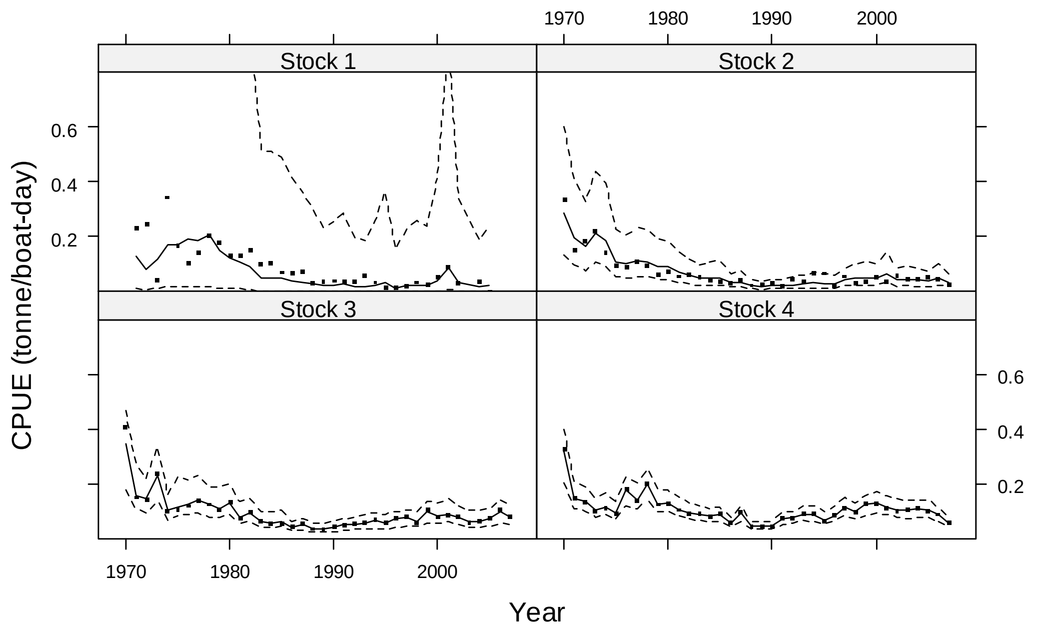


Figure 10.4b) Stock-recruit model estimation of endeavouri catch by P.s grooved fleet (A) and Stock-recruit model estimation of endeavouri catch by P.e brown fleet (B)

Estimated biomass tends to be high in the early years and gradually reduces before 1990 (Figure 10.6). The status of Stock 4 is slightly better than other stocks. The result indicates that biomass was below the B_{msy} level of all stocks in 2007.

The median carrying capacity K is similar among stocks, varying between 1642 and 1879 t. The median intrinsic growth rate *r* ranges from 0.38 to 0.78 for the four stocks. The estimated total MSY is slightly under 1000 tonnes.

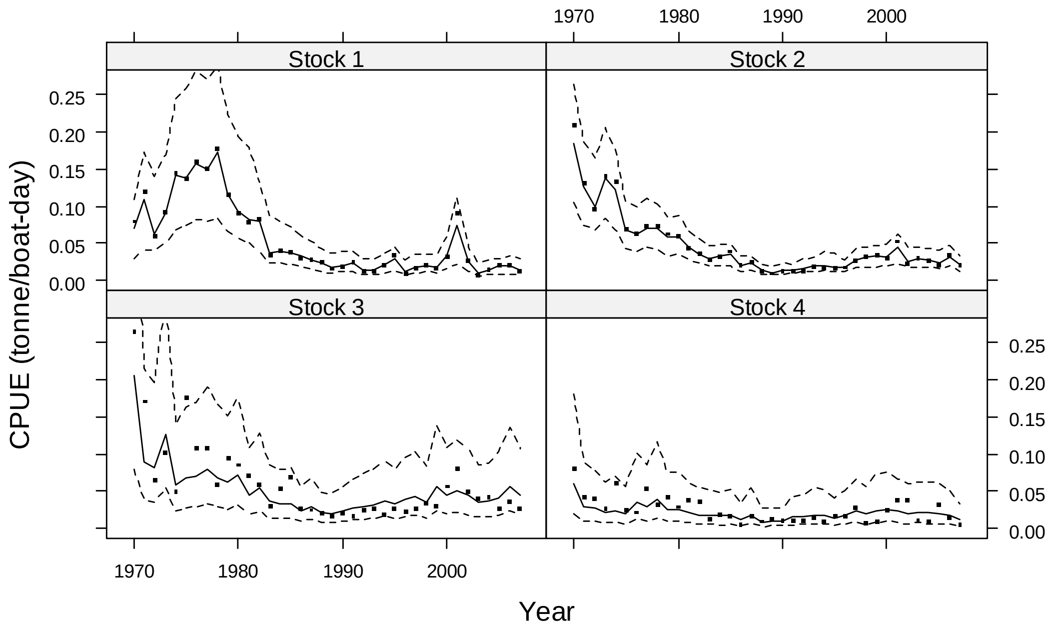


Figure 10.5a. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the semi fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

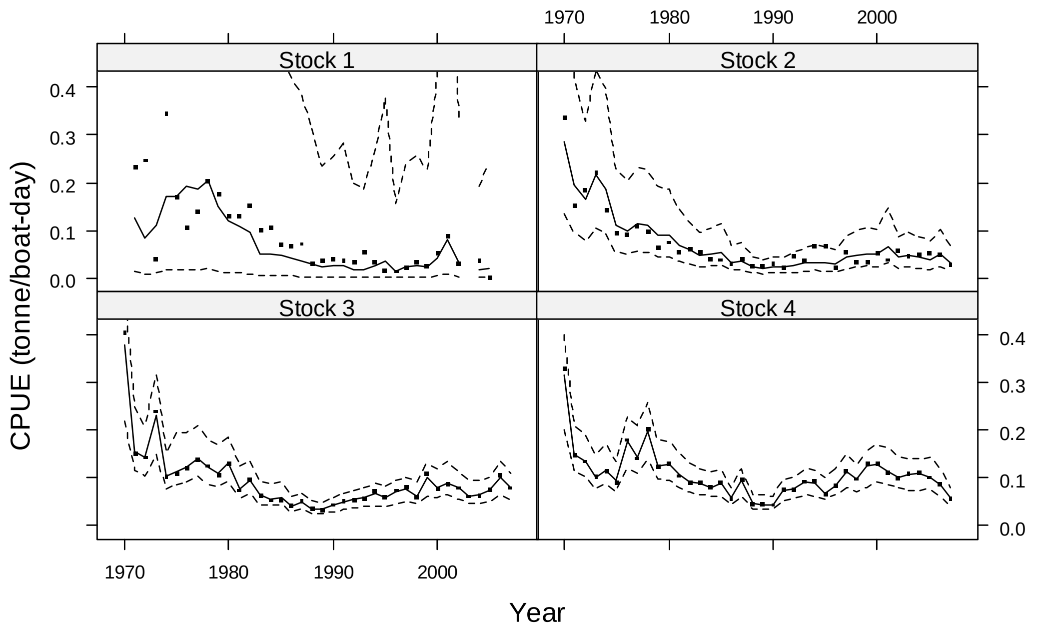


Figure 10.5b. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the escu fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

The fleet targeting *P. esculentus* has a higher catchability than the fleet targeting P. semisculentus. This is in consistence with the observation that blue endeavour tends to associate with brown prawns in their distribution.

Table 10.2a. Posterior distribution for key parameters from SR model. Fleet 1 = semi, Fleet 2 = escu.

Parameter	mean	L95%CI	median	U95%CI
K[1]	2,950	1,346	2,477	6,061
K[2]	2,693	1,362	2,442	5,326
K[3]	2,625	1,351	2,405	5,100
K[4]	2,387	1,129	2,224	4,507
Sum	10,655	5,188	9,548	20,994
MSY[1]	120	31	112	244
MSY[2]	157	74	153	260
MSY[3]	379	208	378	558
MSY[4]	284	146	277	458
Sum	**940**	**460**	**921**	**1,520**
q[1,1]	8.77E-05	5.05E-05	8.59E-05	1.32E-04
q[1,2]	6.89E-05	4.50E-05	6.80E-05	9.79E-05
q[1,3]	4.33E-05	2.95E-05	4.31E-05	5.79E-05
q[1,4]	1.91E-05	1.29E-05	1.89E-05	2.70E-05
Mean	**5.48E-05**	**3.45E-05**	**5.40E-05**	**7.86E-05**
q[2,1]	1.09E-04	6.61E-05	1.03E-04	1.82E-04
q[2,2]	1.09E-04	7.17E-05	1.07E-04	1.57E-04
q[2,3]	7.69E-05	5.34E-05	7.70E-05	1.01E-04
q[2,4]	9.58E-05	6.76E-05	9.49E-05	1.30E-04
Mean	**9.76E-05**	**6.47E-05**	**9.56E-05**	**1.42E-04**
r[1]	1.64	1.23	1.61	2.20
r[2]	1.81	1.38	1.78	2.40
r[3]	2.97	1.69	2.74	5.60
r[4]	2.71	1.57	2.38	5.57
Mean	2.28	1.47	2.13	3.94
tau.B[1]	3.55	1.82	3.23	7.24

tau.B[2]	5.61	3.08	5.42	9.27
tau.B[3]	4.70	2.67	4.58	7.46
tau.B[4]	5.24	3.01	5.11	8.16
Mean	4.78	2.64	4.58	8.03
utau[1,1]	248.2	7.7	75.6	1568.0
utau[1,2]	176.6	9.9	54.5	1157.0
utau[1,3]	6.0	3.4	5.7	10.3
utau[1,4]	3.7	2.2	3.6	5.7
Mean	108.6	5.8	34.8	685.2
utau[2,1]	0.8	0.4	0.8	1.2
utau[2,2]	11.0	4.8	8.7	26.1
utau[2,3]	275.7	16.4	113.0	1546.0
utau[2,4]	388.5	23.2	199.0	1859.0
Mean	169.0	11.2	80.4	858.1

Table 10.2b. Posterior distribution for key parameters. Fleet 1 = semi, Fleet 2 = escu.

Param	mean	2.50%	median	97.50%
K[1]	1,757	1,050	**1,673**	2,888
K[2]	1,715	1,101	**1,642**	2,677
K[3]	1,941	1,308	**1,879**	2,886
K[4]	1,735	1,211	**1,676**	2,584
Total	7,148	4,670	**6,870**	11,035
r[1]	0.38	0.14	**0.38**	0.64
r[2]	0.46	0.24	**0.45**	0.70
r[3]	0.80	0.40	**0.78**	1.28
r[4]	0.59	0.31	**0.58**	0.92
Mean	0.56	0.27	**0.55**	0.88
q[1,1]	1.05E-04	6.00E-05	**9.93E-05**	1.82E-04
q[1,2]	7.81E-05	4.84E-05	**7.62E-05**	1.17E-04
q[1,3]	5.85E-05	3.60E-05	**5.79E-05**	8.44E-05
q[1,4]	2.17E-05	1.35E-05	**2.15E-05**	3.10E-05
Mean	0.00007	0.00004	0.00006	0.00010
q[2,1]	1.30E-04	7.86E-05	**1.22E-04**	2.35E-04
q[2,2]	1.24E-04	7.84E-05	**1.21E-04**	1.87E-04
q[2,3]	1.04E-04	6.52E-05	**1.04E-04**	1.48E-04
q[2,4]	1.09E-04	7.06E-05	**1.08E-04**	1.50E-04
Mean	0.00012	0.00007	0.00011	0.00018
MSY[1]	166	57	**159**	302
MSY[2]	190	100	**185**	301
MSY[3]	370	210	**371**	528
MSY[4]	248	141	**245**	375
Total	974	509	**960**	1,506
tau.U[1,1]	138.8	5.131	**28.72**	1034
tau.U[1,2]	128.2	9.863	**42.66**	878
tau.U[1,3]	6.276	3.449	**5.95**	11.14
tau.U[1,4]	3.725	2.17	**3.634**	5.805
tau.U[2,1]	0.792	0.4479	**0.7745**	1.237
tau.U[2,2]	12.42	4.91	**9.136**	25.36
tau.U[2,3]	166	11.88	**56.85**	1071
tau.U[2,4]	354.7	18.7	**162.5**	1837

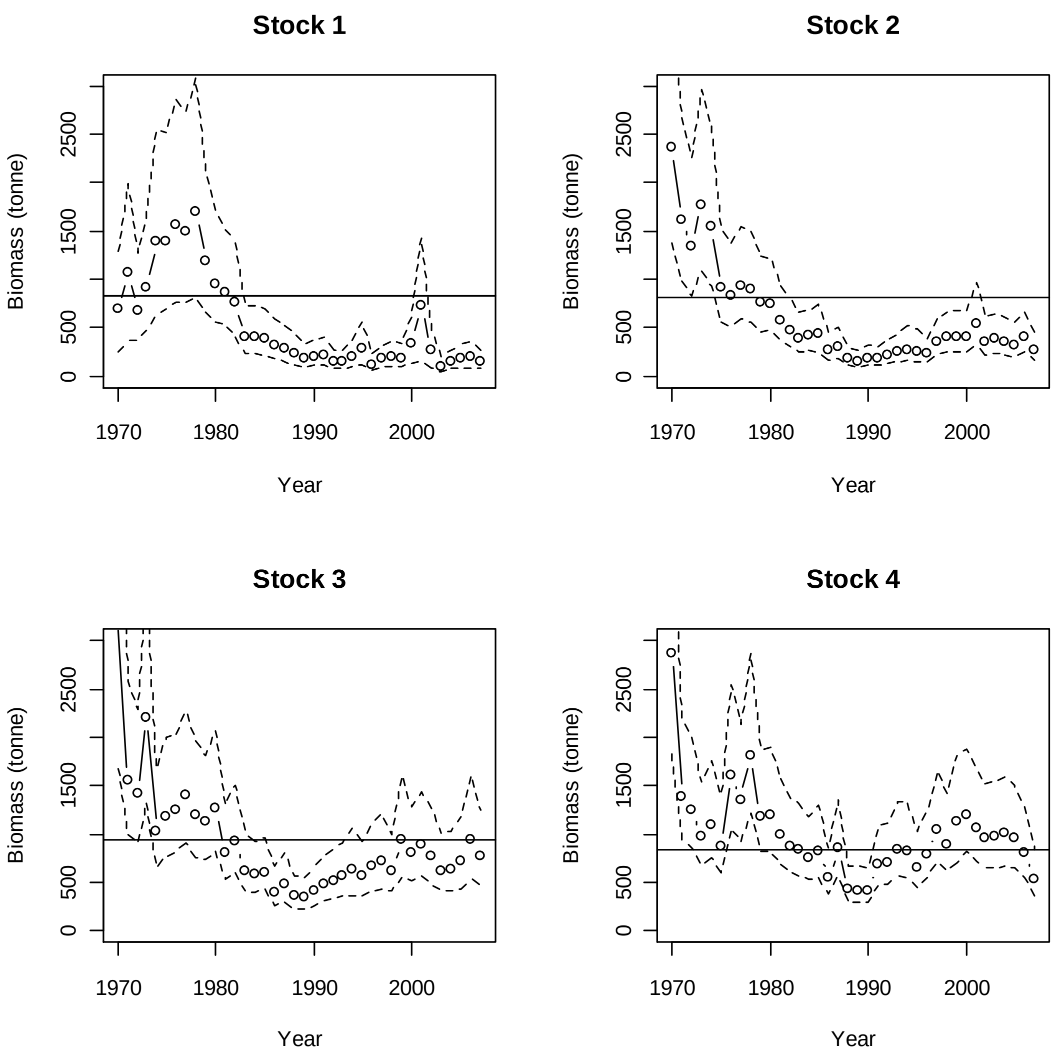


Figure 10.6. Posterior median biomass from 1970 to 2007. The horizontal line is the median B_{msy}.

10.4 Discussion

A variety of stock assessment models exist for crustacean fisheries (Quinn and Deriso 1999; Smith and Addison 2003). Among these available models, biomass dynamics (or surplus production) model is the simplest, which combines life processes and takes no account of population age or size structure. The data needed for fitting biomass dynamics model is minimal: catch and effort data are sufficient. Since we have reasonable high quality of catch and effort data for blue endeavour prawns while we have limited or no information on other type of data (recruitment pattern, natural mortality, catchability, etc.), biomass dynamics model becomes our first choice for assessment of this prawn species.

Different methods have been used to estimate parameters of biomass dynamics model, include Bayesian approach (Chaloupka and Balazs 2007). However, the weakness of classical Bayesian approach is that estimation stability is dependent on the choice of priors, which will alters posterior distributions of estimated parameters (Booth and Quinn 2006). In this paper we explored the hierarchical Bayesian technique and compared with non-hierarchical Bayesian models on combined datasets. It appears this is the first time application of hierarchical Bayesian method for biomass dynamics models. The results demonstrate that hierarchical Bayesian models have the advantage of “lending” information from data-rich stocks to data-poor stocks. This information sharing allows parameter estimation for stocks with limited catch and effort data.

10.5 References

Adkison, M.D., Su, Z., 2001. A comparison of salmon escapement estimates using a hierarchical Bayesian approach versus separate maximum likelihood estimation of each year’s return. Can. J. Fish. Aquat. Sci. 58, 1663-1671.

Booth, A.J., and Quinn, T.J. 2006. Maximum likelihood and Bayesian approaches to stock assessment when data are questionable. Fish. Res. 80: 169-181.

Chaloupka, M. and G. Balazs (2007). Using Bayesian state-space modelling to assess the recovery and harvest potential of the Hawaiian green sea turtle stock. Ecological Modelling 205: 93-109.

Dichmont, C.M., Punt, A.E., Deng, A., and Venables, W. 2003. Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery. Fish. Res. 65, 335–350.

Dichmont, C.M., Deng, A.R., Venables, W.N., Punt, A.E., Haddon, M., and Tattersall, K. 2005. A new approach to assessment in the NPF: spatial models in a management strategy environment that includes uncertainty. FRDC Report 2001/002.

Harley, S.J., Myers, R.A., 2001. Hierarchical Bayesian models of length-specific catchability of research trawl surveys. Can. J. Fish. Aquat. Sci. 58, 1569-1584.

Liermann, M. Hilborn, R., 1997. Dispensation in fish stocks: a hierarchical Bayesian meta-analysis. Can. J. Fish. Aquat. Sci. 54, 1976-1984.

Lucas, C., Kirkwood, G., and Somers, I. 1979. An assessment of the stocks of the banana prawn *Penaeus merguiensis* in the Gulf of Carpentaria. Aust. J. Mar. Freshwater Res. 30: 639-652.

Ludwig, D., and Walters, C.J. 1985. Are age-structured models appropriate for catch-effort data? Can. J. Fish. Aquat. Sci. 42: 1066-1072.

McAllister, M.K., Hill, S.L., Agnew, D.J., Kirkwood, G.P., Beddington, J.R., 2004. A Bayesian hierarchical formulation of the DeLury stock assessment model for abundance estimation of Falkland Islands’ squid (Loligo gahi). Can. J. Fish. Aquat. Sci. 61, 1048-1059.

Meyer, R., Millar, R.B. (1999a). Bayesian stock assessment using a state-space implementation of the delay difference model. Canadian Journal of Fisheries and Aquatic Sciences 56, 37-52.

Meyer, R., Millar, R.B. (1999b). BUGS in Bayesian stock assessments. Canadian Journal of Fisheries and Aquatic Sciences 56, 1078-1086.

Polacheck, T., Hilborn, R., and Punt, A.E. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. Can. J. Fish. Aquat. Sci. 50: 2597-2607.

Quinn, T.J., and Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Raudzens, E. 2007. Northern Prawn Fishery data summary 2006. Australia Fisheries Management Authority, Canberra.

Rivot, E., Prevost, E., 2002. Hierarchical Bayesian analysis of capture-mark-recapture data. Can. J. Fish. Aquat. Sci. 59: 1768-1784.

Rivot, E., Prévost, E., Parent, E., Baglinière, J. (2004). A Bayesian state-space modelling framework for fitting a salmon stage-structured population dynamic model to multiple time series of field data. Ecological Modelling 179: 463-485.

Smith, M.T., and Addison, J.T. 2003. Methods for stock assessment fo crustacean fisheries. Fish. Res. 65: 231-256.

Su, Z., Adkison, M.D., van Alen, B.W., 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. Can. J. Fish. Aquat. Sci. 58, 1648-1662.

Vance, D.J., Staples, D.J., and Derr, J.D. 1985. Factors affectingyear-to-year variation in the catch of banana prawns (*Penaeus merguiensis*) in the Gufl of Carpentaria, Australia. J. Cons. Int. Explor. Mer. 42: 83-97.

Vance. D.J., Bishop, J., Dichmont, C.M., Hall, N., McInnes, K., Taylor, B.R. 2003. Management of common banana prawn stocks of the Gulf of Carpetaria: separating the effects of fishing from those of the environment. CSIRO Report, Project No. 98/0716.

Wang, Y-G., Die, D. 1996. Stock-recruitment relationships of the tiger prawns (Penaeus esculentus and Penaeus Semisulcatus) in the Australian Northern Prawn Fishery. Mar. Freshw. Res. 47, 87–95.

Zhou, S., Punt, A.E., Deng, R., Dichmont, C.M., Ye, Y. and J. Bishop. In review. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Marine and freshwater Research.

APPENDIX 11. ON CALCULATING EFFORT AND CATCH TRAJECTORIES FOR SPECIES MODELLED USING SIZE, DELAY-DIFFERENCE AND PRODUCTION MODELS

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11.1 Summary

A framework is described whereby effort levels and their associated catches consistent with maximizing the net present value of fishery profits over time can be calculated when each harvested species is modelled using a different population dynamics model. Results are presented based on three species (*Penaeus semisulcatus*, *P. esculentus*, and *Metapenaeus endeavouri*) in Australia's Northern Prawn Fishery and three population dynamics models (size-structured, delay-difference, and biomass dynamics). The results indicate that there is considerable between-population dynamics model variation in key model outputs such as the catch predicted for 2008 and the estimated future catches. This variation is comparable with that due to uncertainty about economic parameters when all species are modelled using only a size-structured population dynamics model, highlighting the importance of the need for both good population dynamics models and accurate economic parameter inputs.

11.2 Introduction

Management advice for brown and grooved tiger prawns (*P. esculentus* and *semisculcatus*) in the Northern Prawn Fishery, NPF, has been based on the results from a delay-difference model-based stock assessment (Dichmont *et al*., 2003). Originally, management advice was related to setting fishing effort (and hence fishing mortality) to that corresponding to maximum sustainable yield (MSY), accounting for changes over time in both stock status and fishing power. However, more recently, management advice has related to effort levels which maximize the net present value of fishery profits over time (the functional definition of “achieving maximum economic yield (MEY)”) (Dichmont, *et al*., 2008; Kompas *et al*., submitted). Dichmont *et al*. (2008) compared management strategies based on harvest control rules with a target spawning stock size which was a pre-specified fraction of that corresponding to MSY with strategies based on a harvest control rule which aimed to maximize net present value using Management Strategy Evaluation. They found that the harvest control rules based on economic objectives outperformed those which aimed to maximize catches using several metrics, including cumulative discounted profit and impacts on benthic species.

Punt *et al*. (2010) extended the economics component of the approach of Dichmont *et al*. (2008) and Kompas *et al*. (2008) by taking account of fixed costs, and by imposing the constraints that (a) the profit each year must be non-negative and (b) the number of days fished per vessel each week cannot exceed seven (i.e. making the economic model more explicitly reflect the actual situation for the NPF). Punt *et al*. (2010) also introduced a size-structured population dynamics model for prawns in the NPF. This population dynamics model differs from the delay-difference model used in the past by modelling changes over time in the size-structure of the population. Such changes can be captured within the framework of a delay-difference model (e.g. Schnute, 1987). However, explicitly representing the population in the form of the number of individuals in each size-class allows several additional sources of data (e.g. length-frequency information from surveys and the fishery) as well as information on growth from tagging to be used when estimating the values of the parameters of the population dynamics model. Such data were not available in the past, but have become so in recent years. The use of a size-structured population dynamics model also allows relaxation of the assumptions of the delay-difference model that selectivity and maturation are the same and are knife-edged functions of age.

A disadvantage of the approaches of Dichmont *et al*., (2003, 2008) and Punt *et al*. (2010) is that they require considerable auxiliary information (e.g. an estimate of the rate of natural mortality, *M*, and the annual spawning pattern) which is not available for most prawn species in the NPF. Parameter estimation also requires considerable amounts of data. Zhou *et al*. (2010) outline a framework based on a biomass dynamics model implemented as a hierarchical Bayesian analysis. This framework can be applied to species for which the only data are time-series of catches and catch-rates (and an associated fishing power time-series). The simplicity of this model also allows spatial structure to be incorporated into the population dynamics.

In principle, the annual profit associated with a time-series of future efforts by fishing strategy[21] can be calculated where each of the harvested species is represented using a different population dynamics model. However, the various population dynamics models applied to prawn species in the NPF have been based on different temporal and spatial resolutions (single area and weekly for the delay-difference and size-

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[21] For the application to the NPF, the two fishing strategies are associated with targeting of either *P. semisulcatus* or *P. esculentus*.

structured models and multi-area (multi-stock) and annual for the biomass dynamics model). Furthermore, most applications of the approaches of Dichmont *et al*. (2003, 2008) and Punt *et al*. (2010) have been based on the assumption of deterministic future dynamics and ignoring parameter uncertainty. In contrast, the biomass dynamics model on which the analyses of Zhou *et al*. (2010) are based accounts for process error in the population dynamics as well as parameter uncertainty.

This appendix therefore outlines how an economically optimal catch and effort trajectory can be derived from a mix of models – some species being modelled using the weekly delay-difference and size-structured models while others are modelled using the annual biomass dynamics model. The sensitivity of key model outputs to different choices regarding the modelling framework adopted for three species (brown and grooved tiger prawns and endeavour prawns, *M. endeavouri*) is then examined using this framework.

11.3 Methods

11.3.1 Population dynamics models

The delay-difference and size-structured population dynamics models are specified by Dichmont *et al*. (2003) and Punt *et al*. (2010) respectively. The applications of the biomass dynamics model are based on the "standard" model of Zhou *et al*. (2010), i.e.:

$$B_{i,s,y+1} = [B_{i,s,y} + r_{i,s}(1 - B_{i,s,y} / K_{i,s}) - C_{i,s,y}]e^{\tau_{i,s,y} - \sigma_{i,s}^2/2} \qquad \tau_{i,s,y} \sim N(0;\sigma_{i,s}^2) \qquad (1)$$

where $B_{i,s,y}$ is biomass of stock *s* of species *i* at the start of year *y*, $r_{i,s}$ is the intrinsic rate of growth for stock *s* of species *i*, $K_{i,s}$ is the carrying capacity for stock *s* of species *i*, $C_{i,s,y}$ is the catch (in mass) of prawns of stock *s* of species *i* during year *y*, and $\sigma_{i,s}$ is the standard deviation of the process error for stock *s* of species *i*.

11.3.2 Economics model

The objective function is the maximisation of the net present value (NPV) of the flow of profits over time, from the first year (taken to be 2008 in this study) to the terminal year of the simulation (taken to be 2050), given by:

$$NPV = \sum_{y=1}^{T-1} \pi_y \Big/ (1+o)^{y-1} + \left[\pi_T / o\right] \Big/ (1+o)^{T-1} \qquad (2)$$

where *o* is the discount rate (equivalent to the opportunity cost of capital and assumed to be 5% per annum in this study), π_y is the profit during year *y*, and π_T is the level of profit during the terminal year. Profits were assumed to continue at the level π_T indefinitely on the basis that the system is in equilibrium.

The level of profits in each year (including the terminal year) are given by:

$$\pi_y = \sum_i \tilde{R}_{i,y} - \sum_f (c_K + c_{F,y}) E_y^f - \Omega_y V_y \qquad (3)$$

where $\tilde{R}_{i,y}$ is the net revenue obtained from catches of species *i* during year *y* (net revenue being revenue less costs which are proportional to the size of the catch), E_y^f is the effort expended by fishing strategy *f* (that targeted towards *P. semisulcatus* or *P. esculentus*)[22] during year *y*, c_K is the cost of repairs and maintenance per unit of effort, $c_{F,y}$ is the cost of fuel and grease per unit of effort during (future) year *y*, V_y is the number of vessels (assumed to be 52 for the analyses of this appendix), Ω_y is the average fixed costs associated with a vessel operating during year *y*, and includes a measure of the opportunity cost of capital, such that:

$$\Omega_y = W_y + (o + d)\Psi_y \qquad (4)$$

W_y is the annual vessel costs (i.e. those not related to the level of fishing effort), o is the opportunity cost of capital (equivalent to the discount rate as noted above), d is the economic depreciation rate, and Ψ_y is the average value of capital during year *y*.

The choice of the appropriate formula for net revenue for species *i* during year *y*, $\tilde{R}_{i,y}$, depends on the model of the population dynamics, i.e.:

$$\tilde{R}_{i,y} = \begin{cases} \sum_l \left[(1-c_L)v_{i,y,l} - c_M\right] \sum_w Y_{i,y,w,l}^{\text{Siz}} & \text{Size-structured model} \\ \left[(1-c_L)\bar{v}_{i,y} - c_M\right] \sum_w Y_{i,y,w}^{\text{Del}} & \text{Delay-difference model} \\ \left[(1-c_L)\bar{v}_{i,y} - c_M\right] \sum_s E[Y_{i,y,s}^{\text{Bio}}] & \text{Biomass dynamics model} \end{cases} \qquad (5)$$

where $v_{k,y,l}$ is the average price per kilogram for prawns of species *i* in size-class *l* during (future year) *y*, $\bar{v}_{k,y}$ is the average price per kilogram for prawns of species *i* during (future year) *y*, $Y_{i,y,w,l}^{\text{Siz}}$ is the catch (kg) of prawns of species *i* in size-class *l* during week *w* of year *y* (based on the size-structured model), $Y_{i,y,w}^{\text{Del}}$ is the catch of prawns of species *i* during week *w* of year *y* (based on the delay-difference model), $E[Y_{i,y,s}^{\text{Bio}}]$ is the expected catch of prawns of species *i* in stock area *s* during year *y* (based on the biomass dynamics model), c_L is the share cost of labour (labour costs are assumed to be proportional to fishery revenue), and c_M is cost of packaging and gear maintenance (assumed to be proportional to the fishery catch in weight).

The expected catch of prawns of species *i* in stock area *s* during year *y* based on the biomass dynamics model is the average over draws from the Bayesian posterior distribution as well as future sequences of process error (i.e. $\tau_{i,s,y}$ in Equation 1).

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[22] This implies that costs are assumed to be independent of where in the NPF a vessel fishes.

The population dynamics in the delay-difference and size-structured models require estimates of fishing effort by week while the annual total effort used to update the population dynamics in the biomass dynamics model is the annual effort by stock area. For the analyses of this appendix, the effort by week (and fishing strategy) is computed by multiplying the annual effort by the proportion of effort by week (where, for consistency with previous analyses, the proportion of effort by week is set to the average proportion of effort by week over 2003-7), given by:

$$E_{w,y}^{wf} = \varepsilon_w^f E_y^f \qquad (6)$$

where $E_{w,y}^{wf}$ is the effort expended by fishing strategy *f* during week *w* of year *y*, and ε_w^f is the proportion of total effort expended by fishing strategy *f* during week *w* (such that $\sum_w \varepsilon_w^f = 1$). This proportion is assumed to be static over time (see Punt *et al.* (2010) for analyses that explore the sensitivity of the outcomes of the economics model to different assumptions regarding the proportion of effort by week). The proportion of effort that occurs in each stock area is assumed to be time-invariant and is selected to maximize Equation 2.

The key choice variable in Equation 2 is fishing effort by fishing strategy and year. Effort for the first seven years of the projection period is selected to maximize Equation 2, with effort for the seventh and all future years set to that of the seventh year (Dichmont *et al*., 2008). A key reason for only estimating a subset of the possible time-series of effort levels is that annual effort converges over time to a constant value when the dynamics are deterministic. Moreover, the results of the model would only be used to set harvest and effort levels for the two years following the year for which the most recent data are available. Maximization of Equation 2 is subject to the constraints that annual profit is non-zero, i.e. $\pi_y \geq 0$, that a boat cannot fish for more than seven days each week, and that effort cannot be less than half of that during 2007.

Further constraints have been imposed (when maximising Equation 2) in that effort (and hence catch) is zero if the average spawning biomass over the five years before the year for which an effort (or catch) is needed is less than 50% of S_{MSY} (the stock size corresponding to MSY). However, this constraint does not impact the results of this appendix given the current size of the modelled species.

11.3.3 Parameter estimation

Dichmont *et al*. (2003), Punt *et al*. (2010) and Zhou *et al*. (2010) respectively describe the approaches used to estimate the values for the parameters of the delay-difference, size-structured and biomass dynamics models. The values for parameters of the economics model (c_K, $c_{F,y}$, c_L, c_M, d, K_y, $\overline{v}_{k,y}$, and $v_{k,y,l}$) are set to those in Table 7.2 of Punt *et al*. (2010)(Appendix 7 – this study).

11.3.4 Model outputs and scenarios

The results from the economics model are summarized by the expected catch for 2008, C_{2008}, the long-term catch under an MEY strategy, C_{MEY}, the number of fishing days for 2008, E_{2008}, the number of fishing days in 2014 and later under an MEY strategy, E_{MEY}, the ratio of S_{MEY} to S_{MSY} [23] for each species, and the relative profit. The first two of these quantities are reported by species, and the second two are reported for the fishing strategy which targets *P. semisulcatus* and for that which targets *P. esculentus*. The relative profit is the profit for the scenario under consideration relative to that of the reference case scenario (all species modelled using the size-structured model). The stock sizes in 2007 relative to S_{MSY} and S_{MEY} are also reported to indicate the extent of recovery needed to move each species to the target level. The results for the biomass dynamics model are averages over draws from the posterior distribution and over future sequences of process error. The biomasses by stock area from the biomass dynamics model are aggregated across the entire NPF for comparability with the results from the size-structured and delay-difference models. The scenarios (Table 11.1) examine various choices regarding which species are modelled using which estimation frameworks.[24] Table 11.1 is not a fully-balanced design, but rather reflects the fact that the data for *M. endeavouri* are less informative than those for *P. semisulcatus* and *P. esculentus*, and hence that it is more likely that the biomass dynamics model will be applied to *M. endeavouri* than any of the other species.

Table 11.1. The model configurations by prawn species which define the scenarios considered in the analyses of this appendix "Size", "Delay" and "Biomass" respectively refer to the size-structured, delay-difference and biomass dynamics models.

Case	*P. semisulcatus*	*P. esculentus*	*M. endeavouri*
Reference	Size	Size	Size
1	Delay	Delay	Delay
2	Biomass	Biomass	Biomass
3	Size	Size	Biomass
4	Delay	Delay	Biomass
5	Size	Biomass	Biomass
6	Delay	Biomass	Biomass
7	Biomass	Size	Biomass
8	Biomass	Delay	Biomass

[23] The calculations of MSY are based on the assumption of deterministic dynamics for all species (including those modelled using the biomass dynamics model).

[24] The software is written so that either the size-structured model or the delay-difference model can be applied, but not both simultaneously.

11.4 Results and discussion

11.4.1 Historical trends

Figure 11.1 shows the time-trajectories of spawning stock size for each species and for each population dynamics model.[25] The solid lines for the biomass dynamics model denote the expected time-trajectories (based on 1,000 draws from the posterior distribution), the shadings cover the inter-quartile range for the posterior, and the dotted lines indicate the posterior 90% probability intervals.

All three population dynamics models lead to qualitatively very similar trends (the scales in Fig. 11.1 for the various models are not directly comparable owing to slightly different definitions of spawning stock size).

11.4.2 Results of the economics model

The results for the nine cases in Table 11.1 are summarized in Table 11.2 and Figures 11.2 and 11.3. In Figure 11.2, the time-trajectories for 1999-2021 of catch by species and profit relative to that in 2021 are presented, while the time-trajectories of effort by fishing strategy for these years are shown in Figure 11.3.

Even though the time-trajectories of spawning stock size in Figure 11.1 are qualitatively very similar, there are marked differences in results among the nine cases. For example, while all cases indicate that $S_{\mathrm{MEY}}/S_{\mathrm{MSY}} > 1$, the size of the spawning stock relative to S_{MSY} and S_{MEY} in 2007 is sensitive to how each species is modelled. For example, *P. semisulcatus* is estimated to be above S_{MSY} and S_{MEY} for cases 1, 3 and 5 (cases in which *P. semisulcatus* is modelled using the size-structured population dynamics model). In contrast, only the reference case, and cases 3 and 4, suggest that *P. esculentus* is above S_{MSY} and S_{MEY}.

There is considerable between-case variation in the 2008 and long-term catch corresponding to MEY (for example, between-case CVs of 12.0%, 16.2% and 4.9% for C_{2008} for *P. semisulcatus*, *P. esculentus*, and *M. endeavouri* respectively). However, the total catch aggregated over species is less variable (CVs of 10.1% for C_{2008} and 4.2% for C_{MEY}). The analysis in which the size-structured population dynamics model is used for all three species leads to highest catches (and effort levels) for 2008, but case 8 (delay-difference model for *P. esculentus* and biomass dynamics model for the other two species) leads to highest catch corresponding to MEY.

[25] The appendix provides the detailed results of the application of hierarchical Bayesian method to the data for *P. esculentus* and *M. endeavouri* (similar results for *P. semisulcatus* can be found in Appendix 8).

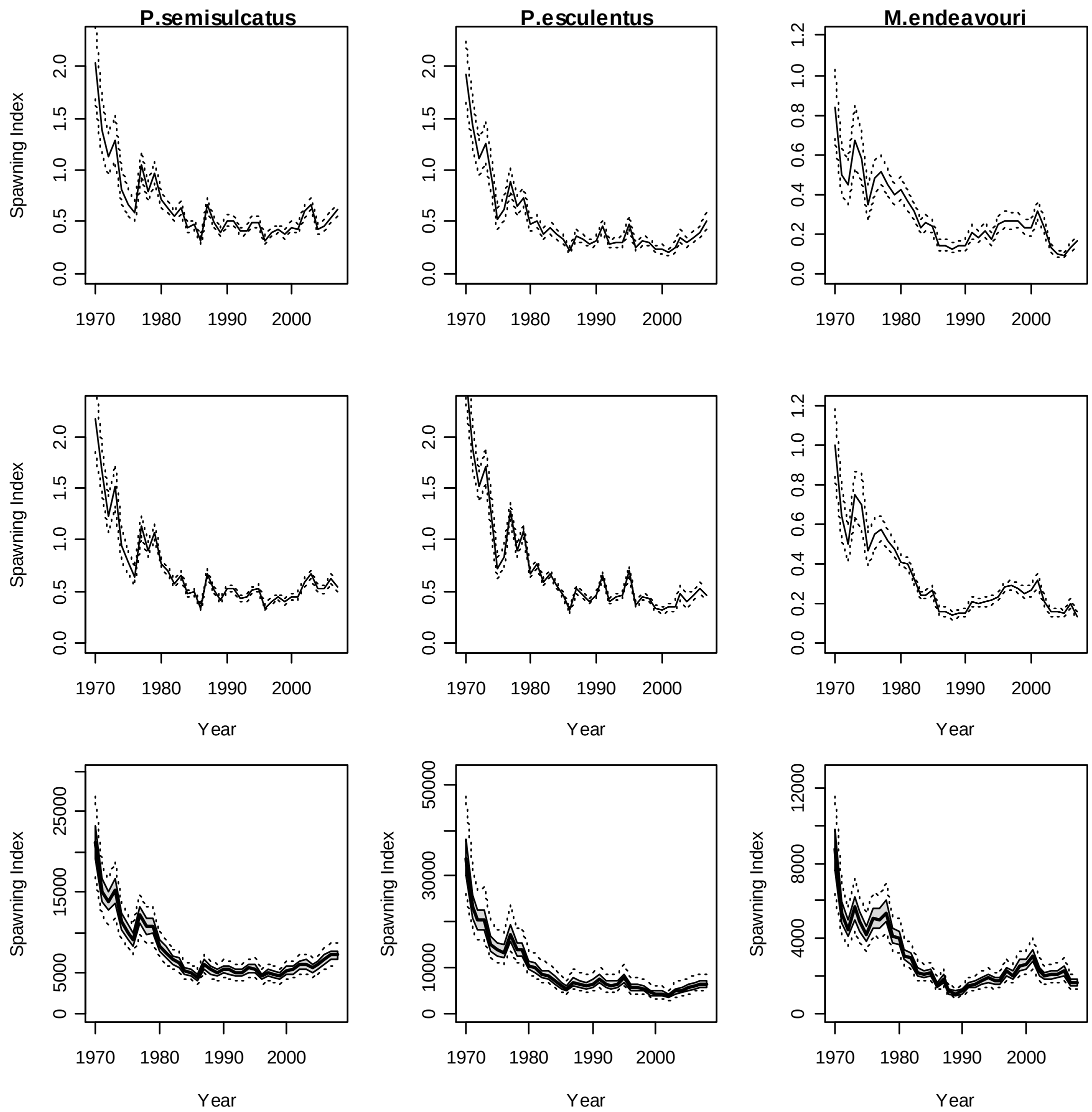

Figure 11.1. Time-trajectories of spawning stock size (1970-2007). Results are shown in the upper panels for the size-structured population dynamics model, in the centre panels for the delay-difference model, and in the lower panels for the biomass dynamics model. The solid lines for the size-structured and delay-difference models indicate the maximum likelihood estimates while the dotted lines for these models are 90% confidence intervals. The solid lines for the biomass dynamics model denote the expected time-trajectories (based on 1,000 draws from the posterior distribution), the shadings cover the posterior inter-quartile range and the dotted lines indicate the posterior 90% probability intervals. Note that spawning stock size is expressed in different units for the three models.

Cases 2, 7, and 8 (the cases in which *P. semisulcatus* is modelled using the biomass dynamics model) lead to considerable inter-annual variation in profit and the catches of *P. semisulcatus* and *M. endeavouri* (Figure 11.2) as well as in the effort by the fishing strategy that targets *P. semisulcatus*.

Table 11.2. Summary of the outcomes of the integrated economics model. Summary statistics include the expected catch for 2008, C_{2008}, the long-term catch under an MEY strategy, C_{MEY}, the number of fishing days for 2008, E_{2008}, the number of fishing days in 2014 and later under an MEY strategy, E_{MEY}, the ratio of S_{MEY} to S_{MSY} for each species, and the relative profit.

Case	C_{2008} (t)	C_{MEY} (t)	$S_{\text{MEY}}/S_{\text{MSY}}$	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Reference								
P. semisulcatus	1039	1447	1.331	1.414	1.063	3587	5602	100
P. esculentus	852	1231	1.164	1.250	1.073	2777	4370	
M. endeavouri	325	646	1.218	0.796	0.653			
Case 1								
P. semisulcatus	824	1608	1.239	0.964	0.779	2777	5392	115
P. esculentus	695	1313	1.081	0.705	0.652	2777	3861	
M. endeavouri	311	691	1.190	0.555	0.467			
Case 2								
P. semisulcatus	715	1668	1.169	1.032	0.883	2777	5875	115
P. esculentus	539	1268	1.025	0.746	0.728	2777	4157	
M. endeavouri	293	793	1.011	0.577	0.571			
Case 3								
P. semisulcatus	852	1450	1.265	1.348	1.065	2777	5623	106
P. esculentus	833	1235	1.071	1.158	1.081	2777	4420	
M. endeavouri	294	857	1.083	0.584	0.539			
Case 4								
P. semisulcatus	824	1616	1.234	0.969	0.786	2777	5462	121

P. esculentus	695	1330	1.077	0.728	0.677	2777	4100	
M. endeavouri	296	853	1.023	0.523	0.511			
Case5								
P. semisulcatus	900	1468	1.277	1.375	1.076	2980	5921	96
P. esculentus	606	1323	1.094	0.686	0.627	2777	3382	
M. endeavouri	320	819	1.112	0.515	0.463			
Case 6								
P. semisulcatus	824	1621	1.223	0.965	0.789	2777	5542	120
P. esculentus	596	1340	1.052	0.704	0.669	2777	3792	
M. endeavouri	311	830	1.027	0.493	0.480			

(Table 11.2 Continued)

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Case 7								
P. semisulcatus	740	1677	1.212	1.016	0.838	2777	5143	87
P. esculentus	833	1242	1.079	1.183	1.096	2777	4569	
M. endeavouri	287	717	1.101	0.655	0.595			
Case 8								
P. semisulcatus	739	1757	1.148	1.026	0.894	2777	5972	122
P. esculentus	695	1332	1.065	0.719	0.676	2777	4058	
M. endeavouri	284	710	1.027	0.608	0.592			

Table 11.3. Sensitivity to the results of the reference case analysis of ignoring the contribution of *M. endeavouri* to revenue.

Case	C_{2008} (t)	C_{MEY} (t)	S_{MEY}/S_{MSY}	S_{2007}/S_{MSY}	S_{2007}/S_{MEY}	E_{2008} (days)	E_{MEY} (days)	Relative profit
Reference								
P. semisulcatus	1039	1447	1.331	1.414	1.063	3587	5602	100
P. esculentus	852	1231	1.164	1.250	1.073	2777	4370	
M. endeavouri	325	646	1.218	0.796	0.653			
M. endeavouri price= 0								
P. semisulcatus	1084	1440	1.340	1.414	1.056	3794	5540	76
P. esculentus	857	1212	1.198	1.250	1.044	2777	4156	
M. endeavouri	330	643	1.245	0.796	0.639			

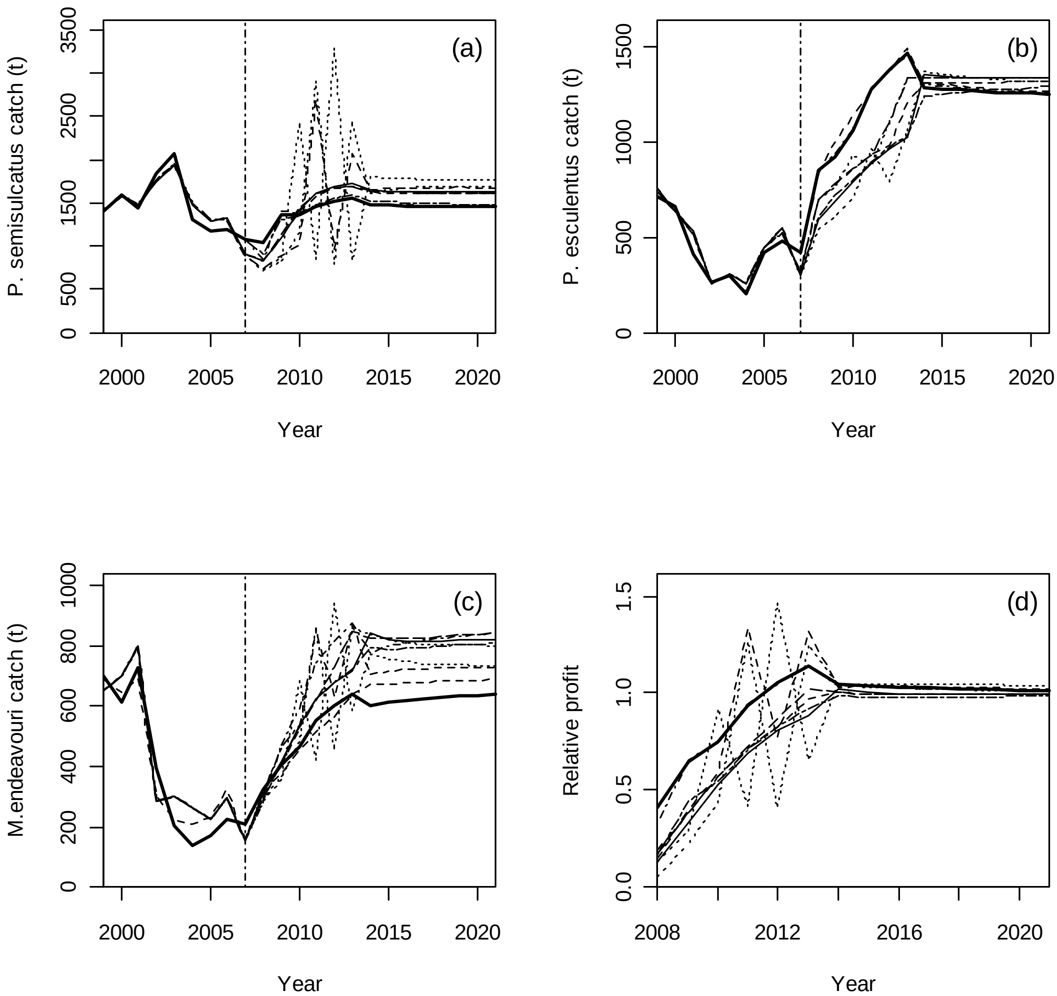

Figure 11.2. Time-trajectories of catch by species, and profit for the nine cases in Table 11.1. The bold line indicates results for the reference case in Tables 11.1 and 11.2.

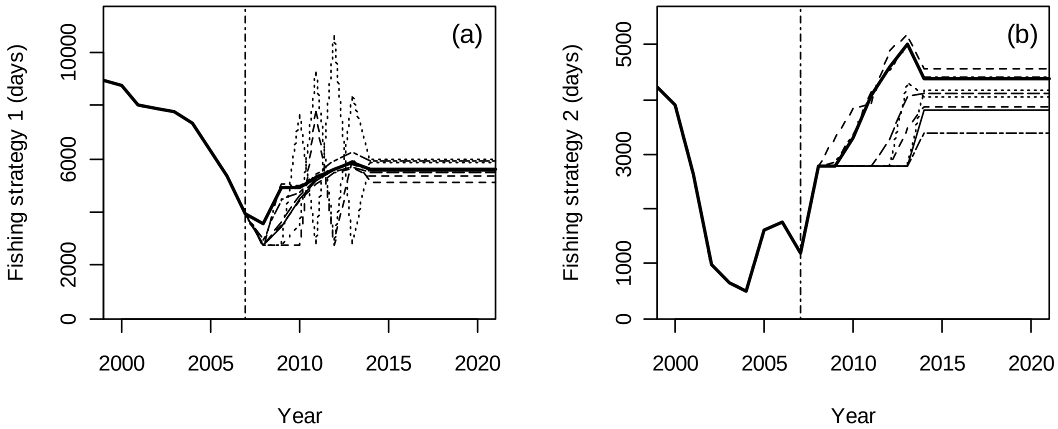

Figure 11.3. Time-trajectories of effort by fishing strategy for the nine cases in Table 11.1. The bold line indicates results for the reference case in Tables 11.1 and 11.2.

11.4.3 General discussion

The approach of this paper provides a flexible framework that enables species which differ in terms of available data and which are consequently modelled using different population dynamics models to be used to estimate net present value and consequently the catch and effort levels which maximize net present value. The framework currently includes three population dynamics models (size-structured, delay-difference and biomass dynamics). However, there is no conceptual reason why it could not be extended to include other models (such as the quarterly model outlined by Plagányi *et al*. (2010) for red-leg banana prawns *P. indicus*). In addition, the number of species which can be analysed simultaneously could be extended beyond three. Possible candidate species for future applications of the framework include red-legged banana prawns *P. indicus*, red endeavour prawns *M. ensis*, blue-legged king prawns *P. latisulcatus* and red-spot king prawns *Melicertus longistylus*.[26] Adding byproduct species would likely lead to higher effort and catch levels because additional species will lead to higher net revenues according to Equation 2, but not necessarily increased costs associated with fishing effort. This is explored in Table 11.3 which compares the results for the reference case analysis with a variant of this analysis in which the price of *M. endeavouri* is set to zero. This change leads to lower long-term catches, but higher short-term catches, of all three species and lower long-term effort levels for both fishing strategies. The higher short-term catches occur because *M. endeavouri* is assessed to be most depleted relative to S_{MSY} and S_{MEY} but there is now no value in reducing short-term harvest rates to allow recovery of this species. Changing the number of species in the analysis changes not only current and future catches but also the estimates of MSY (and hence S_{MSY}), as well as stock status relative to S_{MSY} and S_{MEY} (Table 11.3).

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[26] Ideally, all species that contribute to the profitability of the fleet should be included in the analysis, although data and knowledge limitations currently make this infeasible.

The results in Table 11.1 and Figures 11.2 and 11.3 further highlight the sensitivity of the quantities on which management advice is based to the choice of population dynamics model (and consequently on the data on which the assessment is based; the biomass dynamics model uses only the catch and effort data while the size-structured model uses data on catch-rates, survey index and length-composition as well as tagging data). It should be noted that the extent of variation in model outputs caused by model uncertainty (which model to use) is about the same as that due to assumptions regarding economic parameters for one model (see Punt *et al*. (2010) for details). There is currently no way to definitely select which model is "best" as they use different data sources, although models such as the size-structured model which utilize more of the available data and include more general assumptions regarding biological processes, should, in principle at least, lead to more accurate estimates of key model outputs. However, it may be that the available data are insufficient for these gains to be realized and this issue could be examined during future MSE analyses (if feasible).

The main restrictions on the application of the framework outlined in this appendix is that the harvested species must be represented using a population dynamics model which operates on an annual (or finer) temporal resolution. Also, this model should be "effort-conditioned" so that effort remains the key control variable in Equation 2. If more than one species is assumed to consist of multiple stocks, the stock areas for the various species must be nested.

The results from this modelling exercise can be used to set target effort levels for an effort-managed fishery and target catch levels (TACs) for fisheries managed using output controls. The results in Table 11.2 highlight that catch and effort levels for the most recent year are more uncertain (sensitive to model specifications) than those for the long-term, a result consistent with that of Punt *et al*. (2010). This is not surprising because the long-term catch and effort levels are determined primarily by the parameters of the stock-recruitment relationship, trends in costs and prices and the discount rate. In contrast, catch and effort levels for 2008 depend not only on these parameters, but also on the estimated status and size of each species at present.

The results in Table 11.2 do not account for parameter uncertainty. However, the between-model variation provides one measure of uncertainty that could be used if risk-averse catch and effort levels were desired.

11.5 References

Dichmont, C.M., Punt, A.E., Deng, A., Dell, Q. and W. Venables. 2003. Application of a weekly delay-difference model to commercial catch and effort data in Australia's Northern Prawn Fishery. *Fisheries Research* 65: 335–350.

Dichmont, C.M., Deng, A., Punt, A.E., Ellis, N., Venables, W.N., Kompas, T., Zhou, S. and J. Bishop. 2008. Beyond biological performance measures in management strategy evaluation: Bringing economics and the effects of trawling on the benthos. *Fisheries Research* 94: 238–250.

Kompas, T., Dichmont, C.M., Punt, A.E., Deng, A., Che, T.N., Bishop, J., Gooday, P., Ye, Y. and S. Zhou. Submitted. Maximizing profits and conserving stocks in the Australian Northern Prawn Fishery. *Marine Resource Economics.*

Plagányi, É.E., Bishop, J., Deng, R., Dichmont, C.M., Hutton, T., Kienzle, M., Miller, M., Pascoe, S., Punt, A.E., Venables, W.N. and S. Zhou. 2010. An assessment model of the NPF Red-legged banana prawn (*Penaeus indicus*) fishery. Appendix 11 of this report.

Punt, A.E., Deng, R., Dichmont, C.M., Kompas, T., Venables, W.N., Zhou, S. and S. Pascoe. 2010. Integrating size-structured assessment and bio-economic management advice in Australia's Northern Prawn Fishery. Appendix 9 of this report.

Schnute, J. 1987. A general fishery model for a size-structured fish population. *Canadian Journal of Fisheries and Aquatic Sciences* 44: 924–940.

Zhou, S., Punt, A.E., Deng, R., Dichmont, C.M., Ye, Y. and J. Bishop. 2010. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. Appendix 6 of this report.

Annex A. Application of Bayesian hierarchical model to the data for *P. esculentus* and *M. Endeavouri*.

I. *P. esculentus*

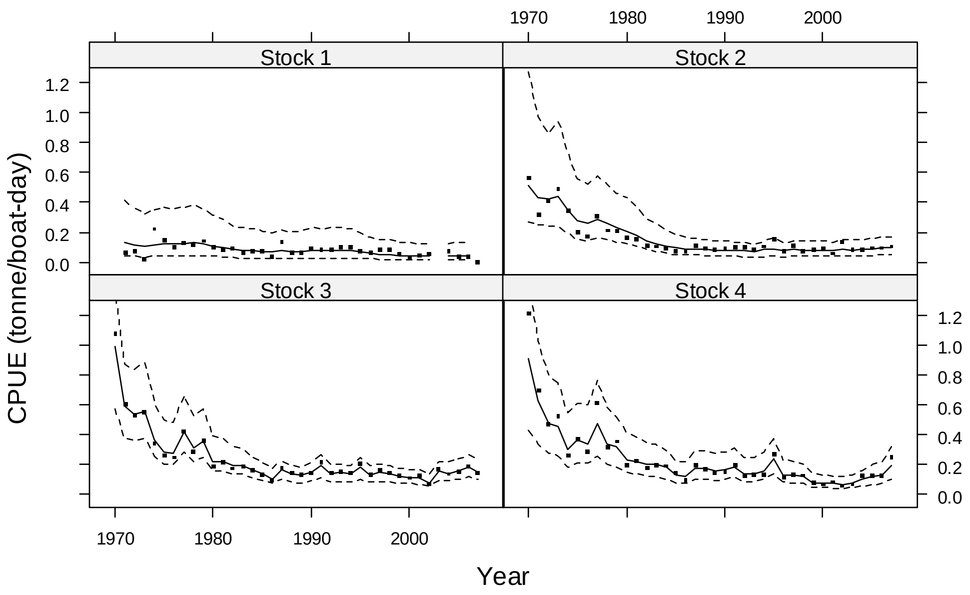

Figure 11A.1. Observed catch-rates (dots) and the posterior median time-trajectories of predicted catch-rate (solid lines) with 95% credible intervals for the target fleet (P. escu fleet). Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

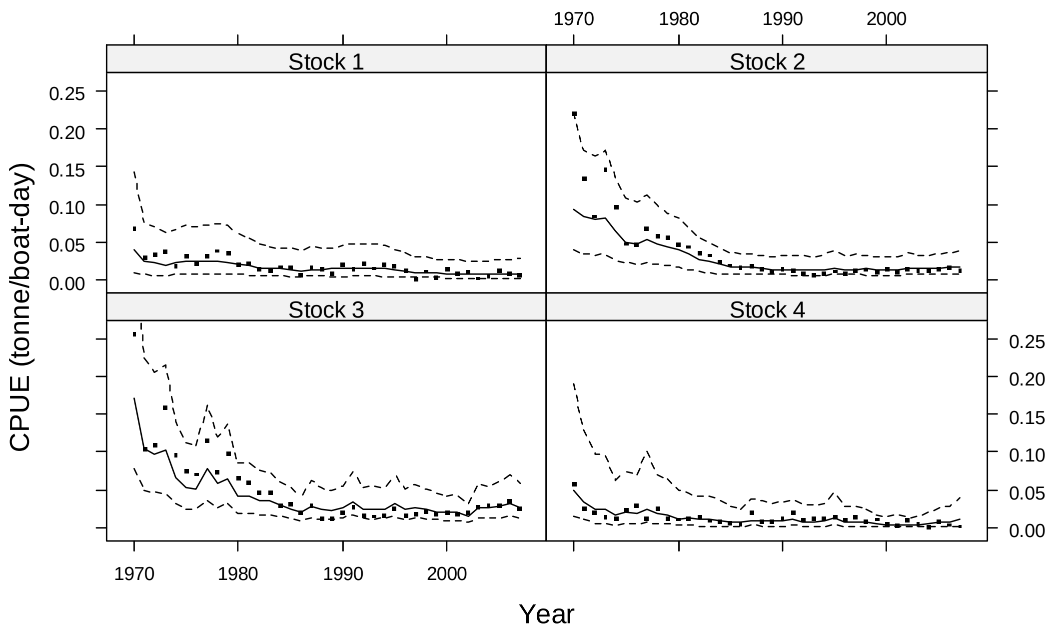

Figure 11A.2. Observed catch-rates (dots) and the posterior median time-trajectories of predicted catch-rates (solid lines) with 95% credible intervals for the bycatch fleet (P. semi fleet). Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

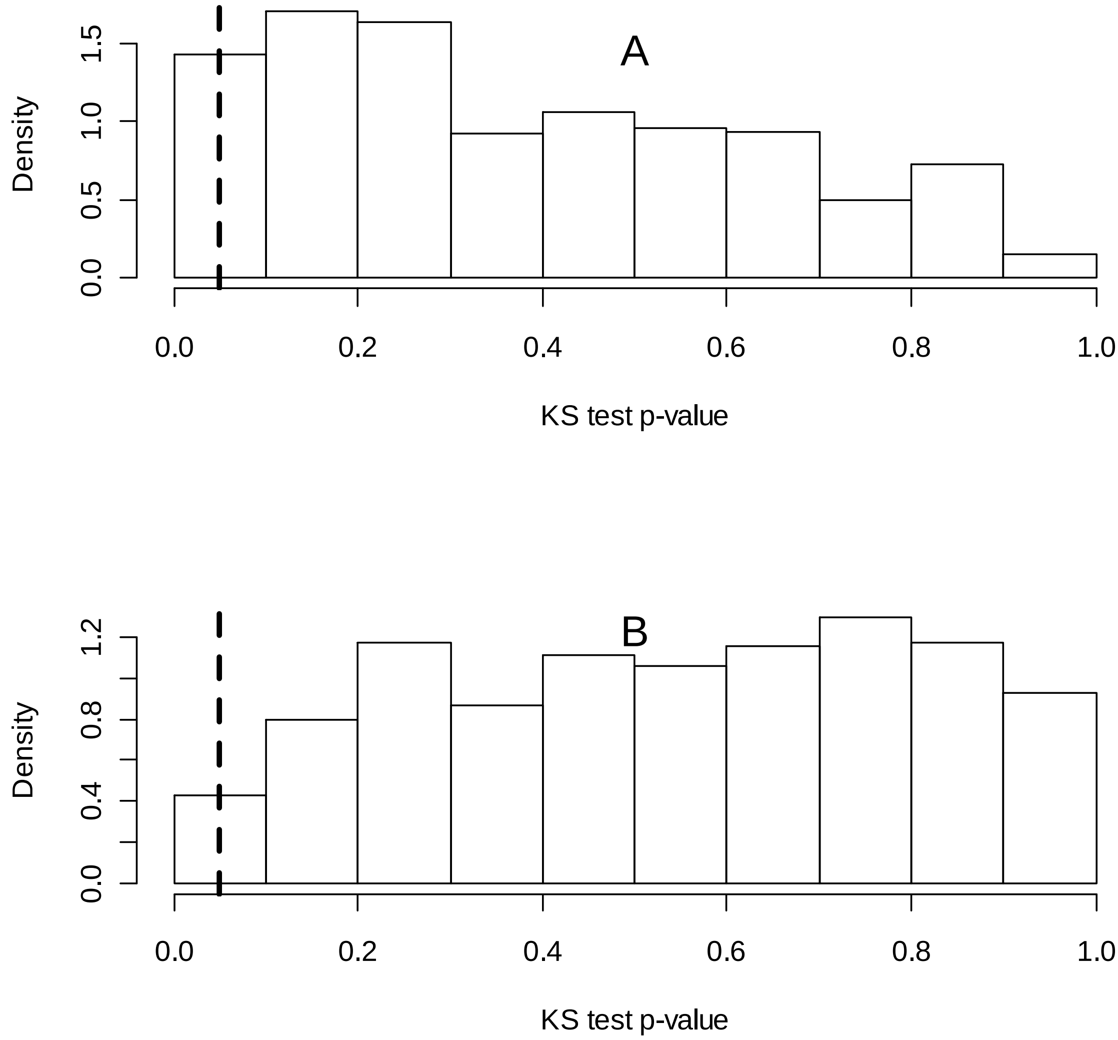

Figure 11A.3. Distribution of Kolmogorov-Smirnov (KS) test *p*-value comparing posterior predictive CPUE from biomass dynamics model and the observed CPUE. The vertical dashed line is where p = 0.05. A: grooved tiger (bycatch) fleet, B: brown tiger (target) fleet.

II. *M. Endeavouri*

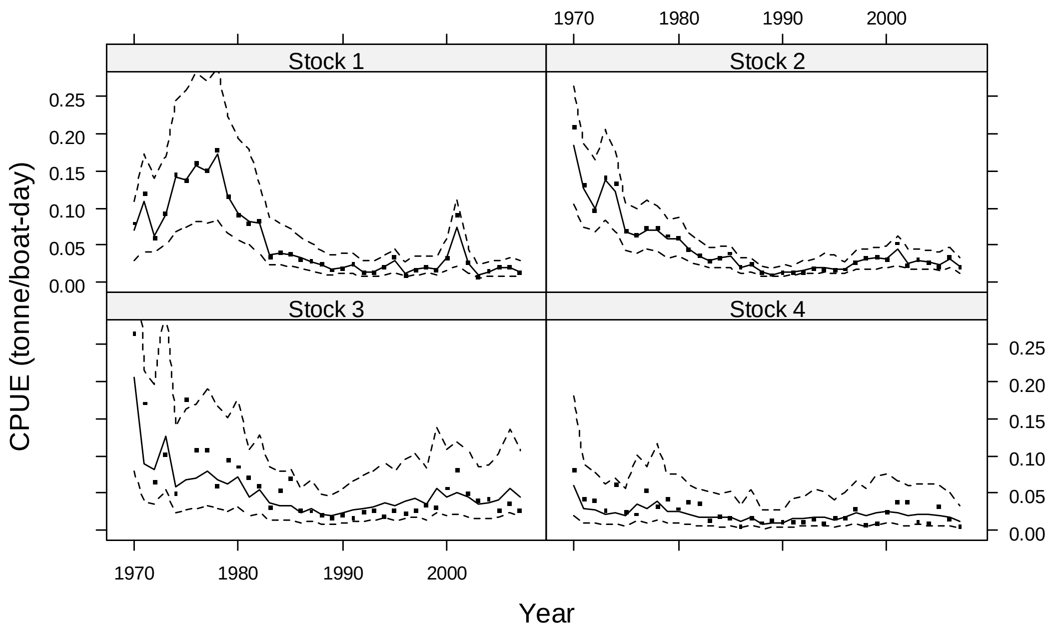

Figure 11A.4. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the semi fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

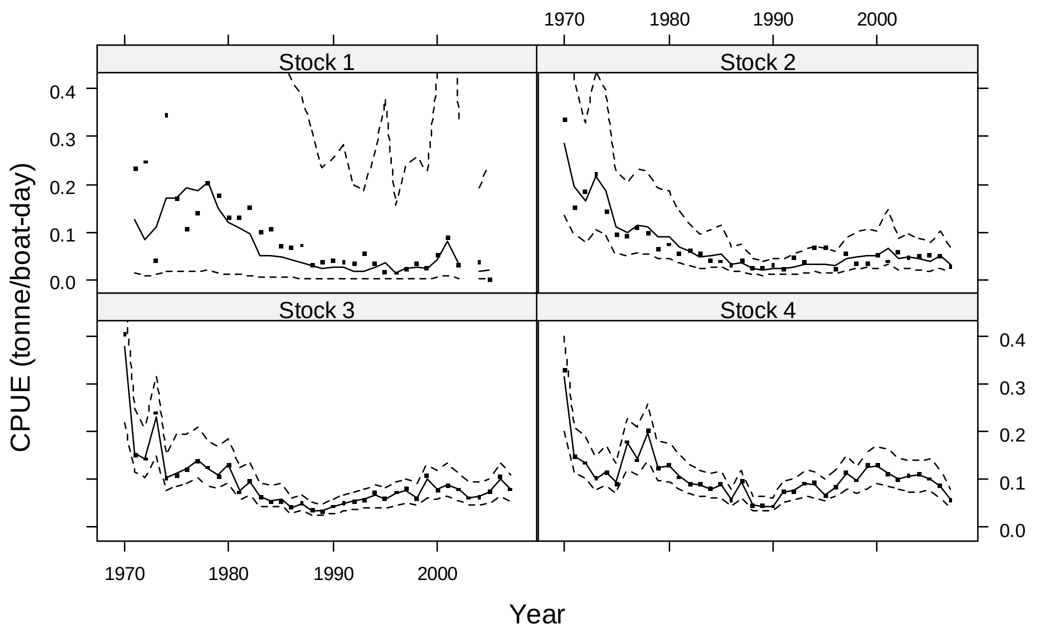

Figure 11A.5. Observed catch-rates and the posterior median time-trajectories of predicted catch-rate with 95% credible intervals for the escu fleet. Stock 1 = Outside GoC, Stock 2 = Groote, Stock 3 = Vanderlins, and Stock 4 = Weipa.

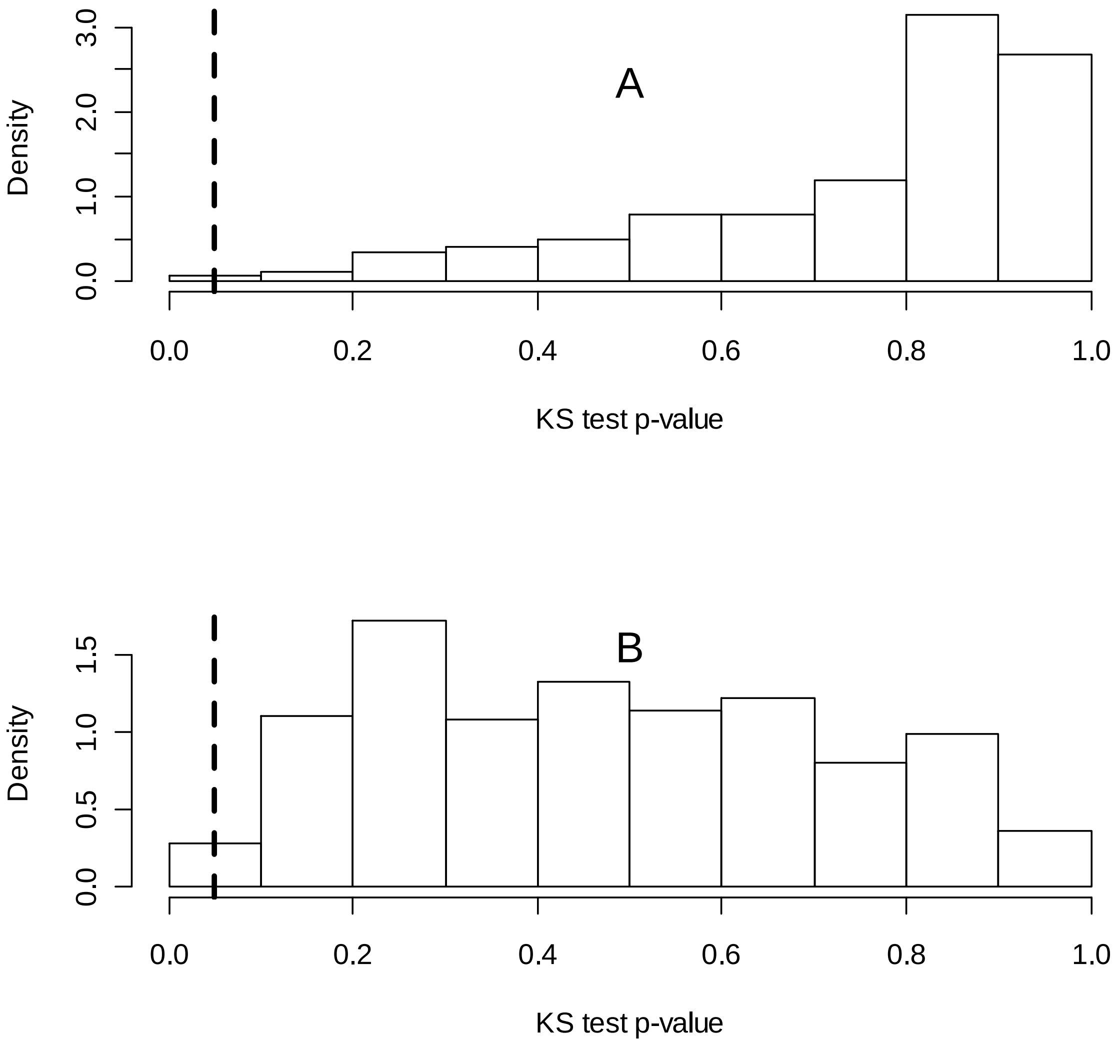

Figure 11A.6. Distribution of Kolmogorov-Smirnov (KS) test *p*-value comparing posterior predictive CPUE from biomass dynamics model and the observed CPUE. The vertical dashed line is where p = 0.05. A: grooved tiger fleet, B: brown tiger fleet.

APPENDIX 12. INCREMENTAL COST-BENEFIT ANALYSIS: AN EVALUATION OF A BANANA PRAWN OUTPUT-BASED MANAGEMENT SYSTEM

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12.1 Summary

This study considers the impact of moving to output controls (catch quotas under an ITQ system) in the common banana prawn (*Penaeus merguiensis*) Northern Prawn Fishery (NPF) using a cost-benefit analysis (CBA)[27]. The overall change in the profitability of the fishing season under different ITQ scenarios compared to the *status quo* (input control system) is evaluated taking into account changes in operational costs under each system and the assumed value of the product.

Catch restrictions have the potential to reduce the extent of the fishing season decreasing fishing costs. Under the current system fishing units tend to race-to-fish, an aspect of the fishery which could be eliminated under a catch quota system when the catch is restrictive and each participant can plan accordingly when and how to take their share. There are also implications for the quality of catch and the price that can be obtained in a fishery under output restrictions. In this analysis of the impact of output controls, the Total Allowable Catch (TAC) is set on the basis of a harvest control rule (HCR) that is either a single constant TAC based on historical catches (that can be set a various levels as part of the evaluation), or an adaptive system where an initial precautionary TAC is set then later updated based on the annual pre-season recruitment survey. These rules only apply to the first season. The potential that there are still common banana prawns in the second season that can be caught is excluded from the analyses. This is because the degree to which this occurs would require a detailed assessment – presently unavailable. The HCRs used within this evaluation should not be seen as final, but rather good examples of the two classes of rules that can be applied.

Several alternative scenarios are presented and compared with the present input control system, the *status quo*. These scenarios relate to the degree with which the

[27] Parts of this report are presented in: A cost benefit analysis of alternative management options for the Australian Northern Prawn Fishery / Sustainable Environment Group. Canberra, A.C.T. : Fisheries Research and Development Corporation, 2009. FRDC Project No. 2008/052.

output system reduces the race to fish, whether the TAC is set conservatively or not whether the TAC is updated or not using the recruitment index (Constant TAC or Updated TAC), and the magnitude of the coefficient of variation around the relationship of the observed catch versus the recruitment survey index. In the scenarios where race-to-fishing is considered, the assumption is made that this phenomenon only occurs in years where the TAC is not restrictive i.e. in cases where the TAC is set (incorrectly) at a higher level than the possible catch. No implementation error is assumed: that is, the actual catch is never greater than the TAC.

A cost-benefit analysis (CBA) is used in a simulation model that includes price and cost data to calculate profit. This is used to test the differences in profit between the present input control system and moving to an output control system. Under the existing system, research has indicated that about 85% of the stock in any year is caught (Zhou *et al.* 2007), thus the magnitude of past catches can be assumed to be a good indicator of the productivity of the stock (in fished areas). Other studies have also made this assumption (Venables *et al.* 2003; Kompas 2007). On the basis of this evidence, the past catch time series (1990-2007) is used to generate model predicted future catches.

The key aspect of the CBA in this study is its direct comparison with the *status quo* (input control), assuming each system could be subject to the same future potential productivity. To assess the relative performance of the different scenarios, relative change in profit to the input control system is calculated (termed incremental profit). Based on the results, the following can be concluded:

1. Output restrictions (TACs: Constant and Updated) reduce excessive effort resulting in lower costs which offset potential revenue losses. This leads to:
    a. higher average incremental profits. The HCRs consider the effects of the precision of the pre-season recruitment survey and the TAC set on the basis of conservative (low) or risk tolerant (high) stock productivity assumptions,
    b. higher average incremental profits are obtained (compared to input control) when output restrictions apply in years when catches are “average” (1500-3500 tonnes); whereas peak years (>5000 tonnes) will not result in higher incremental profits if output is excessively restricted. This occurs because losses in revenue will not be compensated by cost savings (as effort is inadvertently restricted when profitable catches are still available). The degree to which this loss occurs would depend on how many banana prawns can be caught in the second season.
2. Assuming future catches will be in the range of those recently observed over the period 1990-2007, setting a Constant TAC at conservative levels (the 30% quantile of observed catches or lower) results in higher average incremental profits than setting the TAC at risk tolerant levels (the 40%-100% quantile of observed catches). Obviously, as the level of the TAC at a quantile of 100% (of the observed catches) is never restrictive this scenario is equivalent to the input system.
3. Furthermore, again assuming future catches will be in the range of those recently observed over the period 1990-2007, assumptions regarding the precision of the pre-season recruitment survey (Updated TAC) will also affect the magnitude of the average incremental profits obtained, in that as the strength of the relationship of the pre-season recruitment survey to predicted catch decreases, the potential average incremental profit decreases. However, this precision can only be

increased with time rather than necessarily more extensive surveys. At present, there is little contrast in the data as most of the surveys occurred during average catch years.

4. The incremental profits are greater if the assumption is made that when race-to-fishing is not occurring, a price premium is obtained (Updated TAC- price premium). The greater the price premium, the greater the incremental profit. A price premium is only likely to be obtainable if the TAC is restrictive, and incentives are created to enhance the quality of the catch rather than the quantity. If the TACs were not binding, it was assumed that a price premium would not be obtained. However, changes in behaviour as a result of the definition of quota shares may still result in incentives to improve quality. Hence, the benefits of an ITQ system may be understated.
5. Although a Constant TAC results in greater on average incremental profits relative to an input system, in a large number of cases under this scenario the incremental profits can be lower than the *status quo*. Applying an Updated TAC on the basis of a pre-season recruitment survey results in greater than average incremental profits relative to the input system and results in less cases where the incremental profits are lower than an input controlled system (in comparison to the Constant TAC scenario).

Overall, the analysis suggests that an ITQ system for banana prawns could, on average, result in increased benefits to the industry. These benefits may only be marginal if quality cannot be improved and a price premium is not obtained. However, there is evidence that price premium can be obtained in fisheries under ITQs (Grafton 1996; Bernal *et al.* 1999) and that this potential exists for the NPF common banana prawn fishery.

12.2 Introduction

The Australian Federal Government has set in place a policy to manage Commonwealth fisheries (including the NPF) via the introduction of Individual Transferable Quota (ITQ) management type systems by 2010 where feasible. Many of the recommendations from the Ministerial Direction are already implemented in the NPF but some will need reviewing such as the implementation of a TAC/ITQ based management system (AFMA 2006). A quota-based management system restricts catch rather than inputs and represents an output regulated system.

This study considers the potential impact of an ITQ output controlled system on the common banana prawns (*Penaeus merguiensis*) fishery by reducing in-season derby-type fishing (the “race-to-fish”) and assumes if such events are reduced, quality of catch can be improved. For common banana prawns we assume that with improved quality, higher market prices per unit of catch can be obtained. In addition, any fishery that is restricted will expend less effort with significant implications on operational cost. With cost savings, fishing companies could potentially increase profit margins.

Common banana prawns are mostly targeted in the first of two fishing seasons in a year, mostly between April and May. Both revenue and costs are included in the cost-benefit analysis, with various scenarios considered. The model performance indicator computed is incremental profit. That is, the net “additional” profit that is due to either cost savings or increases in prices due to improved quality of catch compared to the current input control system. In some cases, a TAC restriction could result in a lower amount of profit relative to the input control *status quo*. In such cases, incremental profits are negative even though absolute profits may still be positive.

The sensitivity of the outcomes to both: (i) the choice of TAC and (ii) the uncertainty in the recruitment survey estimates were tested. The choice of the level of the base TAC can range from conservative (low) to risk tolerant (high). The uncertainty of recruitment survey estimates was modelled by considering the sensitivity of the performance indicator to the coefficient of variation (*cv*) of the relationship between the recruitment survey and the observed catch.

12.3 Method

Usually one would use a stock-recruitment relationship derived from a stock assessment model to derive future catches. However, a stock-recruitment relationship has not been estimated for the banana prawn stocks. In this study, therefore, future catches are based on historical catches. Under the current system (input controls) research has indicated that a large proportion (about 85%) of the common banana stock in any year is caught (Zhou *et al.* 2007). Therefore the magnitude and distribution of past catches can be assumed to be a good indicator of the potential magnitude of the productivity of the stock (in fished areas). This assumption is also made in other studies (Venables *et al.* 2003; Kompas 2007).

The key aspect of the cost-benefit analysis is its direct comparison with the *status quo*, that is, the input controlled system, with the same future potential catches. As all indices are computed relative to an input controlled system - it is the relative change, between revenues (in one system versus the other) and costs (in one system versus the other) that are estimated. The implications are such: the main performance indicator (profit) under a simulated output controlled system is compared to the potential benefits obtainable under an input controlled system and since this indicator represents the incremental gains relative to the current *status quo*, it is termed *incremental profit*.[28]

12.3.1 Common banana prawns

Catches of common banana prawns over the last 18 years (1990-2007) are shown in Figure 12.1, and the quantiles of these observed catches are presented in Table 12.1[29]. The values in Table 12.1 can be used to set alternative constant TACs at different levels. In order to obtain estimates of common banana prawns, only catches east of

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[28] If the performance indicator is positive then the output system essentially produces greater profits than an input system (and visa versa).

[29] Quantiles are points taken at regular intervals from the cumulative distribution of a variable. Thus the data is ordered and can be divided into X equal-sized data subsets for X-quantiles. The quantiles are the data values marking the boundaries between consecutive data subsets. Dividing the data into 4 parts (X=4) would yield the quartiles and a division into 100 equal parts (X=100) yields the percentiles. Strictly in this analysis the data are divided into 10 equal parts (X=10) called deciles, however since we refer to each individually, they are labelled the n/10-quantiles, where n=1….10.

132.225 degrees longitude were included in order to exclude red-legged banana prawns[30]. This is based on the species split in Venables *et al.* (2006).

Depending on the scenario, a TAC (the output control) can be set on the basis of the observed catches as a constant (Constant TAC) or on the basis of an assumed pre-season recruitment survey (TAC Updated). Note that the TAC Updated scenario follows the logic that a precautionary initial TAC is set, followed by a pre-season *update* that is based on the pre-season recruitment survey. It differs from an in-season update, but is an update all the same. An in-season update (e.g. based on fishery dependent data) was not considered in this analysis as it was the view of NORMAC that the use of in-season catch rate data would create an incentive to race-to-fish, thereby eroding the potential benefits of an output control system with catch quotas as the control variable.

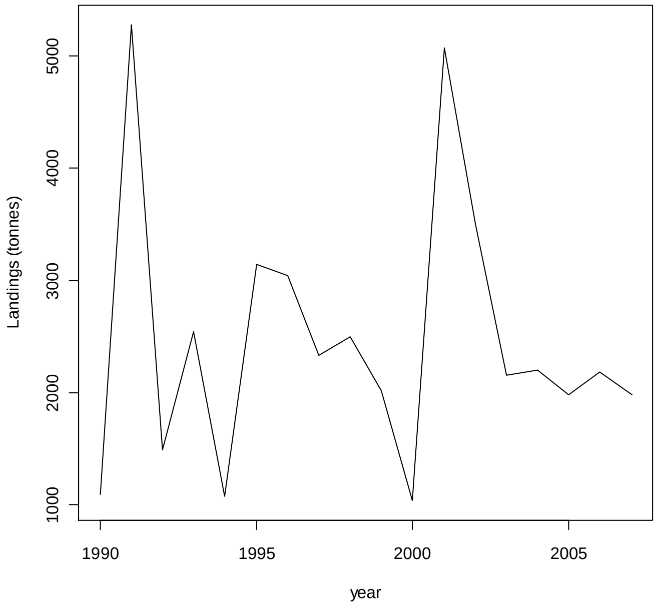

Figure 12.1. Landings of *Penaeus merguiensis* in the Northern Prawn Fishery in tonnes for the years 1990-2007.

Furthermore, in order to simulate the implementation of an output constraint, the simulated catches are based either on: (i) the model predicted TAC or (ii) model predicted future catches [whichever is lower in a given year]. In other words, there may be times when the TAC is set higher than the catch that can be realistically caught in that year. Thus the analysis is a simulation of the effects of alternative harvest control rules (HCRs) and a simulation of the implementation of these rules.

[30] This demarcation between a Western and Eastern Banana prawn stock-region has since been updated. A recommendation was tabled (a line of longitude at about 129^{o}E) at the NPRAG (November 16th-17th 2009).

Table 12.1. The value in tonnes of the quantiles of the observed catches (common banana prawns) for the time period considered (1990-2007) which can be used as alternative constant TACs.

quantile	Common (tonnes)
0.1	1088
0.2	1680
0.3	1983
0.4	2129
0.5	2193
0.6	2361
0.7	2542
0.8	3104
0.9	3976
1	5285

12.3.2 Computing Incremental Profit

Price per tonne is assumed to differ under the various alternative scenarios regarding fleet behaviour. For example, the race-to-fish is reduced when the TAC is restrictive (i.e. the TAC is set much smaller than what could have been obtained under input controls). In this case, we assumed that the incentive to race to fish is much reduced and therefore the quality of the catch can be improved. In this case a price premium could be obtained.

In addition, less effort is required to achieve the TAC and the variable costs are reduced. This cost saving could result in greater profits and the net gains can be computed for each scenario. These gains are presented in the results as incremental profit. On the other hand, when the TAC is set at a value that is non-binding (i.e. TAC is much greater than the actual catch that can be obtained), the race to fish is assumed to still remain as in the input control case. In such a case, no benefit is assumed to be achieved. See the section on “Scenarios modelled” below for more details.

The key aspect of the analysis is its direct comparison with the *status quo*, that is, an input controlled system, with the same potential catches. As all indices are computed relative to the input control case it is the relative change (thus deltas (Δs)), between revenues and costs that matter.

As profit is normally revenue minus costs, the incremental profit in the analysis is given by:

$$\begin{aligned} IP_y &= \Delta Revenue_y - \Delta Cost_y \\ &= \left((\tilde{p}_y(1-c) - o)C_y^{\mathrm{mod}} - (p(1-c) - o)C_y^{obs} \right) - v(E_y^{\mathrm{mod}} - E_y^{obs}) \end{aligned} \tag{1}$$

where IP_y is the incremental profit in year y, C_y^{mod} and C_y^{obs} are the model estimated and observed (actual) catches respectively, E_y^{mod} and E_y^{obs} are the model estimated and observed effort levels (boat days fished) respectively, *p* is the average banana prawn price, $\tilde{p}_y$ is the assumed price received in year *y*, *c* is the crew share of revenue (*c*=0.23), *o* is other variable costs associated with the catch (e.g. freight, packaging, *o*=\$1060) and *v* is the average variable cost per boat day fished (v=\$4000) (data from 2008 tiger prawn assessment see NPFRAG (2008)).

In the base scenario, it is assumed that $\tilde{p}_y = p = 8000$ per tonne. That is, there is no price premium. In other scenarios, a price premium is assumed to exist in years when the TAC is binding and fishers have an incentive to improve their quality by fishing slower. That is,

$$\tilde{p}_y = \begin{cases} 8000 \quad where\, TAC_y \geq C_y^{obs} \\ (8500,\ \ 9000\ \ or\ \ 9500) \quad where\, TAC_y < C_y^{obs} \end{cases} \tag{2}$$

where TAC_y is the total allowable catch in year *y*. The TAC was set in a range of ways depending on the scenario examined. In the second scenario, TACs were set as a constant level over all years, but the constant TAC level was varied between the 10 per cent and 100 per cent quantiles of the observed catches (see Table 12.1).

In the third set of scenarios, the TAC is updated based on a pre-season recruitment survey estimate of the catch (see Annex A) and the *cv* is the assumed *coefficient of variation* representing the accuracy of the recruitment survey. Recruitment survey indices for banana prawns were obtained from Milton *et al.* (2008). At present, a preliminary evaluation of an actual relationship between the recruitment index and catches indicate that a relationship does exist but the *cv* is likely to be in the region of 0.35 at the very best (and greater, that is 0.4 and above, thus we assumed a value of 0.4 for all the analyses) (see Annex A).

The *cv* of the recruitment survey versus observed catch was also varied between 10 per cent and 100 per cent. A *cv* of 10 per cent implies that the relationship is assumed to be known very well, whereas a *cv* of 100 per cent assumes a very poor connection between the recruitment survey index and the subsequent catch.

Annex A also provides the rationale for the assumed harvest control rule. An initial TAC (C_{min}) is set based a quantile of the historical catches (depending on a choice, of one of the values in Table 12.1) and after this first step the pre-season recruitment survey is used to *increase* the TAC if the recruitment survey indicates the potential catch is greater than initial TAC (C_{min}).

$$TAC_y = \begin{cases} C_{\min} \quad where\ C_y^{obs} \leq C_{\min} \\ 1000 + 0.42 C_y^{survey}\ \ where\ C_y^{obs} > C_{\min} \end{cases} \tag{3}$$

In Equation 3 (see also equation A2, in ANNEX A) we use the observed catches because we do not have a long enough abundance series to generate C_y^{survey}. In reality, the HCR should be modified such that it relates to the survey index but this task is outside the scope of this project.

Furthermore, the potential future catch (here drawn from the historically observed catch) may not be the same as the TAC since the TAC can be set higher than what is available. Therefore, the catch in each year in the model under an output control system is either the observed catch (when the TAC is set too high) or the TAC. This can be mathematically expressed as

$$C_y^{\text{mod}} = \begin{cases} C_y^{obs} & where\ TAC_y \geq C_y^{obs} \\ TAC_y & where\ TAC_y < C_y^{obs} \end{cases} \quad (4)$$

The model effort in each year was derived from the assumed catch, and given by

$$E_y^{\text{mod}} = \alpha_y \exp(\beta_y C_y^{\text{mod}}) \quad (5)$$

Where α_y and β_y are year specific coefficients derived from the observed cumulative catch and effort data each year.

The parameter values for α_y and β_y are given in Table 12.2. There is some variation in the functional form of the cumulative effort versus cumulative catch relationships (although the fits are reasonably good for an exponential relationship). Due to the above mentioned variation in the functional form for the cumulative effort versus cumulative catch relationship, in a few years (see Table 12.2) the range over which the model was fitted only included cases where the cumulative catch was at least 850 tonnes. As low catches in this above mentioned range are not part of the simulated time series this is not considered to cause a bias in the results. Values for β are such that the model predicted maximum effort is almost equal to the observed maximum effort in year *y* (<4 per cent difference in any given year *y*).

When these parameters are used to describe the observed trends for each year we obtain the relationships between cumulative catch and cumulative effort presented in Figure 12.2. It is therefore important to note that effort calculated in Equation 5 is not optimised in order to evaluate equilibrium conditions within a bio-economic model.

Table 12.2. The fishing effort (boat days) targeting common banana prawns (in the first fishing season) and the estimated parameters for the cumulative catch/effort relationships including a measure of goodness of fit (R-squared).

Year	Effort	α	β	R-squared
1990	2173	96.6	0.00000285	0.985
1991	4054	211.3	0.000000559	0.983

1992	2511	131.2	0.00000199	0.994
1993	3245	179.8	0.00000114	*0.983
1994	2678	464.1	0.00000162	*0.973
1995	2717	294.9	0.0000007	*0.995
1996	3187	102.9	0.00000112	0.991
1997	2357	73.5	0.00000148	0.994
1998	3131	213.5	0.00000108	*0.992
1999	2574	104.9	0.00000158	*0.959
2000	1958	96.6	0.00000295	*0.979
2001	3826	282.9	0.000000515	*0.972
2002	2502	84.3	0.00000096	0.989
2003	2325	193.1	0.00000117	*0.992
2004	2379	93.01	0.00000149	*0.977
2005	1986	66.9	0.00000171	*0.982
2006	2153	394	0.00000078	*0.991
2007	1777	67.9	0.00000166	0.985

*years in which the relationship was not fitted over all the data (only when catch greater than >800 tonnes or >1000 tonnes) depending on functional form.

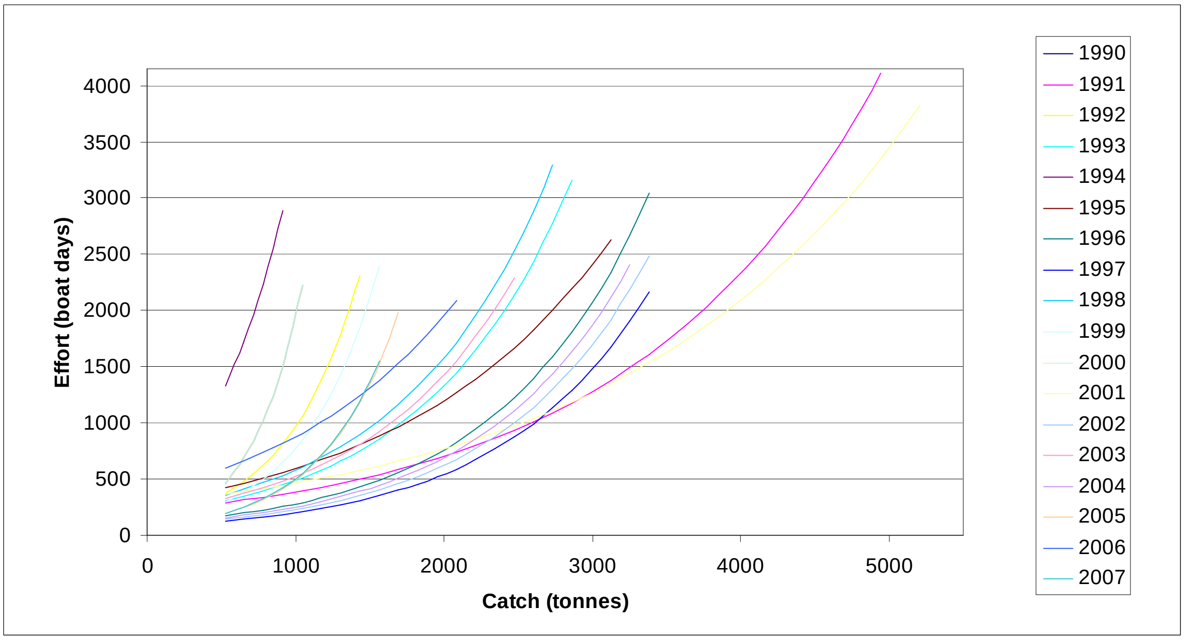

Figure 12.2. Relationship between model cumulative effort versus cumulative catch (1990-2007).

These estimates of how effort will change are included in the estimation of incremental profit for any modelled scenario (see Equation 1). This is an important element of the analysis as changes in operational costs can be significant.

12.4 Scenarios modelled

12.4.1 Common banana prawns

The base case considered in this model is the *status quo*, that is, the present input control system to which all other scenarios must be compared. Essentially, the value of base case scenario (*status quo*) is the profit in each year over the set time period of observed catches (1990-2007), based on a constant price ($8000 per tonne) and the observed effort levels. In this section we provide an outline of the scenarios modelled.

A range of issues are considered in each scenario, essentially:

- the first scenario is included to predict the effects of a TAC set as a constant (Constant TAC). The choice of the TAC level depends on a *conservative* or *risk tolerant* strategy (by choosing a low (0.1) versus high (1) value of the quantile of the observed catches),
- the second scenario is included to predict the effects of updating the TAC based on a pre-season recruitment survey. The update is based on a relationship between the annual recruitment survey index and predicted catch. However, this scenario assumes no change to the price of the catch compared to the input control system (Update TAC-no price premium). When the TAC is constraining benefits are assumed to only be due to cost reductions as the fishing operations cease to fish when their quotas are achieved,
- the third scenario, is similar to the second, except benefits occur due to cost reductions and a price premium is obtained due to improved quality of catch when the TAC is restrictive and racing-to-fish is eliminated (Update TAC-price premium). Racing-to-fish occurs when the fishery is not restricted by the TAC, that is, if the TAC is greater than the potential catch, participants can not be guaranteed to fill their quota. As formulated in the equations above, the assumed price premiums are $500, $1000, $1500 per tonne in *addition* to the base $8000 per tonne.

As a reminder, the sensitivity of the outcomes, in each scenario to both: (i) the choice of the TAC (ranging from *conservative* to *risk tolerant*) and (ii) the uncertainty in the recruitment survey estimates (recruitment survey *cv*: coefficient of variation) were tested.

Note that the TAC Updated scenario follows the logic that a precautionary initial TAC is set, followed by a pre-season *update* that is based on the pre-season recruitment survey. It differs from an in-season update, but is an update all the same. The choice of the default value (=0.3) for the quantile of observed catches on which the precautionary initial TAC is set is based on a precautionary estimate presented in MRAG (2007). Low values in the region of the 25th percentile are considered to be precautionary (thus conservative).

Thus for consistency in the analysis when the sensitivity of the model outputs are compared across the range of recruitment survey *cv*s, the quantile is set to 0.3 and correspondingly when the sensitivity of the model outputs are compared across a range of quantiles of the observed catch the recruitment survey *cv* is set to 0.4. Each scenario was run 1000 times, that is 1000 iterations were modelled to fully explore the characteristics of the performance indicator (incremental profit).

12.5 Results

12.5.1 Common banana prawns

The effect of varying the TAC level

The effect of varying the TAC set at various levels – that is alternative quantiles of the observed catches for the scenarios considered on the performance indicator (incremental profit) is shown in Figure 12.3 as a series of "box and whisker" plots. As a reminder the alternative TAC values are presented in Table 12.1 (Section 2: Method). For the Constant TAC scenario (Figure 12.3a), the incremental profit decreases as the choice of the constant TAC quantile level increases; as can be expected, since there is less chance that the output control (the TAC) is restricting the fishery. The 100% quantile is the same as the input control system.

At low (conservative) base TAC levels (quantile range 0.1-0.4), the median of incremental profits is positive indicating potential gains; although the tails of the box and whisker plots extend into negative values. Where the TACs are set low there is the probability that, in a productive year (i.e., when potential catches are in the region of 5000 tonnes), potential additional revenue will not be obtained. The TAC level is restricting potential high catches and associated revenue. If the TAC is set at a quantile of 0.3 or lower the number of cases where profits in a year are less than *status quo* increases. However, in a productive year, this analysis excludes the possibility of catching the un-caught banana prawns later in the second season of the year. As at least some of these prawns will survive to, and potentially be captured in, the second season, thus the relative losses may be overstated.

At very low TAC levels (quantile=0.1), the 25th percentile of all the values for incremental profit lies below zero indicating that in some years potential gains from a productive stock in that year are not obtained. At high (risk tolerant) TAC levels (quantile range 0.8-1), the difference between a non-restrictive TAC and an input system is minimal as would be obviously expected. In other words, as the quantile increases towards 1, then the system behaves more and more like the input control system as it is increasingly less restricted. At a value of 1 this is exactly like the current input system (*status quo*) and as a result there is no change in profit.

For the Updated TAC-no price premium scenario, the TAC is updated when the pre-season recruitment survey indicates the potential catch could be higher than the constant TAC. As was the case under a constant TAC, setting the TAC at conservative levels (the 30 per cent quantile of observed catches and less) results in higher average incremental profits than setting the TAC at risk tolerant levels (the 40-100 per cent quantile of observed catches) (Figure 12.3b). Any output restriction (the TAC restriction is binding) will result in less effort and variable costs are reduced. This cost saving results in an increased incremental profit.

The effect of large “negative” incremental profits is considerably less if future catches are of an average order of magnitude of those recently observed (1500-3500 tonnes). This is true for all the scenarios. The incremental profits are greater if the assumption is made that in years when “race-to-fishing” is absent a price premium is obtained (Update TAC-price premium) (Figure 12.3c-e). The greater the price premium, the greater the incremental profit (see increases when comparing Figures 12.3c, 12.3d and 12.3e). Higher price premiums reduce the frequency of “negative” incremental profits across the range of the quantile (of the observed catches on which basis the TAC is set) values considered.

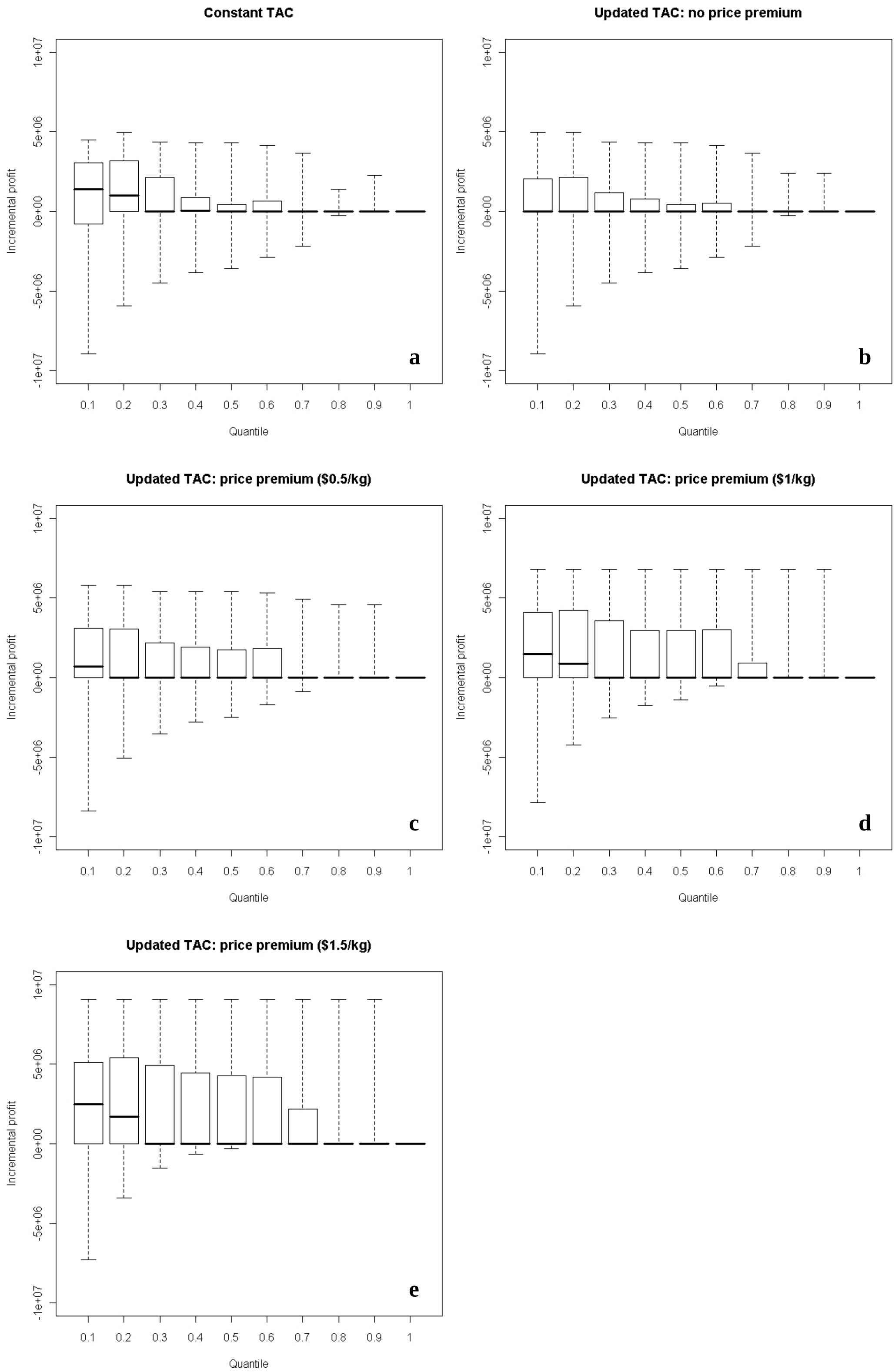

Figure 12.3a-e. Box and whisker plots for the scenarios (a: Constant TAC, b: Updated TAC-no price premium and c-e: Updated TAC-price premium [$0.5, $1 and $1.5 per kg, respectively] showing the effect of varying the quantile (of the observed catches) from 0.1-1 on the incremental profit.

If we assume that \$1/kg as a price premium is probable we can compare the magnitude of incremental profit across the scenarios for the same quantile (for consistency in this case =0.3). If we compare the incremental profit for the Updated TAC-price premium (\$1/kg) the 75th percentile of the incremental profit is greater than the incremental profit in the Updated TAC-no price premium scenario and Constant TAC scenario (both quantile =0.3, respectively). The minimum incremental profit is also greater for the Updated TAC-price premium (\$1 per kg) scenario compared to the other two scenarios.

At low (conservative) base TAC levels (quantile range 0.1-0.4), the median of incremental profits is positive indicating potential gains; although the tails of the box and whisker plots extend into negative values. Where the TACs are set low there is the probability that, in a productive year (i.e., when potential catches are in the region of 5000 tonnes), potential additional revenue will not be obtained. The TAC level is restricting potential high catches and associated revenue. If the TAC is set at a quantile of 0.3 or lower the number of cases where profits in a year are less than *status quo* increases. However, this analysis excludes the possibility of recovery of escaping banana prawns in a productive year in the second season. As at least some of these prawns will survive to, and potentially be captured in, the second season, thus the relative losses may be overstated.

The effect of the recruitment survey index versus observed catch cv

In this section we consider the sensitivity of the performance indicator (incremental profit) to the uncertainty in the observed catch versus pre-season recruitment survey relationship. Note: although the choice of the quantile value (e.g. 0.3) in the HCR is a decision to be made, obtaining a reduction in the uncertainty (the coefficient of variation) in the observed catch versus pre-season recruitment survey relationship is not a given. More years are required, with greater contrast in the data before a well-established relationship can be obtained.

The results of the effect of the recruitment survey *cv* on the scenarios considered are shown in Figure 12.4. For the Constant TAC scenario (Figure 12.4a) the incremental profit is independent of variation in the recruitment survey *cv* as a pre-season recruitment survey is not undertaken.

These values in Figure 12.4a of incremental profit for a constant TAC of 1983 tonnes (quantile value of 0.3) are essentially presented as the all results for the other scenarios need to be compared to these values. For all the other scenarios the value of the quantile (of the observed catches) is set to equal 0.3. Assuming future catches will be in the range of those recently observed over the period 1990-2007, assumptions regarding the precision of the pre-season recruitment survey will also affect the magnitude of the incremental profits obtained. As the pre-season recruitment survey precision decreases (*cv* values increase), the potential incremental profits also decrease (Figure 12.4b).

The negative values are due to situations where the potential catches are high (i.e. >5000 tonnes) and the low precision of the pre-season recruitment survey has resulted in these high potential catches been poorly predicted. The effect of large “negative” incremental profits is considerably less if future catches are of an average order of magnitude of those recently observed (1500-3500 tonnes). This is true for all scenarios.

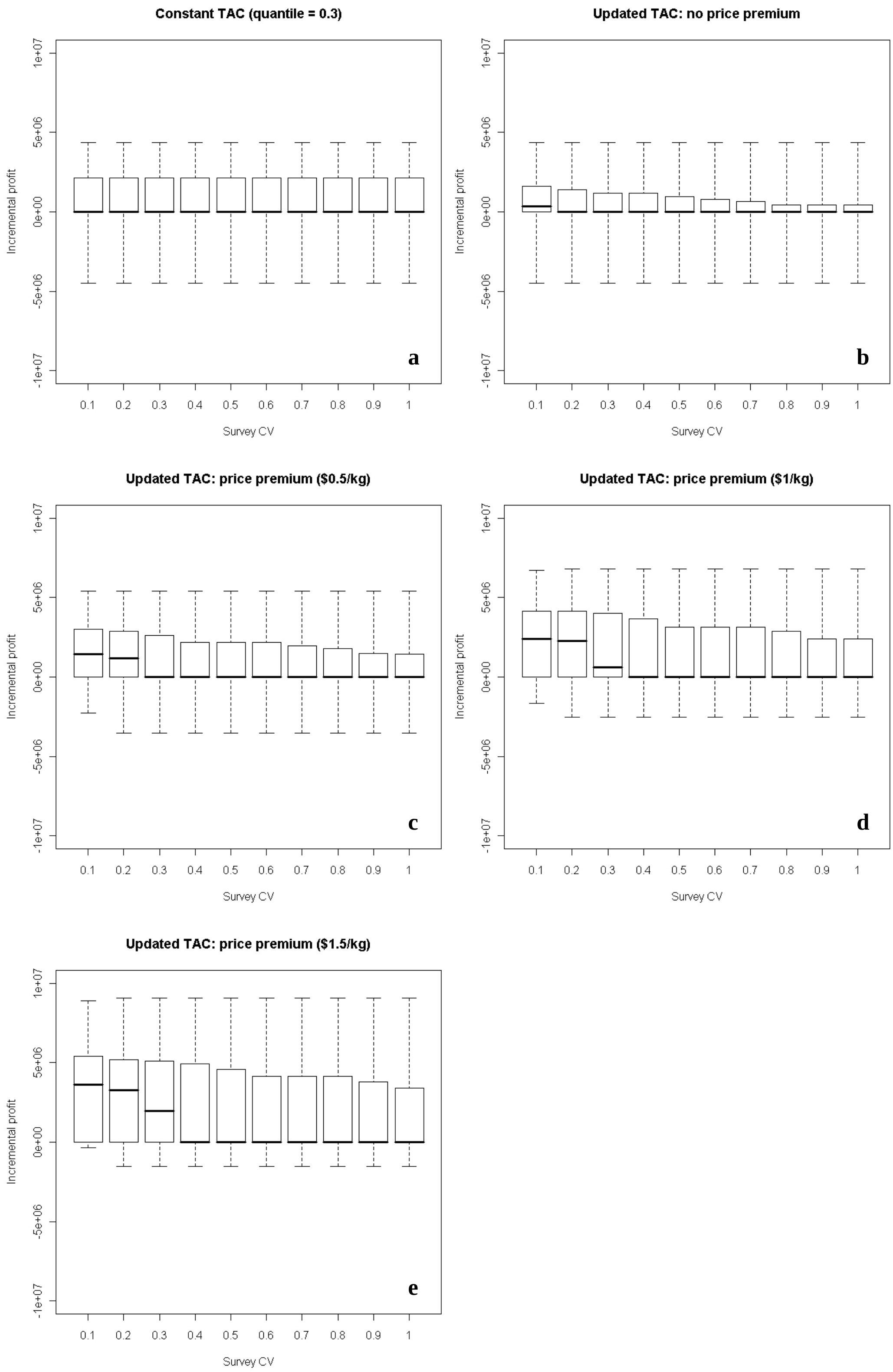

Figure 12.4a-e. Box and whisker plots for the scenarios (a: Constant TAC, b: Updated TAC-no price premium and c-e: Updated TAC-price premium [$0.5, $1 and $1.5 per kg, respectively] showing the effect of the Recruitment survey *cv* from 0.1-1 on the incremental profit.

The distribution of the results outside the inter-quartile range (the box which extends from the 25th percentile to the 75th percentile) must also be considered. Although the extent of the whisker (representing the maximum and minimum incremental profit value) is constant across the range of *cv* values considered (Updated TAC-no price premium) (Figure 12.4b), there are fewer values for incremental profit towards these two extremes as the pre-season recruitment survey precision decreases (i.e. the *cv* value increases). For example, in the case of *cv*=0.4 for the Constant TAC versus Updated TAC-no price premium (compare Figure 12.4a and Figure 12.4b: *cv*=0.4) the whisker extends to the same minimum data; but there are fewer negative incremental profit values below the 25th percentile in the case of the Updated TAC-no price premium as the survey *cv* increases. This results in greater average incremental profits (as an example for *cv*=0.4 and quantile = 0.3, compare Constant TAC average incremental profit = $0.54million versus Updated TAC-no price premium average incremental profit = $0.60million, Table 12.3).

Values of precision in the region of a recruitment survey *cv* of 0.1-0.3 can not be expected considering the characteristics of the stock and the current recruitment survey regime. At present, the actual relationship between the recruitment index and catches indicate that a relationship does exist but the *cv* is likely to be in the region of 0.35 at the very best (and greater, thus we assumed a value of 0.4 for all the analyses) rather than higher levels of precision (see Annex A).

The incremental profits are greater if the assumption is made that a price premium is obtained in years when “racing-to-fish” is absent (Updated TAC-price premium) (Figure 12.4c-e). The greater the price premium, the greater the incremental profit (see increases when comparing Figures 12.4c, 12.4d and 12.4e). Note that if a high price premium can be obtained ($1500 per tonne), the frequency of “negative” incremental profits is reduced, and furthermore reduced across the range of recruitment survey *cv*s considered.

Detailed comparison of a restrictive TAC across three scenarios

In this section, a detailed comparison of likely outcomes is evaluated assuming a recruitment survey *cv*=0.4 across a range of restrictive TACs for the three scenarios. For all the scenarios considered, the presentation of the results as box and whisker plots was highly informative in terms of comparing across the options and likely outcomes, however a more detailed analysis is required to consider the distribution of the performance indicator (incremental profit) for each model run.

In order to present the detailed differences as clearly as possible, in addition to the plots in Figures 12.3 and 12.4, we have supplemented the output statistics with additional metrics presented in Table 12.3. These are the percentage (%) of the times the incremental profit is greater then the profit in an input system (*status quo*), the % times the incremental profit is the same as the *status quo*; and the % times the incremental profit is less than the *status quo*. Note a negative incremental profit does not imply that total absolute profit will be negative.

For the Constant TAC scenario the number of times the incremental profit is greater than the *status quo* (as a percentage) is in the region of 50-56 per cent depending on the quantile value (Table 12.3). This is high and results in a positive average incremental profit relative to the input system (in the region of $0.39 - $0.83 million). This is reflected in the box and whisker plots (see Figure 12.3a) where for the quantile values of 0.1 and 0.2, the median values are greater than zero. However, with every benefit there comes a trade-off since the proportion of times the incremental profit is less than the input controlled system is in the range of 11-22 per cent (Table 12.3). These values reflect the times the stock is productive in a particular year (potential catch greater than 5000 tonnes); however if the TAC is set low relative to the availability of the stock, lower benefits (in terms of potential revenue) are obtained.

Table 12.3. Additional metrics for the performance indicator (incremental profit) versus the three scenarios assuming the recruitment survey index versus observed catch relationship's *cv*=0.4 for a range of restrictive TAC settings (quantile of observed catches = 0.2, 0.3 and 0.4).

	Constant TAC			**Updated TAC - no price premium**			**Updated TAC - price premium ($1 per kg)**		
Quantile	**0.2**	**0.3**	**0.4**	**0.2**	**0.3**	**0.4**	**0.2**	**0.3**	**0.4**
% times > *status quo* (input controls)	56	50	50	47	42	41	53	47	43
% times < *status quo* (input controls)	22	17	11	9	7	5	3	3	3
% times same as *status quo* (input controls)	22	33	39	44	51	53	44	51	54
Average incremental profit ($millions)	0.83	0.54	0.39	0.83	0.60	0.50	2.05	1.78	1.61

The Updated TAC-no price premium scenario allows the management system by using the pre-season recruitment survey to reduce the proportion of times the incremental profit is less than the profit in the current input system (the *status quo*) - to be in the range of 5-9 per cent (Table 12.3) compared to the 11-22 per cent for the same metric in the case of the Constant TAC scenario. The possibility of obtaining a price premium ($1/kg) decreases the proportion of times the incremental profit is less than the profit in the input control system further to 3 per cent (across the range of quantile values considered) (Table 12.3). The average incremental profits in this case (Updated TAC-price premium) are even greater compared to the Constant TAC than the scenario with no price premiums.

The highest value for average incremental profit ($2.05 million (Table 12.3) for the fleet as a whole, or around $40k a boat) occurs when there is a price premium and the

TAC is very conservative (thus restrictive) i.e. a TAC of 1680 tonnes, based on a quantile value of the observed catch of 0.2 (Table 12.1). Without a price premium, average additional profits are relatively small - between $8k and $15k a vessel depending on the HCR.

12.6 Discussion

In this cost-benefit analysis the losses and gains of an output-based system (with restrictive TACs) relative to the current input controlled system are estimated for various scenarios. Output restrictions reduce excessive effort resulting in lower costs which offset potential revenue which lead to higher incremental profits which are presented for a range of scenarios (various assumptions and alternative harvest control rules (HCRs)). The HCRs consider the effects of the precision of the pre-season recruitment survey and the TAC set on the basis of conservative or risk tolerant stock productivity assumptions.

Assuming future catches will be in the range of those recently observed over the period 1990-2007, setting the TAC at conservative levels (the 30% quantile of observed catches or less) results in higher average incremental profits than setting the TAC at risk tolerant levels (the 40%-100% quantile of observed catches). The possibility of negative values for the performance indicator exist during peak years (>5000 tonnes) and the scenario will not result in higher incremental profits if output is excessively restricted. This occurs as losses in revenue will not be compensated by cost savings (as effort is inadvertently restricted).

The precision of the pre-season recruitment survey will also affect the magnitude of the average incremental profits obtained, in that as the pre-season recruitment survey precision decreases the potential average incremental profit decreases. The incremental profits are greater if the assumption is made that when racing-to-fish is not occurring a price premium is obtained. The greater the price premium, the greater the incremental profit.

For the Constant TAC scenario the number of times the incremental profit is greater than the input system is high (>50 per cent of the time) and results in positive average incremental profits. However with every benefit there comes a trade-off as the percentage of times the incremental profit is less than the input controlled system is also high relative to the other options considered (in the range of 11-22 per cent). The probability of incremental profit being negative can be reduced to within a region of 3% by the Updated TAC scenario on a basis of a re-season recruitment survey (with the assumption of a price premium of $1/kg).

While cost savings from reduced fishing effort is likely to result in improvements in profitability in the fishery, the greatest potential improvements in profits arise from a price premium assumed to be associated with improved product quality. Improvements in quality leading to higher prices following the introduction of ITQs have been observed in several fisheries (Grafton 1996; Bernal *et al.* 1999). Slowing down the fishing activity through removing the incentives to race to fish provides an opportunity for fishers to take greater care of their catch. Restrictions on the catch also provide additional incentives to maximise the value of this catch, again providing incentives to improve the product quality. While the magnitude of such a premium is highly uncertain, the range $0.50-$1.50/kg (representing 6-18 per cent of the assumed base price) is not too optimistic. Currently $1/kg is seen as achievable and thus very likely.

The analysis may underestimate the potential revenues following the introduction of ITQs. In particular, the analysis excludes the possibility of uptake of a productive year in a second season. A proportion of the banana prawns not caught in the first season will survive to the second season, supplementing the income in the latter half of the year. This could be particularly important in years with large abundances of banana prawns. Even with relatively high natural mortality rates of 5 per cent a week, between 60 and 70 per cent of any uncaught banana prawns at the end of the first season will still be alive at the beginning of the second season. While it is unlikely that the catch in the second season will offset fully the forgone revenue in the first season, it will reduce the perceived loss.

How surviving common banana prawns might be managed in the second season is not considered to any great extent. In most years, the quantity of additional banana prawns in the second season will still be relatively small and may be considered economic bycatch (even if targeted to some extent). In years of large stock abundance, it is likely that these surviving prawns will be targeted. However, there may be limited benefits from implementing a complicated management procedure in the second season when such events are likely to be relatively infrequent. Given that the main benefits deriving from the fishery will occur in the first season, lower profitability levels from targeting banana prawns in the second season may be acceptable.

The analysis is also based on a number of assumptions that may affect the results. One key assumption is that, in the absence of any restrictions on output, fishers will continue to fish for as long as they wish as if they were within the present input control system. As seen in Annex A, given the input and output price assumptions, this involves fishing beyond the point where the additional costs of fishing exceed the additional revenues. Such behaviour has been observed in recent years (also demonstrated in Annex A), where actual catches are between 25 and 40 per cent higher than the economic optimal. In most years, the season length has acted as a constraint on fishing activity. Consequently, the assumption is reasonably valid. However, even if effort levels would decline in response to the higher fuel prices and lower prawn prices in recent years, the effect of this would be to reduce the magnitude of both the potential benefits and losses each year. The net effect would be a decline in the average benefits of such a scheme, but it would most likely still remain positive.

A further assumption is that price premiums are only achieved in years in which the quotas were constraining. This was the case in 12 of the 18 years in each simulation, with three other years having only a negligible constraint. The rationale for this assumption was that, in years where TACs were not binding, incentives to race to fish would still exist (as the certainty of catching their full quota allocation was reduced or removed). However, allocation of individual quotas may still provide incentives to improve the quality of the catch even in the years where catches are low (and TACs are non-binding). Given on-board management measures will need to be implemented in order to achieve these price premiums in years when quotas are binding, there is no reason why they could not be undertaken in all years. A more cooperative rather than competitive environment in the industry may allow these benefits to occur in all years.

For common banana prawns future studies will have to consider harvest control rules under a TAC controlled system. The HCR used in the analysis was developed as an example only, and potentially greater benefits could be achieved through an alternative specification of the HCR. Defining a definitive HCR was beyond the scope of this study. However, the results suggest that any HCR developed for the fishery needs to be restrictive in order to achieve the greatest economic benefits. Overall, the analysis suggests that an ITQ system for common banana prawns could, on average, result in increased benefits to the industry. These benefits, however, may only be marginal if quality cannot be improved and a price premium is not obtained.

12.7 Annex A: Simulating a harvest control rule, including a catch-recruitment survey index relationship

The definition of a definitive harvest control rule (HCR) is beyond the scope of this study. However, some form of HCR was needed to be implemented in the simulations to estimate the potential benefits of a quota system.

The HCR used in the analysis was based on a number of principles. First, a minimum TAC should exist that is represented by a given percentile of the observed catches. This minimum was varied from the 10th to 100th percentile. Second, the update component of the HCR should attempt to correspond to some level of economically optimal harvest.

12.7.1 Optimal catch levels

An optimal TAC can be given by the point where marginal revenue equals marginal cost. Beyond this point, the additional revenue is less than the additional costs and profits subsequently decrease. Given the effort-catch relationship in equation 4 (main text), a catch-effort relationship can be derived as

$$C = \frac{1}{\beta}\left[\ln E - \ln \alpha\right] \qquad \text{(A1)}$$

where α and β are as defined earlier. Marginal revenue is give by $p\,dC/dE = p/\beta E$, where p is the average net price per kg (assumed $8/kg less 23 per cent for crew payments and less $1.06/kg transport and marketing, giving a net price of $5.10/kg). Marginal costs, c, are assumed constant ($4000/day). Consequently, optimal effort is given by $\hat{E} = p/\beta c$, and optimal catch, $\hat{C}$, can be estimate by substituting the optimal effort level back into equation A1.

The relationship between observed and optimal catch and effort over the period of the data given the (actual) prevailing input and output prices are illustrated in Figure 12A.1, while those with the assumed prices in Figure 12A.2. Prior to 2000, fishers were able to switch to tiger prawns earlier in the season – creating an additional opportunity cost not included in the above set of costs. As a result, catches were either close to, or slightly below the optimal level if banana prawns were considered in isolation. Post 2000, vessels were unable to switch to tiger prawns and tended to remain in the banana prawn fishery. In the last few years, catches generally exceeded the optimal level by between 20 and 30 per cent.

Applying the costs and prices received in 2007 to all years resulted in the optimal catch and effort level being below the observed level (Figure 12A.2). On average, the optimal catch was 70 percent of the observed catch, although this varied considerably as seen from Figure 12A.2. High effort levels in some of the earlier years were also an artifact of the larger fleet size. In 2006 and 2007, optimal catches were around 80 per cent of the actual catches.

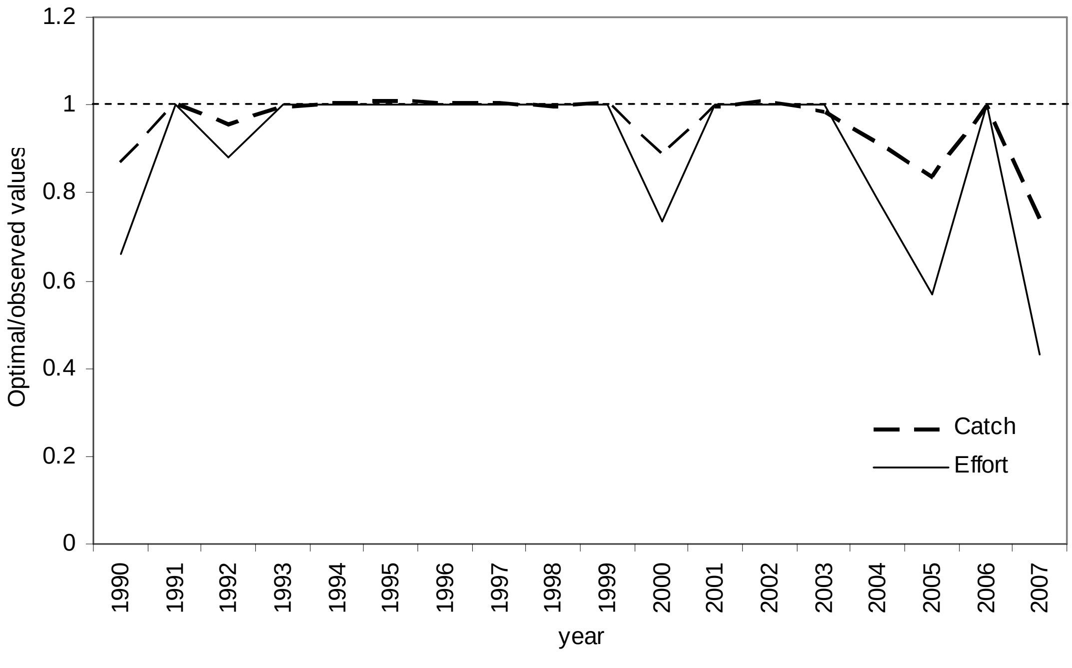

Figure 12A.1. Relationship between optimal and observed catch and effort given actual prices and costs

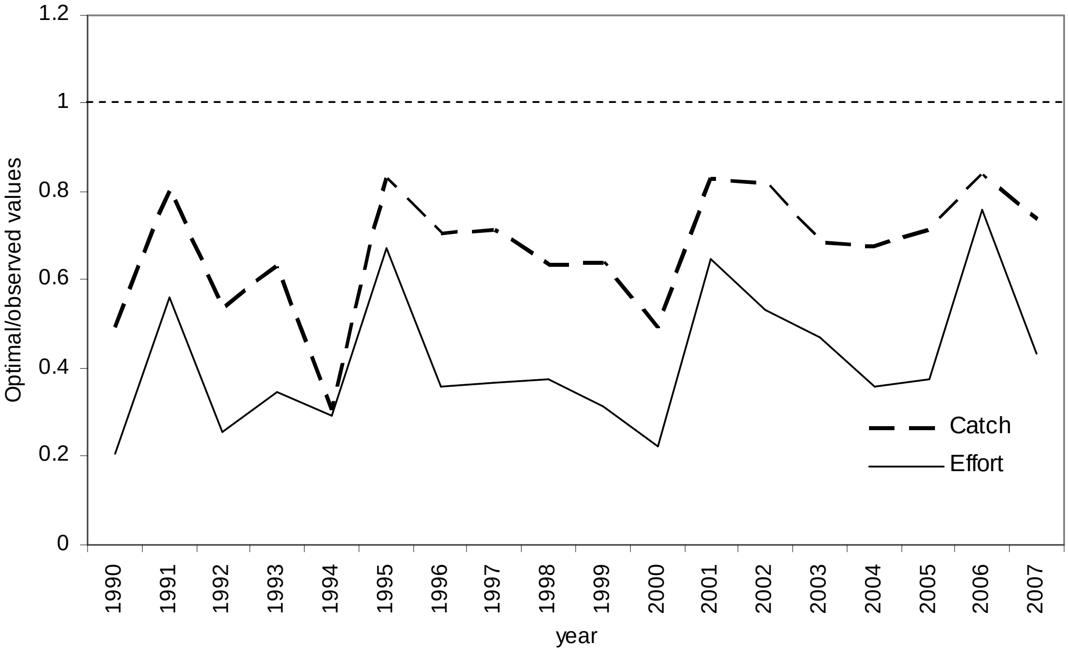

Figure 12A.2. Relationship between optimal and observed catch and effort given 2007 prices and costs

12.7.2 Harvest control rule in the simulations and catch-recruitment survey index relationship

The harvest control rule used in the study was *ad hoc* to an extent but conformed to the general principles outlined above. The rule is given by

$$TAC_y = \begin{cases} C_{\min} & \textit{where } C_y^{obs} \le C_{\min} \\ 1000 + 0.42 C_y^{survey} & \textit{where } C_y^{obs} > C_{\min} \end{cases} \tag{A2}$$

where C_{min} is the minimum TAC defined by the percentile being considered. In Equation A2 we use the observed catches because we do not have a long enough abundance series to generate C_y^{survey}. In reality, the HCR should be modified such that it relates to the survey index but this task is outside the scope of this project. (Of course, in reality the observed catch would not be available at the time the TAC update will be calculated but in this simulation, historically observed catches are a proxy for future catches)

Implicit in the HCR is a relationship between the recruitment survey index and observed catch, such that (presumably) an estimate of “observed” (unrestricted) catch could be determined given a particular recruitment survey index. Such a relationship exists, and takes a similar form to the TAC rule above (Figure 12A.3).

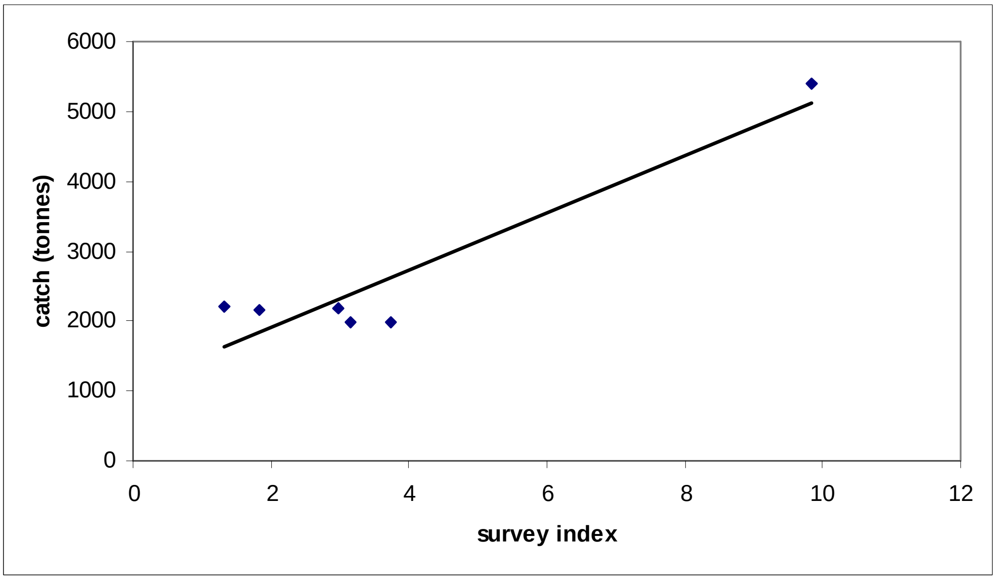

Figure 12A.3. Observed catches versus the recruitment survey index (index values from Milton *et al.* (2008)) for the years 2004-2008, with the 2008 catch being based on preliminary data.

The HCR in the case of the 30th percentile is illustrated in Figure 12A.4 and the implications of the HCR in each year illustrated in Figure 12A.5. On average, the TAC is 86 per cent of the observed catch, roughly consistent with the relationship between optimal and observed catches.

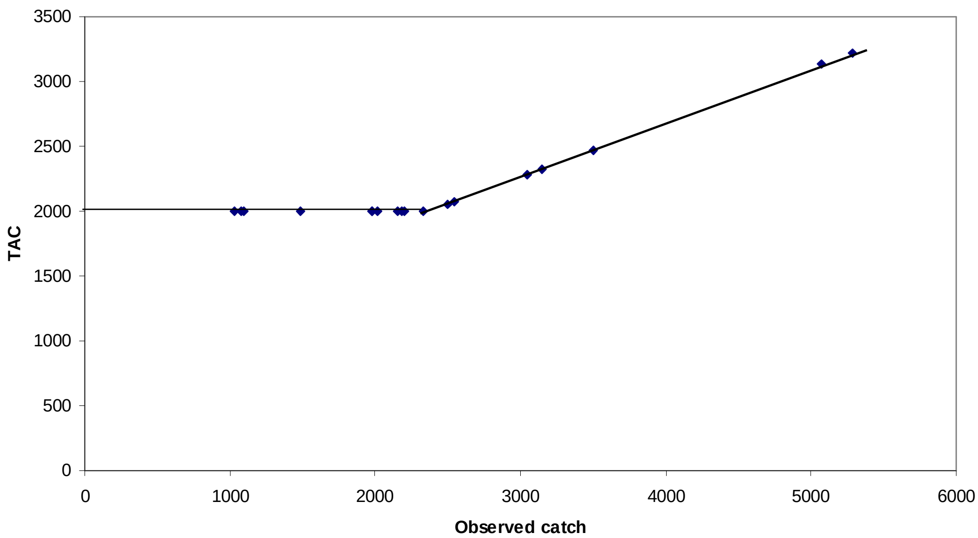

Figure 12A.4. Harvest control rule representing the relationship described in equation A2 where the 0.3 percentile of the observed catches is the value for C_{min}.

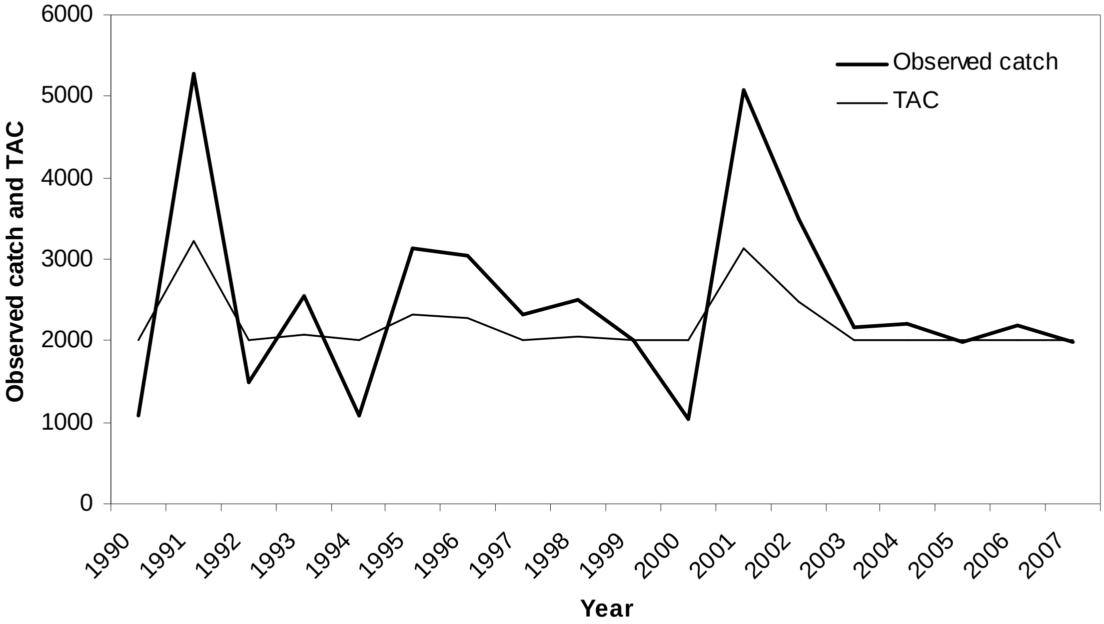

Figure 12A.5. Observed catches and TACs (excluding random error)

The HCR is not definitive and was developed solely for the purposes of the cost benefit analysis. Alternative HCRs exist, and no doubt some of these may result in greater benefits than the HCR used in the study.

12.7.3 Implementing the HCR given recruitment survey error

As the relationship between the recruitment survey index and the observed catch is not perfect (Figure 12A.3), random error is introduced into the analysis to allow for "getting it wrong". The TAC used in each of the stochastic simulations is drawn from a random distribution around the observed catch with varying levels of precision. The distribution is given by $N[TAC_y | C_y^{obs}, \sigma_y]$, where $\sigma_y = cv \bullet C_y^{obs}$. With a *cv* of 10% this relationship is assumed to be known very well, whereas a *cv* of 100% assumes a very poor connection between the recruitment survey index and the subsequent catch.

12.8 References

AFMA, 2006. Response to Ministerial Direction – Northern Prawn Fishery. Australian Fisheries Management Authority. (http://www.afma.gov.au/securing/docs/npf.pdf)

Bernal, P.A., Oliva, D., Aliaga, B. and Morales, C. 1999. New regulations in Chilean Fisheries and Aquaculture: ITQ's and Territorial Users Rights. *Ocean & Coastal Management* 42: 119-142.

Grafton, R.Q. 1996. Individual transferable quotas: theory and practice. *Reviews in Fish Biology and Fisheries* 6: 5-20.

Kompas, T. 2007. Management options for the Australian Northern Prawn Fishery: a preliminary cost-benefit analysis. Sustainable Environmental Group. 21p.

Milton, D.A., R.A.Kenyon, C. Burridge, M. Zhu, R. Pendrey, T. van der Velde, A. Donovan and M. Kienzle 2008. An Integrated Monitoring Program for the Northern Prawn Fishery 2006/08. (R05/1024 l 30/09/2008).

MRAG, 2007. Assessment of alternative approaches to implementing Individual Transferable Quotas (ITQs) in the Australian Northern Prawn Fishery (NPF) and identification of the impacts on the fishery of those approaches. Final Report.

NPFRAG, 2008. Bio-Economic Model Status of Tiger Prawn Stocks at the end of 2007 in the NPF, *Report of the NPFRAG*. CSIRO, Brisbane.

Venables, B., C. Dichmont, P. Toscas, J. Bishop, Y. Ye and R. Deng 2003. Report to NORMAC on Effort Trade-off Proposals for the NPF. CSIRO/NORMAC. 53p.

Venables, W. N., Kenyon, R. A., Bishop J. F. B., Dichmont, C. M., Deng, A. R., Burridge, C. Y., Taylor, B. R., Donovan, A. G., Thomas, S. E., and Cheers, S. G. 2006. Species distribution and catch allocation : data and methods for the NPF, 2002-2004. Final report. AFMA Project No. R01/1149 Canberra: Australian Fisheries Management Authority. 190 p.

Zhou, S., C. Dichmont a, C. Y. Burridge W. N. Venables , P. J. Toscas c, David Vance. 2007. Is catchability density-dependent for schooling prawns? *Fisheries Research* 85: 23–36.

APPENDIX 13. AN ASSESSMENT MODEL OF THE NPF RED-LEGGED BANANA PRAWN (*PENAEUS INDICUS*) FISHERY

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13.1 Summary

A range of assessment approaches have been applied to the major species comprising the Northern Prawn Fishery. This paper summarises a revised assessment model developed for red-legged banana prawns (*Penaeus indicus*) that incorporates suggestions provided by the RAG. Quarterly time steps are used to represent the dynamics and the model is fitted to available Catch and Effort data. These data are standardised using a fishing power series derived for red-legged banana prawns. Key sensitivities are highlighted and some preliminary model results presented. A preliminary assessment of resource status and reference level estimates is provided.

13.2 Introduction

The Northern Prawn Fishery (NPF), at times the most valuable Commonwealth managed fishery, extends from Cape Londonderry in Western Australia to Cape York in Queensland (Gillett 2008). Commencing in the late 1960s, it is a multi-species fishery targeting at least nine species of prawns, including two tiger prawn species (*Penaeus semisulcatus* and *P. esculentus*), two endeavour prawn species (*Metapenaeus endeavouri* and *M. ensis*) and common and red-legged banana prawns (*Penaeus merguiensis* and *P. indicus*). A variety of assessment methods have been applied to these species, ranging from relatively simple biomass dynamic models (Zhou et al. in review Appendix 14), through delay-difference models (Dichmont *et al*. 2003) to size-structured population dynamics model integrated with bio-economic advice (Punt *et al*. 2009)(Annex 3).

Red-legged banana prawns comprise a relatively small percentage of the total prawn catch and are one of the less well assessed species in the NPF, although they are exploited as far afield as East Africa, Madagascar, India, Malaysia, Thailand and Indonesia. The bulk of their range within the NPF lies within the Joseph Bonaparte Gulf (JBG), which corresponds to the recent Stock 1 classification defined by Venables *et al.* (2009).

The *P. indicus* fishery essentially developed in the early 1980s (Fig. 13.1). There have been considerable changes in fishing effort in the JBG, with the number of days fished having increased to a peak of about 2300 boat days in 1986 down to 228 boat days in 2007. The fishing grounds are located in deeper waters than is the case for *P. merguiensis* and fishing takes place both day and night. Fishing effort concentrates on neap tides because of the extremely large tidal range (up to 7m) in the JBG.

This report serves to compile relevant information needed for the development of a population dynamics model, and summarises an assessment model developed for *P. indicus*. Results will be cross-compared with those produced using a multi-fleet Bayesian biomass dynamics model (Zhou *et al*. review Appendix 14).

13.3 Methods

Biological Monitoring information

P. indicus are caught in three banana stock regions in the NPF area: JB, FB, and CM, with substantially larger catches being taken from the JB region (Fig. 13.1). Venables (2009) explored the consequences of different stock boundary options, and the RAG subsequently proposed modeling the JB population only (see Annex 1).

Weekly catch and effort data are available from 1970, but given the almost negligible catches during the 1970s (see Fig. 13.1 and Annex Fig. A.1), the assessment starts in 1980. These data were analysed per week, per month, per quarter and per year and it was considered that the most sensible aggregation would be by quarter, with four quarters defined as corresponding to the four quarters of a calendar year respectively, i.e. Quarter 1 = January – March; 2 = April – June; 3 = July – September and 4 = October – December. A historic catch series per quarter was constructed using all available catch information. The fishery essentially developed in the early 1980s, peaking at around 977 tons in the JBG in 1997 and decreasing to around 131 tons in 2007. The largest catches historically were typically taken in the second quarter (with a peak in May), and in the third quarter (Fig.13.1). Since 2007 the JBG has not been fished during the first seasonal opening (April to June), with fishing occurring during the second seasonal opening from August to November. As evident in Fig. 13.1, there were thus no recorded catches from the JBG during the first season of 2007.

The annual average nominal CPUE trend suggests a marked increase in CPUE over the most recent period (Fig. 13.2). However, when the data are analysed per quarter, they suggest a relatively flat trend for Quarter 4, very large fluctuations for Quarter 3 and a relatively flat trend with an increase in the last year for Quarter 2 (Fig. 13.3). The recent large fluctuations are more a consequence of small sample size than real trends, as evident from the large associated confidence intervals.

There appears to be larger fluctuations in catches and CPUE during the 1990s than during the preceding decade. The end of year NPF closure (1 December – March/April – essentially Quarter 1 in the current model) implemented in 1987 means there are differences in the data for the earlier and later periods. Over the 1988-2006 period, some of the highest catch rates are achieved in Quarter 3 (Fig. 13.4).

The Reference Case model uses a standardised CPUE series which accounts for assumed fishing power effects. Annex 2 summarises the fishing power input series for red-legged banana prawns. Figure 13.5 compares the nominal and standardised CPUE indices. Model results are also presented when using only the nominal CPUE data.

Biological information

Tag-recapture data are available from field tagging and release experiments in the JBG by Die *et al*. (2002). These data suggest fairly high natural mortality of ca. 0.05 per week. The maximum age of red-legged banana prawns is thought to be 12-15 months given no tagged prawns were caught in the year after tagging.

There are large differences between the growth rates of male and female *P. indicus*, with the latter growing much faster (Fig. 13.6). Parameter estimates for males (κ = 0.0103; L_∞ = 34.05 mm and t_0 = -0.06) and females (κ = 0.0053; L_∞ = 49.64 mm and t_0 = -0.34) were obtained from Loneragan et al. (2002) who used the Wang (1995) growth model. Length-weight relationships are taken from Loneragan *et al.* (1997):

Females	Weight (g) = 0.000889 CL (mm) $^{2.914}$
Males	Weight (g) = 0.000372 CL (mm) $^{3.197}$

The average weights (grams) of *P. indicus* landed in the JBG by Newfishing Australia ranges from 25.6 to 40.7 g (Loneragan et al. 2002). The average weights per prawn recorded for six commercial categories ranged from 11g to 57g. Raw length frequency data would be highly informative in developing a model.

Loneragan *et al.* (2002) found no significant differences in the growth of the exploitable phase of *P. indicus* between two years characterised by very different recruitment levels, suggesting there are not overly strong density dependent effects on growth for this species. The population dynamics are likely driven by variability in recruitment levels given the considerable distances between the recruitment and spawning grounds (Kenyon *et al.* 2004, Manson *et al*. 2001).

Spawning and maturity

The size of females at first maturity is 25 mm CL (and 23 mm for males) with the size at mass spawning (defined as corresponding to 50% of females having visible ovaries) being 44 mm CL (Taylor 2002). Female *P. indicus* carry fewer eggs than common banana prawns, and substantially less than tiger prawns.

Loneragan *et al.* (1997) analysed data on the stage of maturity for female *P. indicus* and concluded that the proportion of mature females is low during April to September and high over the period October to March. Using length frequency data from NT fisheries, their rough analysis suggested that a peak in recruitment occurs in March, with 95% of recruits arriving between December and April. Based on the above, the model assumes peak spawning over October to March with substantially lower levels of spawning during the rest of the year.

A number of different scenarios have been tried in the model described below and the Reference Case model assumes that the proportion of the recruited population (i.e. individuals large enough to be recruited to the fishery) that spawn at the start of each of quarters 1-4 are as shown in Table 13.1. These proportions represent a combination of factors including that not all prawns may be large enough to spawn and that not all mature prawns may spawn at that time. Assuming (based on the growth curve information) a roughly 6-month growth period before individuals are large enough to recruit to the fishery, this means that peaks in recruitment to the model population will occur at the ends of March and June. As this constitutes the bulk of the recruitment, recruitment residuals are estimated for the April to June quarter only.

Prawn commercial categories

Annex 3 summarises an analysis using data on the commercial categories of prawn catches to determine whether there is evidence to corroborate the model assumptions that prawns increase in size during the year, and that spawning does not occur continuously through the year but rather is concentrated at certain times. The analysis suggests broadly that there is an increase in the proportional abundance of large prawns later in the year.

Closures in the NPF

A variety of spatial and temporal closures have been implemented over the years in the NPF. A major change to the fishery occurred post-1987 when an end of year (1 December to March/April) and mid-year (22 June to 1 August) closure were introduced. The preliminary model version described here accounts for the end of year closure by setting relative availability to zero for the first model quarter post-

1987, and estimating separate availability parameters for the pre- and post-closure periods. The estimated availability parameters represent the combination of a variety of factors including reduced availability during a 3-month quarter due to partial closures, and fishing selectivity effects such as a proportion of the stock being too small to be fished.

More recently, the JBG has not been fished during the first seasonal opening (April to June). This corresponds to the second quarter in the model, but there is only a single year (2007) represented in the current data. This factor is included in the Reference Case model by estimating a third availability vector for 2007 (Fig. 13.7).

Production Model

A fairly simple discrete population model was constructed for red-legged banana prawns in the JBG as follows. The model time-step is quarterly (3 month quarters), with the number of prawns in year *y* and quarter *s* ($N_{y,s}$) given by:

$$N_{y,s+1} = N_{y,s}\, e^{-M_s} - C_{y,s} + R_{y,s+1} \qquad \text{for } s = 1 \text{ to } 3 \qquad (1)$$

and

$$N_{y+1,1} = N_{y,4}\, e^{-M_4} - C_{y,4} + R_{y+1,1} \qquad \text{for } s = 4 \qquad (2)$$

where

$N_{y,a}$ is the number of recruited prawns (those corresponding to a size large enough to be fished) at the start of quarter *s* in year *y* (which refers to a calendar year),

$R_{y,s}$ is the number of recruits (number of 6-month old prawns) which are added to the population at the end of each quarter *s* in year *y*,

M_s denotes the natural mortality rate during quarter *s* (assumed in the Reference case to be constant throughout the year), and computed by multiplying the weekly natural mortality estimate by 13 (weeks) to reflect a quarterly mortality rate; and

$C_{y,s}$ is the predicted number of prawns caught during quarter *s* in year *y*, with catches arbitrarily assumed taken as a pulse at the end of each quarter.

Given catches are recorded in units of mass, the predicted number of prawns caught during quarter *s* in year *y* is computed from the following relationship:

$$C_{y,s} = A_{y,s} F_{y,s} N_{y,s} e^{-M_s} \qquad (3)$$

where

$A_{y,s}$ is the relative availability for quarter s and for year y, with an availability vector being applied to the early period 1970-1987 and a separate vector to the 1988-2006 (i.e. post end of year NPF closure) and 2007 (first season closure) periods; and

$F_{y,s}$ is the fished proportion in quarter s and year y of a fully selected age class.

The fished proportion reflects the catch by mass ($C^{mass}{}_{y,s}$) in quarter s and year y as a proportion of the exploitable ("available") component of biomass:

$$F_{y,s} = C^{mass}{}_{y,s} \Big/ B^{ex}_{y,s} \tag{4}$$

with

$$B^{ex}_{y,s} = w_s N_{y,s} e^{-M_s} A_{y,s} \tag{5}$$

where

w_s is the average mass of prawns during quarter s.

One of the biggest challenges in constructing a realistic model of *P. indicus* relates to improved information on growth, and in particular quarterly changes in growth. Length frequency data that span a number of periods through the year are needed to better inform this aspect of model development. As a first step, this preliminary model used the female (because the male growth is too slow on its own) von Bertalanffy growth parameters and assumed that individual mass increases through the year. An average length and mass of prawns was thus calculated for each quarter, assuming a median birth date of October.

The number of recruits at the end of quarter s in year y is assumed to be related to the spawning stock size six months previously (i.e. during two quarters previously) by a modified Beverton-Holt stock-recruitment relationship (Beverton and Holt, 1957), allowing for annual fluctuation about the deterministic relationship for Quarters 1 and 2:

$$\begin{aligned} R_{y,s+1} &= \frac{\alpha B^{sp}_{y,s-1}}{\beta + \left(B^{sp}_{y,s-1}\right)^{\gamma}} e^{(\varsigma_{y,s} - (\sigma_R)^2/2)} \qquad s = 1, 2 \\ R_{y,s+1} &= \frac{\alpha B^{sp}_{y,s-1}}{\beta + \left(B^{sp}_{y,s-1}\right)^{\gamma}} \qquad s = 3,4 \end{aligned} \tag{6}$$

where

α, β and γ are spawning biomass-recruitment relationship parameters (note that cases with γ> 1 lead to recruitment which reaches a maximum at a certain spawning biomass, and thereafter declines towards zero, and thus have the capability of mimicking a Ricker-type relationship – the Reference Case has γ=1),

$\varsigma_{y,s}$ reflects fluctuation about the expected recruitment for year *y* and quarter *s*, which is assumed to be normally distributed with standard deviation σ_R (which is input in the applications considered here); these residuals are treated as estimable parameters in the model fitting process, and a single set of residuals is estimated for Quarters 1 and 2 because almost all spawning is assumed to occur during this half of the year and is assumed driven by the same environmental influences each year;

$B^{sp}_{y,s}$ is the spawning biomass at the start of quarter *s* in year *y*, computed as:

$$B^{sp}_{y,s} = f_s \cdot w_s \cdot N_{y,s} \tag{7}$$

where

f_s is a relative index of the amount of spawning during quarter s.

In order to work with estimable parameters that are more meaningful biologically, the stock-recruitment relationship is re-parameterised in terms of the pre-exploitation equilibrium spawning biomass, K^{sp}, and the "steepness", *h*, of the stock-recruitment relationship, which is the proportion of the virgin recruitment that is realized at a spawning biomass level of 20% of the virgin spawning biomass (Table 13.1). Equation (6) can be rewritten in terms of the "steepness" *h*, defined as the fraction of pristine recruitment R_0 that results when spawning biomass drops to 20% of its pristine level, i.e.:

$$hR_0 = R\left(0.2B^{sp}_0\right) \tag{8}$$

which yields the following for the deterministic component of the formulation:

$$R\left(B^{sp}_{y,s}\right) = \frac{4h \cdot R_0 \cdot B^{sp}_{y,s}}{B^{sp}_o\left(1-h\right) + B^{sp}_{y,s}\left(5h-1\right)} \tag{9}$$

It follows that the total spawner stock size and recruitment for calendar year *y* are given respectively by:

$$B^{sp}_y = \sum_s B^{sp}_{y,s} \tag{10}$$

$$R_y = \sum_s R_{y,s} \tag{11}$$

The resource is assumed to be at the deterministic equilibrium (corresponding to an absence of harvesting) at the start of 1980, the initial year considered here. The model estimates the pre-exploitation quarter 1 spawning biomass, from which the starting number of prawns can be calculated using Equation (7), and it follows:

$$R_{0,1} = \left(1 - e^{-M_1}\right) \cdot B_{0,1}^{sp} / \left(f_1 \cdot w_1\right) \qquad (12)$$

and similarly for the pristine numbers and recruitment levels in the remaining quarters, which can then be added together to provide total spawning biomass and recruitment values for the year. The model sets the starting spawning biomass in the first quarter $B_{0,1}^{sp} = K^{sp}$. Given the total pre-exploitation spawning biomass B_0^{sp}, it follows that:

$$B_0^{sp} = \frac{\sum_s f_s \cdot w_s \cdot R_{0,s}}{\left(1 - e^{-M_s}\right)} \qquad (13)$$

which can be solved for R_0, and hence the stock recruit parameters.

Likelihood function

The model is fitted to all available CPUE data for each of the four quarters. The likelihood contribution is calculated assuming that the observed abundance index is log-normally distributed about its expected value:

$$I_y^s = \hat{I}_y^s e^{\varepsilon_y^s} \qquad \text{or} \qquad \varepsilon_y^s = \ln(I_y^s) - \ln(\hat{I}_y^s) \qquad (14)$$

where I_y^s is the abundance index (with fishing power effect added) for year *y* and quarter *s*,

> $\hat{I}_y^s = q^s B_{y,s}^{ex}$ is the corresponding model estimated value, where $B_{y,s}^{ex}$ is the model value for exploitable resource biomass corresponding to quarter *s*, given by equation (5).
>
> q is the constant of proportionality which is assumed to be the same for each of the quarters, and
>
> ε_y^s from $N\left(0, \left(\sigma_y^s\right)^2\right)$.

The contribution to the negative of the log-likelihood function (after removal of constants) is given then by:

$$-\ln L = \sum_y \left[\sum_s \ln \sigma_y^s + \left(\varepsilon_y^s\right)^2 / 2\left(\sigma_y^s\right)^2 \right] \qquad (15)$$

with the standard deviation of the residuals for the logarithms of the abundance series assumed to be independent of y, and estimated in the fitting procedure by its maximum likelihood value:

$$\hat{\sigma}^s = \sqrt{\frac{1}{n}\sum_y\sum_s\left(\ln I_y^s - \ln \hat{I}_y^s\right)^2} \tag{16}$$

where n is the number of data points across all years and quarters.

The catchability coefficient q is estimated by its maximum likelihood value:

$$\ln \hat{q} = \frac{1}{n}\sum_y\sum_s\left(\ln I_{y,s}^s - \ln \hat{B}_{y,s}^{ex}\right) \tag{17}$$

Stock-recruitment function residuals

The stock-recruitment residuals are assumed to be log-normally distributed and in initial model development no serial correlation is assumed. Thus, the contribution of the recruitment residuals to the negative of the (now penalised) log-likelihood function is given by:

$$-\ell n L^{pen} = \sum_{y=y1+1}^{y2} \left(\lambda_{y,s}\right)^2 \Big/ 2\sigma_R^2 \tag{18}$$

where

$\lambda_{y,s}$ is the recruitment residual for year y and quarter s, which is estimated for years $y1$ to $y2$ (see equation 6),

ε_y from $N\left(0,(\sigma_R)^2\right)$,

σ_R is the standard deviation of the log-residuals, which is input.

Estimates of Management Variables

Given the large variability in recruitment, it is difficult to precisely estimate resource status as a proportion of the initial (1980) spawning biomass. The RAG proposed that a useful historic reference level to be used as an index of current stock status is the median of the 1987-2006 recruitment residuals multiplied by the average recruitment over that period. This gives an estimate of historic recruitment levels which can be compared with the current recruitment estimate.

Precise estimation of reference levels such as Maximum Sustainable Yield (MSY) and the corresponding spawning biomass level (B_{MSY}) are difficult for short-lived variable stocks because yield is determined predominantly by the strength of recruitment, and hence annual sustainable yields can be expected to fluctuate widely about the deterministically predicted estimates (Plagányi *et al*. 2009). The estimated quantities correspond to deterministic assumptions regarding the stock-recruit relationship. A further complication is that these estimates depend to some extent on when in the year fishing occurs, and it is thus important to distinguish between results based on the fishing pattern during 1989-2006 and 2007 when the first season was closed in the JBG (Fig. 13.7). Alternative MSY estimates are thus computed under each of these two scenarios and assumed that the relative distribution of catches per quarter is the same as the average of that observed a) during the past five years (quarter 1: 0; q2: 0.35; q3 0.51 and q4: 0.14) and b) in 2007. Given insufficient time to refine estimation of the Maximum Economic Yield (MEY), it is assumed that this is achieved at a biomass level corresponding to 1.2 times that required to achieve MSY.

Sensitivity Analysis

A number of key sensitivities will be tested in the model, and include testing sensitivity of model outputs to the following assumptions:

- Adjustments for possible changes over time in fishing power
- Steepness *h* (stock recruitment relationship)
- Level of variability in stock recruit residuals
- The assumed natural mortality rate (e.g. try lower value of $M = 0.04$ wk^{-1})
- Assumed seasonal trend in spawning intensity

13.4 Results and Discussion

Model-estimated parameter values and associated Hessian-based standard deviations are shown in Table 11.2. Comparisons between the nominal CPUE data for each season (quarter) and model-predicted CPUE values are shown in Figure 13.7. The model fits to each of the quarters separately, but as an additional diagnostic the quarterly predictions were added together for the purposes of comparison with the annual averaged CPUE values (Fig. 13.8). The model fit is reasonable, particularly over the most recent period.

The model-estimated availability per quarter is shown in Fig. 13.9 and highlights the changes (largely due to closures) that have occurred over time. Future work will explore possible correlation between parameter *q*, which is assumed independent of quarter and assumptions of the availability estimates which vary across quarters. The Reference Case model estimates a single set of recruitment residuals associated with recruits that are spawned the previous October and recruit to the fished population at the start of quarter 2 (Fig. 13.10a). Although lower levels of recruitment are modelled as occurring during the other quarters, accounting for the variability associated with one (the major) of these events only was shown to be sufficient to adequately represent resource dynamics ((Figs 13.8-9) and hence the RAG recommended adopting this simpler model version as the Reference Case model. Future work will explore assuming recruitment deviations are common amongst quarters. There is considerable variability associated with the estimated recruitment time series, with a peak in the mid-1990s followed by a more recent peak (Fig. 13.10a). There are no obvious patterns evident from a plot of the stock-recruit residuals (Fig. 13.10b).

The highest JBG catch of 977 tons was taken in 1997, with 687 tons of this taken during the second quarter. Although the average CPUE for that year seems reasonable, when this is disaggregated to year quarters, it is evident that catch rates were very high initially but then decreased substantially and remained low the following year (Fig. 13.5). Model results suggest that the very high catch taken in 1997 was unsustainable and across a wide range of alternative model scenarios the proportion fished (proportion of population available to be fished) hit the upper limit of 95% in the second quarter. The resource appears to have increased in response to reduced catches over the following period (Fig. 13.11).

The total annual spawning biomass trajectory is shown in Figure 13.11. The prawn population is predicted to have declined after 1995, but is predicted to have increased in recent years in response to the low recent catches and good recruitment. The spawning biomass trajectory together with the associated Hessian-based 90% confidence intervals is shown in Fig. 13.12.

Sensitivity analyses

Sensitivity to fishing power assumption

As a test of the effect of adjusting the CPUE data to take account of fishing power effects, the Reference Case model (which uses the input fishing power series) was compared with a version that applied no fishing power effect (Fig. 13.13, Table 13.3). Figure 13.14 compares the total annual spawning biomass trajectories using the Reference Case (with fishing power fp), and when not applying any fishing power effect. In general, there are minor effects only of applying the fishing power assumptions.

Stock recruitment steepness parameter h:

This is fixed at h=0.6 in the Reference Case model. Increasing h to 0.7 did not result in a significantly different fit or dramatically change model predictions such as a current depletion estimate (computed as the 2007 spawning biomass relative to the starting level) (Table 13.3). Decreasing h to 0.5 resulted in almost no change in the overall likelihood, but a slight reduction in current depletion (Table 13.3).

Input variability re stock recruit residuals

A number of sensitivity scenarios were examined using both lower input values (sigma = 0.3 versus the Reference Case value of 0.6) but the model was relatively insensitive to the choice of this parameter (Table 13.3).

Natural mortality

The natural mortality is set at 0.05 per week and a sensitivity test was run changing this to 0.04 per week (note that the value used for tiger prawns is 0.045 wk^{-1}). The model fit improved significantly with this being the preferred model based on the AIC criterion (Fig. 13.15, Table 13.3). The model-predicted spawning biomass trajectories remain fairly similar under the two scenarios (Fig. 13.16), although the sensitivity scenario predicts a lower current depletion level (Table 13.3). Across all model sensitivities current depletion estimates exceed one. The Reference Case *M* was the preferred choice because it is based on data, but future work should consider using the lower estimate of *M*.

Sensitivity to model assumptions regarding the timing of recruitment

Model results are robust to small changes in the assumptions regarding the timing of spawning and recruitment, and experimentation with the model suggests that the data are consistent with their being seasonal peaks in recruitment. As an alternative to this, a sensitivity test was done which assumed recruitment was spread equally throughout the year, and as expected this resulted in a significantly worse fit (Table 13.3).

Summary of Estimates of Management Variables

The 2007 recruitment estimate was compared with the 1987-2006 median recruitment residual multiplied by the average recruitment over that period. This yields an estimate of 1.47 suggesting the resource in 2007 is well above the 1987-2006 reference level.

Estimates of MSY depended on the fishing pattern and hence were computed separately for the fishing patterns as per 1989-2006 and 2007 which incorporated a first season closure in the JBG (Fig. 13.7). Alternative MSY estimates were computed under each of these two scenarios and assumed that the relative distribution of catches per quarter is the same as the average of that observed a) during the past five years (quarter 1: 0; q2: 0.35; q3 0.51 and q4: 0.14) and b) in 2007. This resulted in estimates of MSY of approximately 750 t (1989-2006 selectivity) and 900 t (2007 selectivity) (Table 13.1) achieved at spawning biomass levels of 1106 t and 979 t respectively. The former seems reasonable when compared to the historic catch estimates (Fig. 13.17). The reason for the differences in these estimates are because fishing occurs during the second quarter when using the 1989-2007 selectivity but only from the third quarter under the 2007 selectivity scenario. There are more smaller individuals present during the second quarter (under the model assumption that individuals increase in size during the year), and hence the MSY estimate is lower under the first scenario.

The corresponding average estimate of F_{MSY} is approximately 0.35 for the first scenario but much higher for the second scenario (Table 13.1) because it involves concentrating catches over a shorter period. The estimate of (B_{MSY}) is similarly uncertain (1100 t), and has been used to obtain a rough estimate of B_{MEY} (through multiplication by a factor of 1.2) of 1300 t (Table 13.1). These analyses suggest that the resource has dropped below this level in the past, has then recovered to the maximum economic yield level, and during the most recent period has increased to well above this level (Fig. 13.17). Given the lower *M* sensitivity scenario was highlighted as important, the MSY was computed using the 1989-2006 selectivity and suggested a decrease to around 650 t. This is not unexpected given that a lower mortality rate implies a lower stock productivity. These results should be interpreted broadly given the point made above that the annual sustainable yields depend on the strength of recruitment each year and this likely depends on other factors too such as environmental variability. Overall model results suggest that the JBG redleg resource is currently (2007) above the B_{MEY} level and correspondingly that current catches are well below the MSY level.

13.5 Acknowledgements

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13.6 References

Beverton, R.J.H., and Holt, S.J. 1957. *On the dynamics of exploited fish populations*. Fisheries Investment Series 2, Vol. 19, U.K. Ministry of Agriculture and Fisheries, London. 533pp.

Bishop, J., Venables, B., Kienzle, M., Hutton and C. Dichmont. 2009. Fishing Power in the Northern Prawn – Tiger Prawn Fishery, 1970 – 2007. A Report to the NPF RAG, November, 2009.

Dichmont, C.M., Punt, A.E., Deng, A., and Venables, W. 2003. Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery. *Fisheries Research* 65, 335–350.

Die, D.J., Loneragan, N.R., Kenyon, R.A. and B. Taylor. 2002. Growth and mortality of red-legged banana prawns. The growth, mortality, movements and nursery habitats of red-legged banana prawns (*Penaeus indicus*) in the Joseph Bonaparte Gulf, FRDC Project 97/105. (Loneragan, N., Die, D., Kenyon, R., Taylor, B., Vance, D., Manson, F., Pendrey, B., and B. Venables).

Gillett, R. 2008. Global study of shrimp fisheries. FAO Fisheries Technical Paper 475. Rome, FAO. 331 pp.

Kenyon, R.A., Loneragan, N.R., Manson, F.J., Vance, D.J. and W.N. Venables 2004. Allopatric distribution of juvenile red-legged banana prawns (*Penaeus indicus* H. Milne Edwards, 1837) and juvenile white banana prawns (*Penaeus merguiensis* de Man, 1888), and inferred extensive migration, in the Joseph Bonaparte Gulf, northwest Australia. *Journal of Experimental Marine Biology and Ecology* 309: 79-108.

Loneragan, N., Kenyon, R., Die, D., Pendrey, B. and B. Taylor. 1997. The impact of changes in fishing patterns on red-legged banana prawns (*Penaeus indicus*) in the Joseph Bonaparte Gulf. Final report to the FRDC.

Loneragan, N., Die, D., Kenyon, R., Taylor, B., Vance, D., Manson, F., Pendrey, B., and B. Venables. (2002). The growth, mortality, movements and nursery habitats of red-legged banana prawns (*Penaeus indicus*) in the Joseph Bonaparte Gulf. FRDC Project 97/105. CSIRO Marine Research.

Manson, F.J., Loneragan, N.R., McLeod, I.M. and R.A. Kenyon. 2001. Assessing techniques for estimating the extent of juvenile prawn habitats: topographic maps, aerial photographs and Landsat TM imagery. *Marine and Freshwater Research* 52: 787-792.

Plagányi, É.E., Dennis, D., Kienzle, M., Ye, Y., Haywood, M., Mcleod, I., Wassenberg, T., Pillans, R., Dell, Q., Coman, G., Tonks, M. and N. Murphy. 2009. TAC estimation and relative lobster abundance surveys 2008/09. Australian Fisheries Management Authority Torres Strait Research program Final Report. AFMA Project number: 2008/837.

Punt, A.E., Deng, R., Dichmont, C., Kompas, T., W. Venables, Zhou, S. and S. Pascoe. 2009. Integrating Size-Structured Assessment and Bio-Economic Management Advice in Northern Prawn Fishery. A Report to the NPF RAG, May, 2009.

Taylor, B. 2002. The red legged banana prawn (*Penaeus indicus*) in Australia with emphasis on the Joseph Bonaparte Gulf. A report prepared for Northern Prawn Fishery operators. CSIRO Marine Research, 21 pp.

Venables, B., van der Velde, T., Donovan, A. and R. Kenyon. 2009. Updated Species Distribution Data and Models: A Report to the NPF RAG, May, 2009.

Venables, B. 2009. Partitioning the NPF Banana Prawn Fishery into Eastern and Western Regions for Separate TAC Allocation. A Report to the NPF RAG, November, 2009.

Wang, Y-G. 1995. An improved Fabens method for estimation of growth parameters in the von Bertalanffy model with individual asymptotes. *Canadian Journal of Fisheries and Aquatic Science* 55: 397-400.

Zhou, S., Punt, A.E, Deng, R., Dichmont, C.M., Ye, Y. and J. Bishop. In review. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. *Marine and Freshwater Research*

Table 13.1. Summary of the parameters of the population dynamics model.

Parameter	**Treatment**
Pre-exploitation equilibrium spawning biomass, K^{sp}_{1980}	Estimate $K^{sp}_{1980,1}$ for first quarter, compute values for other quarters using equilibrium assumptions, and set $K^{sp}_{1980} = \sum_{seas} K^{sp}_{1980,seas}$
Natural mortality, *M*	Fixed at 0.05 wk^{-1}
Recruitment and spawning	
"Steepness", *h*, of the stock-recruitment relationship	Fixed at 0.6 (preliminarily)
Recruitment residuals , R_s for quarter 2	Estimated – 26 pars for 1981-2006
Proportion of recruited stock that spawn each quarter, f_s	Assumed known [0.3; 0.05;0.05;0.6]
Stock-recruitment relationship parameters, α, β	Computed using estimated values of K^{sp}_{1980} and *h*
Variance in recruitment, σ_r	Fixed at 0.6 (sensitivities tested)
Fishing mortality related	
Catchability – *q (x10^{-4})*	Computed 2.7
Availability during each quarter for period 1980-1988, $A_{y,s}$	Estimated [0.50 ; 0.84; 1.00; 1.00]
Availability during each quarter for period 1989-2006, $A_{y,s}$	Estimated *(except for pars in italics)* [*0* ; 1.00; 1.00; 0.67]
Availability during each quarter for period from 2007, $A_{y,s}$	Fixed at 1989-2006 estimates for quarters 3-4 [*0 ; 0; 1.00; 0.67*]
Growth parameters	
Von Bertalanffy growth curve parameters	Assumed known
Length-weight regression	Assumed known
The observation model	
Observation error variance, σ	Estimated [0.48]
Reference level estimates	
Maximum Sustainable Yield (MSY)	750 t (1988-2006 selectivity); 900 t (2007 selectivity)
Spawning biomass level corresponding to MSY	1106 t; 979 t

(B_{MSY})	
Spawning biomass level corresponding to MEY (B_{MEY})	1327 t; 1175 t
2007 Bsp relative to B_{MEY}	1.2
F_{MSY} (average) [Quarter 2; 3; 4] y^{-1}	0.35 [0.33; 0.43; 0.28] (1988-2006 selectivity); 0.68 [0; 0.55; 0.81] (2007 selectivity)
Current spawning biomass (and STD)	1737.9 t (364.2)

Table 13.2. Summary of model-estimated parameters and their corresponding Hessian-based standard deviations.

Parameter	Value	SD
K_{1980}^{sp}	4.7 ($B_{0,1}^{sp}=109.7$ t; hence $B_{0}^{sp}=1234.7$ t)	0.18
Availability during each quarter for period 1980-1988, $A_{y,s}$	Estimated [0.50 ; 0.84; 1.00; 1.00]	[0.15; 0.21; 0.00; 0.00]
Availability during each quarter for period 1989-2006, $A_{y,s}$	Estimated *(except for first quarter)* [*0* ; 1.00; 1.00; 0.67]	[- ; 0.00; 0.00; 0.09]
Recruitment residuals , R_s for quarter 2	26 pars for 1981-2006:	
	RecPar1, 0.387	0.379
	RecPar2, -0.040	0.407
	RecPar3, 0.171	0.396
	RecPar4, -0.151	0.406
	RecPar5, 0.125	0.401
	RecPar6, -0.239	0.428
	RecPar7, 0.379	0.359
	RecPar8, 0.186	0.380
	RecPar9, 0.627	0.377
	RecPar10, -0.362	0.431
	RecPar11, -0.284	0.401
	RecPar12, -0.467	0.413
	RecPar13, -0.231	0.389
	RecPar14, -0.055	0.414
	RecPar15, 0.172	0.418
	RecPar16, 0.270	0.412
	RecPar17, -0.247	0.423
	RecPar18, 0.135	0.394
	RecPar19, -0.099	0.423
	RecPar20, 0.805	0.381
	RecPar21, 0.232	0.533
	RecPar22, -0.483	0.458
	RecPar23, -0.165	0.421
	RecPar24, 0.392	0.461
	RecPar25, 0.198	0.457
	RecPar26, 0.084	0.395

Table 13.3. Summary of the results of sensitivity tests as shown. Model-estimated parameters (except for the 26 recruitment residuals) and corresponding negative log likelihood values are shown

Parameter	Value						
	Reference Case	S1 – no fishing power effect	S2 – decrease *h* from 0.6 to 0.5	S3 – increase h to 0.7	S4 – sigma residuals = 0.3	S5 - *M* = 0.04	S6 – recruitment spread equally fs = [0.25; 0.25; 0.25;0.25]
K_{1980}^{sp} (t)	2169	2048	3825	1652	1789	3145	2098
$A_{y,s}$ (1980-1988)	[0.50 ; 0.84; 1.00; 1.00]	[0.31; 0.59; 0.72; 0.73]	[0.44; 0.74; 0.97; 1.00]	[0.56; 0.94; 1.00; 1.00]	[0.52; 0.81; 1.00; 1.00]	[0.50; 0.82; 1.00; 1.00]	[0.49; 0.89; 1.00; 0.61]
$A_{y,s}$ (1989-2006)	[0 ; 1.00; 1.00; 0.67]	[0.00; 0.95, 1.00; 0.67]	[0.00; 0.89, 1.00; 0.70]	[0.00; 1.00, 1.00; 0.59]	[0.00; 1.00, 1.00; 0.68]	[0.00; 0.96, 1.00; 0.67]	[0.00; 0.92, 1.00; 0.34]
$A_{y,s}$ (2007)	[0 ; 0; 1.00; 0.67]	[0.00; 0.00; 1.00; 0.67]	[0.00; 0.00; 1.00; 0.70]	[0.00; 0.00; 1.00; 0.59]	[0.00; 0.00; 1.00; 0.68]	[0.00; 0.00; 1.00; 0.67]	[0.00; 0.00; 1.00; 0.34]
Catchability – *q*	2.7E-04	5.5E-04	2.3E-04	2.7E-04	3.0E-04	2.6E-04	2.5E-04
-lnL:overall (zero penalties)	-14.5	-15.5	-15.0	-12.2	-9.9	-17.0	-9.1
Observation error variance, σ	0.48	0.48	0.48	0.50	0.52	0.47	0.52
Current depletion - Bsp(2007) relative to B_{1980}	1.41	1.42	1.20	1.42	1.34	1.23	1.58
No. parameters	34	34	34	34	34	34	34
AIC	39	36.9	38.0	43.7	48.2	34.0	49.8

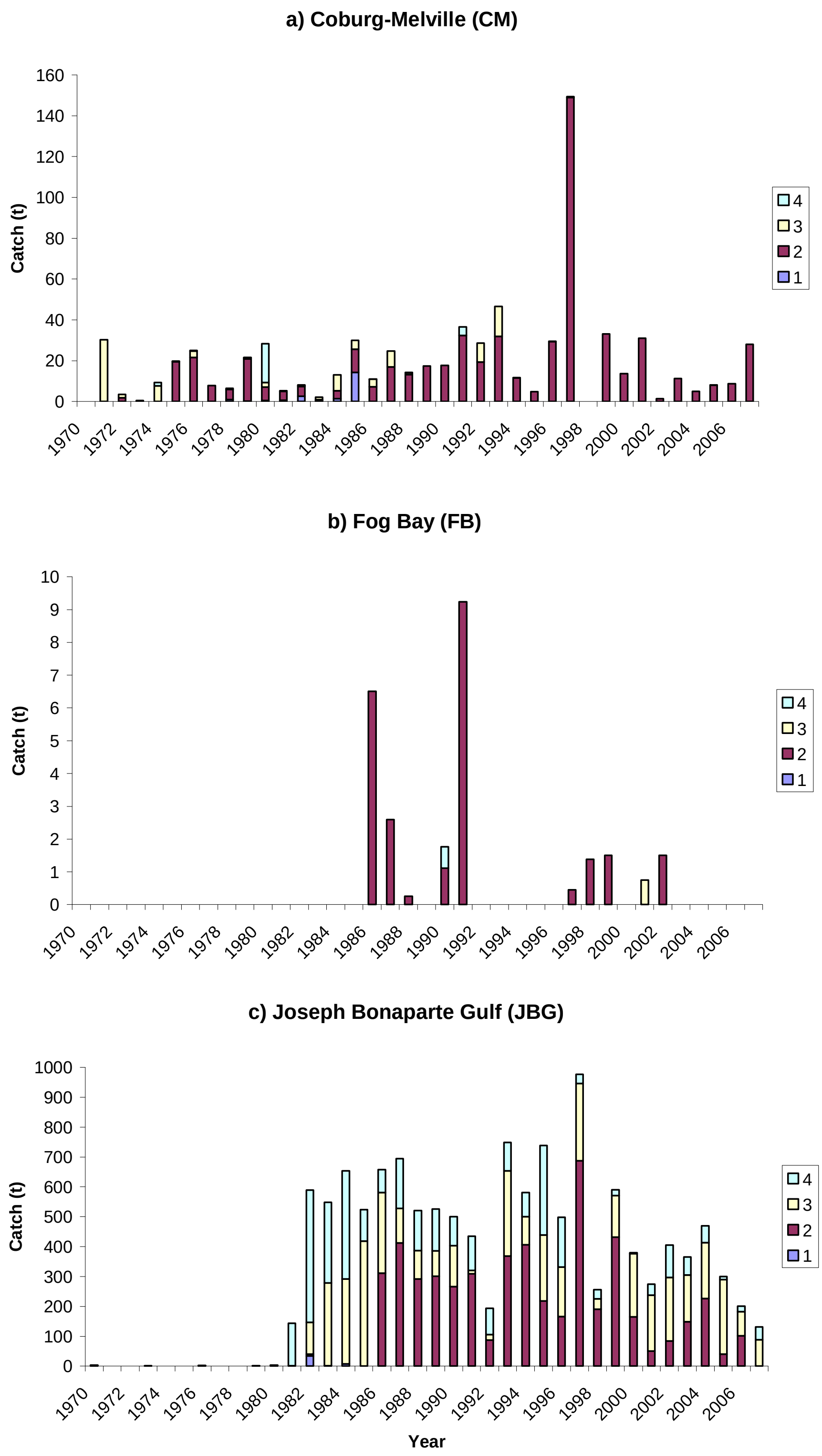


Fig. 13.1. Total historic catch (tons) series (1980-2007) for red-legged banana prawns (*Peneus indicus*) in the a) Coburg-Melville, b) Fog Bay and c) Joseph Bonaparte Gulf, shown per quarter, where Quarter 1 = January – March; 2 = April – June; 3 = July – September and 4 = October – December. Note that there are very few catches prior to 1980 and that most catches are taken from the JBG, so that the model uses a 1980 starting date and focuses exclusively on the JBG region.

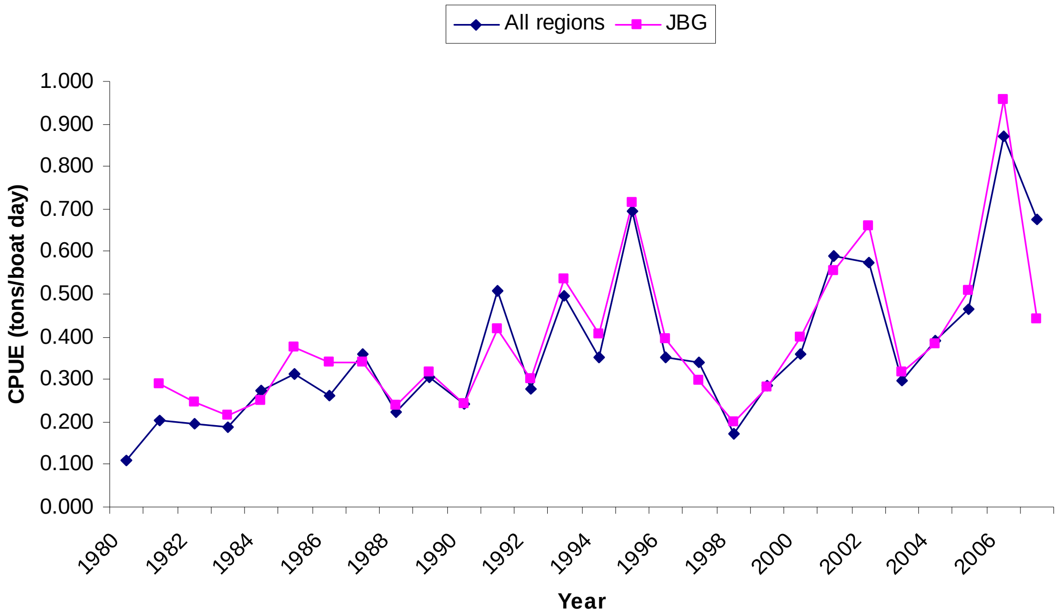


Fig. 13.2. Annual average nominal CPUE series for the period 1980-2007 for red-legged banana prawns (*Peneus indicus*) in the JBG.

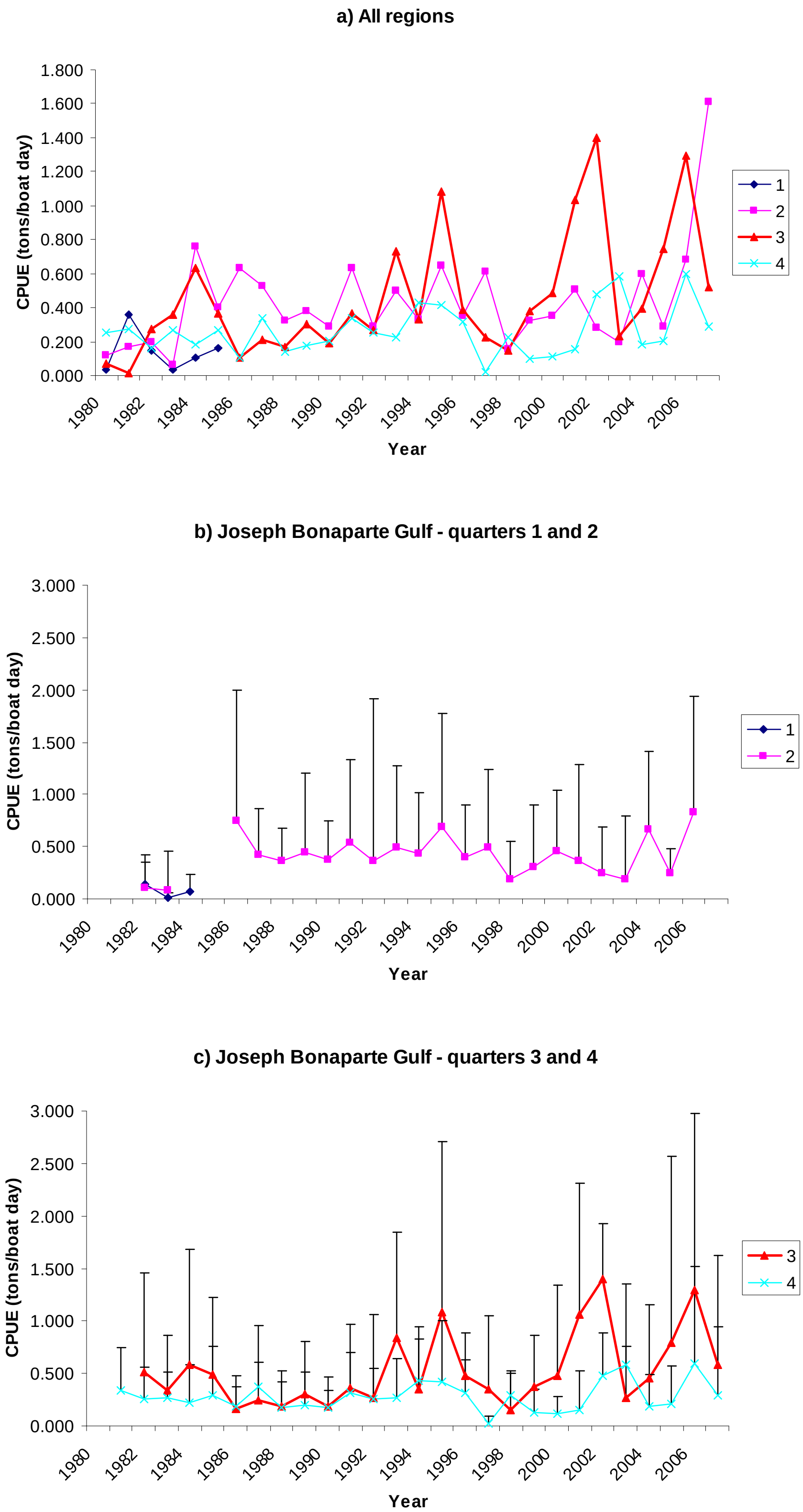


Fig. 13.3. The nominal CPUE (+ 95% Confidence Intervals in lower plots) per quarter shown for the period 1980-2007 for red-legged banana prawns (*Peneus indicus*) when a) averaged across all regions and b) - c) for the JBG. Quarter 1 = January – March; 2 = April – June; 3 = July – September and 4 = October – December.

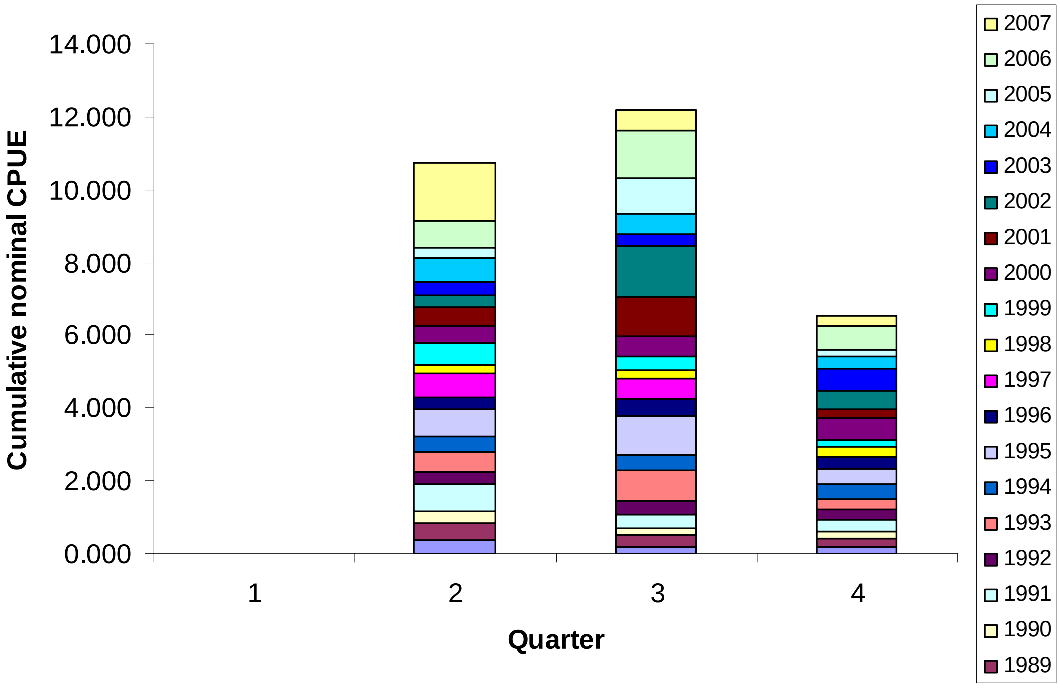
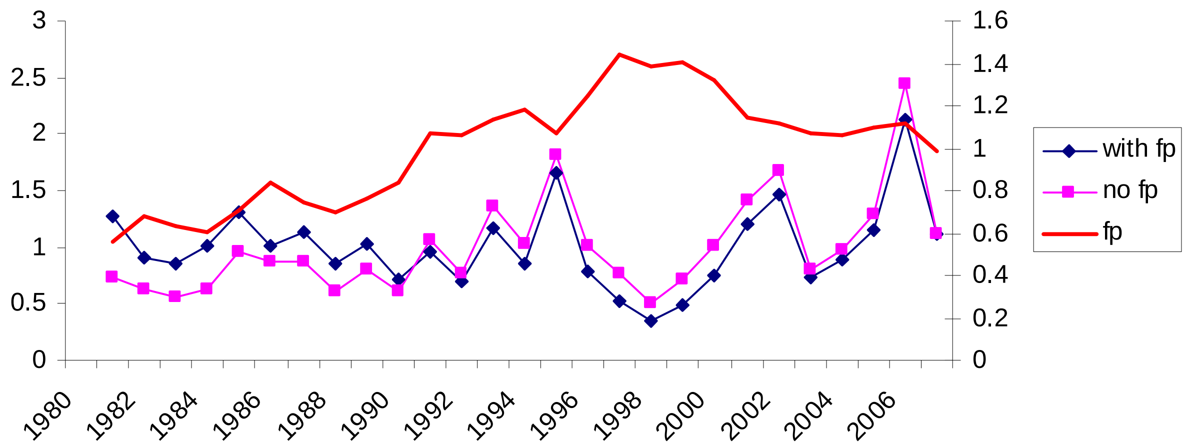


Fig. 13.4. The nominal CPUE for red-legged banana prawns for each year as shown plotted against quarter on the horizontal axis. Data are shown for 1988-2007 only, being the period following the end of year NPF closure, and hence there are no catches in Quarter 1.

a)



b)

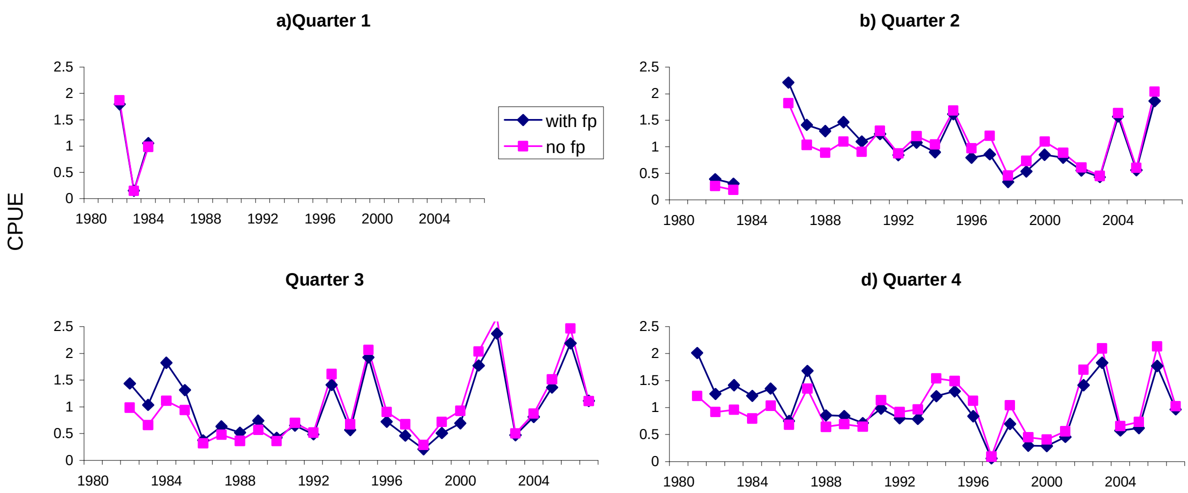


Figure 13.5. Comparison of the nominal and standardised CPUE indices after applying the fishing power (fp) input series. The top figure (a) shows the annual average CPUE whereas the lower four panels (b) are shown per season. Both series have been normalised to 1.

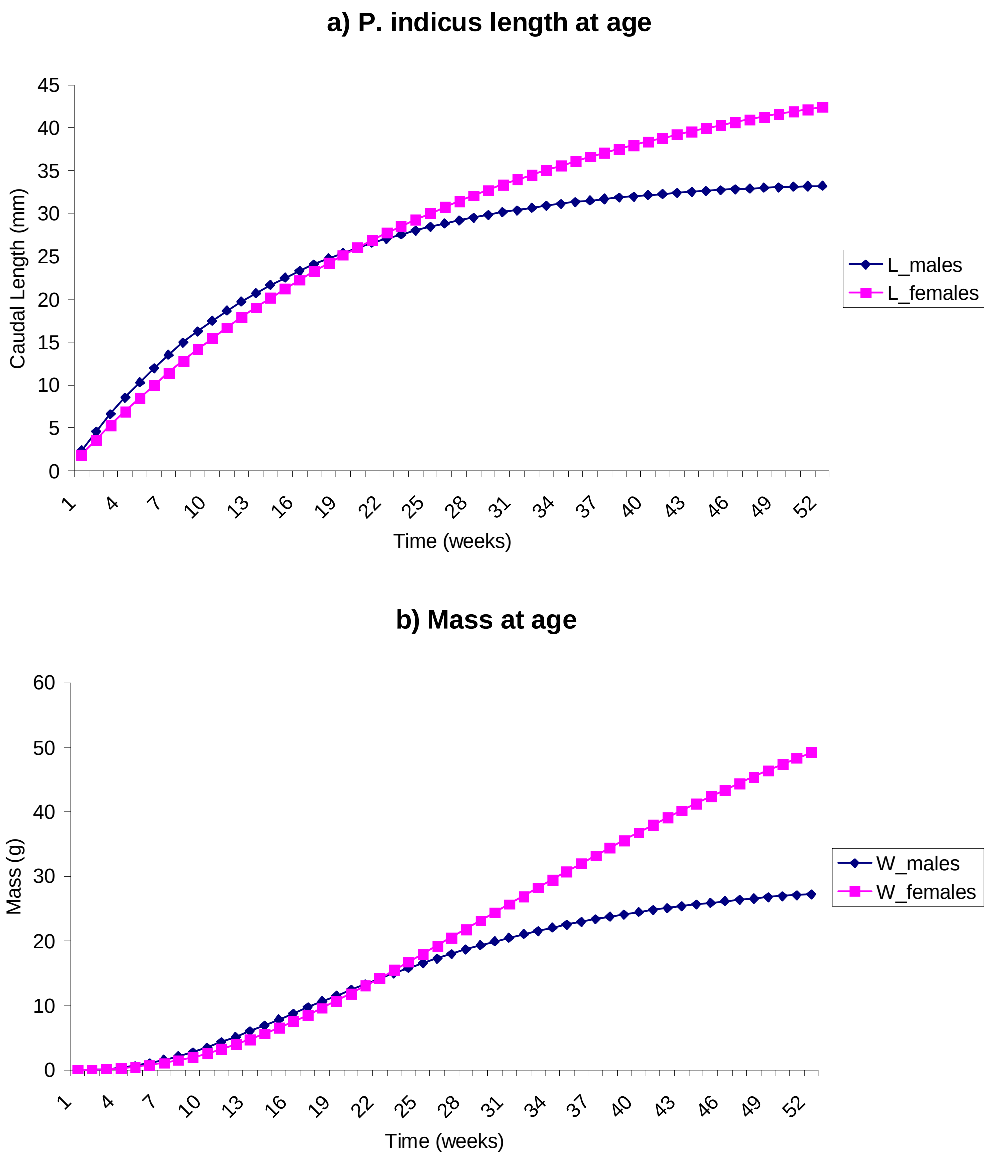


Fig. 13.6. Length- and mass-at-age relationships for *P. indicus* males and females.

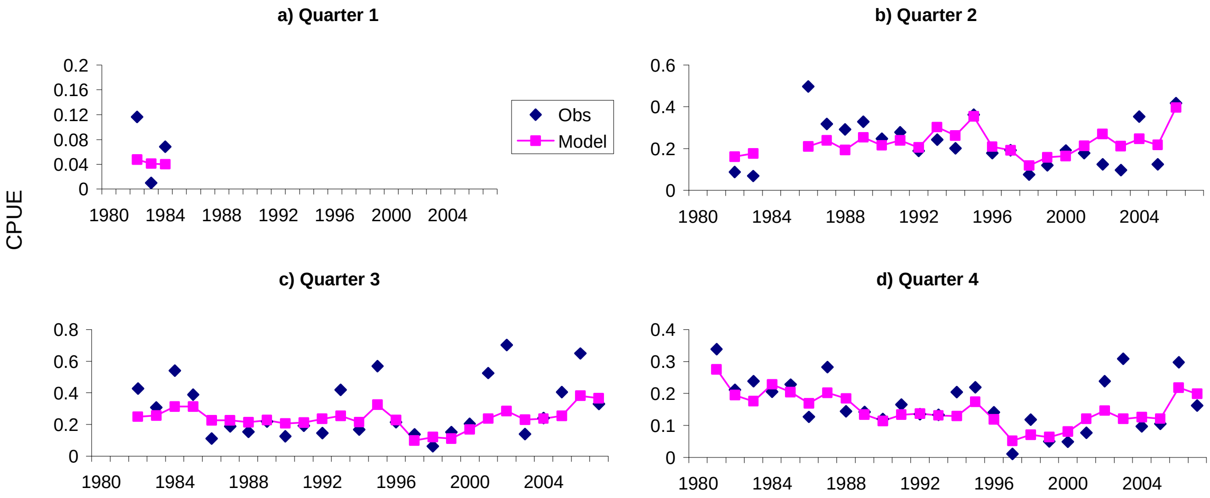


Fig. 13.7. Comparisons between the nominal CPUE data for each quarter (quarter) and model-predicted CPUE values using the base-case model version.

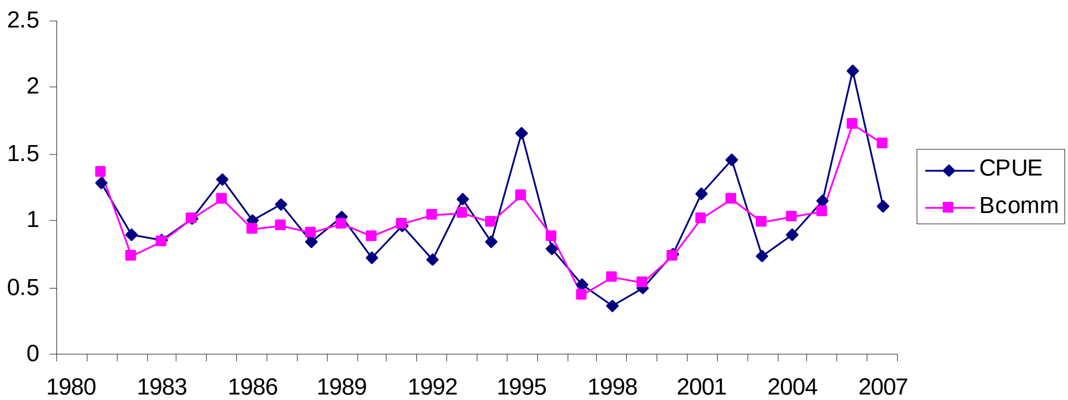


Fig. 13.8. Comparisons between the average annual nominal CPUE data and overall model-predicted commercially available *P. indicus* biomass.

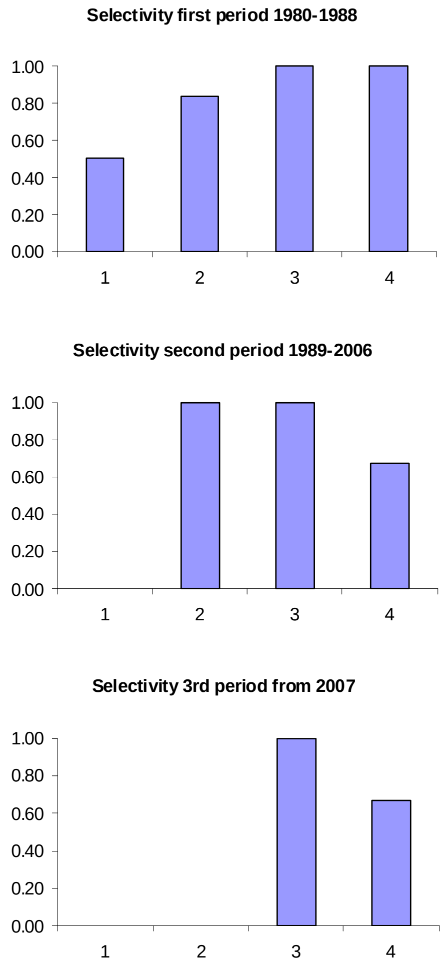
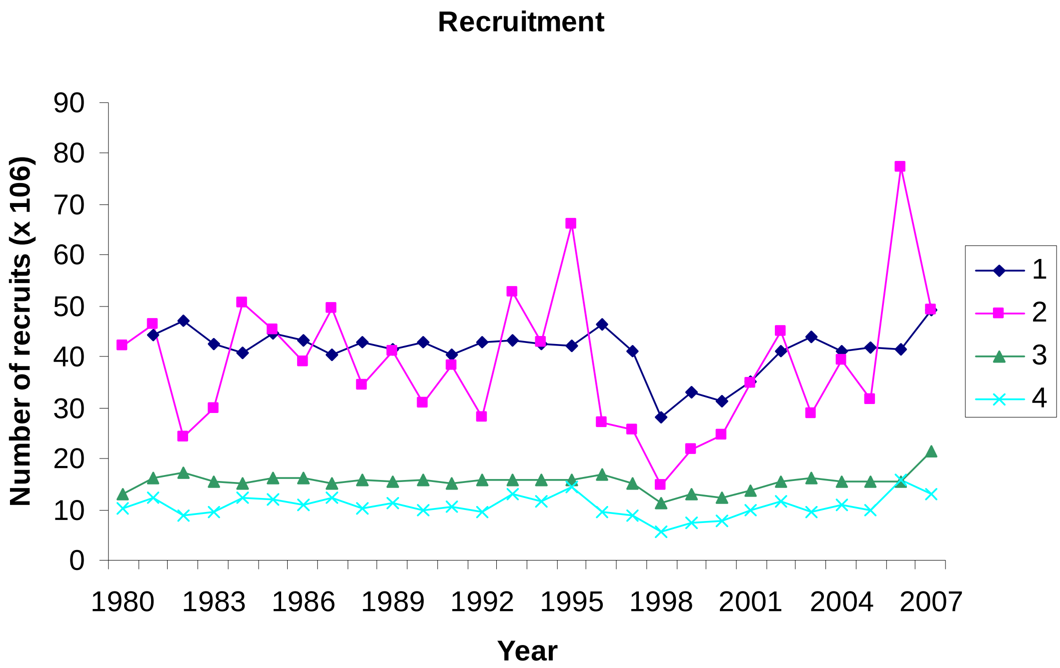


Fig. 13.9. Schematic summary of Reference case model availability vectors for the three periods a) 1980-1988, b) 1989-2006 and c) 2007.

(a)



(b)

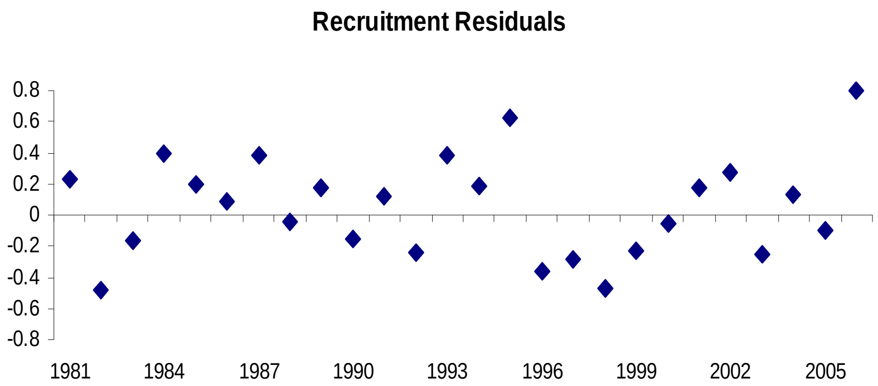


Fig. 13.10. Reference Case model (a) estimated recruitment per quarter as indicated for the period 1980-2007, and b) stock recruit residuals as estimated for the start of the second quarter for all years from 1981 to 2006.

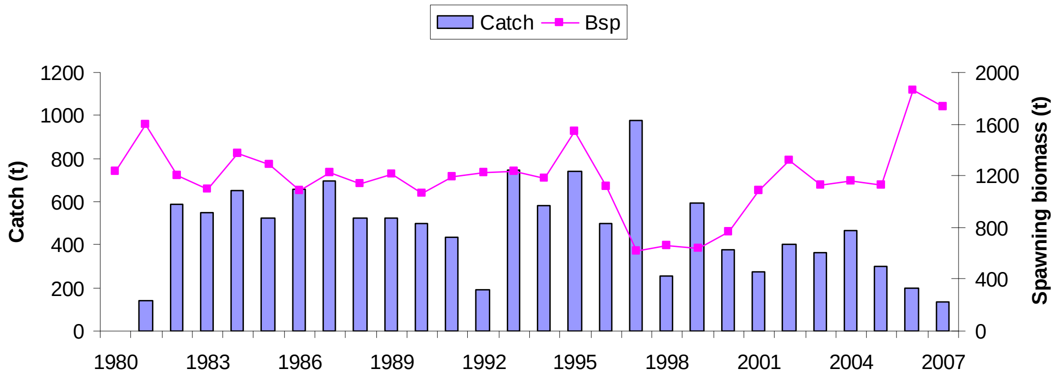


Fig. 13.11. Total annual spawning biomass trajectory using the Reference Case model, with total annual catches plotted as bars.

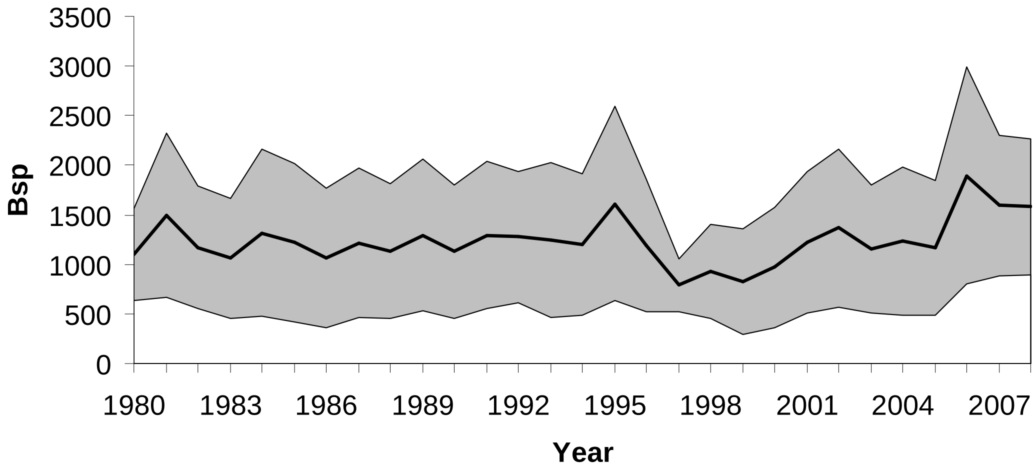


Fig. 13.12. Total annual spawning biomass trajectory for the period 1980 to 2007. The shaded areas represent the associated Hessian-based 90% confidence intervals.

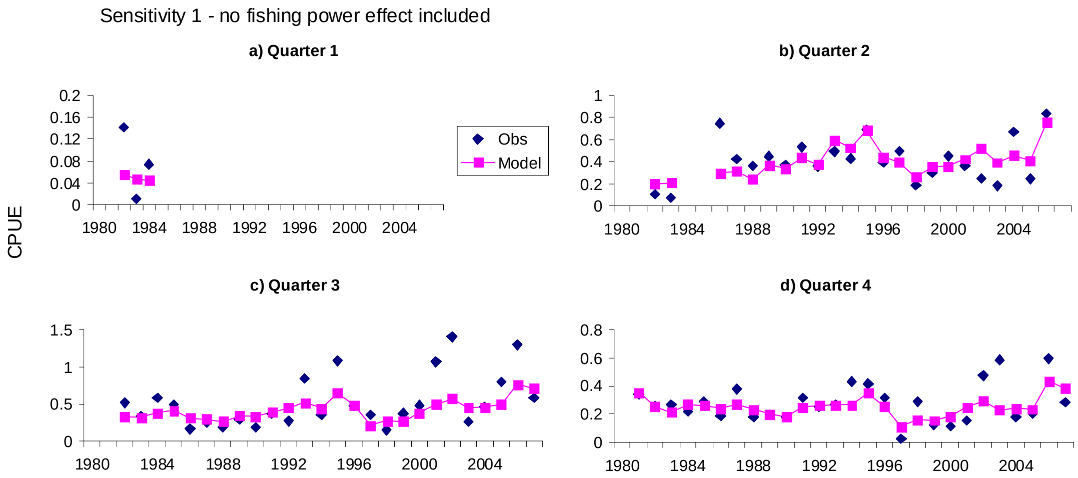


Fig. 13.13. Model fit for sensitivity scenario when using nominal CPUE data with no adjustment for fishing power effects.

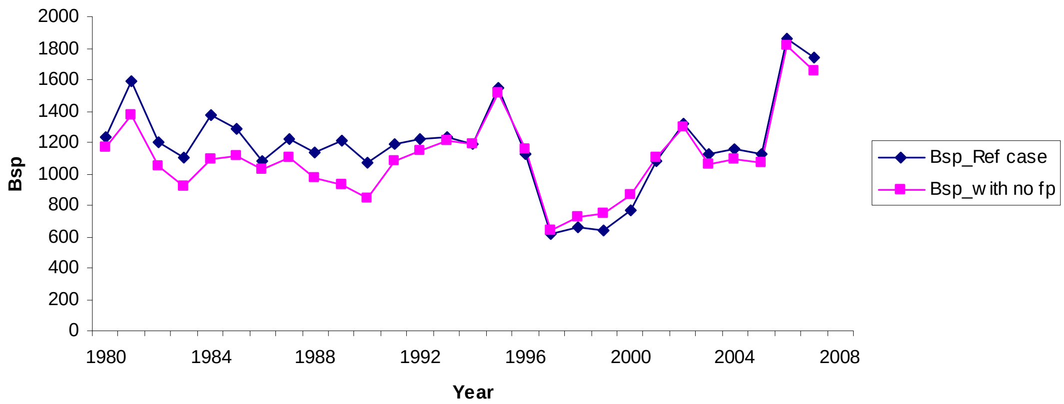


Fig. 13.14. Comparison between total annual spawning biomass trajectories using the Reference Case (with adjustments for fishing power fp) and when not applying any fishing power effect.

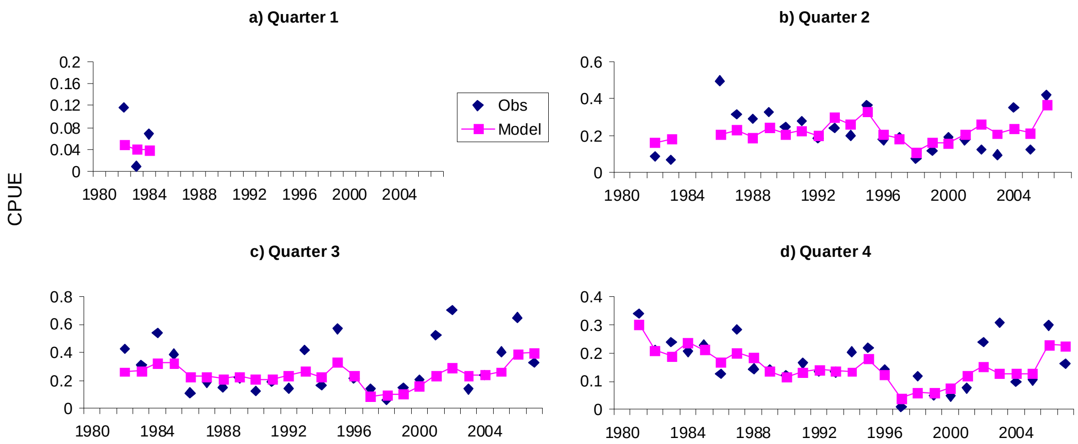


Fig. 13.15. Model fit for sensitivity scenario with a lower natural mortality M=0.04 instead of the Reference Case value of 0.05.

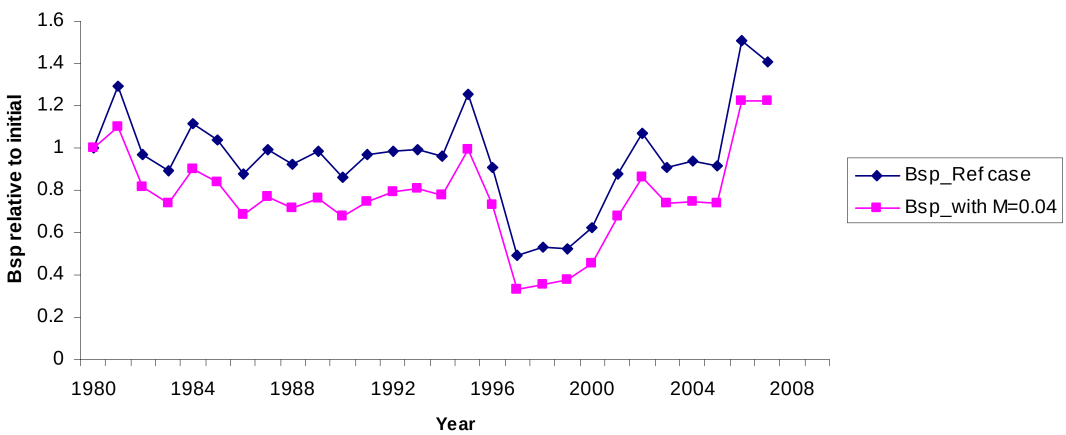
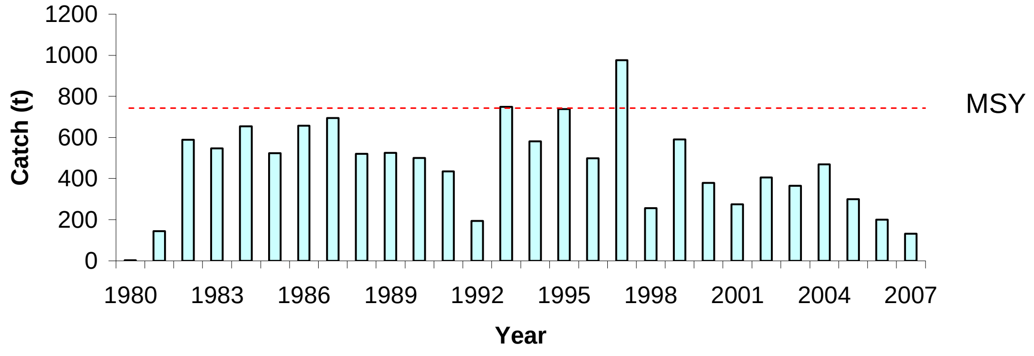


Fig. 13.16. Comparison between total annual spawning biomass trajectories using the Reference Case (with M=0.05) compared to when using with a lower natural mortality M=0.04.



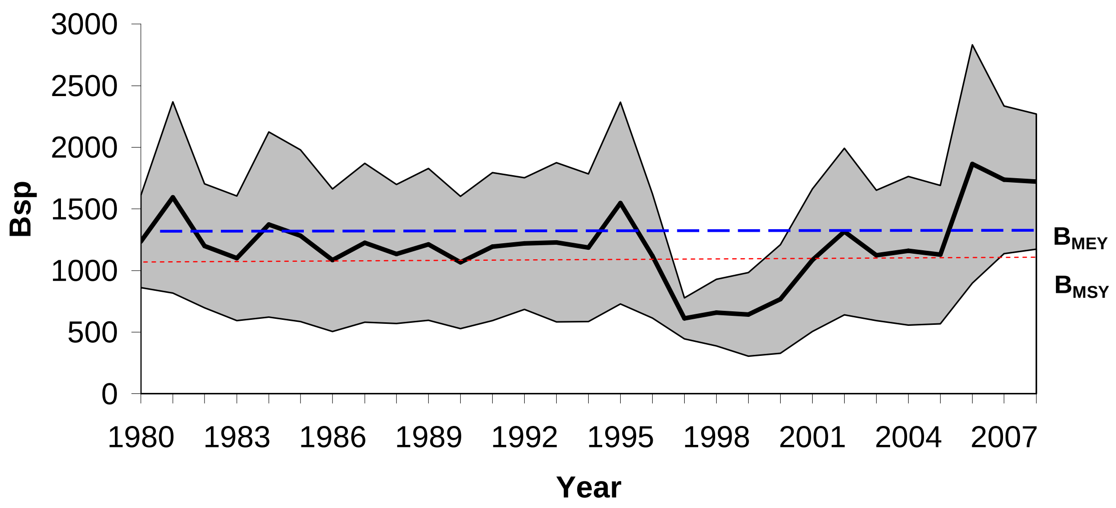


Fig. 13.17. Catch history for the period 1980-2007 and Reference Case spawning biomass estimates shown relative to model estimates of Maximum Sustainable Yield (MSY) under the 1989-2006 selectivity scenario, together with the corresponding spawning biomass level (B_{MSY}) and biomass level (B_{MEY}) corresponding to Maximum Economic Yield (MEY).

Annex 1 – Analysis of considering only the JB redleg banana prawn stock in the assessment process

A sustainable catch needs to be computed for each of the Common and red-legged banana prawn species (*Penaeus merguiensis* and *P. indicus*). *P. indicus* are caught in three banana stock regions in the NPF area: Joseph Bonaparte Gulf (JB), Fog Bay (FB), and Coburg-Melville (CM), with the majority of catches (+90%) being taken from the JB region (Fig. A.1). For simplicity in what follows the JB region is differentiated from the so-called Top-end region (FB and CM).

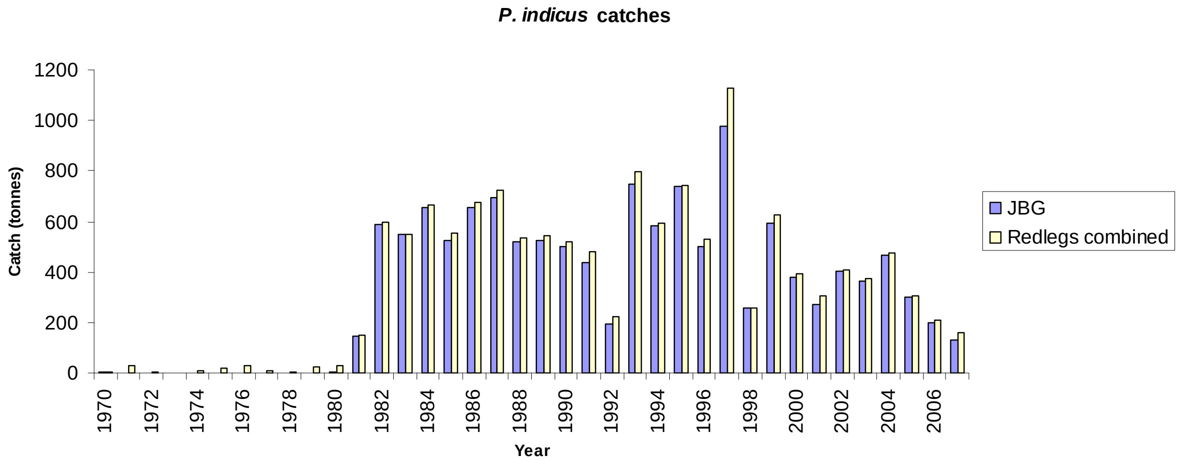


Fig. A.1. History of total *P. indicus* catches highlighting that most catches are taken from JB.

The RAG suggested using for management purposes a dividing line, at 129.3567^{0}E ("The JBG green line") (from Venables 2009) which contains a negligible proportion of the *P. merguiensis* catch, but contains the majority of the *P. indicus* stocks. It splits the JBG from the Top-end region and hence it was proposed that the assessment model focus on the JBG stock as catches from the Top-end are minor by comparison (Fig. A.1).

Annex 2 - Estimation of fishing power time series for the red-legged banana prawns (*Penaeus indicus*) fleet operating in the Joseph Bonaparte Gulf from 1981 to 2007

Summary

A delta-log-normal model was used to assess relative fishing power, because this approach specifically accounts for search effort and harvest effort. Harvest power increased to a peak in the late 1990s-2000, and subsequently declined. Relative fishing powers reflect changes in harvest power, with negligible contribution due to search power. The main contributions to the increase in harvest power were the increase in average hours fished per day (1985-97), fleet renewal (1988+) and within vessel change in technology, especially swept area rate (increased 1981-86, 1993-98; decreased 1987, 2000+) and innovations in electronics during the 1990s. A model was identified for use as a sensitivity test in the development of methods and models for stock assessments of red-legged banana prawns. This model is not suitable for ongoing use in full routine assessments without further confirmation.

Introduction

Description of features of the fishery and history that the fishing power models need to account for.

The fishery has been strongly managed by input controls including controls on vessels and gear, and a system of spatial and seasonal closures. In addition to the mid-year and end-year closed seasons of the entire NPF, two special closures affect the red-legged banana prawn fishery (Figure A2.1). The first was from mid-April to September each year, introduced in 1988. The affected area comprised 26 six-nautical-mile grid squares, mostly less than 70m depth. This ban would have affected roughly 25% of annual effort, considering the typical effort pattern over the history of the fishery. The second closure was a complete ban on fishing in the month of November, introduced in 2000. The affected area comprised 6 six nautical mile grids, less than 70m depth. This ban would have displaced approximately 5% of annual effort, based on considering the typical effort pattern over the history of the fishery. The remainder of the fishing grounds, with no special closures, comprise 105 six nautical mile grids, mostly deeper than 70m.

Currents are extremely strong in the JBG so while trawl speed over the ground may be low, trawl speed through the water may high, for example 5 knots. Effort is said to be restricted to neap tides; trawling does not occur during strongest currents at spring tides.

The fleet that targets red-legged banana prawns (91 vessels at peak, declined to 9 vessels more recently, Figure A2.2) was a subset of the entire NPF fleet. Purpose-designed steel trawlers built after 1986 gradually replaced 40% of the older trawlers (Figure A2.3). Average swept area performance of tiger prawn nets in the fishery for red-legged banana prawns peaked in 1986, and again in 1998-2001 (Figure A2.4).

The decline in 1987 reflected the ban of quad gear accompanied by a cap in headline length. The decline after 2001 was due to a series of management cuts in allowed headline length. There was a strong bimodal seasonal pattern in catch rates with the first peak during April-May and the second peak during August-September (Figure A2.5). Average hours fished per day increased from around 15 hours or less in the early 1980s to 20 or above since the later 1990s (Figure A2.6). There has been a marked contraction in the number of grids fished per year (Figure A2.7).

Methods

Data

Catch and effort data were available from the daily commercial logbooks, which have usually been deemed reliable. Catch of species group is recorded in the logbooks, but species are not distinguished. The two species of banana prawns have fairly separate spatial distributions with only a small overlap, and the separation is excellent when time of year is also considered. Therefore, effort in the fishery for red-legged banana prawns was defined according to a statistical model that predicted probable target species for every commercial fishing day, based on location and time of year (Venables, Kenyon, Bishop *et al.* 2006). Effort in the fishery for red-legged banana prawns between April and December in the Joseph Bonaparte Gulf (JBG), along with corresponding catch of banana prawns, was selected for inclusion in the fishing power model. This JBG catch comprised 95% of all landings of red-legged banana prawns in the NPF.

Banana nets are used by some vessels but others use tiger nets; headline heights are set higher than for tiger prawns. It was not possible to obtain the specifications of banana nets within the scope of the current project. Expected swept area performance rate (SAR) of the tiger nets, according to an engineering model of nets, boards, engines and propellers, (the Prawn Trawl Performance Model, Sterling, 2005) were used as a proxy.

Targetting red-legged banana prawns involves fishing gear settings that are intermediate between those for targetting common banana prawns and those for targeting tiger prawns. Therefore, each candidate technological improvement for which data was available was assessed for inclusion in the red-legged banana prawn fishing power models.

A vessel dataset with some imputed values in the 1980s was used for the evaluation of relative fishing power (this was the same “reconstructed fleet” as used for the tiger prawn fishing power evaluation). Imputation methods included cluster analysis, assumptions based on sister ships and adjacent years, and random allocation in the proportions expected fleetwide according to published descriptions (Dichmont *et al.,* 2003).

Analysis

There were 9% days with zero catch (Figure 8). The distributions of log-transformed daily catches of red-legged banana prawns, using log (catch+3), suggest that the zero catch days do not form a natural part of the continuous distribution of catches (Figure A2.9). However, the distribution of positive catches appears likely to be modelled acceptably by a model with log-normal errors.

A delta – log-normal model (Maunder and Punt, 2004) was used to model the probability of locating red-legged banana prawns in a days searching, and the conditional daily harvest rate of prawns given that any prawns had been found, as functions of effort (hours), abundance (candidate terms were year, season or month, depth stratum, sin and cos functions of lunar phase), and vessel and gear characteristics (candidate terms are listed in Table A2.1). The delta-log-normal model represented the probability of daily catch as follows:

$$\Pr(Y = y) = \delta + (1-\delta)F(y) \qquad \text{(Equation 1)}$$

where Y is the daily catch of red-legged banana prawns in kg,

δ is the probability of a zero-catch day

$$F(y) = \int_0^t f(t)dt$$

The overall fitted values for the delta-log-normal model were obtained from two sub-models. The daily success or failure in locating red-legged banana prawns was modelled by a logit function. This model will be referred to as the search model:

$$\log(\frac{\delta}{1-\delta}) = \alpha + \sum \beta_i X_i + \sum \tau_j V_j + \chi \log(E_t) \qquad \text{(Equation 2)}$$

where explanatory variables included terms for abundance and availability (X_i = year, season, depth, lunar phase), vessel and gear characteristics (V_j) and the natural logarithm of effort hours (E_t).

The harvest rates (conditional on a catch being made) were modelled by a linear regression fitted to the natural logarithm of positive daily catch weights of red-legged banana prawns. This model will be referred to as the harvest model:

$$\log(y) = \alpha + \sum \beta_i X_i + \sum \tau_j V_j + \chi \log(E_t) + \varepsilon \qquad \text{(Equation 3)}$$

Standardised catch rates (per vessel, in the “Reconstructed fleet”, when fishing at baseline abundance) were obtained from the predicted probability of success in locating prawns (from the search model), multiplied by the predicted conditional catch rate (from the harvest model).

Relative fishing power of the reconstructed fleet each year was the average per-vessel standardised catch rates for the year, weighted for the contribution of effort of each vessel.

The two sub-models of the delta-log-normal fishing power model for red-legged banana prawns were fitted to daily (unaggregated) commercial logbook records from April to December, 1980 to 2007 (27,200 daily records of which 24,943 had catch). In the estimation of fishing power, technology status was fitted as dummy variables to represent three states: Present, Absent, and Unknown.

Selection of terms for inclusion in the final model was guided by AIC and R^2, and the stability and significance of estimated coefficients. Model fit was assessed by inspection of residuals.

For some vessel technology terms there was insufficient contrast in the data to estimate coefficients at all. In these cases, external information was sought, including advice from industry about the important features of the fishery, and evidence from published research in similar fisheries on related species. Some items were tentatively fixed in the model by means of offsets. In the search model, the impact of colour echo-sounders was fixed at 0.05 or 0.1. In the harvest model, the impact of TED/BRDs was fixed at -6% in 2000 and -3% thereafter (Brewer, Heales, Milton *et al.* 2006), and the impact of trygear was fixed at 0.05 or 0.1.

Exploratory models investigated various options for model structure, particularly for the terms and interactions to represent abundance, aggregation of the data, and spatial and temporal scales. The terms in the preferred model (Model 1) are listed in Table A2.2. An alternative model (Model 2) is also presented, for the purpose of illustrating the sensitivity of the fishing power outcome to some of the modelling decisions. Model 1 is at season (4 month) time step and Model 2 is at a monthly time step.

Results

Fishing power models

The predicted probability of success in locating prawns was similar from both Model 1 and Model 2: reasonably constant, at around 91% -- there was no evidence of any trends in search power; (Figure A2.10). Thus, according to the search model, the observed fluctuations in percentage of days with catch (Figure A2.8) were attributed to fluctuations in abundance.

The harvest model proved sensitive to the structure of the abundance terms. In addition, some decisions about the inclusion of technology (which could not be well-estimated from the available data) were somewhat influential. The coefficient for log swept area performance (of tiger prawn gear) ranged from 0.93 to 0.96 in red-legged banana prawns harvest model alternatives, while the coefficient for log hours trawled was estimated as 0.76. In this way the red-legged banana prawns harvest models estimated that the efficiency of the red-legged banana prawns banana headline/trawl speed / hours combination was approximately 4-7% lower than the equivalent when targeting tiger prawns.

Figure A2.11 illustrates the two harvest model outcomes. Harvest power increased to a peak in the late 1990s-2000, and subsequently declined. Both series reflect the major events in the fishery history that we expect to contribute to fluctuations in fishing power. The main contributions to the increase in harvest power were the increase in average hours fished per day (1985-97), fleet renewal (1988+) and within vessel change in technology, especially swept area rate (increased 1981-86, 1993-98; decreased 1987, 2000+) and innovations in electronics during the 1990s.

The overall trends in relative fishing powers (Figure A2.12) reflect changes in harvest power, with negligible contribution due to search power.

Discussion

Model 1 appears to be a reasonable and mid-range fishing power series, relative to all the models investigated so far. The “model 1” fishing power series (listed in Table A2.2） is suitable for use as sensitivity test in the development of methods and models for stock assessments of red-legged banana prawns. A main reason for the selection of Model 1 for the current project is that it has a similar scale in the abundance terms as does the stock model (which uses 3-month time blocks).

Model 1 is not suitable for ongoing use in full routine assessments without further confirmation. Some issues that should be addressed include:

- Some decision-process is required for the inclusion of fixed values for technology items colour echo-sounder, and trygear, which could not be estimated from the models.
- The sensitivity of the harvest power to the structure of abundance terms in the model requires some explanation and stabilisation.
- Any impact of the observed contraction in number of grids fished was not accounted for in the models.
- Changing the numbers of boats fishing nearby in the same week may affect search power for red-legged banana prawns. It is most likely that any impact of the observed decline in number of vessels could be assessed by adopting the “local effort” approach that was introduced for use by the tiger prawn fishing power models. However, local effort data were not available for inclusion in the red-legged banana prawn fishing power model within the scope of this project.
- Inspection of residuals for the search model shows that the model does not fit well. A simpler structure of abundance terms may be preferred.

- The swept area performance was approximated as 93-96% of tiger SAR, which may be reasonable; advice from the industry may help to determine whether full specifications are required for the gear used when fishing for red-legged banana prawns.

Acknowledgments

We are grateful to the fishers of the NPF who provided their logbook and gear data. For invaluable assistance in providing data we thank Shannon Evans (NPFI), John Garvey, Narelle Williams and Selvy Coundjidapadam (AFMA), and Margaret Miller and Wayne Rochester (CSIRO).

References

Brewer, D., Heales, D., Milton, D., Dell, Q., Fry, G., Venables, W., and Jones, P. 2006. The impact of Turtle Excluder Devices and Bycatch Reduction Devices on diverse tropical marine communities in Australia's Northern Prawn Trawl Fishery. Fisheries Research. 81:176-188.Maunder, M.M., and Punt, A.E. 2004. Standardizing catch and effort data: a review of recent approaches. Fisheries Research, 70: 141-159.

Sterling, D. 2005 Modelling the physics of prawn trawling for fisheries management. PhD thesis, School of Applied Physics, Curtin University of Technology, Perth. 270 pp.

Venables, W.N., Kenyon, R.A., Bishop, J.F.B., Dichmont, C.M., Deng, R.A., Burridge, C., Taylor, B.R., Donovan, A.G., Thomas, S.E., Cheers, S.J. 2006. Species distribution and catch allocation: data and methods for the NPF, 2002-2004. Final project AFMA No R01/1149.

Table A2.1: Candidate terms to represent vessels, gear and technology

Swept area rate (SAR) according to an engineering model Prawn Trawl Performance Model (Sterling, 2005), Contributors to SAR include number of nets, headline (HL), spread ratio (SR), engine power. PTPM calculates drag, thrust, spread ratio, trawl speed. SAR=HL*SR*speed
Hull age and construction [Hull Group],
By-catch reduction devices [TED/BRDs],
Trygear,
Colour echo-sounder,
Navigational accuracy of GPS, DGPS, and satellite navigation systems [described in the Appendix of relative fishing power of tiger prawns (Appendix 3),
Computer linked to satellite communications [PC-Sat],
Satellite phone,
Plotter,
Plotter software,
Sonar

Table A2.2: Terms in two search models and two harvest models

	Model 1	Model 2
Search	Year, season, depth, lunar phase	Year month
	hull group, offset echo sounder	log (hours) plotter PC_SAT offset echo sounder
Harvest	Year, season, year*season interaction, depth, lunar phase	Year month
	hull group, log (SAR), navigation accuracy class, offset BRD, offset Trygear 0.1	log (hours) hull group log(SAR) navigation accuracy offset BRDs

Table A2.3: Estimated fishing power, Joseph Bonaparte Gulf fishery for red-legged banana prawns.

Year	Relative Fishing Power
1981	1.000
1982	1.212
1983	1.119
1984	1.082
1985	1.263
1986	1.500
1987	1.334
1988	1.248
1989	1.366
1990	1.497
1991	1.909
1992	1.890
1993	2.025
1994	2.112
1995	1.898
1996	2.222
1997	2.563
1998	2.468
1999	2.500
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2001	2.030
2002	1.994
2003	1.899
2004	1.897
2005	1.963
2006	1.995
2007	1.759

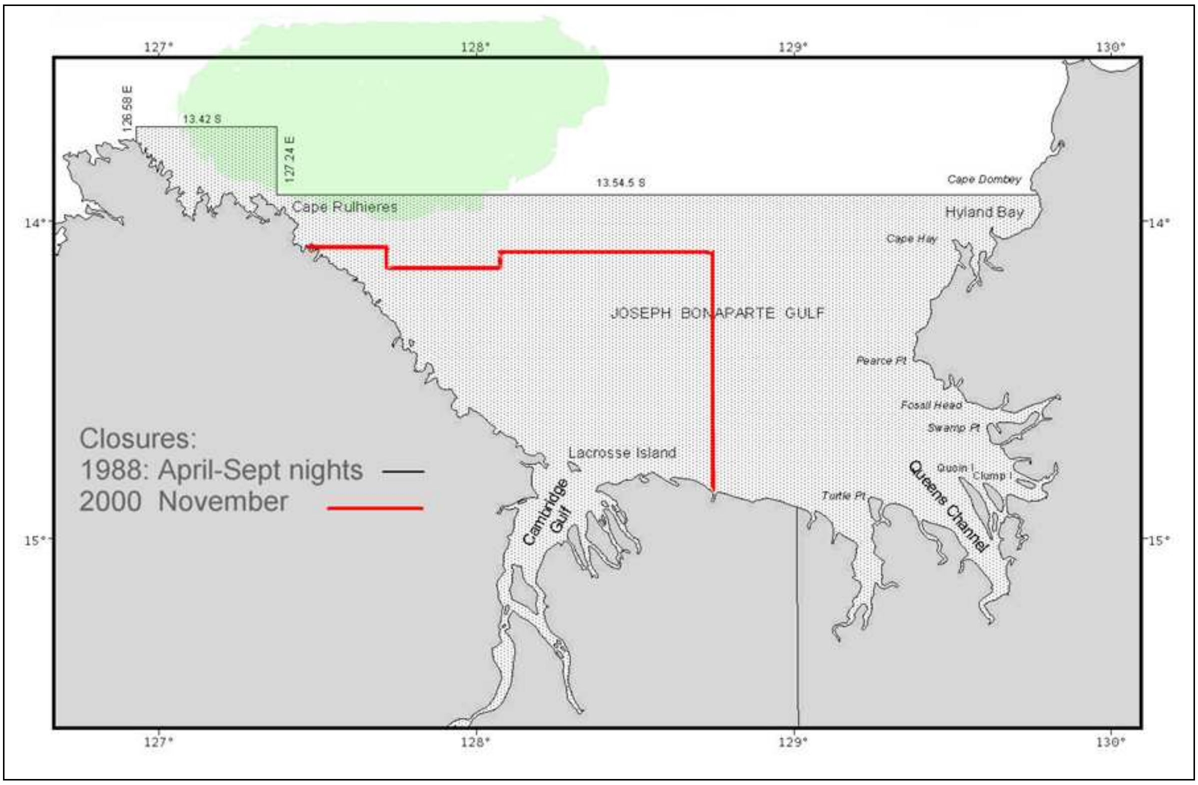

Figure A2.1. Closures in Joseph Bonaparte Gulf

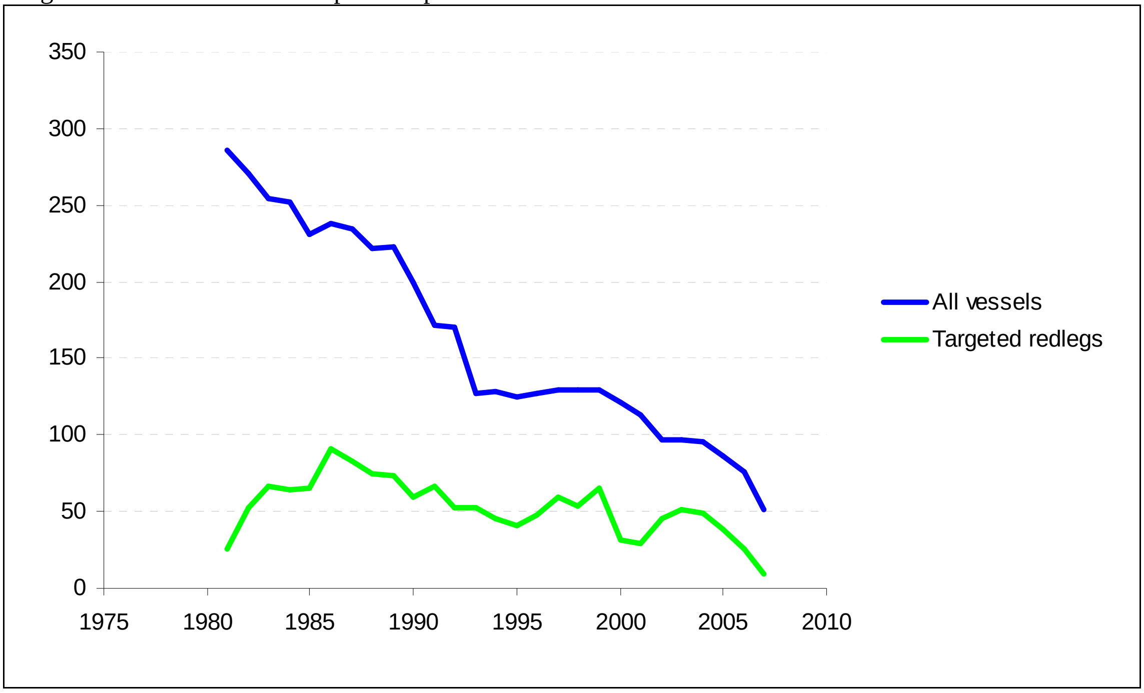

Figure A2.2. Number of vessels in the entire NPF fishery and the number in the specialised sub-fishery for red-legged banana prawns.

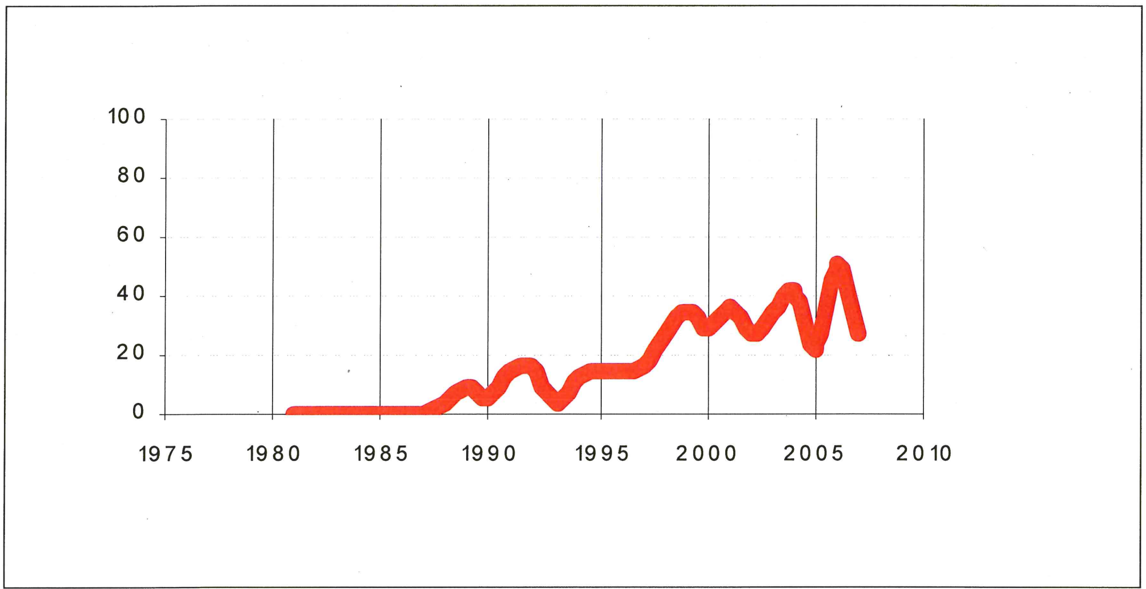

Figure A2.3. Cumulative percentage of the red-legged banana prawns fleet that were purpose -designed trawlers built after 1986.

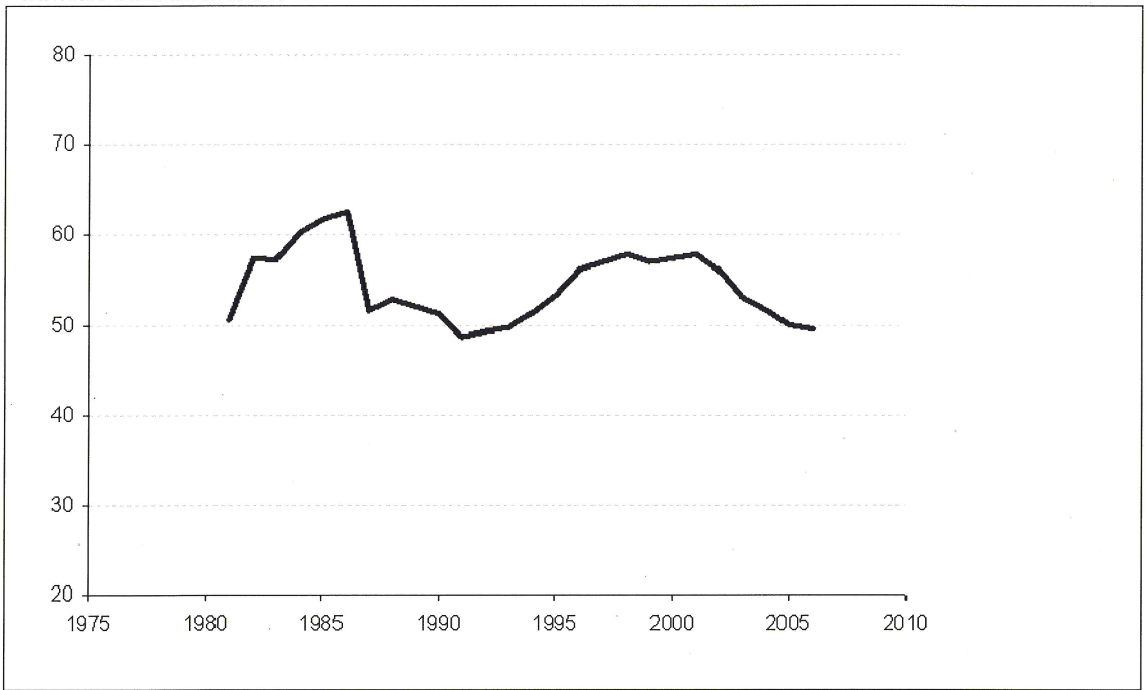

Figure A2.4. Average swept area performance, m^2/sec, tiger nets on board vessels in the fishery for red-legged banana prawns. Source: Prawn Trawl Performance Model, Sterling, 2005.

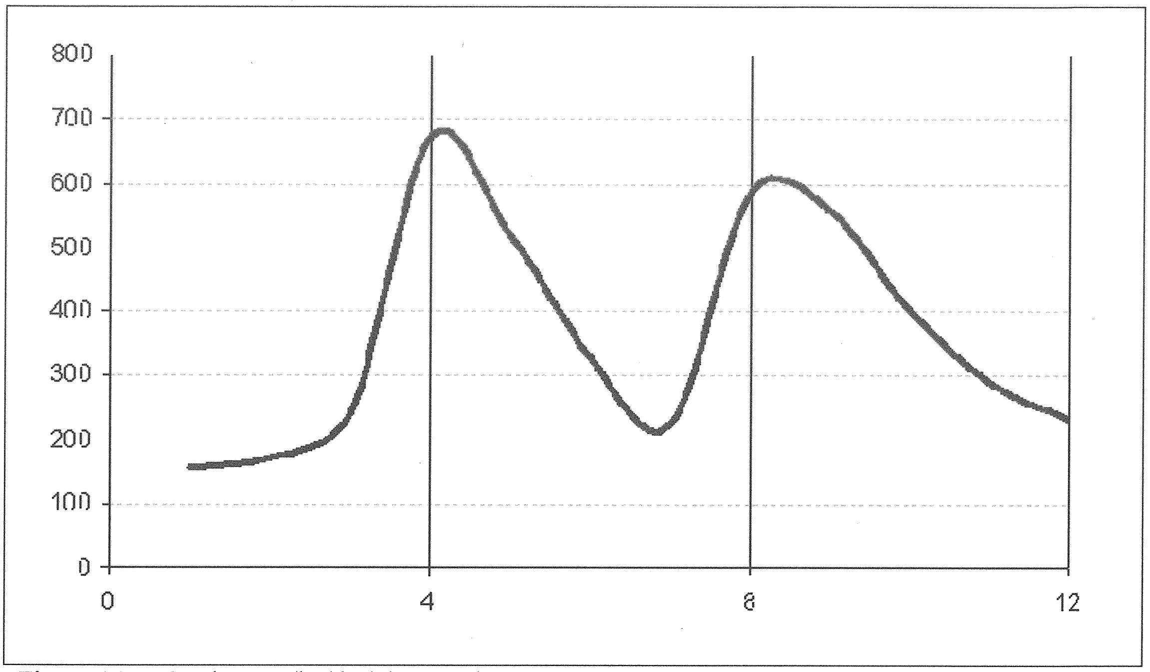

Figure A2.5. Catch rates (kg/day) by month

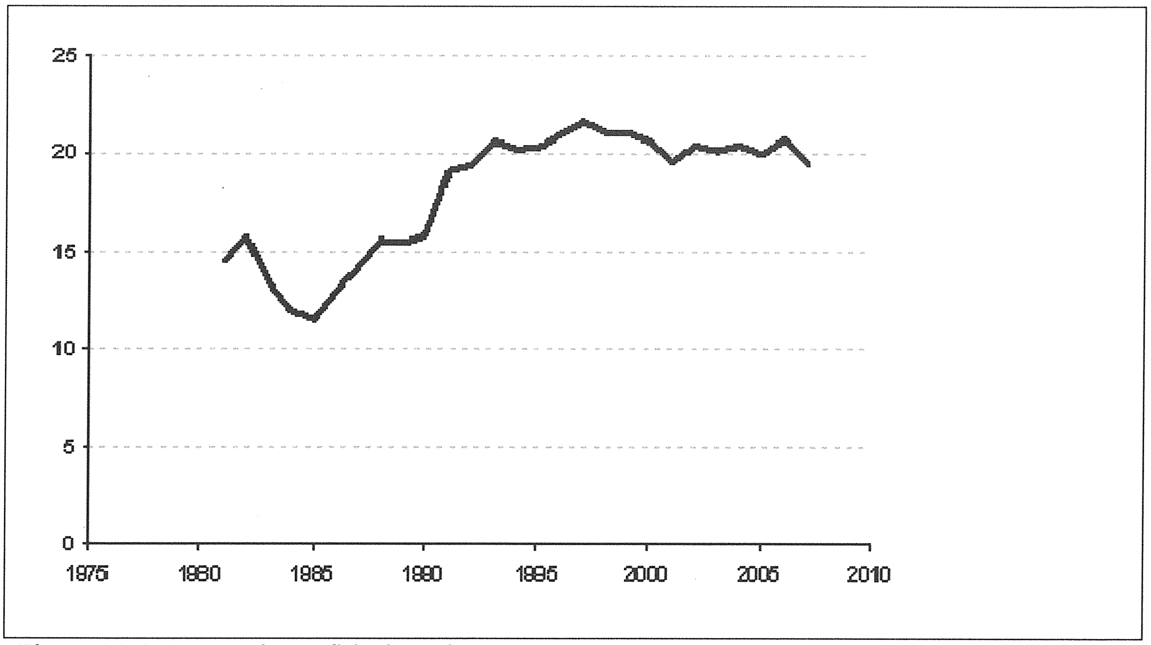

Figure A2.6. Average hours fished per day

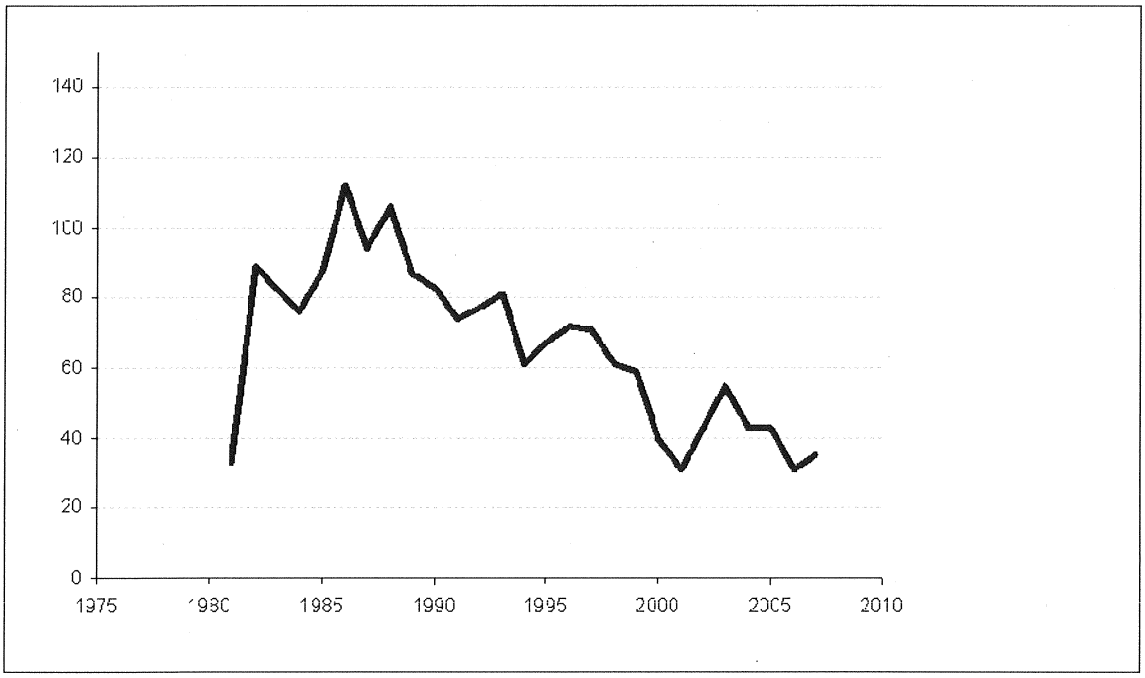

Figure A2.7. Number of grids fished in the JBG red-legged banana prawns fishing grounds, per year

Figure A2.8. Percentage of fishing days with catch

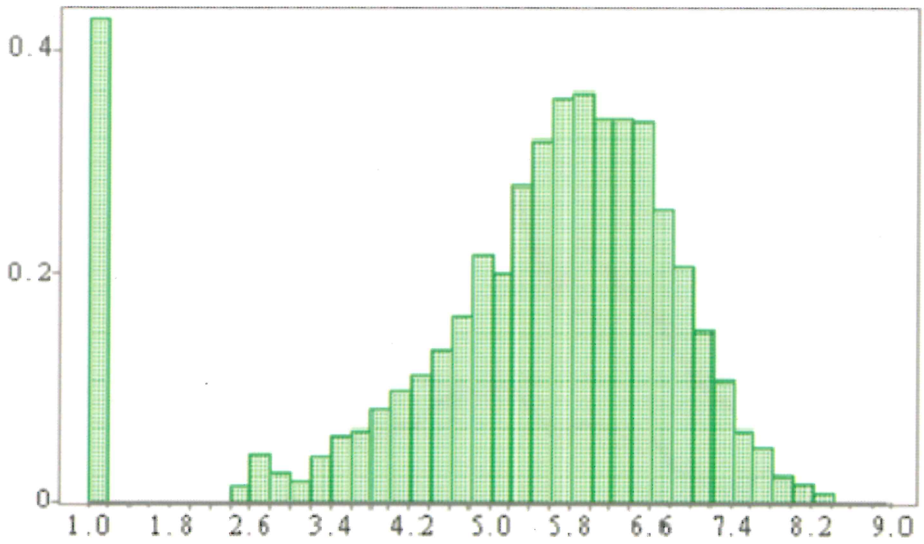

Figure A2.9. Density of log(catch+3kg)

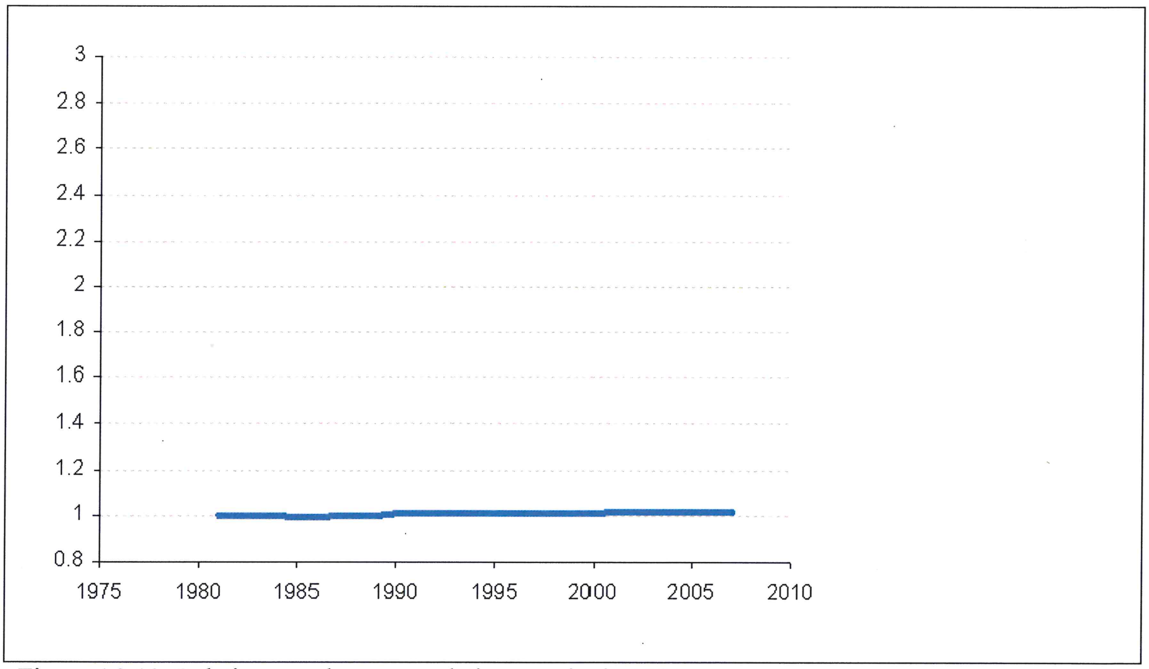

Figure A2.10. Relative search power, relative to unity in 1981

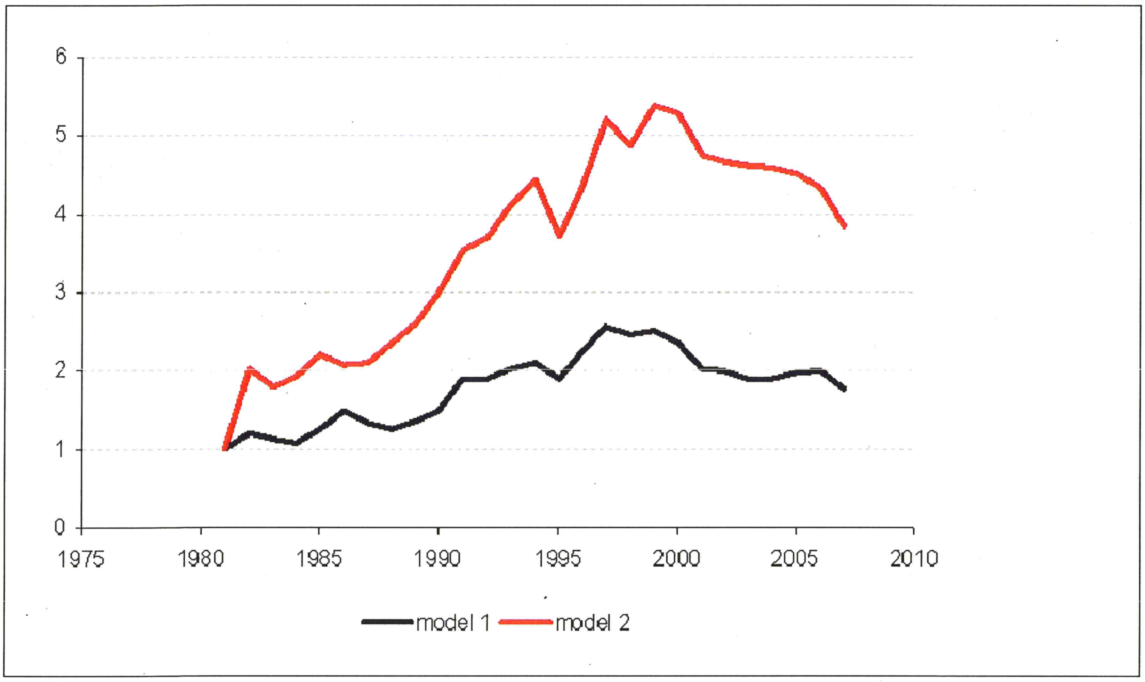

Figure A2.11. Trends in harvest power, relative to unity in 1981. Model 1 is at season (4 month) time step and Model 2 is at a monthly time step.

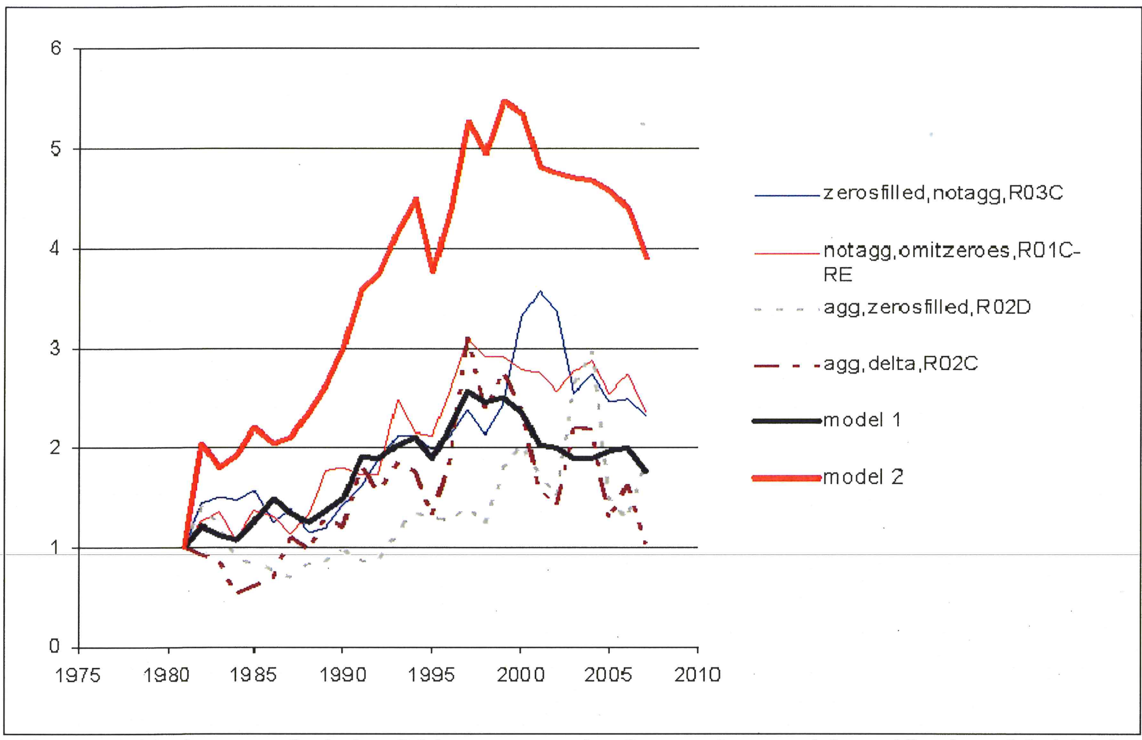

Figure A2.12. A range of relative fishing powers arise from various model specifications. Model 1 is recommended for use in developing a model for stock assessment.

Annex 3. Summary of analysis of commercial category data.

There is a paucity of length frequency data for redleg banana prawns. Such information would be useful to corroborate the model assumptions that prawns increase in size during the year, and that spawning does not occur continuously through the year but rather is concentrated at certain times. This is supported to some extent by consultation with some industry representatives who have reported that "With regards to prawn size they get larger as the year progresses and the smaller prawns are around earlier in the year". Moreover, the commercial database has included information on the commercial category of prawn catches, with Table A3.1 below summarizing the average weight of prawns for each commercial category. This information was used to construct very rough length frequency distributions of prawns caught at different times of the year, for the years 2004-2008. This suggests broadly that there is an increase in the proportional abundance of large prawns later in the year (for example, compare the low relative abundance of category U10 / average 57g prawns during the months April-May compared to Sept – November)(see Tables A3.2a and A3.2b).

Annex Table A3.1. Assumed average count and average weight (g) of individual prawns for each commercial category (from Loneragan *et al.* 1997).

Category	Count per pound	Wt per prawn (g)
U10	8	57
U15	13	35
10/20	15	30
15/25	20	23
21/30	26	17
31/50	40	11

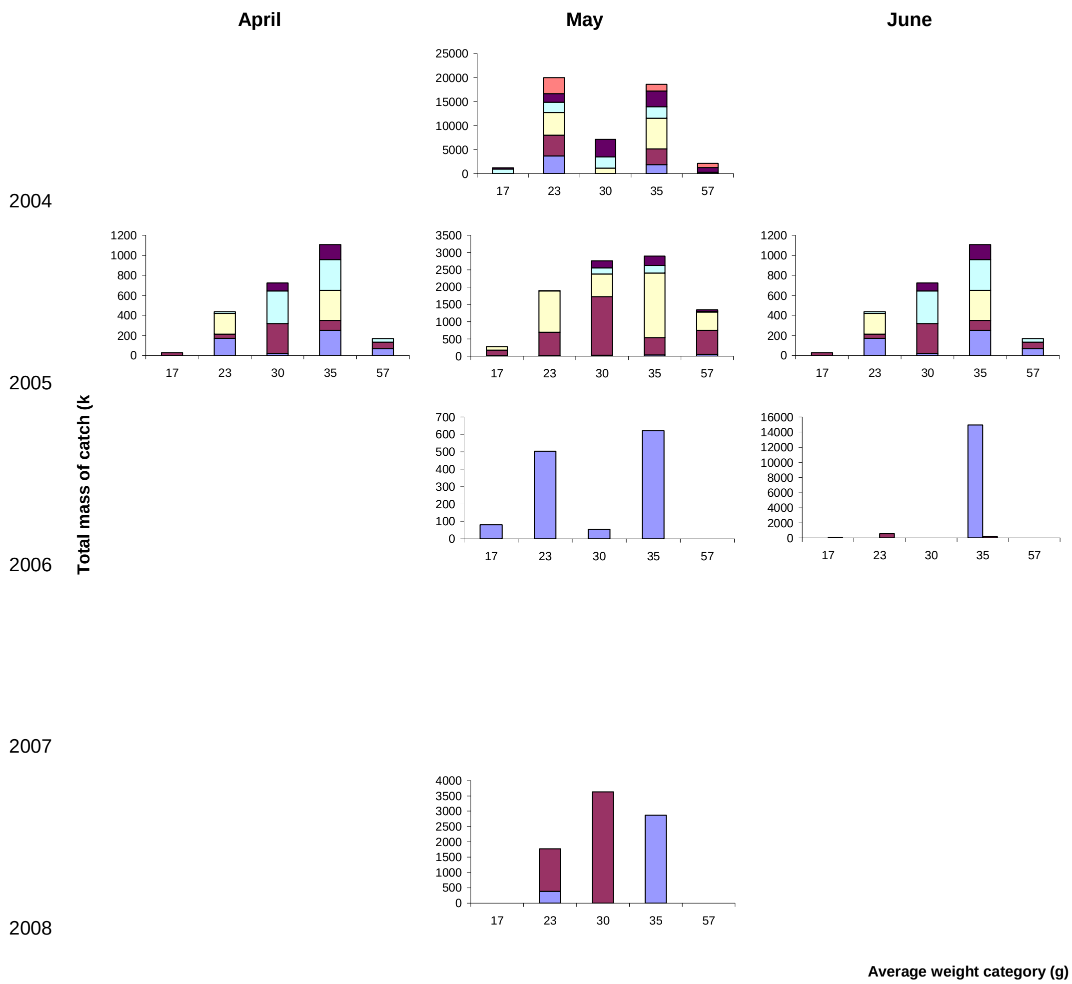

Fig. A3.2a. Summary of the relative abundance of prawns in average weight categories ranging from 17 – 57 g (based on the conversions in Table A3.1) for each of the months as shown and for years 2004-2008.

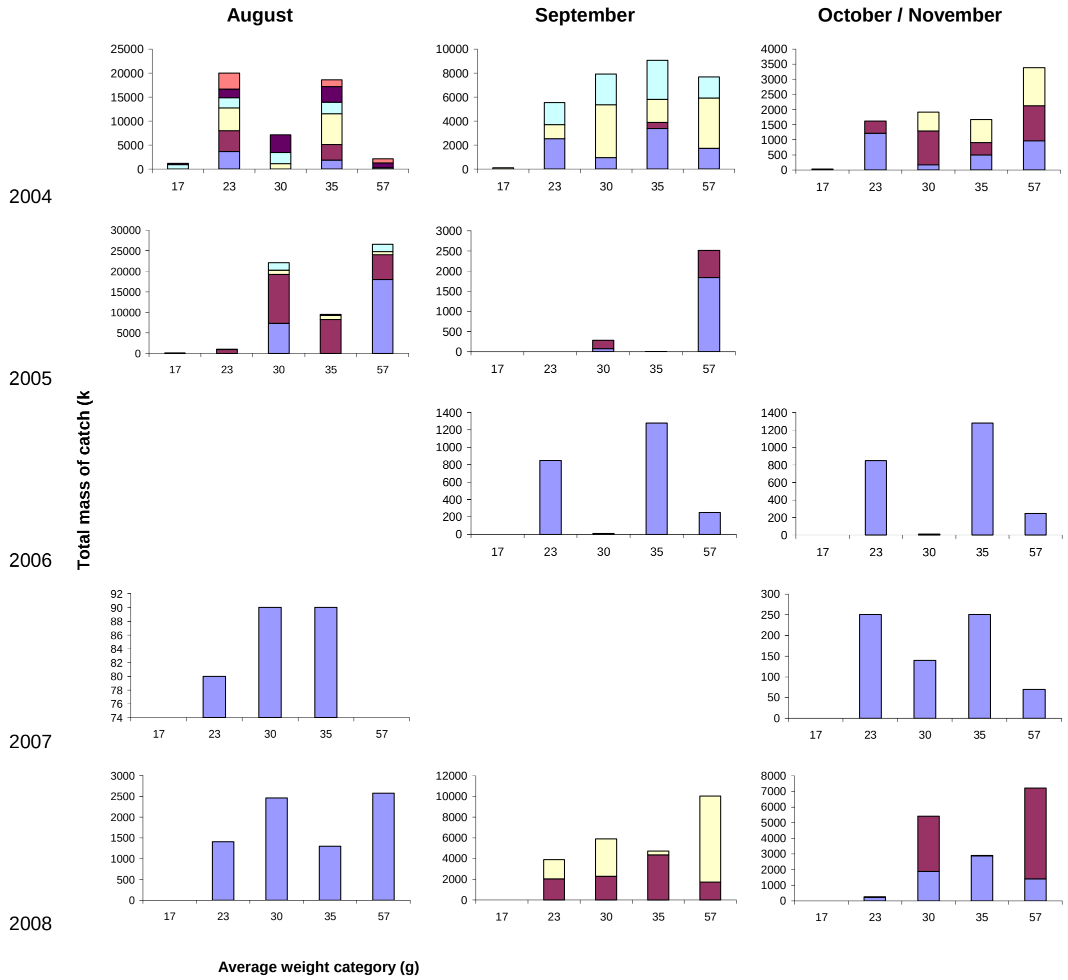

Fig. A3.2b. Summary of the relative abundance of prawns in average weight categories ranging from 17 – 57 g (based on the conversions in Table A3.1) for each of the months as shown and for years 2004-2008

APPENDIX 14. STOCK ASSESSMENT OF RED LEGGED BANANA PRAWNS USING MULTI-FLEET BAYESIAN BIOMASS DYNAMICS MODEL

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14.1 Introduction

Formal quantitative stock assessment has not been conducted for the red legged banana prawns *Penaeus indicus* in the Northern Prawn Fishery due to the relatively small scale of the fishery and limited information on this species (Loneragan *et al.* 2002). We applied a Bayesian state-space biomass dynamics model for red legged banana using catch and effort data alone. The method is similar to that developed and tested for the grooved tiger prawns (Zhou *et al.* 2009)(Appendix 8).

14.2 Methods

Data
We used catch and effort data in the commercial logbook from 1981 to 2007 for the assessment of red leg banana prawns. This species has been caught in three banana stock regions in the NPF area: JB, FB, and CM (Figure 14.1). Because catch in CM and FB regions are relatively small, we combined three stock areas into a single aggregated stock.

The red legged banana prawns are caught by multiple fleets targeting different species: the semi fleet targeting on *P. semisulcatus*, the escu fleet targeting on *P. esculentus*, the indi fleet targeting on *P. indicus*, and the merg fleet targeting on *P. merguiensis*. Because *escu* and *merg* fleets catches insignificant number of red legged banana, we excluded the catch rate data for these two fleets in the model fit (but included in the total catch for biomass estimation). Figure 14.2 shows the catch versus effort relationship for the fleet included in the model (*indi*)

Multi-fleet biomass dynamics models
As the catch-effort data are the main reliable information we have for brown tiger prawns, biomass dynamics models seem to be the most appropriate tool for stock assessment. The advantages of using biomass dynamics model are that information on survival, growth,

catchability, recruitment, etc. are not needed. The deterministic version of the biomass dynamics model can be written as:

$$B_y = B_{y-1} + rB_{y-1}\left(1 - \frac{B_{y-1}}{K}\right) - \sum_{f=1}^{4} C_{f,y-1}\,, \tag{1}$$

where B is biomass (in ton), r is the intrinsic growth rate, K is the carrying capacity, C is the catch. The subscript y is year and f is fleet.

The values for the parameters in equation 1 were estimated by fitting them to catch rate (CPUE) data from four fishing fleets. For a multi-fleet fishery the model-estimate corresponding to the catch-rate for fleet f, and year y, $\hat{U}_{f,y}$ is:

$$\hat{U}_{f,y} = q_f P_y B_y\,, \tag{2}$$

where q_f is the catchability coefficient for fleet f, and P_y is the relative fishing power during year y. We adopted "based case high" fishing power estimated for the tiger prawns in this analysis because they are caught in a similar way, although the red legged banana prawns are caught in more restricted areas, much deeper and with only limited access times. The observed catch-rate was assumed to be log-normally distributed about its expected value in common with most applications of biomass dynamics models:

$$U_{f,y} \sim \text{log-normal}\{\ell\text{n}(\text{E}[\hat{U}_{f,y}], \tau_{U,f})\} \tag{3}$$

where $\tau_{U,f}$ is the precision (the inverse of the variance) of the observation error for the catch-rate data for fleet f. $\tau_{U,f}$ is allowed to differ among fleets because it would not be expected that fleets that target a species and which take it as by-catch would lead to indices of abundance with the same extent of precision as would be the case for a target fleet.
We assumed that deviations about the expected biomass are log-normally distributed, i.e.:

$$B_y \sim \log-\text{normal}\{\ell n(E[B_y]), \tau_B\} \tag{4}$$

where τ_B is the precision of the process error.
It is necessary to specify prior distributions for all of the parameters of the model to implement each of the two state-space models within a Bayesian framework. We assumed that r, K and q for each stock and fleet were log-normally distributed, i.e.

$$\begin{aligned} &r \sim \text{log-normal}(\mu_r, \tau_r) \\ &K \sim \text{log-normal}(\mu_K, \tau_K) \\ &q_f \sim \text{log-normal}(\mu_q, \tau_q) \end{aligned} \tag{5}$$

Where μ_θ and τ_θ are the prior means and the corresponding prior precisions. We used a relative non-informative priors (cv = 100%). Given the assumptions regarding the nature of the state-space model and the priors for the parameters, the posterior distribution is proportional to:

$$\begin{aligned} &p(K \mid \mu_K, \tau_K)\, p(B_{1981} \mid \mu_K, \tau_K)\, p(r \mid \mu_r, \tau_r)\, p(q_f \mid \mu_q, \tau_q)\, p(\tau_B)\, p(\tau_{U,f}) \\ &\prod_y \left(p(B_y \mid B_{y-1}, K, r, C_y, \tau_B) \prod_f p(U_{f,y} \mid B_y, q_f, P_y, \tau_{U,f}) \right) \end{aligned} \tag{6}$$

where the underlined parameters denote a vector or matrix over year y.
The Gibbs sampler, a Markov chain Monte Carlo (MCMC) technique, implemented using the WinBUGS package (http://www.mrc-bsu.cam.ac.uk/bugs) was used to sample parameter vectors from the posterior distribution (Eqn 6). Three Markov chains were conducted based

on dispersed initial values, and the results of the first 11,000 cycles of each chain taken as the burn-in period. The results of an additional 20,000 cycles from the three chains were saved, which formed the basis for further analysis. Whether the MCMC algorithm converged adequately to the posterior was evaluated by visually examining the three chains for each parameter in Eqn 6 and using the Gelman-Rubin diagnostic statistic

From these estimated parameters, we derive the management parameter, the maximum sustainable yield MSY for stock *s*:

$$MSY = \frac{rK}{4}. \qquad (7)$$

14.3 Results

Table 14.1 lists the key parameters from the biomass dynamics model. The estimates have high uncertainty, especially for the upper boundary. The target fleet has a higher catchability than the bycatch fleet, which is expected. The model precision is higher for the target fleet than the bycatch fleet (Fig. 14.3), which is also expected.

The posterior median biomass was above the median posterior B_{msy} in most years during 1981 to 2007 (Fig. 14.4). Since 2000 median biomass has always been greater than the median B_{msy}.

14.4 References

Loneragan, N., Die, D., Kenyon, R., Taylor, B., Vance, D., Manson, F., Pendrey, B., and B. Venables. (2002). The growth, mortality, movements and nursery habitats of red-legged banana prawns (*Penaeus indicus*) in the Joseph Bonaparte Gulf. FRDC Project 97/105. CSIRO Marine Research.

Zhou, S., Punt, A.E, Deng, R., Dichmont, C.M., Ye, Y. and J. Bishop. 2009. Modified hierarchical Bayesian biomass dynamics models for assessment of short-lived invertebrates: a comparison for tropical tiger prawns. *Marine and Freshwater Research* 60, 1298-1308.

Table 14.1. Summary of the posterior distribution of key parameters.

Para	mean	SD	2.50%	median	97.50%
K	3041	1902	1305	2324	8817
R	1.35	0.58	0.39	1.32	2.51
MSY	827	242	473	782	1455
q_indi	2.08E-04	6.46E-05	1.02E-04	2.02E-04	3.53E-04
q_semi	4.73E-06	2.76E-06	1.56E-06	4.09E-06	1.16E-05
tau.B	4.91	3.53	1.64	4.00	13.11
tau_indi	96.28	276.70	4.57	17.08	826.00
tau_semi	0.16	0.05	0.08	0.15	0.26

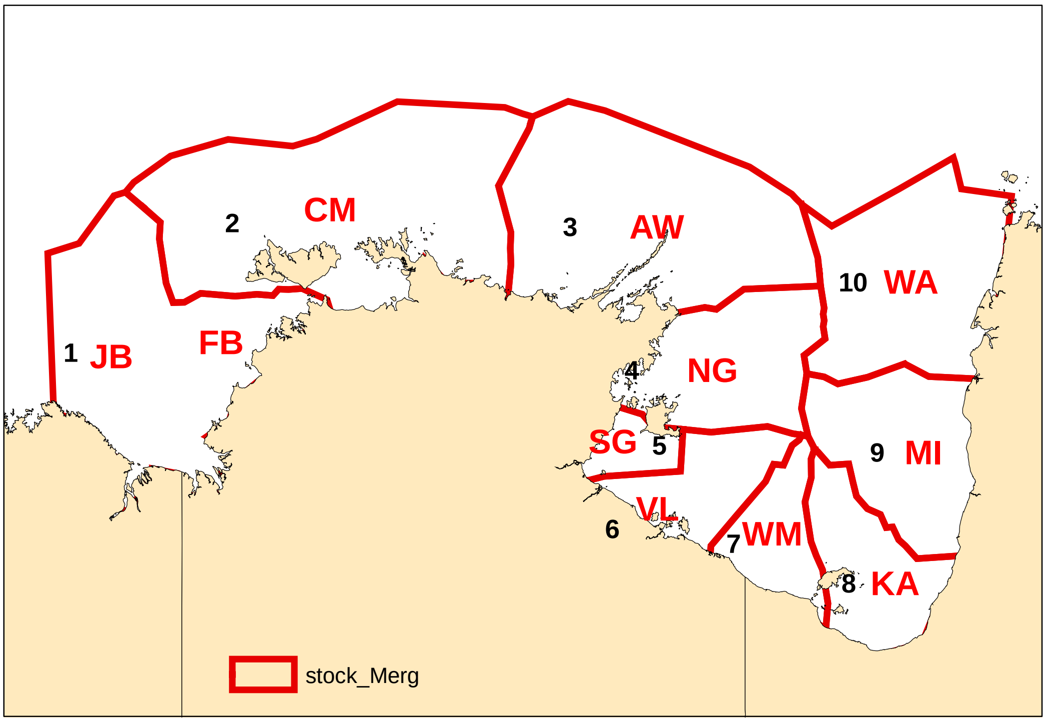

Figure 14.1. Banana prawn stock regions in NPF. The red legged banana are caught in JB, FB, and CM only.

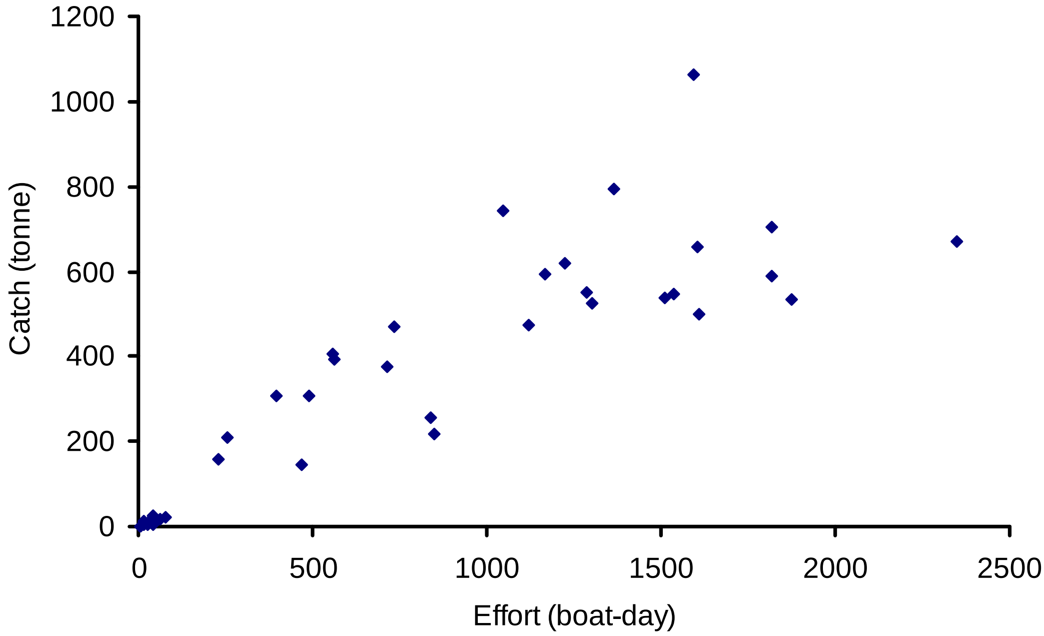

Figure 14.2. Scatter plot of catch and effort for the indi fleet targeting red legged banana prawns.

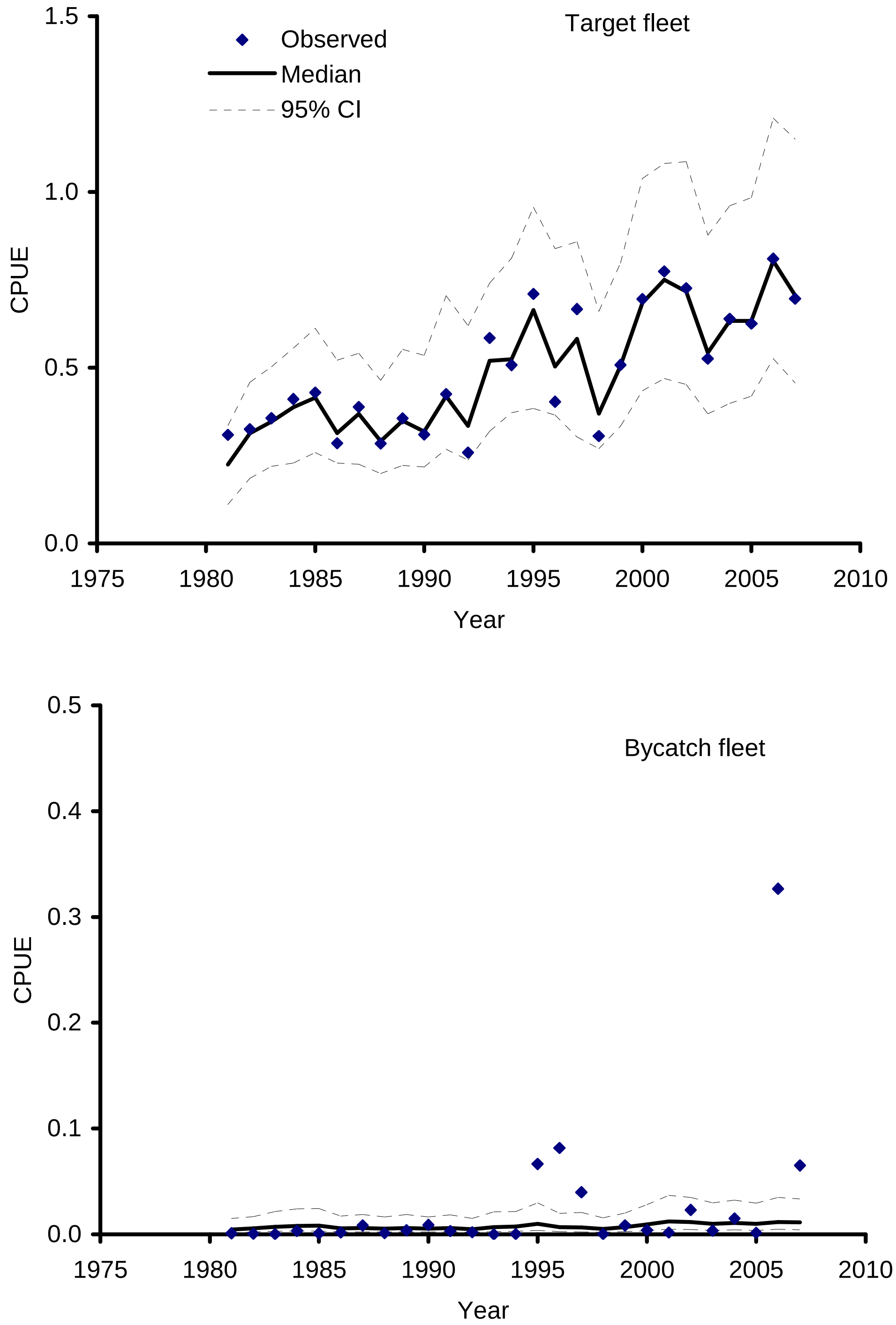

Figure 14.3. Observed catch rates (dots) and the posterior predictive catch rate distributions (medians and 95% credibility intervals) for fleet targeting red legged banana (top) and fleet by-catching red legged banana prawns while targeting grooved tiger prawns (bottom).

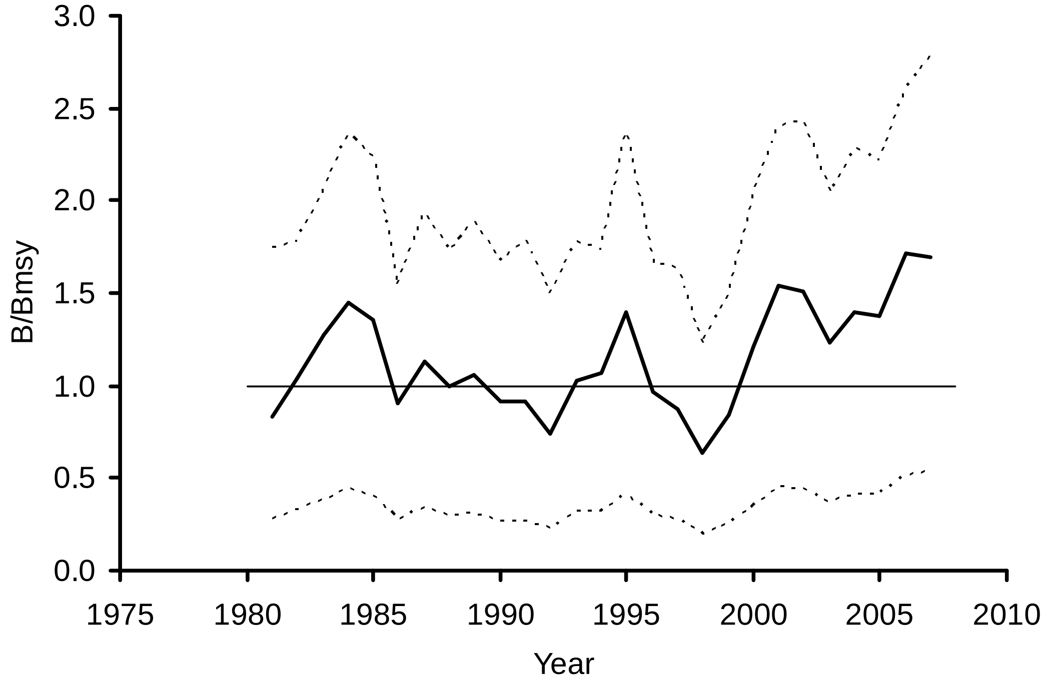

Figure 14.4. Posterior median time trajectory for the red legged banana prawns' ratio of B/B_{msy} in JBG. The dotted lines are the 2.5% and 97.5% credible intervals.

APPENDIX 15. OPTIMAL VESSEL SIZE AND OUTPUT IN THE AUSTRALIAN NORTHERN PRAWN FISHERY: A RESTRICTED PROFIT FUNCTION APPROACH

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15.1 Abstract

Individual transferable quotas (ITQs) are to be introduced into Australia's Northern Prawn fishery in the near future. Total allowable catches (TACs) are to be set with the objective of maximising economic efficiency in the fishery. Under ITQs, vessel owners have the ability to adjust their fishing activities in order to maximise profits, and changes in fleet structure resulting from management changes need to be considered when determining TACs. A restricted profit function for the fishery was estimated to determine the optimal vessel characteristics and output levels as a guide to how the fleet may adjust under an ITQ system. Vessels were found to be currently close to their optimal size given average historic prices and current stock conditions. However, higher tiger prawn stocks are expected to result in the average size of vessels increasing, with rising fuel prices also likely to result in capital being substituted for fishing days. Optimal average vessel level catches of the main species are lower than current average vessel catches for a wide range of input and output prices. These changes in vessel characteristics and behaviour need to be incorporated in the derivation of the optimal TACs if economic efficiency objectives are to be achieved.

Keywords: profit function; fuel prices; optimal vessel size, individual transferable quotas

15.2 Introduction

The introduction of individual transferable quotas (ITQs) in the Australian Northern Prawn Fishery (NPF) will provide a greater incentive for vessel owners to adjust their input use and scale of operation in light of changing economic conditions. Fishers will have an incentive to adjust their input and output mix to either minimise costs for a given level of output (as determined by their quota allocation), or alter both their input and output levels to maximise profits. Determining how fishers will adjust their input and output mix requires an understanding of the cost structures facing the industry, and also the impact of changing prices on vessel profits. Dual approaches, such as cost and profit functions, are appropriate to analyse fisher behaviour and performance in light of changing management conditions (Jensen 2002).

The need to determine how fleets may respond to the changing management-induced incentives is even greater for the NPF, as the fishery has an explicit goal of achieving maximum economic yield (MEY) – the first large commercial fishery in the world to do so. Total allowable catches (TACs) for the main species are to be set using a bioeconomic model of the fishery (Dichmont *et al.* 2008). Incorporating expectations of changes in cost structures into the analysis is essential if appropriate TACs are to be set and the objective of MEY to be achieved. In this paper, a restricted profit function is estimated for the NPF using economic data collected from individual fishers since the early 1990s. The model is used to derive estimates of the individual vessel size and output level that maximises individual vessel profits given different input and output price levels.

The remainder of the paper is organised as follows. First, a brief description of the fishery is provided. Then, a description of the methods used is presented, followed by a description of the economic data. Next, the empirical results are presented, followed by a discussion and conclusions.

15.3 The northern prawn fishery

The NPF is one of Australia's most valuable fisheries in terms of total landed value. In 2007-08, the gross value of product was estimated to be around $74m (ABARE 2009), although in previous years it had been in excess of $150m (Newton *et al.* 2007). In more recent years, profitability in the fishery has been adversely affected by falling prawn prices (Figure 15.1) and rising fuel prices (Figure 15.2). Declining prawn prices have largely been due to a combination of increased aquaculture supply of prawn on the world market and, in the last few years, a strengthening of the Australian Dollar against the currencies of major importers of Australian prawns, especially the US Dollar and Japanese Yen (Wood et al. 2008). The increase in fuel prices has resulted in fuel costs increasing from 15 per cent of total costs in 1994-95 to almost 40 per cent in 2005-06 (Brown 1997; Vieira and Hohnen 2007) (Figure 15.2).

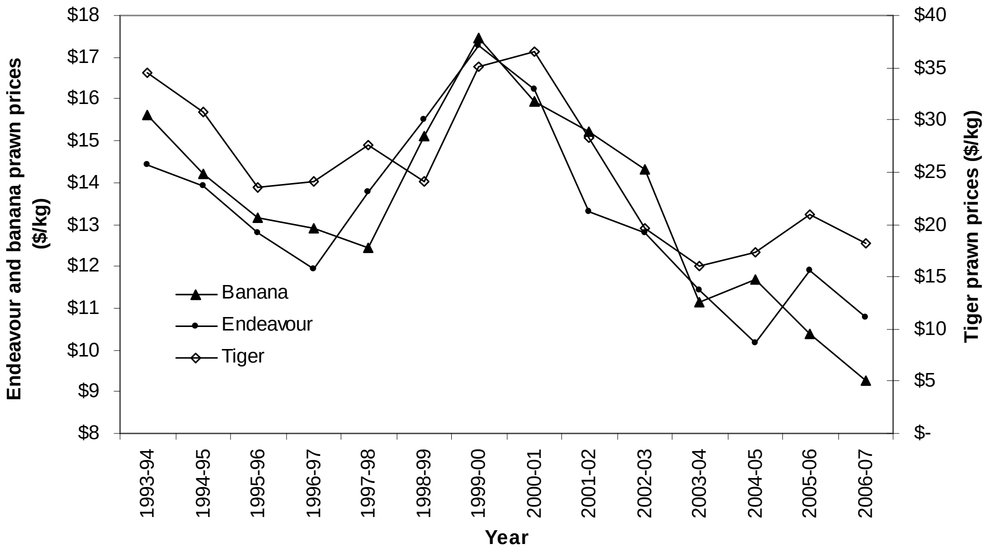

Figure 15.1 – Real prices of the main species caught in the northern prawn fishery (2006 prices).

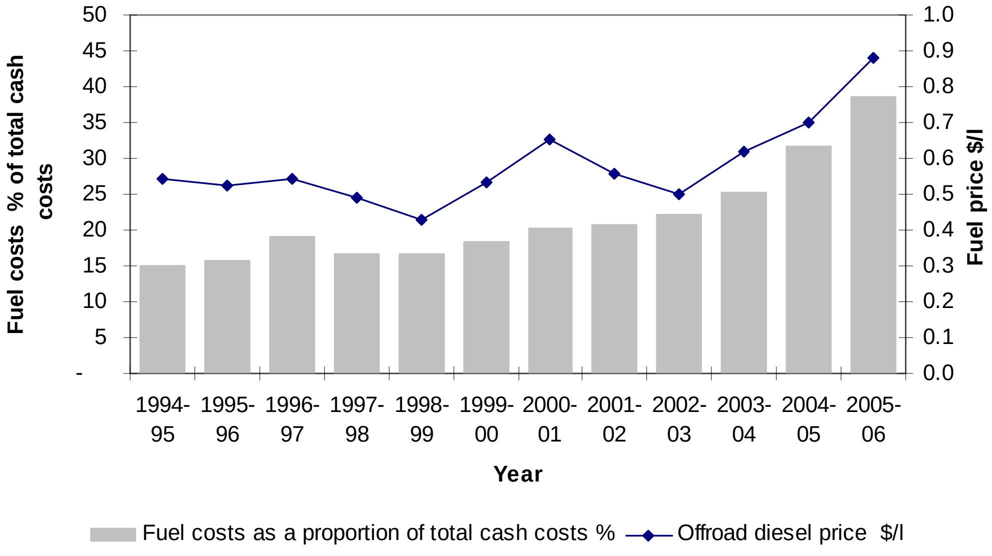

Figure 15.2 – Fuel cost shares and real off-road diesel price, northern prawn fishery (2005-06 prices).

The fishery occurs over two "seasons" each year, which can also effectively be considered as two separate sub-fisheries – namely a "banana prawn fishery" and a "tiger prawn fishery". The banana prawn fishery occurs during the first season which generally runs from March/April to June. White banana prawns (*Fenneropenaeus merguiensis)* caught in the Gulf of Carpentaria dominate the total catch during the first season, when these prawns form dense spawning aggregations. As a consequence, large quantities of *F. merguiensis* can be caught over the relatively short season (Die and Ellis 1999).

The tiger prawn fishery occurs during the second season which generally runs from August/September to October/November/December. The key species caught during the second season are brown tiger prawns (*Penaeus esculentus*), grooved tiger prawns (*P. semisulcatus*) and two endeavour prawn species (*Metapenaeus endeavouri* and *M. ensis*). These species are generally more dispersed relative to *F. merguiensis* so different fishing gears and behaviours are consequently employed. Catches of these species are predominantly taken in the Gulf of Carpentaria. A number of other prawn species (e.g. red-legged banana prawns, king prawns) as well as fish, cephalopods and other crustaceans are also caught as by-products during both seasons.

The fishery is rather unique – both in Australia and internationally – as it has an explicit management objective of maximizing the economic returns from the fishery (Larcombe 2008). The fishery is currently managed using a combination of input controls, primarily seasonal closures and individual transferable gear units. Effort levels in the tiger prawn fishery are set using a bio-economic model that optimizes economic returns in the fishery over time rather than on a year-by-year basis (Dichmont *et al.* 2008). Over the last decade, the fleet size has more than halved, from 133 vessels in 1998 to 52 in 2008, largely as a result of management action resulting in an industry-funded reduction in 2001 (which removed 36 vessels), and a government-funded vessel buyback in 2006 (which removed 43 vessels) and consolidation of gear units (DAFF 2006; Larcombe 2008). More recently, the decision has been made to implement ITQs in the fishery, although when this will occur has yet to be determined. A draft management plan outlining the characteristics of the ITQ system to be used is expected to be completed in June 2010.

15.4 Methodology

The key objective of the study was to estimate the average optimal vessel size and catch, taking into consideration expected changes in prices and stock conditions. The move to ITQs in the fishery will provide incentives for fishers to adjust their activity levels in response to these conditions, and any estimation of future TACs will need to take into account the expected future cost structure of the industry as well as expected changes in input and output prices. An advantage of using a profit function to estimate the optimal size and activity levels is that it allows for variation in both inputs and outputs, with both assumed to be endogenous with respect to their relative prices.

Following Squires (1987) and Andersen *et al.* (2008), the most general form of the restricted profit function is given as $HR(p,z)$, where HR is the short-term restricted profit defined as total revenue less the variable costs, p is a vector of variable input and output prices, and z is a vector of quasi-fixed inputs. The function is restricted because it depends on the existing level of quasi-fixed inputs. Total profits can be given by $HT(p,p_z,z)=HR(p,z)-p_{z'}z$, where p_z is a vector of the (market) user prices of the quasi-fixed inputs. From Hotelling's lemma (Hotelling 1932), $\delta HR(p,z)/\delta p = Q(p,z)$ and $\delta HR(p,z)/\delta z = -p_z^*$, where $Q(p,z)$ is the profit maximising level of outputs or inputs given the set of prices and the level of quasi-fixed factors, and p_z^* is the shadow prices of the quasi-fixed factors. The optimal level of the quasi-fixed factors is determined by equating the shadow price to the service price, such that $\delta HR/\delta z = p_z$ (Squires 1987). Given this, the optimal equilibrium level of inputs and outputs (i.e. after quasi-fixed factors have been optimised) is given by $\delta HR(p,z^*(p,p_z))/\delta p$, where $z^*(p,p_z)$ is the long run equilibrium level of the quasi-fixed factors given the set of prices. Although restricted profit functions have been estimated for a wide range of industries, relatively few attempts to estimate profit functions have been made in fisheries (Squires 1987, 1988; Asche *et al.* 2007; Andersen *et al.* 2008). This is most likely due to a lack of an appropriate time series of economic information in most fisheries.

A range of functional forms of the profit function are available, the most frequently used being the translog. This is a relatively flexible functional form, because it does not impose assumptions about constant price elasticities nor elasticities of substitution between inputs and outputs. The generic form of the translog profit function is given by

$$\begin{aligned}\ln HR = {} & \alpha_0 + \sum_i \alpha_i \ln P_i + \frac{1}{2}\sum_{i\neq j}\sum_{j\neq i}\alpha_{ij}\ln P_i \ln P_j + \sum_i \alpha_{ii}\ln^2 P_i + \\ & \sum_k \beta_k \ln Z_k + \sum_{k\neq l}\sum_{l\neq k}\beta_{kl}\ln Z_k \ln Z_l + \sum_k \beta_{kk}\ln^2 Z_k + \sum_i\sum_k \beta_{ik}\ln P_i \ln Z_k + \\ & \gamma\, t + \gamma_{tt}t^2 + \sum_i \gamma_i \ln P_i t + \sum_k \gamma_k \ln Z_k t\end{aligned} \tag{1}$$

Where *HR* is the observed level of short-run profit, P_i and P_j are the prices of the variable inputs and outputs *i* and *j*; Z_k and Z_l are the quasi-fixed input quantities *k* and *l*, and *t* is a time trend used to estimate the effects of technical progress.

The restricted profit function was normalised by the price of one of the outputs (P_1), with the functional form of the estimated model given by

$$\begin{aligned}\ln(HR/P_1) = {} & \alpha_0 + \sum_{i>1}\alpha_i \ln(P_i/P_1) + \sum_{i\neq j\neq 1}\sum_{j\neq i\neq 1}\alpha_{ij}\ln(P_i/P_1)\ln(P_j/P_1) + \sum_{i>1}\alpha_{ii}\ln^2(P_i/P_1) + \\ & \sum_k \beta_k \ln Z_k + \sum_{k\neq l}\sum_{l\neq k}\beta_{kl}\ln Z_k \ln Z_l + \sum_k \beta_{kk}\ln^2 Z_k + \sum_{i>1}\sum_k \beta_{ik}\ln(P_i/P_1)\ln Z_k + \\ & \gamma_t t + \gamma_{tt}t^2 + \sum_{i>1}\gamma_i \ln(P_i/P_1)t + \sum_k \gamma_k \ln Z_k t\end{aligned} \tag{2}$$

Homogeneity in input and output prices requires $\sum_i \alpha_i = 1$, $\sum_i \alpha_{ij} = 0$, $\sum_i \beta_{ik} = 0$ and $\sum_i \gamma_i = 0$, while symmetry in input and output prices requires $\alpha_{ij} = \alpha_{ji}$. Hence, the parameters of the output used in the normalisation can be derived using the homogeneity conditions (e.g. $\alpha_1 = 1 - \sum_{i>1}\alpha_i$).

From Hotelling's lemma, the partial derivative of the profit function with respect to the input and output prices ($\ln P_i$) yields a set of profit share equations, given by

$$S_i = \alpha_i + 2\alpha_{ii}\ln P_i + \sum_{j\neq i}\alpha_{ij}\ln P_j + \sum_k \beta_{ik}\ln Z_k + \gamma_i t \tag{3}$$

where $S_i = P_i Q_i / HR = (P_i / P_1) Q_i \big/ (HR / P_1)$ is the profit share of the i^{th} input or output, and Q_i is the quantity of the input/output used or produced. These share equations also represent the input demand and output supply equations.

The profit function in equation 2 and the associated set of share equations given by equation 3 need to be estimated simultaneously. The system of equations is estimated using Zellner's seemingly unrelated regression (Zellner 1962). Restrictions are imposed across the system to ensure that the estimated coefficients in each equation are equivalent (i.e. that the α_i coefficients estimated in the share equations take the same value as the α_i coefficients in the profit function).

The partial static equilibrium own and cross price elasticity of input demand or output supply can be derived from the share equations, given by

$$\eta_i = (\alpha_{ii} + S_i^2 - S_i)/S_i\ ,\ \eta_{ij} = (\alpha_{ij} + S_i S_j)/S_i \qquad (4)$$

These short-run elasticities are only valid at the given level of quasi-fixed factors, and exclude the effects of changes in these factors in response to the set of prices. In contrast, long-term elasticities including both expansion and substitution effects can be given by

$$\varepsilon_{ii} = (\alpha_{ii} + S_i^2 - S_i)/S_i \ - (\beta_{iz} + S_i S_z)^2 \big/ S_i \left(\beta_{zz} + S_z^2 - S_z\right) \qquad (5)$$

$$\varepsilon_{ij} = (\alpha_{ij} + S_i S_j)/S_i - (\beta_{iz} + S_i S_z)(\beta_{jz} + S_j S_z) \big/ S_i \left(\beta_{zz} + S_z^2 - S_z\right) \qquad (6)$$

$$\varepsilon_{zz} = S_z \big/ (\beta_{zz} + S_z^2 - S_z) \qquad (7)$$

$$\varepsilon_{iz} = S_z (\beta_{iz} + S_i S_z) \big/ S_i (\beta_{zz} + S_z^2 - S_z) \qquad (8)$$

$$\varepsilon_{zi} = (\beta_{iz} + S_i S_z) \big/ (\beta_{zz} + S_z^2 - S_z) \qquad (9)$$

where $S_z = -p_z z/HR$ (Squires 1987; Andersen *et al.* 2008). All long run elasticities are evaluated at the optimal levels z*.

15.5 Data

Annual cost and earnings data for the fishery are collected by the Australian Bureau of Agricultural and Resource Economics (ABARE). The data set considered for the model was limited to the period 1994-95 to 2005-06. Although earlier data were available, these were not included in the modelling because the industry went through a substantial restructuring in 1993-94. Data after 2005-06 were not available at the time of the analysis.

The industry again went through a substantial restructuring during 2005 and 2006. The data set was limited to only those vessels that remained in the fishery in 2007 since the aim of the analysis was to estimate how the fleet may change from its current structure. The remaining vessels were, on average, 15 per cent larger than those that left the fishery in terms of engine power (although this difference was not statistically significant at the 5% level), and had, on average, 26 per cent higher catches of banana prawns (again, not statistically significant at the 5% level). Average headrope length and catches of other prawn species for the remaining boats were almost identical to those which left the fishery.

The final data set contained 265 observations over the 12 year period, and included 27 of the remaining 52 boats in the fishery. The panel data set was unbalanced as vessels entered the economic survey at different points in time, although at least 10 continuous years of data were available for the majority of boats.

The exact average prices paid to vessels for their catch was not known, as this is affected by the size composition of the catch. However, information was available on average prices of the different species, the total catch of each species (in kg), and the total revenue of the vessels (across all species). Annual vessel level prices were estimated by scaling up (or down) the average price by the ratio of the estimated total revenue from the product of the catch and average price data to the total revenue reported in the annual economic survey. The assumption underlying this is that differences in price reflect vessel-specificity in the size compositions of the catch. A necessary implicit assumption also was that the prices could be adjusted by the same proportion for all species. In all cases, the adjusted prices were within the observed size-related price range of the various prawn species. All prices were inflated to their 2006 equivalent real value using the Australian consumer price index.

As prices of the main species were highly correlated (r>0.8), the species were aggregated into two groups reflecting the seasonal differences in catch – banana prawns and a tiger prawn group which included both species of tiger prawns and endeavour prawns. The two tiger prawn species are not marketed separately so share an identical price. Endeavour prawns are primarily a bycatch species. The average price for the group at the vessel level was determined by the total estimated revenue (derived from the catch of each species by the vessel multiplied by its estimated vessel-specific price) divided by the sum of the vessel's catches of these species.

As in many fisheries, crew are generally paid a share of the revenue. That is, there is no explicit price for labour, and crew payments are directly related to catches and prawn prices, not profit. The effective price received by the owner is the prawn price less the share paid to the crew, so prawn prices were adjusted to a price net of crew share. Similarly, freight- and marketing-related costs are based on a $/kg basis, which could be derived from the survey and catch information for each vessel and for each year. This was also deducted from the prawn price. An implicit assumption in the analysis is that investment and production decisions are made not on the market price per se, but on the effective price received by the vessel owner after crew and marketing deductions.[31]

Other information included in the analyses was derived from logbook and vessel registry databases. This included boat engine power and the length of headrope used by the vessel when trawling. The combination of these variables influences the area swept by the vessel per unit of time. Finally, annual stock indexes were incorporated into the analysis. For the tiger

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[31] A reviewer suggested an alternative approach would be to either include an opportunity cost measure for labour (Clark and Munro 1980; Squires 1987, 1988), or to treat crew payments as part of short-term profit. This would have enabled estimation of an optimal vessel size and output from a broader societal perspective, but production decisions in the fishery are made by the vessel owner based on their returns on their investment. Hence, optimality conditions in a fishery operating under a share system are defined in terms of the share weighted index of input and output prices rather than observed market prices (McConnell and Price 2006).

and endeavour prawns, the stock indexes were derived from exploitable biomass estimates derived from stock assessments (Dichmont *et al.* 2003; Deng *et al.* 2008). A composite stock index was derived based on revenue shares. No stock assessment is undertaken for banana prawns, so an index of relative stock abundance for this component of the catch was estimated based on the average catch per (effective) hour in the first week of the season as catch rates decline from the first few weeks of the season. The length of both the banana and tiger season (in days) was included as explanatory variables as these potentially constrain individual vessels' catches.

As the data were panel data, dummy variables for each boat were also included in the analysis to capture any fixed vessel effects. These fixed effects are related to a measure of the relative efficiency of the different vessels.

A summary of the data used in the analysis is given in Table 15.1. For the analysis, all variables were normalised by dividing through by their mean value. Consequently, the normalised variables had a mean value of 1, and a logged mean value of zero. Prices were further normalised by the banana prawn price in order to ensure homogeneity. The estimated equations, then, only explicitly include tiger prawn and fuel prices, headrope length, engine power, season length (for each season), stock indexes for both banana and tiger prawns, a time variable and vessel dummy variables. Since the restricted share equations sum to unity, one must be excluded from the analysis. In this case, the fuel share equation was not explicitly estimated, but the parameters relevant to fuel supply can be derived from the profit function. The parameters relevant to the banana prawn output are derived from the homogeneity conditions. Hence, *ex ante* homogeneity expectations are realised *ex post* (Squires 1987).

Table 15.1. Summary of key data used in the analysis (2006 prices)

	Mean	St. Dev	Minimum	Maximum
Restricted profit ($'000/boat)	801.9	349.3	68.8	1737.6
Banana price[a] ($/kg)	11.1	2.5	6.7	21.1
Tiger price[a] ($/kg)	17.9	4.6	10.7	34.1
Fuel price (c/litre)	53.4	10.1	40.3	82.9
Headrope length (m)	13.2	1.4	7.8	16.0
Banana season (days)	57.9	13.2	42.0	74.0
Tiger season (days)	106.8	12.8	91.0	121.0
Engine power (kW)	388.3	43.4	261.0	450.0

Share tiger revenue	0.67	0.38	0.00	4.83
Share banana revenue	0.70	0.30	0.04	2.66
Share fuel costs	-0.37	0.45	-6.49	-0.11

a. Net of crew share (% of revenue) and freight costs ($/kg); "Tiger" price is a weighted average of tiger and endeavour prawn prices.

15.6 Results

Several variants of the model were tested. Initial analysis indicated that the season length and time variables were correlated, and a complete model with season and time interactions with the other variables could not be estimated due to singularity problems. The models were estimated with different combinations of season and time interactions. The best model, based on the Akaike Information Criterion, excluded the interactions terms between the two season variables and also the time variables with the other explanatory variables (Table 15.2).

Table 15.2. AIC for different model specifications varying time and season interactions

		Season length		
		$\varsigma, \varsigma_{ss}, \varsigma_i, \varsigma_k \neq 0$	$\varsigma_i, \varsigma_k = 0$	$\varsigma, \varsigma_{ss}, \varsigma_i, \varsigma_k = 0$
Time	$\gamma, \gamma_{tt}, \gamma_i, \gamma_k \neq 0$	na	71.62	89.09
	$\gamma_i, \gamma_k = 0$	70.60	63.26	83.95
	$\gamma, \gamma_{tt}, \gamma_i, \gamma_k = 0$	78.98	88.80	103.95

Note: $\gamma, \gamma_{tt}, \gamma_i, \gamma_k$ are the parameters relating to time and its interactions with prices and other variables (including season); $\varsigma, \varsigma_{ss}, \varsigma_i, \varsigma_k$ are the parameters relating to the two seasons and their interactions with prices and other variables (including time).

The estimated coefficients of the final restricted profit function are presented in Table 15.3, along with some basic goodness-of-fit statistics. The coefficients relating to banana prawn price were derived from the base model using the homogeneity conditions, and are also included in Table 15.3. The coefficients for the share equations are embedded in the profit function so are not repeated separately. The estimated restricted profit function explained around two thirds of the observed variability in vessel profits, while the share equation had a lower R^2 value. While these R^2 values may appear low, they are consistent with those for other estimated profit functions (Asche *et al.* 2007). More importantly, the coefficients generally have the expected sign and many are significant at the 10 per cent level or greater.[32]

The squared term coefficient relating to technical change in the revised model was significant and negative, suggesting that profitability declined over time, ceteris paribus. Technical change appeared to be unrelated to vessel characteristics, suggesting that these changes arose from external factors (i.e. disembodied technical change). Technical change in this context is change in individual vessel profitability not explained by price changes or vessel characteristics. The fishery was subject to numerous restrictions over the period of the analysis that may have accounted for this apparent decline, including potential transitional difficulties in the introduction of gear units in 2000 and the subsequent restrictions on headrope length, the introduction of turtle excluder devices and bycatch reduction devices (believed to have initially reduced productivity by around 6 per cent (Brewer *et al.* 2006)), and the change in the opening date of the second season from 1 August to 1 September in 2002-03 to 2004-05. This latter change was implemented with the explicit aim to reduce catches of one of the tiger prawn species. The season was extended at the other end by three weeks, but the timing of the season has a different impact to its length.

Table 15.3. Parameter estimates of the restricted profit function

	Coefficient	t-statistic			Coefficient	t-statistic	
Constant	1.376	6.445	***	*Vessel dummies*			
Tiger prawn price	0.674	33.590	***	D2	-0.043	-0.625	
Banana prawn price	0.372	4.883	***	D3	-0.455	-5.496	***
Fuel price	-0.045	-0.611		D4	-0.522	-6.436	***
Tiger stock index	0.883	4.429	***	D5	-0.438	-5.809	***
Banana stock index	0.086	1.263		D6	-0.428	-5.133	***
Headrope length	0.527	1.752	*	D7	-0.434	-4.961	***
Engine power (kW)	0.712	2.751	***	D8	-0.259	-3.076	***
Banana season length	-0.752	-2.612	***	D9	-0.443	-5.155	***
Tiger season length	-0.384	-0.830		D10	-0.441	-5.035	***
Tiger price**2	0.260	3.127	***	D11	-0.378	-4.068	***
Banana price**2	0.705	3.722	***	D12	-0.354	-4.318	***
Fuel price**2	0.107	0.770		D13	-0.313	-3.546	***

[32] The potential for heteroscedasticity was tested using White's general heteroscedasticity test (White 1980), and no significant problems were identified. The software used (SHAZAM) was unable to provide a specific test for panel data autocorrelation when a system of equations was estimated. However, the non-parametric runs tests suggested that no autocorrelation existed in the main profit function, but some positive autocorrelation may exist in the share equation. This may result in some of the standard errors for the variables in this model being underestimated.

Tiger stock index**2	-0.479	-0.476		D14	-0.300	-3.558	***
Banana stock index**2	-1.304	-3.168	***	D15	-0.547	-5.884	***
Banana season **2	2.009	2.891	***	D16	-0.507	-5.412	***
Tiger season **2	-39.050	-5.075	***	D17	-0.342	-3.766	***
Headrope**2	0.566	0.572		D18	-0.586	-6.217	***
Engine power (kW)**2	-3.858	-3.193	***	D19	-0.445	-3.779	***
Tiger price*fuel price	0.169	2.161	**	D20	-0.354	-3.915	***
Tiger price*banana price	-0.429	-4.928	***	D21	-0.458	-5.478	***
Tiger price*tiger stock	0.116	0.479		D22	-0.269	-2.546	**
Tiger price*banana stock	-0.323	-4.846	***	D23	-0.263	-2.236	**
Tiger price*headrope	-0.583	-2.545	**	D24	-0.421	-4.377	***
Tiger price*engine power	0.130	0.785		D25	-0.533	-5.361	***
Banana price*fuel price	-0.276	-1.803	*	D26	-0.459	-3.859	***
Banana price*tiger stock	-0.476	-0.896		D27	-0.482	-4.658	***
Banana price*banana stock	0.296	1.305		D28	-0.297	-2.850	***
Banana price*headrope	-0.364	-0.507		D29	-0.187	-1.770	*
Banana price*engine power	-0.649	-1.557					
Fuel price*tiger stock	0.360	0.732					
Fuel price*banana stock	0.027	0.123					
Fuel price*headrope	0.947	1.354					
Fuel price*engine power	0.519	1.319		R^2			
Tiger stock *headrope	-1.472	-0.997		System		0.6734	
Banana stock*headrope	-1.836	-2.496	**	Profit function		0.6734	
Tiger stock*engine power	2.748	3.030	***	Tiger prawn share		0.2255	
Banana stock*engine power	0.538	1.341					
Tiger stock*banana stock	-1.854	-2.803	***	Raw moment R^2			
Headrope*engine power	2.276	1.640		Profit function		0.6734	
Time	0.047	1.308		Tiger prawn share		0.8169	
Time**2	-0.011	-3.585	***				

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

The coefficients on season length were also generally negative, suggesting that average profits decreased with increasing season length. Given that most boats are operated by employed skippers and crew who are paid on the basis of catch (not profit), it is unsurprising that fishing activity continues beyond the point where falling catch rates, and subsequently marginal revenues, are less than the marginal cost of fishing.

The vessel dummy variables were generally significant and all negative. The base vessel was chosen on the basis that it was one of four vessels for which data were available for all years, and by coincidence appears to be the most efficient vessel. The relative economic efficiency[33] of the vessels can be derived assuming the base vessel has an efficiency score of 1. Most vessels were operating at between 60 and 70 per cent efficiency (Figure 15.3).

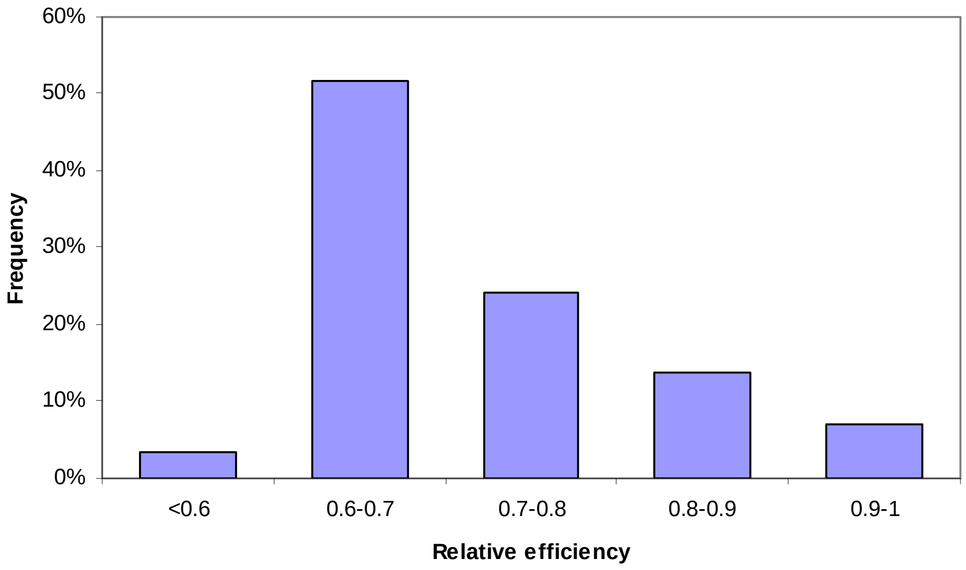

Figure 15.3. Relative economic efficiency of the vessels in the sample

15.6.1 Short and long run price elasticities

Derivation of short- and long-run input demand and output supply price elasticities requires an estimate of the optimal level of the quasi-fixed inputs. As noted previously, the long-run equilibrium level of the quasi-fixed factors (engine power and headrope length) is given by $\delta HR(p,z^*(p,p_z))/\delta p=p_z$, where p_z is the real capital service price. As all prices have been normalised, then the appropriate "average" user price is 1. An analytical solution is not possible, requiring a numerical solution (Squires 1987). The optimal engine power and headrope length were estimated at varying fuel and prawn price combination using a non-linear programming model developed in GAMS (Brooke *et al.* 1996). Several starting values were used to ensure that the solution was a global optimum. Engine power was initially optimised keeping headrope length at the average observed level, and then headrope length was optimised given the optimal engine power. Except for the case of low fuel prices, the optimal headrope length was found to be equivalent to the average over the period of the data (i.e. $z^*=1$).

The optimal relative engine power given the sample mean set of prices and average conditions was estimated to be 1.03, and given the error in the parameter estimates is not

[33] The measure is a combination of both technical and allocative efficiency, as both quantity of catch and input use is taken into consideration given the set of relative prices.

likely to be significantly different to 1.[34] The short and long run elasticities assuming $z^*=1$ for both engine power and headrope length are presented in Table 15.4.

Most of the elasticities were not significant, but most had the expected sign. As expected, output supply was positively related to own price and negatively related to fuel prices, while input demand was positively related to output prices but negatively related to own prices. Also as expected, the input demand and output supply are more price elastic in the longer term. Morishima elasticities of substitution between outputs were also estimated (Table 15.4), and indicated substitution between the two outputs in the long run (as expected given they are produced in separate time periods). Similarly, substitution potential between fuel use and engine power was also indicated.

Table 15.4: Own and cross price elasticities of input demand and output supply

Prices	Output supply			Input demand		
	Tiger prawns	Banana prawns		Fuel		Engine power
Short-run						
Tiger prawns	0.060	0.063		0.225		
Banana prawns	0.066	0.705	**	1.437	**	
Fuel	-0.126	-0.768	**	-1.661	**	
Long run						
Tiger prawns	0.296	0.626		0.336		0.292
Banana prawns	-0.271	2.106		2.504	**	-1.036

[34] A method for estimating the standard error of the estimate is given by Squires (1987). Given the proximity of the estimate to unity, a formal test was not undertaken.

Fuel	-0.514	-1.696 *	-2.809 *	-0.482
Engine power	-0.434	-0.638	-1.282	0.538

Morishima elasticities of substitution (long run)

	Tiger prawns	Banana prawns	Fuel	Engine power
Tiger prawns		-2.377 *		
Banana prawns	0.330			
Fuel				2.327
Engine power			-1.820 *	

** significant at the 5% level; * significant at the 10% level

15.6.2 Optimal vessel size given expected changes in stock size

A key aim of the paper was to estimate how vessels may adjust to the set of conditions relating to MEY and given that they are also able to maximise their individual profits. A number of assumptions were necessary to estimate the optimal output and input use under an ITQ regime. Stock conditions were assumed to be average for banana prawns. However, assuming maximum economic yields can be achieved, stock levels are expected to be 27.6% higher than the average over the period of the data for the tiger/endeavour prawn group, based on the outputs of the bioeconomic model (Deng *et al.* 2008). Prices of both fuel and prawns are also expected to change over time, and a range of price combinations was included in the analysis. The estimates of MEY from the bioeconomic model, however, were based on the assumptions that prawn prices would be 2.6% higher than the average over the period of the data used in this analysis, and fuel prices would be 77% higher (Deng *et al.* 2008).

Under an ITQ system, it was also assumed that season length would cease to be a constraint as the negative relationship between season length and profits was an artefact of the input control system, and an optimal catch can be taken within the existing seasons. Similarly, the negative disembodied technical change was also ignored, as it was assumed that the management restrictions causing this could also be removed under the output control system.

The optimal vessel engine power was estimated under a set of price conditions (Figure 15.4a), and this used to estimate the optimal catch of each species. The resultant estimates of optimal vessel size and output levels, and the impact of prices on these estimates, are illustrated in Figure 15.4. Given the price assumptions in the bioeconomic model and the associated stock size at MEY, vessels are likely to increase their engine power (and presumably their overall size) by around 20 per cent in the long run.

Fuel use is expected to decrease by around 20 per cent relative to the average over the period of the data for a wide range of prices (Figure 15.4b), suggesting that larger engines are partially being substituted for days fished. This particularly large decrease is mostly driven by the relatively high fuel prices. However, lower levels of fuel consumption were optimal for all price scenarios (both inputs and outputs), suggesting that cost savings through effort reduction would more than offset reduced revenue arising from the subsequently lower catches.

The optimal individual catches per vessel of the two species groups are also lower given the price assumptions.[35] There is a general apparent "shift" from banana prawns to the more valuable tiger prawns as prawn prices decrease, and fuel prices increase. The optimal catch of banana and tigers prawns is around 80 and 85 per cent respectively of their average over the period 1994-95 to 1995-96, *ceteris paribus* at the assumed long run relative fuel and prawn prices in the bio-economic model (Figures 15.4c and 15.4d).

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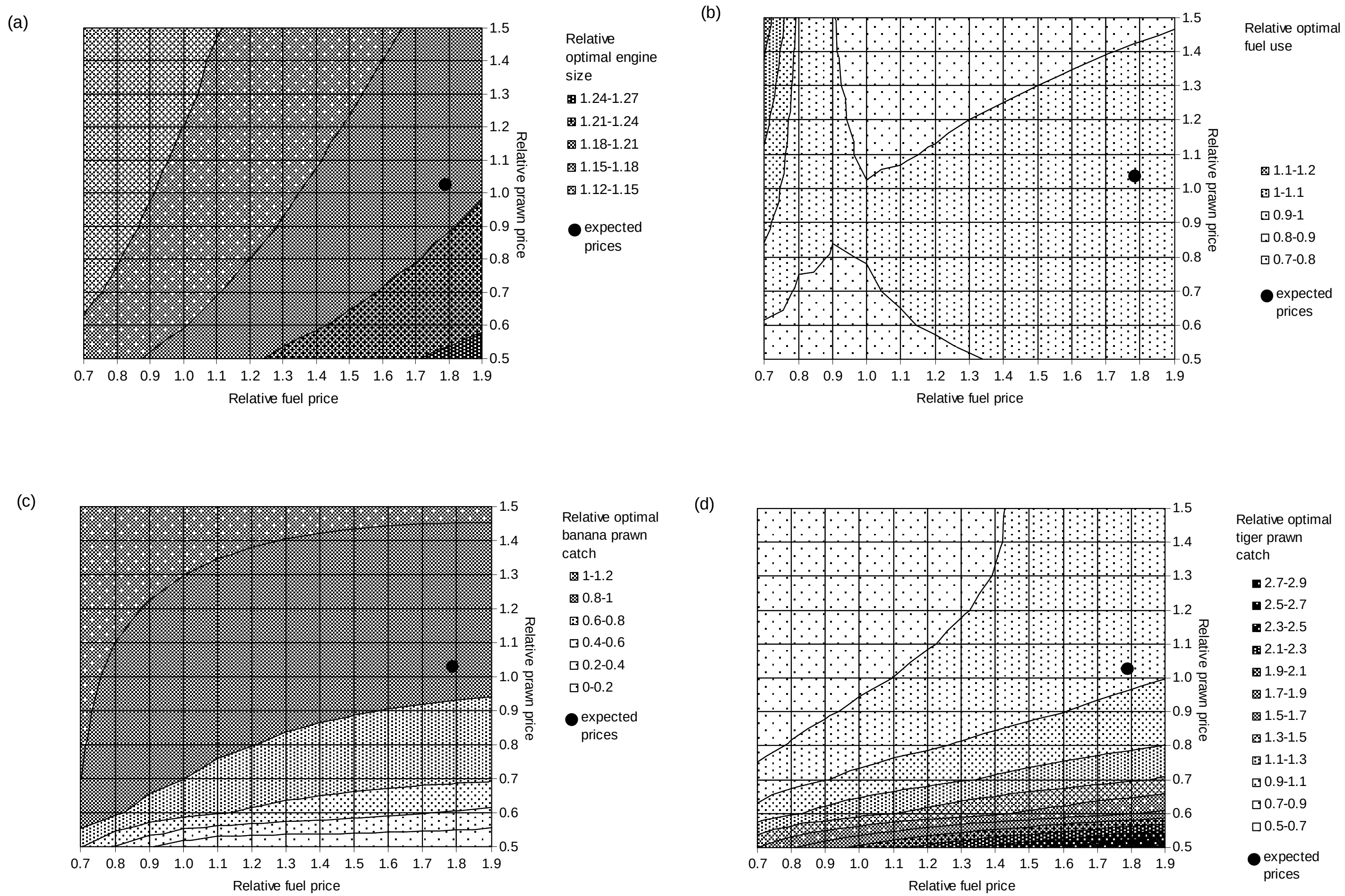
[35] As noted by a reviewer, the introduction of ITQs will result in a price for quota that has not been considered in the analysis. This may also affect optimal input usage as input demand is related to optimal output supply. However, as the optimal output is less that their current harvest level, and quotas are likely to exceed the optimal output, then quotas are likely to be non-binding and the shadow price effectively zero.

Figure 15.4. Optimal input use and catches: a) engine power, b) fuel use, c) banana prawn catch, and d) tiger group catch



15.7 Discussion and conclusions

The northern prawn fishery is fairly unique in that maximising economic returns is an explicit management objective. The fishery is also dominated by fishing companies, most of which have recently amalgamated into a single incorporated company to achieve economies in terms of input purchases and marketing of outputs. Hence, the motivation to maximise profits in the fishery is high. The move to ITQs will provide incentives for vessel owners to adjust their quota holdings as well as fishing activities to their most economically efficient configuration.

Previous bioeconomic studies have attempted to model the banana and tiger prawn fisheries separately (Kompas *et al.* 2004; Dichmont *et al.* 2008; Kompas *et al.* 2008), using either catch and effort information only or limiting cost information to variable costs. Generally, more fuel is consumed per day in the banana prawn fishery as a result of more hours fished per day and more intensive racing-to-fish, and it is believed that some costs such as gear and repair costs vary between the fisheries (Deng *et al.* 2008), again reflecting the differences in fishing intensity. However, over the period of the data, the same vessels operated in both fisheries (using the same set of fixed inputs) and faced the same set of input and output prices in each fishery. While it is possible that some vessels may specialise in one fishery or the other under ITQs, it is more likely that most vessels will continue to operate in both fisheries. Hence, the determination of an optimal vessel size required consideration of both fisheries simultaneously.

In most fisheries under ITQs, consolidation of quota results in a smaller fleet than pre-ITQ management (Campbell *et al.* 2000; Aslin *et al.* 2001; Stewart *et al.* 2006). Further, in most fisheries where ITQs have been introduced, TACs are initially lower than recent catches, which further creates incentives for vessels to adjust. Based on the model results, the optimal individual catch levels would result in the TAC – if based on maximum economic yields – not being achieved with the existing fleet. The bioeconomic model of the fishery (Deng *et al*. 2008) estimates that, given the price assumptions noted previously, the tiger prawn TAC at MEY would be 26 per cent higher than the average catch over the period of the data used in this analysis, and the endeavour prawn TAC would be 12 per cent higher.

The results of the model are generally consistent with most other studies that suggest that fewer, larger vessels are likely to emerge from an ITQ system (Nostbakken 2006; Eggert and Tveteras 2007; Hoff and Frost 2007; Pascoe 2007; Asche *et al.* 2008). The optimal move to larger vessels in the NPF, if it occurs, is driven primarily by the increase in fuel prices and the substitution of fishing power for fishing days. In contrast, the potential autonomous adjustment that is generally assumed to occur as a result of ITQ management had already taken place through the recent buyback program.

The amount of quota available to the individual vessels is likely to exceed what is optimal for them to catch given the current number of vessels. This will reduce the incentive for the vessel owners to adjust their behaviour to maximise profits, and hence the potential benefits of an ITQ system may not be achieved. Allowing the re-introduction of vessels during the process of stock recovery may overcome this problem. This is currently not possible given the restriction on boat licences which is expected to continue, at least in the short-term. However, increases in vessel numbers following ITQs have been observed in other countries, but only after stocks have recovered and also following an initial reduction in vessel numbers (Batstone and Sharp 1999).

The study highlights the importance of considering vessel behaviour when trying to estimate MEY in fisheries. In this case, the current estimate of MEY assumes the existing fleet is willing and able to increase their output as stocks recover, whereas this study suggests that profit maximising fishers would aim to decrease their individual output. Hence, the assumptions underlying the estimation of MEY are inconsistent with the incentives facing the fishers.

From the model results, the allocation of ITQs should provide incentives to reduce individual fishing effort and catches. The fishers, however, are familiar with operating in a competitive environment where the incentives are to increase input use in an attempt to increase catches. If fishers are unable to sell their surplus quota (i.e. to new boats entering the fishery) when stocks recover, the incentive to reduce effort and catch will directly conflict with the habit of increasing effort and catch. Habits are a strong determinant of behaviour in fisheries (Holland and Sutinen 2000), and may result in the full potential economic benefits of ITQs not being achieved initially.

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15.9 References

ABARE (2009). Australian Fisheries Statistics 2008. ABARE, Canberra.

Andersen, T.B., Roll, K.H. and Tveterås, S. (2008). The price responsiveness of salmon supply in the short and long run, *Marine Resource Economics* 23: 425-437.

Asche, F., Gordon, D.V. and Jensen, C.L. (2007). Individual Vessel Quotas and Increased Fishing Pressure on Unregulated Species, *Land Economics* 83: 41-49.

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

Aslin, H.J., Connor, R.D. and Fisher, M. (2001). Sharing in the catch or cashing in the share? Social impacts of Individual Transferable Quotas and the South East Fishery. Bureau of Rural Sciences, Canberra.

Batstone, C.J. and Sharp, B.M.H. (1999). New Zealand's quota management system: the first ten years, *Marine Policy* 23: 177-190.

Brewer, D., Heales, D., Milton, D., Dell, Q., Fry, G., Venables, B. and Jones, P. (2006). The impact of turtle excluder devices and bycatch reduction devices on diverse tropical marine communities in Australia's northern prawn trawl fishery, *Fisheries Research* 81: 176-188.

Brooke, A., Kendrick, D. and Meeraus, A. (1996). *GAMS release 2.25; a user's guide*. GAMS Development Corporation Washington, DC.

Brown, D. (1997). Australian fisheries surveys report 1997: Physical and financial performance in selected Australian fisheries, 1994-95 to 1996-97. ABARE, Canberra.

Campbell, D., Brown, D. and Battaglene, T. (2000). Individual transferable catch quotas: Australian experience in the southern bluefin tuna fishery, *Marine Policy* 24: 109-117.

Clark, C.W. and Munro, G.R. (1980). Fisheries and the processing sector: some implications for management policy *The Bell Journal of Economics* 11: 603-616

DAFF (2006). Round Two Outcomes – Announcement made 22 December 2006, (Serial online). Available from URL: www.daff.gov.au/fisheries/domestic/fishingfuture/business_exit_assistance [accessed April 2008].

Deng, A., Dichmont, C.M. and Kompas, T. (2008). Bio-Economic Model Status of Tiger Prawn Stocks at the end Of 2007 in the NPF, *Report to the NPFRAG*. CSIRO, Brisbane.

Dichmont, C.M., Punt, A.E., Deng, A., Dell, Q. and Venables, W. (2003). Application of a weekly delay-difference model to commercial catch and effort data for tiger prawns in Australia's Northern Prawn Fishery, *Fisheries Research* 65: 335-350.

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

Die, D.J. and Ellis, N. (1999). Aggregation dynamics in penaeid fisheries: banana prawns (Penaeus merguiensis) in the Australian Northern Prawn Fishery, *Marine and Freshwater Research* 50: 667-675.

Eggert, H. and Tveteras, R. (2007). Potential rent and overcapacity in the Swedish Baltic Sea trawl fishery for cod (Gadus morhua), *ICES J. Mar. Sci.* 64: 439-445.

Hoff, A. and Frost, H. (2007). Optimal Vessel Quotas and Capacity of a Danish Trawler Fleet Segment: A Dual Approach, *Marine Resource Economics* 22: 1-14.

Holland, D. and Sutinen, J. (2000). Location choice in New England trawl fisheries: old habits die hard, *Land Economics* 76: 133-149.

Hotelling, H. (1932). Edgeworth's taxation paradox and the nature of demand and supply functions, *Journal of Political Economy* 40: 577-616.

Jensen, C.L. (2002). Applications of Dual Theory in Fisheries: A Survey, *Marine Resource Economics* 17: 309-334.

Kompas, T., Che, T.N. and Grafton, R.Q. (2004). Technical efficiency effects of input controls: evidence from Australia's banana prawn fishery, *Applied Economics* 36: 1631 - 1641.

Kompas, T., Che, N. and Grafton, R.Q. (2008). Fisheries Instrument Choice under Uncertainty, *Land Economics* 84: 652-666.

Larcombe, J. (2008). Northern Prawn Fishery. in Larcombe, J. and Begg, G. (eds.), *Fishery status reports 2007: status of fish stocks managed by the Australian Government*. Bureau of Rural Sciences, Canberra, pp 25–38.

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

Newton, P., Wood, R., Galeano, D., Vieira, S. and Perry, R. (2007). Fishery Economic Status Report, *ABARE Report 07.19 Prepared for the Fisheries Resources Research Fund*. ABARE, Canberra.

Nostbakken, L. (2006). Cost Structure and Capacity in the Norwegian Pelagic Fisheries, *Applied Economics* 38: 1877-1887.

Pascoe, S. (2007). Estimation of cost functions in a data poor environment: the case of capacity estimation in fisheries, *Applied Economics* 20: 2643-2654.

Squires, D. (1987). Long run profit functions of multiproduct firms, *American Journal of Agricultural Economics* 69: 558-569.

Squires, D. (1988). Production Technology, Costs, and Multiproduct Industry Structure: An Application of the Long-Run Profit Function to the New England Fishing Industry, *The Canadian Journal of Economics / Revue canadienne d'Economique* 21: 359-378.

Stewart, J., Walshe, K. and Moodie, B. (2006). The demise of the small fisher? A profile of exiters from the New Zealand fishery, *Marine Policy* 30: 328-340.

Vieira, S. and Hohnen, L. (2007). Australian Fisheries Surveys Report 2007: Results for Selected Fisheries, 2004-05 and 2005-06, *ABARE Report Prepared for the Fisheries Resources Research Fund*. ABARE, Canberra.

White, H. (1980). A heteroscedasticity consistent covariance matrix estimator and a direct test of heteroscedasticity, *Econometrica* 48: 817-818.

Wood, R., Hohnen, L., Newton, P., Fairhead, L., Vieira, S. and Gooday, P. (2008). Fish and seafood: trends in production and trade and outlook to 2012-13, *Australian Commodities* March Quarter 08.1: 99-111.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests for aggregation bias, *Journal of the American Statistical Association* 57: 348-368.

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