ERA extension to assess cumulative effects of fishing on species

Shijie Zhou, Ross Daley, Mike Fuller, Cathy Bulman, Alistair Hobday, Tony Courtney, Paul Ryan, Doug Ferrel

FRDC Project No. 2011/029

28 October 2013

Fisheries Research &Development Cooperation

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

Author:	Zhou, Shijie, author.
Title:	**ERA extension to assess cumulative effects of fishing on species**
ISBN:	978-1-4863-0153-9 (PRINT) 978-1-4863-0154-6 (ONLINE)
Subjects:	Fisheries--Australia. Fisheries--Environmental aspects--Australia. Ecological risk assessment--Australia
Other Authors/ Contributors:	Daley, Ross, author. Fuller, Mike, author. Bulman, Cathy, author. Hobday, Alistair J., author. Courtney, Tony, author. Ryan, P. J. (Paul James), author. Ferrel, Doug, author. CSIRO. Marine and Atmospheric Research, issuing body.
Dewey Number:	639.20994

Citation

Shijie Zhou, Ross Daley, Mike Fuller, Cathy Bulman, Alistair Hobday, Tony Courtney, Paul Ryan, and Doug Ferrel. 2013. ERA extension to assess cumulative effects of fishing on species. Final Report on FRDC Project 2011/029. Canberra, Australia.

Contents

List of figures

List of tables

Non Technical Summary

2011/029: ERA extension to assess cumulative effects of fishing on species

PRINCIPAL INVESTIGATOR: Dr Shijie Zhou

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

OBJECTIVES:

1. Scope the range of applications and review existing methods for measuring cumulative effects of capture fishing on species that are caught across a number of different fisheries or sub-fisheries.
2. Scope the different data sources that are currently available and those that may be required to include assessment of cumulative effects under future ERAs.
3. Develop methods for assessing cumulative risk from multiple fisheries or sub-fisheries including recreational and international fisheries, where feasible, on each individual fish species and stock, especially methods that can be applied to data poor fisheries.
4. Apply the method to selected Commonwealth fisheries that operate in the same area with high levels of effort and multiple gear types, e.g., in the southeast region, with further consultation with AFMA.
5. Describe the trade-off between the costs of collecting data for ERA as compared to the benefit of the approach returned to the industry/management.

Outcomes achieved to date

- Data from various Commonwealth and State agencies were compiled and integrated. These data include scientific surveys, fisheries observer data, commercial and recreational fishery catch and effort data.
- Statistical methods were developed to estimate catchability for multiple gears using survey and observer data. These methods were then applied to examples of populations with contrasting distribution patterns: random vs. aggregated.
- Quantitative models of heterogeneous fish density were developed. The results facilitate the estimation of fishing impacts from a range of gear types (fisheries).
- Statistical models were developed for estimating biological reference points from simple life

history parameters. Sustainability can be gauged from a combination of growth coefficient, maximum length, and maximum age, or from a growth coefficient alone, enabling a quantitative assessment to be undertaken when time series of catch and effort data are unavailable.
- The quantitative methods developed were then used to assess cumulative effects of fishing for selected bycatch species. These case studies demonstrate the utility of the methodology.
- The analysis revealed a nonlinear relationship between cumulative fishing mortality and the number of fisheries that were included in the assessment. This general pattern transforms to a nonlinear relationship between the costs of research (i.e., collecting data and conducting ERA) and the benefit returned to the industry/management (i.e., accuracy of the assessment results). The cost-effective approach is to focus research on key fisheries that have disproportionately large impacts on the species.

An exploited population of a fish species may be subjected to fishing mortality from multiple fisheries or gear types. Previous ecological risk assessment methods assess stressors separately on a fishery by fishery basis. By contrast, it is the cumulative impact from all fisheries and gears on each individual species that determines the species' overall sustainability. However, assessing the cumulative risk to a species is technically challenging. Qualitative and semi-quantitative methods may have difficulties in fully quantifying the cumulative impacts across multiple fisheries. There is an urgent need to develop methods and conduct ecological risk assessments on the cumulative impact of fishing on fish species encountered by multiple fisheries.

The Australian Fisheries Management Authority (AFMA) and the Commonwealth Fisheries Research Advisory Board (ComFRAB) have identified developing cumulative risk assessment methods as a priority for research. In this multi-agency project, we first briefly reviewed methods for measuring cumulative fishing effects. The review concluded that although qualitative and semi-quantitative methods may be used in assessing cumulative effects from multiple stressors, there are unique challenges, including difficulty in quantifying uncertainty, subjectiveness of opinions, and heavy reliance on expert input. Sustainability assessment for fishing effects (SAFE) is an existing method that has the required quantitative capability, but improvements and extension were necessary to achieve greater accuracy and precision in assessments.

The team explored the potential of a wide range of data sources for assessing cumulative impacts. We chose the Australian southeast region as a pilot study area because of the high level of overlap between many fisheries and gear types. Major databases include: AFMA Logbook, AFMA Observer, CSIRO historical scientific surveys, NSW research vessel *Kapala* surveys and Bioregional mapping (Bioreg data) (Last et al. 2010), etc. The combined survey-observer database contains over 886,000 shot by shot records covering both Commonwealth and State waters, which were used to estimate gear efficiency and to derive fish density. Data scoping revealed that over 40 fishing gears have been used in Commonwealth fisheries. Similarly over 40 gears have been used in New South Wales fisheries, over 30 in Victorian fisheries, and over 20 in Tasmanian fisheries. The scoping process also uncovered some issues in data assemblage. Many datasets appear to be unverified. Obvious errors were not uncommon. Each agency collects different types of information, uses different codes, terms, units, formats, etc., which makes data integration difficult.

The project achieved three major advances in methodology development. A statistical method was developed to estimate gear efficiency for both randomly distributed and aggregated populations. The method is referred to as cross-sampling because it uses data from multiple gears that catch individuals from the same population at the same location and time. Computer simulations were carried out to examine a range of distribution scenarios. A robust mixture statistical distribution model stood out as the best estimate of gear efficiency and abundance for the most complicated situations: non-random fish distributions with varying abundance for each sampling observation. The key strength of this model is the ability to account for variation in efficiency between multiple gear types—the mixture of parametric statistical distributions between spatial grids and within spatial grids. The model uses a Bayesian approach to estimate relevant parameters.

Reliable estimates of gear efficiency enable fish density to be calculated from catch data. A general additive model is then developed for smoothing density across the distributional range in each year. Distributional ranges are stratified (by Core area, Bioreg area, eastern region, and western region) to better capture heterogeneous density patterns. These results, combined with actual fishing effort and distribution or actual catch data, allow fishing mortality to be derived for each gear type or fishery. Consequently, cumulative fishing mortality is readily estimated.

It is important to note that fishing mortality alone, even in the absence of any other impacts, is insufficient to determine whether mortality rates are sustainable for a particular species. Any estimate of sustainability requires a comparison between the predicted fishing mortality and some type of reference point. Here we provide a meta-analysis of 248 data-rich species to link fishing mortality-based reference points with simple life history parameters (LHPs). Although natural mortality is potentially the best predictor, measuring natural mortality rate directly is rarely possible for any fish species, and for hundreds of species it is simply not plausible. Instead natural mortality is normally derived from other LHPs using various types of methods that are subject to varying levels of uncertainty. Here we develop reference points based on basic LHPs: growth coefficient, maximum length, and maximum age. Three reference points based on these alternative methods were developed: F_{msy} from stock assessment, F_{proxy} from per-recruit analysis, and $F_{0.5r}$ from demographic analysis. Bayesian error-in-variable models are used to take measurement error in LHPs into consideration. A range of models with alternative combinations of LHPs and assumptions about the hyper priors are investigated. The best model with the lowest DIC involves all three LHPs. However, a model with growth coefficient as a single predictor can be adequate if maximum length and age are not available. The results show that the importance of a particular LHP depends on whether the fish is a chondrichthyan or a teleost, and the former exhibits a lower sustainability for the same LHPs values.

Here we apply the methodology described above to two selected case study species, both of which are endemic temperate chondrichthyans: Bight Skate (*Dipturus gudgeri*) and Draughtboard Shark (*Cephaloscyllium laticeps*). Gear efficiency was estimated for three gear types (longline, trawl, and Danish seine) for Bight Skate. With the defined gear affected area, trawl is most efficient while longline is the least.

Bight Skate is largely distributed in a narrow depth range along the continental shelf outside state jurisdictions. We included 15 gear types in Commonwealth fisheries for their cumulative effect. Results indicate the greatest impact is from the otter trawl sector, followed by auto-longline. Other sub-fisheries have minor impacts, mainly due to their low fishing effort. The estimated cumulative F varied between 0.057 in 2010 to 0.063 in 2007. Comparing the cumulative fishing mortality rates with the estimated reference points, it is concluded that Bight Skate was at least at medium risk ($F \geq F_{\mathrm{msy}}$) in 2007 to 2010.

For Draughtboard Shark, gear efficiencies were estimated for four gear types (longline, Danish seine, gillnet, and trawl). Within the area defined by the effect of the gear, gillnet is the most efficient capture method while longline is the least. We estimated fishing mortality for each of 21 gear types in both Commonwealth fisheries and State fisheries for their cumulative effect. The greatest impact on fishing mortality is from the gillnet sector, followed by trawl and longline. Other sub-fisheries and state fisheries have minor impacts, mainly due to their low fishing effort. The estimated cumulative *F* varied between 0.043 in 2007 to 0.050 in 2010. Comparing these cumulative fishing mortality rates with the estimated reference points, it appeared that the cumulative estimates of fishing mortality rates in 2007-2010 were within sustainable limits for Draughtboard Shark ($F \le F_{msy}$).

Finally, we outline the trade-off between the costs of collecting data for ERA as compared to the benefit returned to the industry/management by the approach. Clearly, strategic assessment requires adequate data to assess fishery impacts on bycatch. Simply speaking, the cost of not collecting data and performing assessment is potential closure of the fishery, or at least further restrictions imposed on the fishery, though this depends on the degree of precaution exercised by managers in the absence of information. The methods we have developed can utilize existing data, particularly fishery-dependent data sources. This has greatly reduced the cost of collecting specific data for ecological risk assessment of fishing effects. For the purpose of assessing cumulative impacts, it is necessary to scope and include as many fisheries as possible. The process of data gathering, understanding, validation, standardisation, comparison, and inclusion is a time-consuming job. Our assessments show that cumulative impact does not increase linearly as the number of fisheries increases. Typically, only a few fisheries cause the majority of the fishing mortality to particular species while many fisheries have very minor effects. For example, four out of 15 sub-fisheries cause 98% of the total fishing mortality for Bight Skate, and five out of 21 fisheries cause 99% of the total fishing mortality for Draughtboard Shark. As such, the relationship between the cost of research and the benefit to the fisheries and environment is nonlinear. If we can identify major sources of impact, for example, by examining fishing effort and its distribution before carrying out thorough risk assessments, significant costs and effort could be saved.

This research will benefit fisheries management in many ways. The initial beneficiaries of the outputs will be commonwealth fisheries, but other state fisheries will benefit from the project by adopting the methods developed herein, and/or by implementing management arrangements for overlapping species. The publication of the results is likely to be picked up globally as Australia is currently leading research in this field. The tools developed from the project will enable AFMA to finalise comprehensive and effective ecological risk management (ERM) for Commonwealth fisheries. It is anticipated that the project has potential to reduce the ecological risks to all bycatch species that are incidentally caught at unsustainable levels. Hence, the research will improve management practices and efficiencies and enhance resource sustainability.

Key words: Ecological risk of fishing effect, quantitative assessment, gear efficiency, abundance, distribution, bycatch, fishing mortality, reference points, sustainability

Acknowledgments

The project was jointly funded by the Fisheries Research and Development Corporation (FRDC project 2011/029), CSIRO Wealth from Oceans Flagship, Australian Fisheries Management Authority (AFMA), State of New South Wales (NSW), and State of Queensland. Tony Smith provided advice and comments. We are grateful to Dr Rick Fletcher who provided many references and constructive comments. We thank members of the oversight reference panel, Nathan Hanna of the Department of Sustainability, Environment, Water, Population and Communities, and Trixi Madon of the Commonwealth Fisheries Association for their input and advice. We thank many people who provided data and information for this project: David Makin (NSWDPI), Caleb Gardner, Klaas Hartman, Jeremy Lyle and Sean Tracey (TAFI), Paula Baker (MAFRI), Matias Braccini (Department of Fisheries, Western Australia), Adrian Linnane, Tim Ward, Cameron Dixon, and Anthony Fowler (SARDI).

1 Background

The implementation of an Ecological Risk Management (ERM) framework is a major step toward Ecologically Sustainable Development (ESD) in Australian Commonwealth-managed fisheries (http://www.afma.gov.au/managing-our-fisheries/environment-and-sustainability/ecological-risk-management). Risk assessment and management are key elements in ESD. The ERM framework includes hierarchical assessments for fishing effects on five aspects of the marine ecosystem: target species, byproduct and discard species, Threatenend, Endangered and Protected (TEP) species, habitats and communities (Hobday et al. 2011). The assessment methods progress from qualitative Scale Intensity and Consequence Analysis (SICA), to semi-quantitative Productivity and Susceptibility Analysis (PSA), to quantitative sustainability Assessment of Fishing Effects (SAFE). These methods focus on individual fishery stressors— whereas it is the cumulative effects from all sources of stressors—for fishing effects—multiple fisheries and sub-fisheries that determine whether a species can sustain to external impacts. However, assessment of such cumulative impacts is technically challenging. As currently formulated, SICA and PSA do not combine multiple impacts in a quantitative fashion as susceptibility attributes are scored on a relative scale. Implementation of ERM across multiple stressors thus requires additional development, ideally at the quantitative level (Level 3 in the ERAEF hierarchy). Discussions with fisheries managers on this need have preceded the development of this proposal and the idea of carrying this research forward has been widely encouraged by Commonwealth and State fisheries managers.

This project is listed as one of the "ComFRAB and Fishery Specific Research Opportunities – 2010". AFMA and ComFRAB previous indicated their support for cumulative risk assessment. The need for methods to undertake cumulative risk assessments in a range of fisheries has been identified by fisheries managers. AFMA has advised us that the objective is to develop a Commonwealth methodology which is applicable to a wide range of fisheries, including SESSF, SPF, and ETBF.

2 Need

National and international fisheries management policies require that the exploitation of fisheries resources should be conducted in a manner consistent with the principles of ecologically sustainable development, in particular the need to consider the impact of fishing activities on non-target species and the long term sustainability of the marine environment. AFMA's Ecological Risk Management (ERM) framework details a process for assessing and progressively addressing the impacts that fishing activities have on marine ecosystems based on the ecological risk assessment for the effect of fishing (ERAEF). The ERAEF, which assesses species-by-species impacts of fishing on all species encountering a particular fishing activity, is perhaps the most comprehensive assessment method supporting ecosystem-based fisheries management currently available. This method has been applied to the majority of Commonwealth fisheries. However, these assessments only take account of risk to individual species from individual Commonwealth fisheries or sub-fisheries. It is the cumulative impact from all fisheries/sub-fisheries on each individual species that determines the species' overall sustainability. However, the cumulative risk to a species across all Commonwealth and state-managed fisheries in which it is captured cannot currently be quantified at level 2 in ERAEF, the productivity-susceptibility assessment (PSA), nor at level 3 sustainability assessment for fishing effect (SAFE) for most fisheries. A recent study shows potentially very high levels of geographic overlap with fishing effort for many species across several Commonwealth fisheries, and some state-based fishery assessments have also highlighted the importance of a extending the ERAEF toolbox to include cumulative risk assessment. There is an urgent need to develop methods and conduct ecological risk assessments on the cumulative impact of all fish species encountered by multiple fisheries.

3 Objectives

1. Scope the range of applications and review existing methods for measuring cumulative effects of capture fishing on species that are caught across a number of different fisheries or sub-fisheries.
2. Scope the different data sources that are currently available and those that may be required to include assessment of cumulative effects under future ERAs.
3. Develop methods for assessing cumulative risk from multiple fisheries or sub-fisheries including recreational and international fisheries, where feasible, on each individual fish species and stock, especially methods that can be applied to data poor fisheries.
4. Apply the method to selected Commonwealth fisheries that operate in the same area with high levels of effort and multiple gear types, e.g., in the southeast region, with further consultation with AFMA.
5. Describe the trade-off between the costs of collecting data for ERA as compared to the benefit returned to the industry/management of the approach.

4 Methods

4.1 Review of methods for measuring cumulative fishing effects

We collected and reviewed risk assessment methods from three major sources. First, we reviewed and compared literature collected from our previous research and regular alerts reported from literature gathering websites. Our existing literature and articles from alerts includes general risk assessment methodology, particularly pertaining to fishery management. Secondly, we conducted literature searches from the internet, for example, in Science Direct (http://www.sciencedirect.com/), Google Scholar (http://scholar.google.com.au/), Web of Science (http://science.thomsonreuters.com), and EBSCO (http://www.ebsco.com/). The search mainly focused on research relevant to cumulative risk assessment. Both peer-reviewed publications and grey reports are included in our review. We examined literature for their suitability for assessing cumulative effects of fishing. The third source was to directly approach scientists working on fisheries risk assessment to obtain materials that we might have missed in literature review. A brief summary of the results was presented and discussed in a project workshop to help determine the most appropriate approach for this project.

4.2 Data source exploration

We explored and reviewed major Commonwealth fisheries and their data availability for possible cumulative impact assessment. A recent AFMA report by Bromhead and Bolton (2005) titled "Potential interactions between Commonwealth managed fisheries" was used as a key document. This report identified two key areas in Australian waters where the level of fishing effort and multiple gears use are high: (1) the southeast (latitudes 35-50°S and longitudes 125 -155°E) and (2) off the central and north-eastern Australia (Coral Sea region: latitudes 15-30°S and longitudes 145 -160°E). The southeast region has 11 fisheries and 19 different gear types operating in the area, with high effort levels associated with many of these gears. The percentage similarity in species catch composition (occurrence) for these fisheries is very high. In the project workshop, data sources and availability in these two key areas were discussed. The data sources included both Commonwealth and State fisheries. In the workshop and the following discussions among collaborators including AFMA, we determined the species and fisheries geographic distribution suitable for consideration in the pilot study for assessing cumulative impacts in a comprehensive fashion.

Because of the large number of bycatch species and the range of fisheries and sub-fisheries that may potentially cause fishing mortality to them, the project focused on priority fish species (e.g. those species previously assessed as high risk in ERAEF projects and known to be subject to a range of cumulative impacts). Previous ERAEF reports and the report by Bromhead and Bolton (2005) were used as primary references to select these priority species. Overlaps between Commonwealth and State fisheries were taken into consideration. Available data in these fisheries, particularly in the State waters, were sought and included for assessing the total combined impact.

4.3 Development of methods for assessing cumulative effects

Based on our literature review, workshop discussion, as well as previous experience, it is clear that qualitative and semi-quantitative approaches, such as the Productivity-Susceptibility analyses (PSA) undertaken to date have not fully quantified cumulative impacts from a range of fisheries. Quantitative methods, such as the level 3 SAFE in the ERAEF hierarchy, may have the capacity to take multiple impacts into consideration for each individual species. However, due to its simplicity and minimal data requirement, when the existing SAFE method was applied to some fisheries (e.g., SESSF), some fairly large assumptions had to be made. First, for many data-poor species, the method assumed that the distribution of the species has a random or uniform distribution with their distribution range. A method to capture their heterogeneous distribution patterns could be more appropriate for many species. Second, a three-level gear efficiency was typically assumed for data-poor species, i.e., Q = 0.33, 0.66, and 1.0. This quantity directly affects the estimated fishing impact. For a rigorous assessment, an estimation based on data is preferred over assumed values. Furthermore, other fisheries have different geographic coverages, stock boundaries, species compositions, and data availability. Even for the SESSF, the cumulative impacts only included impacts from five Commonwealth sub-fisheries and none from overlapping state, international, or recreational fisheries. It is necessary to extend the existing methods, and develop new methods for these fisheries. The goal is to apply advanced statistical and mathematical techniques to limited existing data to quantify cumulative fishing effects from various sources. The techniques include parametric statistical distributions, Bayesian theory, as well as general mathematical calculations. The Results section describes three major components of the method developments: gear efficiency, heterogeneous density, and reference points.

4.4 Apply the method to selected Commonwealth fisheries

Within the Commonwealth fisheries, spatial overlap and species caught by multiple gears are common. We applied the method developed in this report to selected Commonwealth fisheries and priority species. We also included impacts to the selected species by fisheries managed by State governments. Overlap between Commonwealth fisheries and the state fisheries were integrated into the cumulative impact assessment.

The existing ERM framework was reviewed to determine its suitability to assess the cumulative effects of fishing. At the beginning of this project, AFMA undertook a project “Review of scientific & economic information arrangements” (AFMA 2011). The expert panel in that project identified that ecological risk assessments and ecological risk management as one of the key driving research requirements. The panel also highlighted the importance of cost-effective data collection and cost-effective research. Specifically, the panel considered that industry-mediated data collection was likely to be cost-effective. We have made best use of existing fishery-dependent data for estimating gear efficiency, fish distribution, and fish density, from which cumulative estimates of fishing mortality can be derived.

5 Results and discussion

This “Results and discussion” chapter contains five sub-sections. Each of these five sub-sections aims to address the five objectives described in chapter 3—Objectives. Section 5.1 provides a brief review of existing methods for measuring cumulative effects of capture on species that are caught across a number of different fisheries or sub-fisheries. Section 5.2 describes various data sources that are currently available and those that may be required to include assessment of cumulative effects under future ecological risk assessments (ERAs). Section 5.3 is the foundation of the report where we developed quantitative methods for assessing cumulative risk from multiple fisheries. Section 5.4 applies the methods to selected species that are impacted by a range of fisheries (including Commonwealth and States’ fisheries). Finally, in Section 5.5 we discuss the cost-benefit trade-off for conducting an assessment of cumulative fishing effects.

5.1 Brief review of methods for measuring cumulative fishing effects

A range of methods have been developed and used in the assessment of fishing effects on non-target species. The methods can be generally categorized as qualitative, semi-quantitative, and fully quantitative (Scandol et al. 2009; Hobday et al. 2011). Most of the existing methods are appropriate for analysis of fisheries with a single fishery or gear type. The cumulative fishing effects represent multiple, often simultaneous, fishing pressures acting on species in a community and their habitat. The frameworks and techniques for cumulative risk assessment in the ecological domain are relatively new and mostly directed at the health risks associated with exposure to combinations of chemicals. Because of data limitation, cumulative risk assessment for fishing effects on bycatch species is an emerging research area, although the question has been raised for years. We briefly discuss major categories of methods used in fishery risk assessment.

5.1.1 QUALITATIVE AND SEMI-QUANTITATIVE METHODS

Qualitative and semi-quantitative risk assessment methods produce ordinal (e.g. high, medium, low, or score on a scale of 1 to 10) risk scales. They often involve the use of descriptive scales for consequence and likelihood in a table form which are then combined into a risk matrix where risks are assigned to priority classes based on their consequence and likelihood (Scandol et al. 2009, Pears et al. 2012). Several qualitative or semi-quantitative methods have been developed in Australia (Fletcher et al. 2002, 2005; Astles et al. 2006, 2009; Stobutzki et al. 2001; Hobday et al. 2011) and have been applied to many individual fisheries. The two groups of methods are similar in nature so distinction between the two is vague (Scandol et al. 2009; Hayes et al. in review). For example, in the assessment of consequence of fishing on bycatch species, the qualitative risk analysis (consequence X likelihood) determines the consequence category (Minor, Moderate, Major, and Extreme) by considering the take in one particular fishery and comparing this level to total take by all fisheries (Fletcher et al. 2002; Fletcher 2010; http://www.fao.org/fishery/eaf-net/eaftool /eaf_tool_4/en).

Similarly, the semi-quantitative Productivity Susceptibility Assessments (PSA) determines a susceptibility score (1 to 3) in each fishery by considering species availability, encounterability, selectivity and post-capture mortality. Some of these attributes can be fully quantitative but the thresholds for assigning high, medium and low risk can be somewhat arbitrary (e.g., whether 80% or 95% of population impacted should be classified as high risk). When the consequence category or susceptibility score has been assigned to each species within each fishery (gear or sub-fishery), integrating them across multiple stressors (i.e. gears and sub-fisheries) becomes challenging. Consequence categories or susceptibility scores across multiple stressors cannot be simply added together. For example, two Minor consequences do not necessary accumulate to a Moderate consequence, nor do three Moderate consequences necessarily accumulate to an Extreme one. In theory the PSA method can be used for cumulative impacts of capture fishing a given unit individual units (species/habitats), by adding the risk values from different fisheries for a given susceptibility attribute. Productivity attributes remain unchanged because they are independent of the fishery. The advantage of this method is that it does not require catch volumes, which are often not available for bycatch species in many fisheries.

The Ranked Risk Assessment of Multiple Fisheries (RRAMF) method has made integrating qualitative risks possible (Evans and Molony 2010). For example, to allow an estimate of bycatch across a region to be determined, this method ranks the relative abundance of each species in the bycatch in each fishery from 1 to 5. Those species that were rare in the bycatch were given a rank of 1 and those that were highly abundant were given a rank of 5. Because there are different levels of effort and catch in different fisheries, the fisheries are weighted according to their comparative catch. Scaled-up estimates of catch demonstrate the relative impact of fisheries on the bycatch and are used for weighting fisheries, i.e. the weighting was based on the order of magnitude differences between the scaled-up data for the fisheries. However, this method requires catch abundance data, which may not be available for many bycatch species.

The Consequence-Likelihood approach has been widely used in fisheries risk assessment, particularly in Western Australia (Fletcher et al. 2002; Fletcher 2005, 2010; Fletcher et al. 2012a). This approach has been used to combine individual risk values to a regional level (Fletcher et al. 2011; Fletcher et al. 2012b, 2012c). The process uses the branch structure of the component trees to combine multiple risk categories. Each of the branches represents groups of "like risks" that can be managed collectively (Fletcher et al. 2012a). The method has been applied to the West Coast Bioregion of Western Australia, and the resulting priorities are used as the basis for annual budget preparation by the State Department of Fisheries. This type of risk assessment is simple to apply in fields where there is a large database of accidents or failures. In fisheries, the consequence-likelihood method can be prone to error and inaccuracy due to lack of data so a larger precautionary buffer should established in their use. From efficiency point of view, the simple qualitative methods can be useful as an early screening process to identify the major source of stressors before quantitative assessments are carried out.

For qualitative methods, the scale (e.g. 1 to 3 or 1 to 10) and risk thresholds for attributes can be arbitrary; different applications may use different scales (e.g., 1 to 3, 1 to 5, or 1 to 10) and even attributes (e.g., which life history traits to be used) (Scandol et al. 2009; Hayes et al. in review). Although these methods may use mathematical operations, such as summation and multiplication to derive individual scores, the relative scales for some attribute remain arbitrary (Hayes et al. in review). Qualitative and semi-quantitative methods are flexible and suitable for screening potential risk in data-poor situations (Bulman et al. 2008; Daley et al. 2007; Hobday et al. 2007; Smith et al. 2007). However, one of the main difficulties with these methods is the uncertainty around the risk scores/consequences. Since data uncertainty and threshold values (e.g., vaguely high, low risk) intermingle, it is problematic to evaluate uncertainty. Thus qualitative and semi-quantitative analyses generally do not provide explicit uncertainty values (Hayes, 2011). Importantly though, the application of the precautionary principle to missing data means that risk scores in the PSA method always represent the worst risk scenario.

Qualitative and some semi-quantitative approaches often use stakeholder and expert knowledge to help determine risk scores. This process may lead to better outcomes (Beierle 2002) but depending on experts and stakeholders, it can be prone to biases, particularly when there are multiple stressors (Kynn 2008). This can result from overconfidence or higher weight from more influential participants in the discussion group (Burgman, 2005).

5.1.2 QUANTITATIVE METHODS

Quantitative methods use numerical data from a variety of sources in the analysis. They typically involve mathematical models, which assume some scientific understanding of the biological process. Quantitative methods span many orders of complexity, from simple linear mechanistic models to nonlinear, high dimensional statistical models (Sharp and Smith 2009; Fock 2011; Zhou et al. 2011). Furthermore, because ecological risk assessments generally involve multiple components, a specific assessment approach may encompass a range of models with varying degrees of complexity. Technically, traditional stock assessments, multispecies ecosystem modelling, and management strategy evaluation (MSE) that have the capability to assess cumulative fishing impact all belong with the quantitative method category. All numerical values used in the quantitative assessment are biologically meaningful, hence, they allow mathematical computation while the biological meanings are preserved and progressed in the whole assessment process. This is the type of method that has the capacity to straightforwardly deal with cumulative effects in an ecological process. In particular, we determined that the Sustainability Assessment for Fishing Effects (SAFE, see Zhou and Griffith 2008; Zhou et al. 2009; Zhou et al. 2011) method has the potential to be extended and improve the assessment of cumulative fishing impacts on species with limited information. In this study, cumulative fishing mortality result from multiple fishing gears, fisheries and sub-fisheries. The risk endpoint is a stock or population of a species under a given jurisdiction. In other words, our aim is not to assess the entire species across its full geographic range. In this report, we focus on the development of quantitative methods for assessing cumulative fishing effects on case study species.

5.2 Scope of different data sources

After exploring data availability and reviewing literature and fisheries, the project team discussed options and decided to use the southeast region as our case study area. Consequently, we focussed on compiling data pertaining to this region.

Multiple sources of data were assembled during the project. Both Commonwealth government agencies and State governments agencies were requested to provide their data. For the purpose of estimating species distribution and density, we attempted to gather two major categories of data: scientific surveys and fishery-dependent observations. For the purpose of estimating cumulative fishing impacts, we collected as many fisheries as possible, including Commonwealth sectors (Table 5-1) and a range of State fisheries in New South Wales, Victoria, and Tasmania.

Our major database includes: AFMA Logbook; AFMA Observer; CMAR Warehouse, including historical scientific surveys; and NSW *Kapala* surveys. We have streamlined data extracts from these databases. This function enables a single query to generate extracts across all databases. Queries include spatial domains that can change the underlying grid easily. Fishing effort details can be extracted from the CMAR Warehouse and observer data.

The combined survey-observer database contains over 886,000 shot by shot records covering both Commonwealth and State waters (Figure 5-1). Information includes survey name, region, bottom type, IMCRA polygon, time, fishery, fishing method (gear type), effort, species CAAB code, species name, location (latitude and longitude), depth, trawling length, headrope length, catch in weight, catch in number, etc. However, not all these fields have data for many records. Yet, this is the most useful piece of data for estimating bycatch species distribution, density, and gear efficiency.

Bioreg Database contains species spatial distribution. We used existing ERA distributions from the Bioreg database. A data query method has been developed to join tables in other databases, e.g., logbook.

At least 41 fishing methods (gear types) have been used in Commonwealth fisheries (Table 5-1). Many of these gears are used in the southeast region fisheries. Our assessment focused on impacts of these gears used in Commonwealth fisheries.

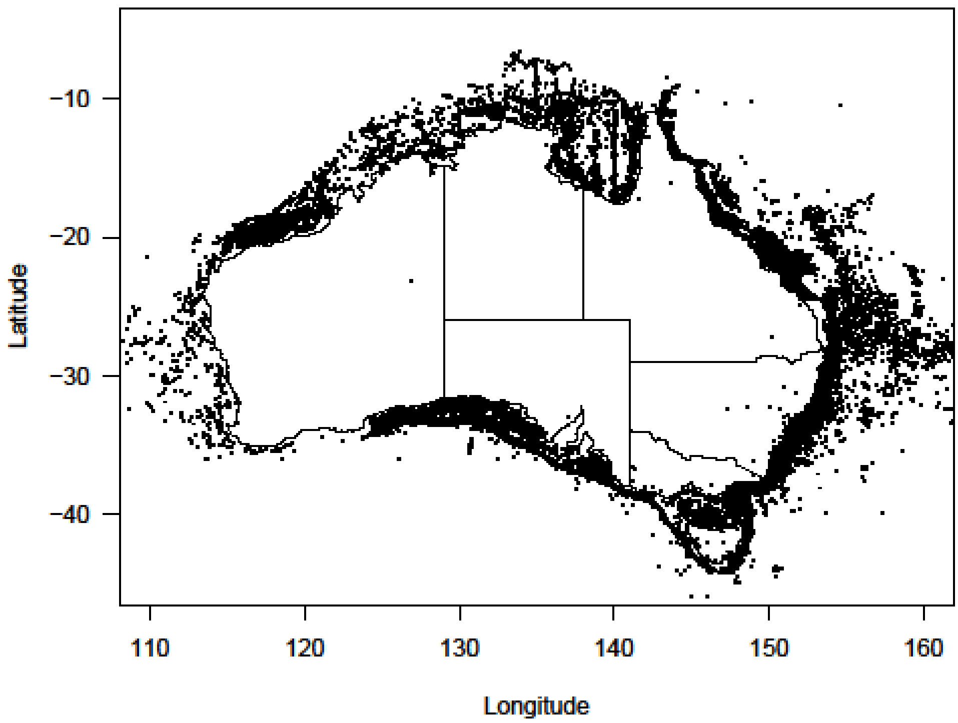

Figure 5-1. Locations of scientific surveys and observer data in the database used for the report.

New South Wales data: fishing time (year, month, and date), fishing method, effort, grid code, site code, species code, common name, catch weight, etc. There are over 119,000 daily shot by shot records in 2009/10 and 2010/11, and 2011/12 years. We also examined the data before 2009. However, the reporting system has changed and resolution has increased since 2009. Hence, data before 2009 are not compatible with more recent data and are not used in the analysis.

Forty-two fishing methods (gear types) have been used in NSW (Table 5-2). About a dozen gear types are applied in ocean fisheries. Impacts from these fisheries are included in the assessment.

Tasmania: time, gear, effort, depth, location, species, estimated weight, etc., are included in the database. There are at least 21 gear types used in Tasmania fisheries (Table 5-3). We also compiled research data from gillnet fisheries, line fishing, and rock lobster trap fishing. The fisheries recorded dozens of bycatch species but for many observation only number or size were recorded. For many observations only summaries were provided without precise locations and times.

Victoria: fishing time (year, month), area code, depth, gear code, effort, species code, catch in weight, etc. There are about 47,000 records from 2007 to 2011. About thirty methods (gear types) are used in Victoria (Table 5-4). Fisheries that have potential impact on case study species are included in the assessment.

South Australia: Great Australian Bight (GAB) historic survey data were obtained for the period 1965– 1989. A total of 61 species were recorded. The data fields include location, depth, species, catch in weight, etc.

There were many difficulties compiling these data. Each agency has its own format, type of information, codes of each data field, etc. It was challenging to understand the data and standardise the fields from different sources to make them compatible. In addition, cleaning up errors in all data sources was time consuming.

A preliminary exploration of these data indicated that the sample size was sufficient and the reporting was precise enough to conduct quantitative risk assessment for cumulative fishing impacts for a range of bycatch species. However, for some species, the quality of assessment will be limited by the amount of available data and the simple assumptions may have to be applied (i.e., assuming homogeneous distribution, and three fixed levels of catch efficiencies). For example, the method for estimating gear efficiency for the particular species (see below) and low-efficient gears relies on comparing catch rates from different fishing methods at the same location and time where effort overlaps. This may limit available sample size because the normal intended use of the different fishing gears is to target different substrates. For example, line gear can be used over the roughest ground but trawl gear cannot. It is important to note that while direct empirical comparisons were possible, low sample sizes limit the confidence in these estimates.

Table 5-1. Fishing methods (gears) used in Commonwealth fisheries.

Method code	Description	Method code	Description
AL	Automatic longline		
BL	Demersal Longline	LLP	Pelagic Longline
BS	Beach Seine	ML	Minor Line
CP	Crab/Lobster Pot	MT	Midwater Trawl
DG	Dredging	OP	Octopus Trap
DI	Diving (General Fishing Method)	OT	Otter Trawl
DIF	Diving Free Dive Method	PB	Pole & Bait
DIH	Diving Hooker Method	PL	Pole
DL	Drop Line	PS	Purse Seine
DN	Dip Net	RR	Rod And Reel
DO	Dory	SJ	Squid Jig
DS	Danish Seine	SL	Setline
FP	Fish Trap	SP	Spear
GA	Graball	TC	Traps (Crab)
GN	Gillnet	TF	Traps (Fish)
GND	Gillnet Drift	TL	Trotline
GNF	Gillnet Fixed	TO	Traps (Octopus)
GNP	Gillnet Pelagic	TR	Trolling
HL	Handline	TRL	Traps (Lobster)
HN	Hauling Net	TW	Trawling
HNT	Hand Net	TWDS	Trawling (Danish Seine)
J	Jigging	TWOB	Trawling (Otter)

Table 5-2. Gear types and effort units in New South Wales fisheries.

Code	Method	Effort unit	Used in ocean in 2009-2011
	Nets		
BTN	Bait net	Total number of shots	
DSF	Danish seine trawl net (fish)	Total trawl time (hrs)	
DSN	Dip or scoop net (prawns)	Hours fishing (hrs)	
DHNC	Drag or hauling net (carp)	Hours fishing (hrs)	
FHN	Flathead net	Length of net (m)	
GFN	Garfish net (bullringing)	Total number of shots	
GFC	Garfish net (hauling)–beach based	Total number of shots	
GBB	Garfish net (hauling)–boat based	Total number of shots	
GLN	Gill net	Length of net (m)	
HHP	Hand-hauled prawn net	Hours fishing (hrs)	
HHY	Hand hauled yabby net	Length of net (m)	
HLN	Hauling net (general purpose)	Total number of shots	
HLF	Hoop or lift net	Number of nets	
MHN	Meshing net	Length of net (m)	Yes
OTF	Otter trawl net (fish)	Total trawl time (hrs)	
OTP	Otter trawl net (prawns)	Total trawl time (hrs)	Yes
PABC	Pilchard, anchovy & bait net	Total number of shots	
	Beach based		
PABB	Pilchard, anchovy & bait net	Total number of shots	
	Boat based		
PNH	Prawn net (hauling)	Hours fishing (hrs)	
PNS	Prawn net (set pocket)	Total number of hours set (hrs)	
PRN	Prawn running net	Hours fishing (hrs)	
PSN	Purse seine net	Total number of shots	
SRN	Push or scissor net (prawns)	Hours fishing (hrs)	
SNP	Seine net (prawns)	Hours fishing (hrs)	
SCN	Spanner crab net	Number of nets	Yes
TWN	Trumpeter whiting net (hauling)	Total number of shots	
	Line		
DTL	Driftline	Number of hooks	
DPL	Dropline	Number of hooks	Yes
HDL	Handline	Number of hooks	Yes
JGG	Jigging	Number of lures	Yes
PLG	Poling	Number of hooks	
STD	Setline (demersal)	Number of hooks	Yes
STL	Setline	Number of hooks	
TLG	Trolling	Number of lures	Yes
TTL	Trotline (bottom set)	Number of hooks	Yes

Code	Method	Effort unit	Used in ocean in 2009-2011
	Traps		
CPT	Carp trap	Number of traps	
CBT	Crab trap	Number of traps	
ELT	Eel trap	Number of traps	
FTD	Fish trap (bottom/demersal)	Number of traps	Yes
YBT	Yabby trapping	Number of traps	
	Other		
ETF	Electro-fishing	Hours fishing (hrs)	
HDG	Hand gathering	Hours hand gathering (hrs)	Yes
SND	Skindiving	Hours diving (hrs)	

Table 5-3. Gear types and effort units in Tasmania fisheries.

Code	Description	Effort units
BL	Bottom longlining	Line lifts, hooks
BS	Beach seining	Metres, shots
CP	Cray pots	Pot lifts, hrs
DL	Droplining	Line lifts, hooks
DN	Dip net	Fishers, hrs
DS	Danish seine	Metres, shots
FP	Scalefish trapping	Trap lifts, hrs
GN	Graball netting	Metres, hrs
HC	Hand collection	Fishers, hrs
HL	Hand lines	Lines, hrs
MN	Small mesh netting	Metres, hrs
MT	Midwater trawling	
OP	Octopus trapping	Pot lifts, hrs
OT	Otter board trawling	Shots, hrs
PS	Purse seining	Metres, shots
SJ	Hand squid jigging	Jigs, hrs
SL	Shark longline	Line lifts, hooks
SN	Shark netting	Metres, hrs
SP	Flounder spearing	Fishers, hrs
TL	Trotlining	Line lifts, hooks
TR	Trolling	Lines, hrs
XX	Other	

Table 5-4. Gear types and effort units in Victoria fisheries.

Code	Descript	Effort units
DL	Drop Line	Days, C_Shots, C_Hours, C_HookLift, C_HookHour
DS	Danish Seine	Days, C_Shots, C_Hours, C_ShotMesh, C_ShotCoil
FR	Fish Trawl (sweeps attached)	Days, C_Shots, C_Hours
FT	Fish Trap	Days, C_TrapLift, C_TrapHour
H2	Bait Seine (Small Mesh < 30mm)	Days, C_Shots, C_M-lifts, C_Hours
H3	Haul Seine (Medium Mesh 30-59mm)	Days, C_Shots, C_M-lifts, C_Hours
H4	Haul Seine (Large Mesh 60-100mm)	Days, C_Shots, C_M-lifts, C_Hours
H5	Garfish Seine (Floating 25-29mm)	Days, C_Shots, C_M-lifts, C_Hours
H6	Ringing Seine (Bottom Set 25-45mm)	Days, C_Shots, C_M-lifts, C_Hours
HJ	Hand Squid Jig	Days, C_Hours
HL	Hand Line	Days, C_Shots, C_Hours, C_HookLift, C_HookHour
M1	Multifilament Mesh < 60mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
M2	Multifilament Mesh 60-74mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
M3	Multifilament Mesh 75-94mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
M4	Multifilament Mesh 95-124mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
M5	Multifilament Mesh 125-130mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
M6	Multifilament Mesh > 130mm	Days, C_Shots, C_M-lifts, C_M-hours, C_Hours
N1	Non-shark Monofilament Mesh < 60mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
N2	Non-shark Monofilament Mesh 60-74mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
N3	Non-shark Monofilament Mesh 75-94mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
N4	Non-shark Monofilament Mesh 95-124mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
N5	Non-shark Monofilament Mesh 125-130mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
N6	Non-shark Monofilament Mesh > 130mm	Days, C_Shots, C_M-lifts, C_M-hours, C_SerchHrs
OP	Octopus Trap/Pot	Days, C_PotLifts, C_PotDays
PS	Purse Seine	Days, C_Shots, C_M-lifts, C_Hours, C_SerchHrs
PT	Prawn Trawl (no sweeps attached)	Days, C_Shots, C_Hours
RL	Lobster Pots	Days, C_Pot-lift
SL	Shark Long Line	Days, C_HookLift, C_HookHour,
SN	Snapper Long Line	Days, C_Shots, C_HookLift, C_HookHour
TR	Troll Line	Days, C_Hours, C_HookLift, C_HookHour

5.3 Development of methods for assessing cumulative risk

Our brief review indicates that quantitative methods may be more appropriate for handle cumulative risks for bycatch species in capture fisheries that lack catch statistics and comprehensive annual independent surveys, providing there are fishing effort data (when catch data are not available) and reliable observer data or some historical survey data. In particular, we identified specific improvements that can be made to the Sustainability Assessment for Fishing Effects (SAFE) method to improve its utility for this purpose. The general SAFE approach involves estimating fishing mortality rate and corresponding reference points. The basic principle is similar to that used in target species stock assessment. Because population sizes (abundance or biomass) are difficult to estimate for hundreds of bycatch species, SAFE focuses on the relative quantity—the fishing mortality rate—as the most easily obtainable indicator. Fishing mortality can be derived from spatial overlap between species distribution and fishing effort distribution, catchability resulting from probability of encountering the gear and size-dependent selectivity, and post-capture mortality. Cumulative impacts from multiple fishing sources on regional stocks of bycatch species are a linear function of each single stressor. Therefore, estimation of cumulative effects of capture fishing is feasible when the impact from each single fishing sector can be derived.

In this project, we extended and improved the SAFE method in several ways. This project achieved three major new method developments: estimating gear efficiency by Bayesian mixed statistical distribution models and simulation, estimating fish density via modelling, and developing sustainability reference points based on simple life history traits. We present these new methods in the following sub-sections.

5.3.1 ESTIMATING GEAR EFFICIENCY AND ABUNDANCE FROM CATCH DATA: CROSS-SAMPLING METHOD

5.3.1.1 Introduction

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

The traditional way to estimate gear efficiency is by field experiments and most typically for trawls. Somerton et al. (1999) categorized four techniques for studying trawl efficiency: (1) gear comparison experiments where Q is estimated as the quotient of fish density (catch per area swept) from the trawl to density estimates from a gear type believed to be completely (i.e., 100%) efficient, such as visual transects from a ROV or minisub; (2) depletion experiments where Q is estimated by repeatedly trawling on a small closed population then fitting a model to the decline in cpue as a function of cumulative catch; (3) tagging experiments where Q is estimated by determining the fate of individual fish, identified with acoustic transponding tags, that were initially positioned in the trawl path; and (4) experiments focused on vertical herding, horizontal herding, and escapement. The estimates of Q are then obtained by combining the three components in a mathematical model of the catching process. As these approaches are costly, only a few studies have been conducted for a limited number of species and trawl types. In addition, gear efficiency can be affected by many factors, including selectivity, fish behaviour, fisher skills, and environmental conditions (Arreguin-Sanchez 1996; Dickson 1993). This makes the result for one species in one study difficult to be applied to another species or in a new region.

Estimating gear efficiency is even more difficult for other gear types, such as hook and lines, seine, gillnets, and traps. Studies on these gear types often focus on relative selectivity rather than overall efficiency (Borgström and Plahte 1992; Prchalová et al. 2009). Unlike trawl, clearly defining gear affect area is not easy for gears that do not physically swept a measurable area. Absolute abundance estimation based on these gear types is less common.

Recently, promising methods have been developed in ecology to estimate animal abundance and survey detectability. Detectability in ecological studies is similar to gear efficiency in fisheries. These methods have been applied in terrestrial populations such as birds (Martin et al. 2011; Royle 2004; Wenger and Freeman 2008). It has been demonstrated that estimating detectability and abundance from repeated observations is possible when the animals are randomly distributed within the study area. However, it is challenging to estimate Q and B for a non-random, aggregated distribution, which is generally the case for marine fish species.

In this section, we develop statistical methods to estimate gear efficiency for multiple gear types catching a population with either random or aggregated distribution patterns. The methods can simultaneously estimate population density or abundance. We carry out simulations to test the performance of the methods and apply them to real fish populations.

5.3.1.2 Methods for estimating gear efficiency

The method developed here for estimating gear efficiency (catchability, detectability) and abundance involves two processes. The first component is the distribution pattern of fish individuals over the spatial range where fishing or surveys have taken place. The second component is to catch (sample) fish from such a population distribution pattern.

Distribution process

Population distributions fall into two general patterns, a random distribution and an aggregated distribution. In ecology, a random distribution is typically modelled by a Poisson distribution while the aggregated distribution is modelled by a negative binomial distribution. The Poisson distribution is relatively simple, involves only one parameter, and the mean population size equals its variance. If the number of individuals in grid cell i is N_i, the probability mass function of Poisson distribution is:

$$f_{Pois}(N_i;\lambda) = \frac{\lambda^{N_i}}{N_i!}e^{-\lambda} \qquad \textbf{(5-1)}$$

where λ is mean population size. Non-random distribution is considered more common in ecology and is certainly typical for fish species. Let us assume that individuals of a particular species are independently distributed in an aggregated non-random pattern in the study area. We use negative binomial distribution (NBD) to describe the spatial distribution of aggregated populations. The number of individuals N_i in grid cell *i* can be described by one of the parameterizations of NB probability density function:

$$f_{NB}(N_i;\mu,r) = \frac{\Gamma(N_i + r)}{\Gamma(r)\times N_i!}\times\frac{\mu^{N_i} r^r}{(\mu + r)^{N_i + r}}, \qquad \textbf{(5-2)}$$

where μ is the mean and *r* is the shape parameter. The variance of the mean is

$$\sigma^2 = \mu + \frac{\mu^2}{r}. \qquad \textbf{(5-3)}$$

The shape parameter *r* describes the extent of aggregation so measures overdispersion and $r > 0$. As $r \rightarrow \infty$, the negative binomial converges in distribution to the Poisson so the variance approaches the mean.

WinBUGs uses the following alternative parameterization:

$$f_{NB}(N_i;p,r) = \frac{\Gamma(N_i + r)}{\Gamma(r)\times N_i!}p^r(1-p)^{N_i} \qquad \textbf{(5-4)}$$

where *r* (> 0) is the same as in equation (2), and *p* [$\in (0, 1)$] is the success probability in each experiment. The mean is $\mu = r(1 - p)/p$ and the variance is $\sigma^2 = r(1 - p)/p^2$.

The catch process

Given an individual fish is present in cell *i*, there are two possible outcomes when fishing gear passes over it: caught or not caught. Hence, it is natural to assume that the number of fish of a particular species caught in grid cell *i*, sample time *j* by gear type *k*, follows a binomial distribution:

$$C_{ijk} \sim bin(Q_k, N_i) \qquad \textbf{(5-5)}$$

where Q_k is the probability of being caught (called gear efficiency in fishery research) by gear type *k*, and N_i is the number of fish within the gear-affected area from previous equations.

In the marine environment, the sizes of grid cells are often large. Abundances available for capture within the gear-affected area may change even when repeated samples are taken during a short time period in the same cell. Hence, it may be more realistic to assume varying N_{ij}, or even N_{ijk}. Alternative models are explored below.

A more complicated situation arises when scientific surveys or fishing operations take place in locations not occupied by a species that is of interest to the study. This will result in zero catches in excess of the zeros modelled by the equations above. When zero catch data are collected, it is logical to use zero-inflated distribution models, such as zero-inflated Poisson (ZIP) or zero-inflated negative binomial distribution (ZINB). A zero-inflated model is a two-component mixture model combining a point mass at zero with a normal Poisson or negative binomial count distribution. There are two sources of zeros: from the point mass and from the count component. For the ZINB, the probability function is expressed as (Zhou et al. 2012a):

$$f_{ZINB}(N_i;\mu,r,\psi)=\begin{cases}\psi f_{NB}(N_i>0\mid\mu,r), & \text{for } C_{ijk}>0\\(1-\psi)+\psi f_{NB}(N_i=0\mid\mu,r), & \text{for } C_{ijk}=0\end{cases} \quad \textbf{(5-6)}$$

where ψ is the probability of occupancy, and C_{ijk} is again the number of a particular fish species caught in grid cell *i*, sample *j*, by gear type *k*.

Parameter estimation

The distribution and catch processes are modelled in a Bayesian hierarchical framework. For the Poisson distribution, the abundance in cell *i* is generally modelled as:

N_i ~ pois(λ).

Catch data are then modelled as a binomial distribution:

C_{ij} ~ binorm(Q, N_i).

We use a lognormal distribution for the mean λ to ensure non-negative abundance and use beta distribution for the gear efficiency parameter since Q must be limited between 0 and 1. Weak priors are assumed for these two parameters: Q ~ beta(1,1), and λ ~ lnorm(0, 0.01)

For non-random distribution patterns, abundance in a cell is modelled by

N_i ~ negbin(p, r).

For similar reasons, we use beta distribution for probability parameter p and lognormal distribution for the shape parameter *r: p* ~ beta(1,1), and r ~ lnorm(0, 0.01).

For the zero-inflated models, the mean abundance in a cell taking excessive zeros into account, N_i^Z, is the product of the two components: occupancy probability and the mean from a statistical distribution (either Poisson or NB). In the model, it is estimated by (Wenger and Freeman 2008):

$$N_i^Z = Pre_i \times N_i$$

where N_i is from previous equations, and the Pre_i is binary value for presence or absence, which is modelled as

$$Pre_i \sim Bernoulli(\psi_i).$$

Further, occupancy probability ψ varying between 0 and 1, and may be often affected habitat condition. To facilitate predicting occupancy from environmental covariates, we estimate this parameter by

$$logit(\psi_i) = \mathbf{X\alpha}$$

where **X** is a vector of covariates and $\boldsymbol{\alpha}$ is parameter. Similarly, other parameters, such as p, r, λ, and μ, can also link to environmental covariates, including depth, latitude, year, sample time (day or night), swept area, bottom type, etc.

Simulation

We carry out a range of simulations representing different scenarios. We then build alternative models to examine their performances. Data are generated by using the R software package, while the Bayesian models are implemented in WinBUGS. The negative binomial distribution can be modelled either by the built-in distribution function dnegbin(p, r), or using mixture of Poisson distribution and gamma distribution:

$N_i \sim Poisson(\lambda_i)$ and $\lambda_i \sim gamma(r, \Lambda_i)$.

Here, the shape parameter r is the same as above, while $\mu = r\Lambda$ and its variance $\sigma^2 = r\Lambda^2$.

We run three chains with varying initials. Convergence is assessed by visual examination of chain trajectories and by Gelman-Rubin statistics Rhat. The data generation and MCMC sampling are run from R package R2WinBUGS. MCMC continues for sufficient iterations after convergence before additional iterations are kept for parameter inferences.

5.3.1.3 Results of simulation for gear efficiency and abundance

Scenario 1

Data generation: This is the simplest case where fish are assumed to be randomly distributed across 100 grid cells (Table 5-5). The mean number of fish for this Poisson distribution is 100. Each cell is sampled 10 times using one type of gear that has an efficiency of $Q = 0.5$. The abundance is assumed to be fixed at each sampling time.

Table 5-5. Summary of data simulation and modelling process for Scenario 1.

	Data generation	Modelling
Number of grids	100	
Mean fish per grid	100	
Distribution between grids	N_i ~ pois(100)	N_i ~ pois(λ)
Distribution within grid	Fixed	Fixed

Gear type	1	1
Gear efficiency	0.5	
Number of samples per grid	10	
Catch process	C_{ij} ~ bin(Q, N_i)	C_{ij} ~ bin(Q, N_i)

Note: i = grid, j = shot. Prior for gear efficiency Q ~ beta(1, 1).

Table 5-6. Input data and model results for Scenario 1.

	Input	True value	Posterior median (95% CI)
Mean of individuals per grid	100	98.95	96.23 (88.9-103.4)
Gear efficiency	0.5	0.50	0.511 (0.48-0.55)

Bayesian model: The model has the same assumptions as in data generation, i.e., Poisson distribution between grids and fixed abundance within each grid when each and all samples are taken.

Model performance: We use three chains with very different starting initials, and discard the first 30k iterations (converged at about 15k). The median of posterior Q is 2% higher than the true value, while the posterior N is about -3% lower than the true mean abundance N (Table 5-6). For this random distribution and fixed abundance at each sampling, the Bayesian model can estimate the abundance fairly well (Figure 5-2).

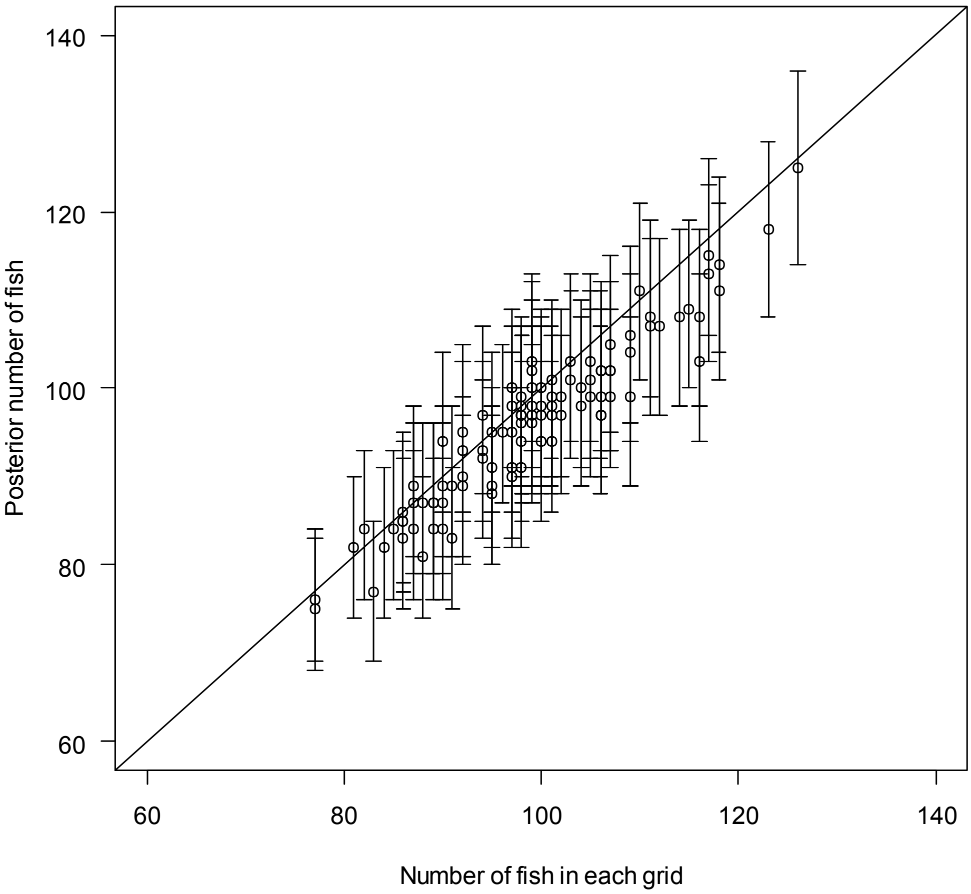

Figure 5-2. Comparison of true abundance and the posterior median abundance (and their 95% CI) for Scenario 1.

Scenario 2

Data generation: Fish are assumed to follow an aggregated distribution among 100 grid cells. The mean number of fish for this negative binomial distribution is 100. The shape parameter *r* is set to 5. Such a negative binomial distribution has a variance about 46 times of its mean. Each cell is sampled 10 times using one type of gear that has an efficiency of $Q = 0.5$. The abundance is assumed to be fixed at each sampling time (Table 5-7).

Table 5-7. Summary of data simulation and modelling process for Scenario 2.

	Data generation	Modelling
Number of grids	100	
Mean fish per grid	100	

Distribution between grids	N_i ~ negbin(100, 5)	N_i ~ negbin(p, r)
Distribution within grid	Fixed	Fixed
Gear type	1	1
Gear efficiency	0.5	
Number of samples per grid	10	
Catch process	C_{ij} ~ bin(Q, N_i)	C_{ij} ~ bin(Q, N_i)

Note: i = grid, j = shot. Prior for gear efficiency Q ~ beta(1, 1), p ~ beta(1, 1), r ~ lnorm(0, 0.01).

Table 5-8. Input data and model results for Scenario 2.

	Input	True value	Posterior median (95% CI)
Shape r	5		4195
Mean of individuals per grid	100	103.8	56.8
Gear efficiency Q	0.5	0.50	0.861 (0.85-0.87)

Bayesian model: The model has the same assumptions as in data generation, i.e., negative binomial distribution between grids and fixed abundance within each grid when each and all samples are taken.

Model performance: This model performs poorly (Table 5-8). The median of posterior Q is 72% higher than the true value, while the posterior N is about -45% lower than the true mean abundance N.

The result indicates that for a population having an aggregated distribution pattern, gear efficiency and abundance are difficult to estimate using one single gear type.

Scenario 3

Data generation: This scenario is similar to Scenario 2. Fish are assumed to follow an aggregated distribution among 100 grid cells (Table 5-9). The mean number of fish for this negative binomial distribution is 100. The only difference is that three gear types are used to catch the same population. Their gear efficiency is 0.2, 0.5, and 0.8, respectively. Each cell is sampled 10 times by each of the three gears. The abundance is assumed to be fixed at each sampling time.

Bayesian model: The model has the same assumptions as in data generation, i.e., negative binomial distribution between grids and fixed abundance within each grid when each and all samples are taken. Fishing operation is a binomial process for each gear type.

Model performance: Three chains with different starting initials are used. Convergence is good if the starting initials are appropriate (Figure 5-3). It is difficult to achieve convergence when the initial N is too far off (e.g., 700). When three chains are not mixing with each other for a long time, it may be necessary to change to a new initial. When the three chains mix well, the posterior appears to be accurate (Figure 5-4).

The range of the MCMC trajectories tends to be narrow, resulting in small credible intervals. The median of posterior Q and abundance N are very close to the true values (Table 5-10, Figure 5-5).

Table 5-9. Summary of data simulation and modelling process for Scenario 3.

	Data generation	Modelling
Number of grids	100	
Mean fish per grid	100	
Distribution between grids	N_i ~ negbin(100, 5)	N_i ~ negbin(p, r)
Distribution within grid	Fixed	Fixed
Gear type	3	3
Gear efficiency	0.2, 0.5, 0.8	Q_1, Q_2, Q_3
Number of samples per grid	10	
Catch process	C_{ijk} ~ bin(Q_k, N_i)	C_{ijk} ~ bin(Q_k, N_i)

Note: i = grid, j = shot, k = gear. In all models, gear efficiency Q ~ beta(1, 1), p ~ beta(1, 1), r ~ lnorm(0, 0.01).

Table 5-10. Input data and model results for Scenario 3.

	Input	Mean true value	Posterior mean (sd); median (95% CI)
Mean of individuals per grid	100	103.8	102.3 (1.56); 102.3 (99.4-105.5)
Shape r	5		4.61 (0.66); 4.57 (3.43-6.01)
Gear efficiency	0.2	0.20	0.20 (0.001); 0.204 (0.20-0.21)
	0.5	0.50	0.50 (0.005); 0.503 (0.49-0.51)
	0.8	0.80	0.81 (0.662); 0.811 (0.80-0.82)

We were curious about the performance of a slightly different (incorrect) Bayesian model. This alternative model assumes a Poisson distribution with each cell where the true abundance is fixed. The result is a slight overestimation of Q (about 5% for the three gear types) and slight underestimation of N (-5%).

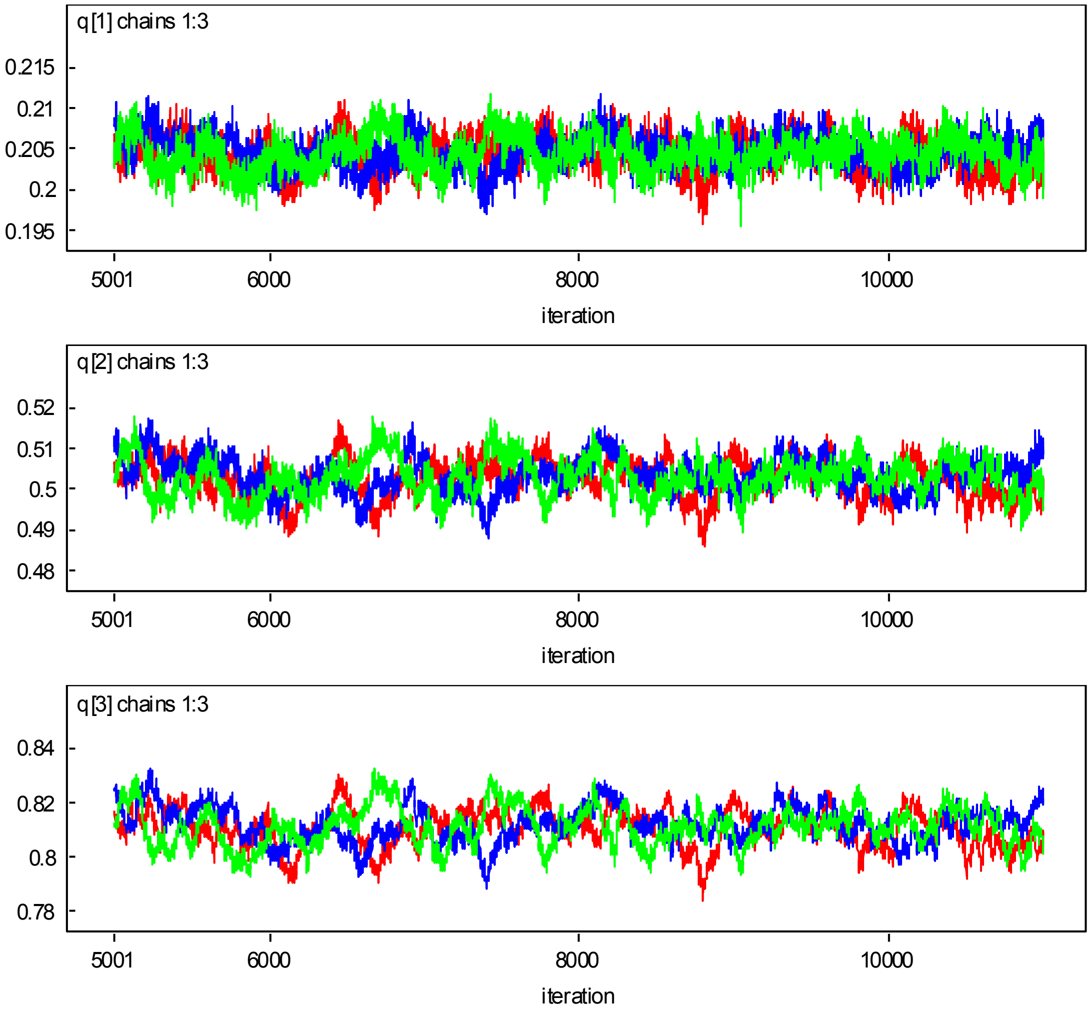

Figure 5-3. Three MCMC trajectories for the gear efficiency parameter, Q_k for Scenario 3. From the top to the bottom panels are Q_k = 0.2, 0.5 and 0.8, respectively. Different colours represent chains of different starting initials.

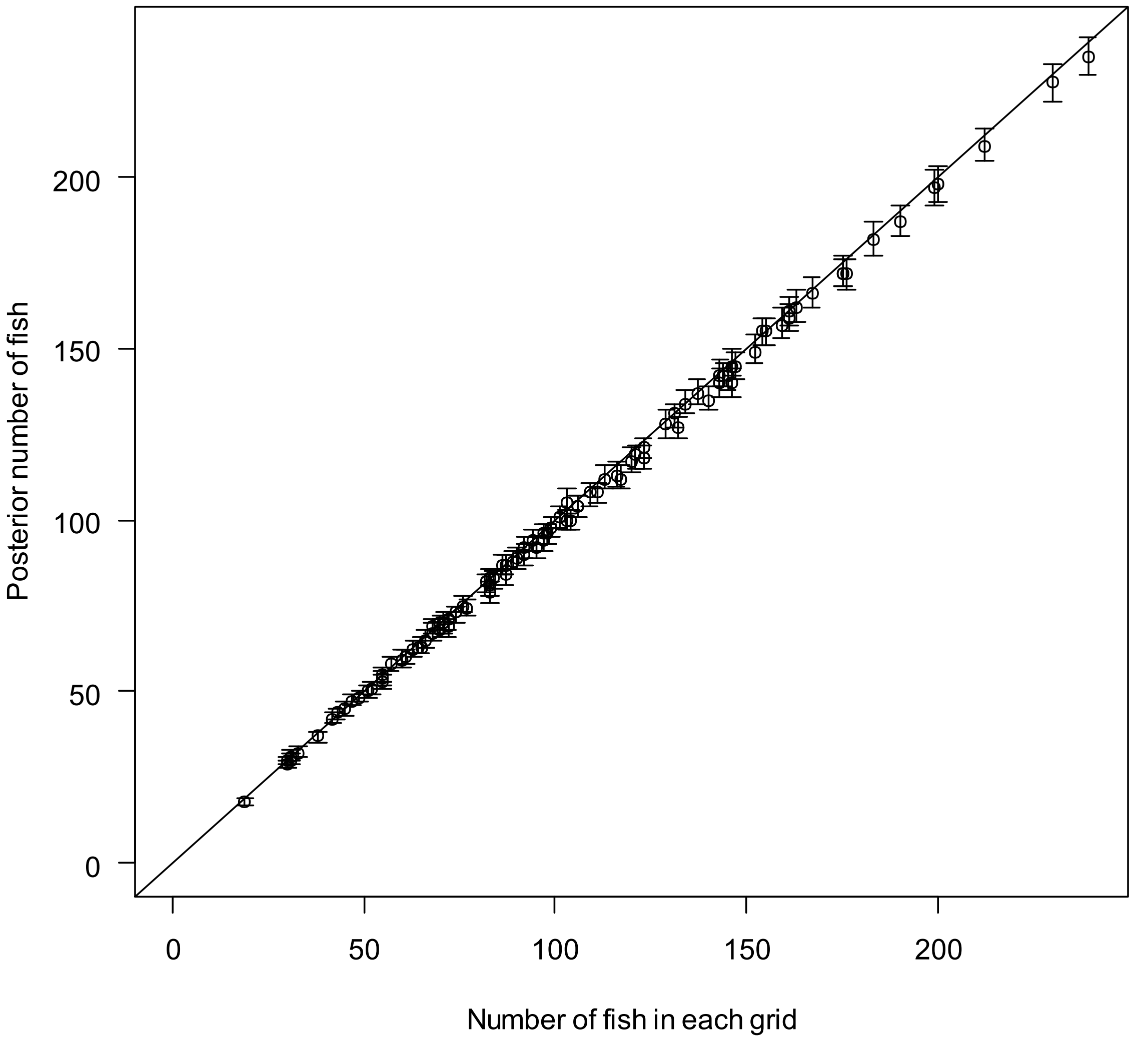

Figure 5-4. Comparison of true abundance and the posterior median abundance (and their 95% CI) for Scenario 3.

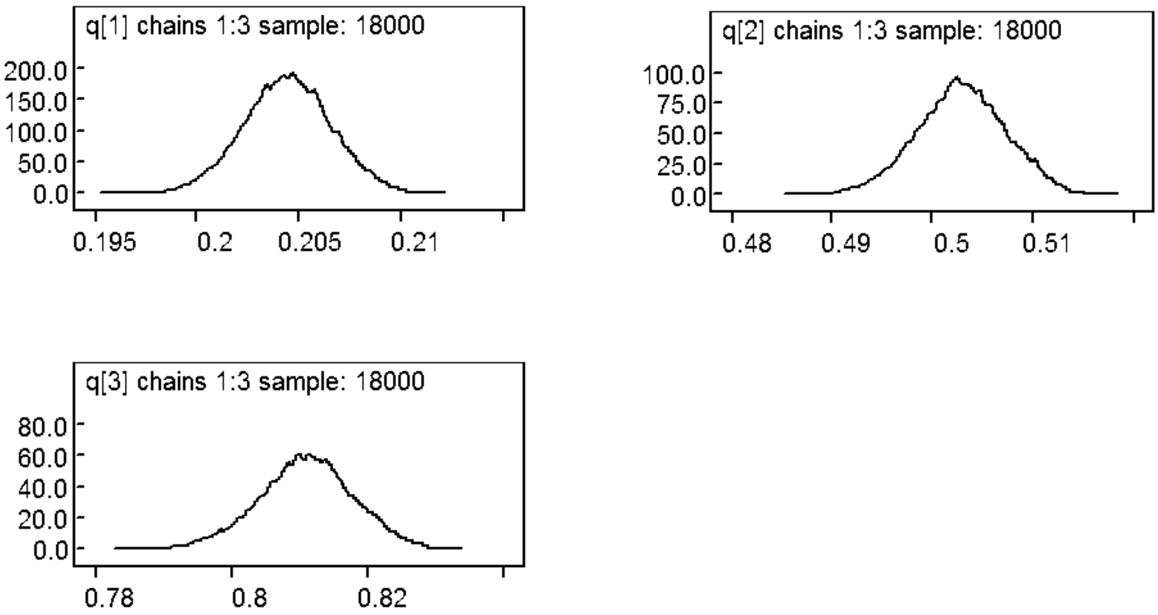

Figure 5-5. Density of MCMC samples for the gear efficiency parameter, Q_k for Scenario 3.

Scenario 4

Data generation: Fish are assumed to follow an aggregated distribution among 100 grid cells. In addition, abundance within each cell is assumed to vary at each sample time for each gear type. This is close to the most real cases when the grid cell is sufficiently large and the available fish within the gear-affected area may change even when multiple samples are taken during a short time period in the same cell. We assume this within-cell abundance variation follows a Poisson distribution (Table 5-11). Again, three gear types are used to catch the varying population in each cell. Gear efficiency is again 0.2, 0.5, and 0.8, respectively. Each cell is sampled 10 times by each of the three gears. The fishing operation is again a binomial process for each gear type. We test several models which differ slightly in specification.

Table 5-11. Summary of data simulation and modelling process for Scenario 4.

	Data generation	Modelling
Number of grids	100	100
Mean fish per grid	100	
Distribution between grids	N_i ~ negbin(100, 5)	N_i ~ negbin(p, r)
Distribution within grid	$N2_{ijk}$ ~ pois(N_i)	$N2_{ijk}$ ~ pois(N_i)
Gear type	3	3

Gear efficiency	0.2, 0.5, 0.8	Q_{i1}, Q_{i2}, Q_{i3},
Number of samples per grid	10	10
Catch process	C_{ijk} ~ bin(Q_k, $N2_{ijk}$)	C_{ijk} ~ bin(Q_{ik}, $N2_{ijk}$)

Bayesian model 4.1:

This model uses a negative binomial distribution between cells, and a Poisson distribution within a cell when each sample is taken but not for each gear type (that is, three gears catch the same abundance at each of the 10 sampling times). A fixed gear efficiency is assumed for each gear type.

N_i ~ negbin(p, r)

$N2_{ij}$ ~ pois(N_i)

C_{ijk} ~ bin(Q_k, $N2_{ij}$)

This model does not perform well (Figure 5-6). Random variation of abundance within each grid is difficult to deal with, even when three gear types are used. Gear efficiency is generally underestimated. In this example, all *Qs* are underestimated by about -36% (Figure 5-7). Interestingly, the ratio between three gear types is the same as true values.

When increasing the sample size from 10 shots by grid per gear to 50 shots per grid per gear type, the result does not improve. Convergence was slow and difficult; even after 12000 iterations convergence was still not achieved.

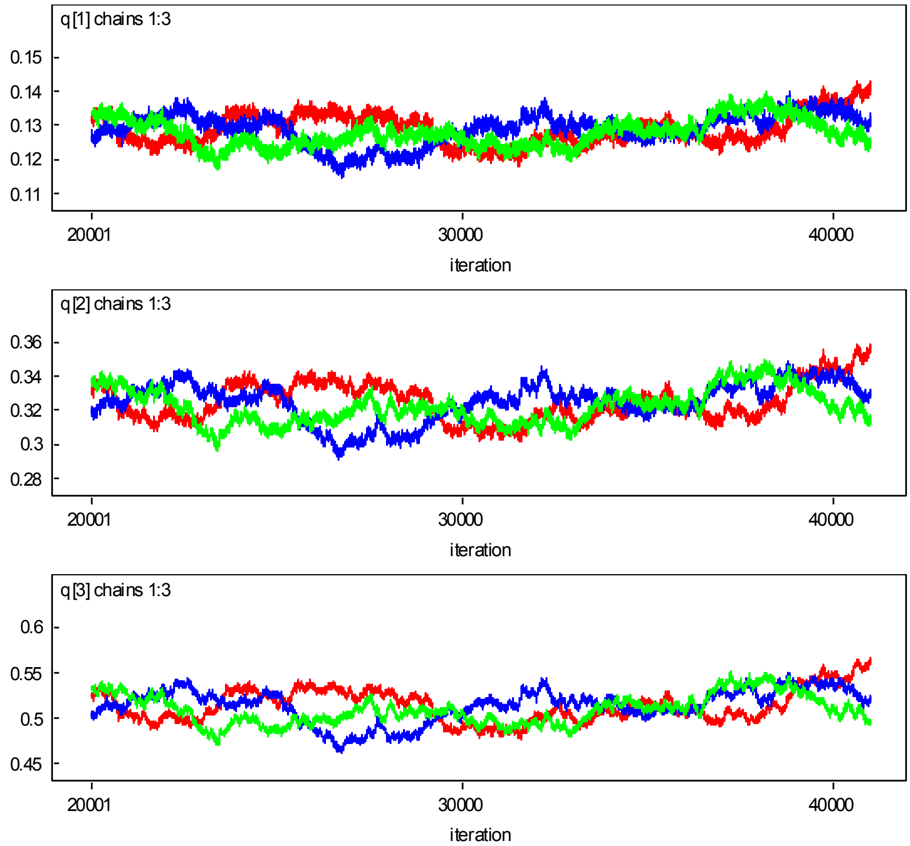

Figure 5-6. Three MCMC trajectories for the gear efficiency parameter, Q_k for Scenario 4 using model 4.1.

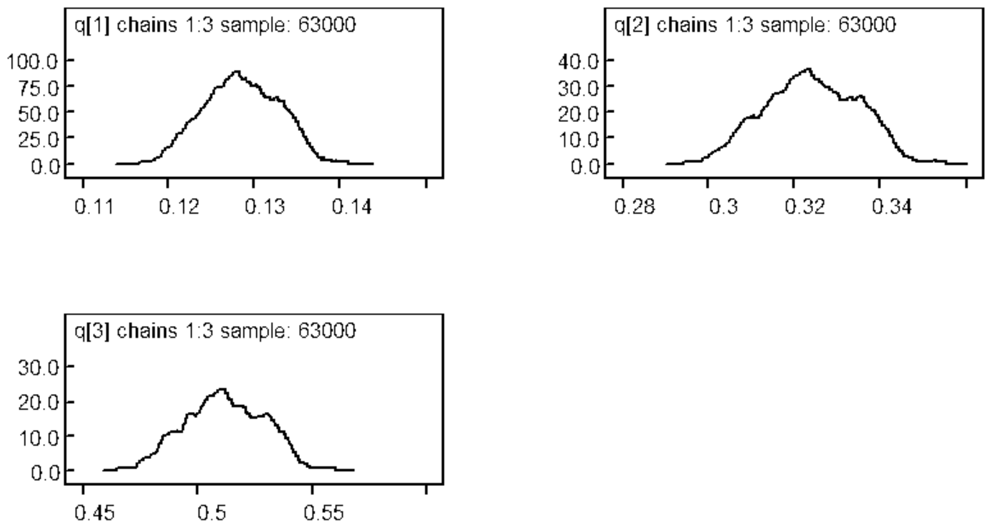

Figure 5-7. Density of MCMC samples for the gear efficiency parameter, Q_k for Scenario 4 using model 4.1.

Bayesian model 4.2

This model differs from model 4.1 by assuming that abundance is different for each shot (i.e., same as the data generation process). This means abundance varies by grid *i*, sample time *j*, and gear type *k*:

$N_i \sim \text{negbin}(p, r)$

$N2_{ijk} \sim \text{pois}(N_i)$

$C_{ijk} \sim \text{bin}(Q_k, N2_{ijk})$

This model produces median and mean Q = 0.25, 0.624, 1.0 (all overestimated by 25%), because the random variation in available abundance at each sampling time (grid, shot, and gear) allows the most efficient gear to catch all available fish. Three chains are easy to converge and the variance is very small for all parameters.

Bayesian model 4.3

The main difference between this model and model 4.1 is that a Poisson distribution is assumed for each sample time and each gear type within a cell (same as Model 4.2). This model differs from model 4.2 in that it assumes a varying gear efficiency in each cell, i.e., [$Q_{ik} \sim \text{beta}(1,1)$] (Table 5-12):

$N_i \sim \text{negbin}(p, r)$

$N2_{ijk} \sim \text{pois}(N_i)$

$$C_{ijk} \sim \text{bin}(Q_{jk}, N2_{ijk}) \qquad (5\text{-}7)$$

Model 4.3 performance: three chains mix reasonably well after sufficient iterations (Figure 5-8). The posterior means and medians for either Q or N are nearly identical (Table 5-13). The model slightly over-estimates Q by 13%, 12%, and 9%, respectively for the three gear types, and underestimates N by 9%.

Table 5-12. Input data and model results for Scenario 4, model 4.3.

	Input	True value mean (range)	Posterior mean (sd); median (95% CI)
Mean N per grid	100	93.7 (12-248)	83.7 (3.87); 83.6 (76.5-91.69)
Shape r	5		5.87 (0.94); 5.80 (4.22-7.90)
Gear efficiency Q_1	0.2	0.20 (0.05-0.41)	0.22 (0.003); 0.22 (0.22-0.23)
Q_2	0.5	0.50 (0.29-0.85)	0.56 (0.008); 0.57 (0.55-0.58)
Q_3	0.8	0.80 (0.53, 1.00)	0.88 (0.011); 0.88 (0.86-9.04)

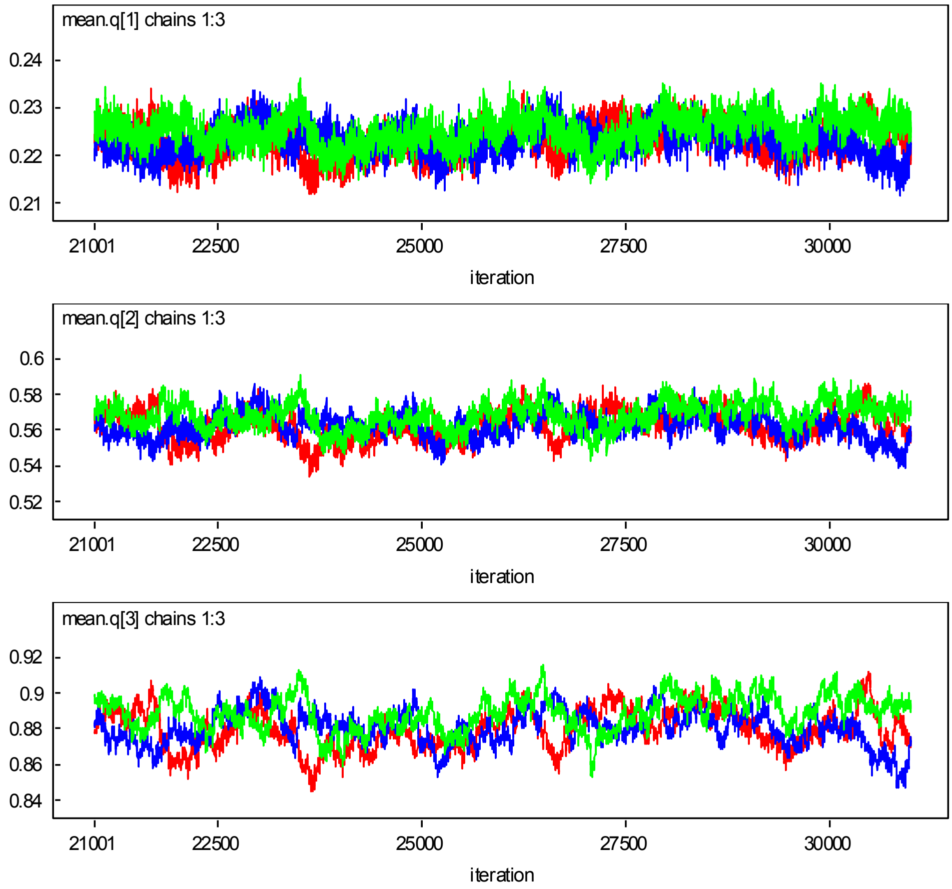

Figure 5-8. Three MCMC trajectories for the mean gear efficiency parameter, $Q_{\bullet k}$ for Scenario 4 using model 4.3.

Scenario 5

Data generation: This is perhaps the worst case where fish exhibit an aggregated distribution between cells and within each cell. Again, three gear types are used to catch the varying population in each cell. Gear efficiencies are again 0.2, 0.5, and 0.8, respectively. Each cell is sampled 10 times by each of the three gears. The fishing operation is again a binomial process for each gear type (Table 5-13).

Bayesian model 5.1:

We use the same model 4.3 as in Scenario 4 to estimate parameters, that is, the model assumes a negative binomial distribution between cells and a Poisson distribution within each cell. For the catch process, we allow Q to vary across cells and gears, i.e., Q_{ik} ~ beta(1,1).

Model performance: model implementation and consequent results are similar to Model 4.3 in Scenario 4 (Table 5-14, Figure 5-9, and Figure 5-10). This is unexpected. The reasonably good outcomes may reflect that the focus of the parameters is the means (or medians) from all samples within each cell rather than for each specific fishing operation.

Table 5-13. Summary of data simulation and modelling process for Scenario 5.

	Data generation	Modelling
Number of grids	100	100
Mean fish per grid	100	
Distribution between grids	N_i ~ dnegbin(100, 5)	N_i ~ negbin(p, r)
Distribution within grid	$N2_{ijk}$ ~ pois(N_i)	$N2_{ijk}$ ~ dpois(N_i)
Gear type	3	3
Gear efficiency	0.2, 0.5, 0.8	Q_{i1}, Q_{i2}, Q_{i3},
Number of samples per grid	10	10
Catch process	C_{ijk} ~ bin(Q_{k}, $N2_{ijk}$)	C_{ijk} ~ bin(Q_{ik}, $N2_{ijk}$)

Table 5-14. Input data and model results for Scenario 5, model 5.1.

	Input	True value mean (range)	Posterior mean (sd); median (95% CI)
Mean N per grid	100	93.7 (12-248)	85.2 (4.2); 85.0 (77.39-93.86)
Shape r	5		5.05 (0.81); 5.00 (3.63-6.76)
Gear efficiency Q_1	0.2	0.20 (0.05-0.41)	0.23 (0.004); 0.23 (0.22-0.23)
Q_2	0.5	0.50 (0.29-0.85)	0.56 (0.009); 0.56 (0.54-0.57)
Q_3	0.8	0.80 (0.53, 1.00)	0.87 (0.012); 0.87 (0.85-0.89)

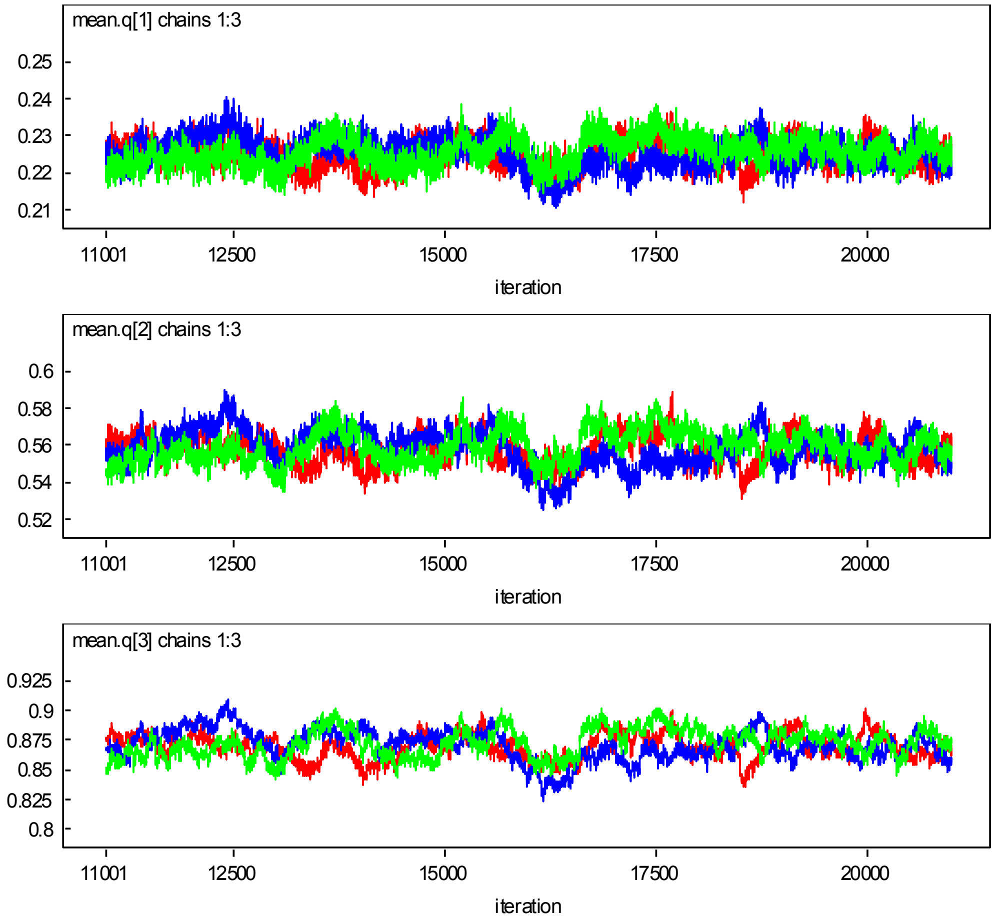

Figure 5-9. Three MCMC trajectories for the mean gear efficiency parameter, $Q_{\bullet k}$ for Scenario 5.

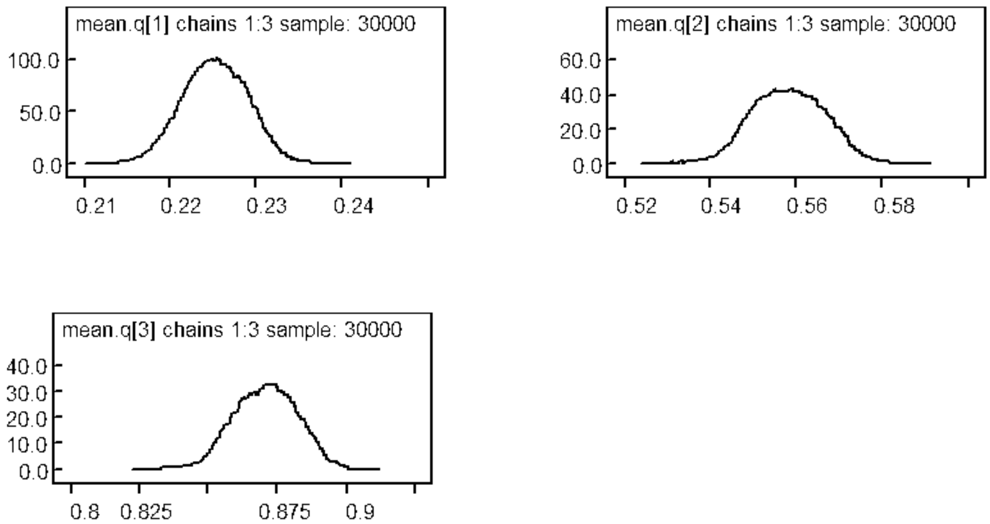

Figure 5-10. Density of MCMC samples for the gear efficiency parameter, $Q_{\bullet k}$ for Scenario 5.

Bayesian model 5.2:

Since the data represent a non-random distribution between cells and within each cell, it would be interesting to see how a similar model that assumes a non-random distribution between and within grid cells functions. Using a negative binomial model for within-cell distribution causes wide variations in abundance and makes MCMC hard to continue. We opt to use a "quasi-NB" approach where a random error is added to a Poisson mean:

N_{ijk} ~ pois(λ_{ijk}), and

$\lambda_{ijk} = N_i \exp(\varepsilon_i)$, where ε_i ~ norm(0, 0.1).

This model 5.2 does not work well, as it allows true variation in abundance to be offset by ε_i. The consequence is to pull three Qs toward the largest value of 0.8. Hence, abundance in each cell is significantly underestimated.

Scenario 6

Data generation: They key difference between this scenario and the previous 5 scenarios is that a large number of zero catches is included in the data (Table 5-15). Of the total 100 grid cells, we assume 70 of them are "habitable" while the other 30 are "uninhabitable". In the habitable grids, the number of individuals follow a negative binominal distribution with mean μ = 10 and shape parameter r = 1. There are no fish in the uninhabitable grids. During the catch process, we assume abundance is fixed at each sampling time, and three samples are taken in each of the 100 grid cells with gear efficiency Q = 0.5 in all samples. For simplicity, we do not assume the distribution and capture processes vary with environmental variables. This data generation process results in a total abundance N = 624, N_i between 0 and 41, occupancy rate ψ = 0.65, and catch C_i between 0 and 22.

Bayesian model: the model is parameterized in the same way as data generation: zero-inflated negative binomial distribution. The shape parameter r has a lognormal distribution with a mean of 1 and variance of 0.25. In WinBUGS, the negative binomial distribution is coded as a mixture of Poisson and gamma distributions:

$K_i \sim Poisson(\lambda_i)$ and $\lambda_i \sim gamma(r, \Lambda_i)$.

Here the shape parameter r is the same as in equations 2 and 4, while $\mu = r\Lambda$ and its variance $\sigma^2 = r\Lambda^2$.

Model performance: The Bayesian abundance model performs reasonably well for the simulated data. The median posterior total N is 659.6, which is 6% higher than the true value (Table 5-16). The median posterior probability of occupancy is 0.67, which is 3% higher than the true value. The posterior N_i and its 95% credible interval for all grid cells are shown in Figure 5-11. However, the aggregation parameter r is slightly overestimated, with a median of 1.8 (95% CI between 0.02 and 2.67).

The median posterior gear efficiency is 0.47 (95% CI between 0.34 and 0.58), underestimating the true value of 0.5 by 5%.

Table 5-15. Summary of data simulation and modelling process for Scenario 6.

	Data generation	Modelling
Number of cells	100	100
Number of inhabitable cells	70	
Mean fish per habitable cell	10	
Distribution between grids	N_i ~ negbin(100, 1)	N_i ~ negbin(p, r)
Distribution within grid	Fixed	Fixed
Gear type	1	1
Gear efficiency	0.5	
Number of samples per grid	3	3
Catch process	C_{ij} ~ bin(Q, N_i)	C_{ij} ~ bin(Q, N_i)

Table 5-16. Input data and model results for Scenario 6.

	Input	True value	Posterior median (95% CI)
Total N	700	624	659 (622-723)
Shape r	1	1	1.8 (0.02-2.67)
Occupancy	0.7	0.65	0.67
Gear efficiency	0.5	0.50	0.47 (0.34-0.58)

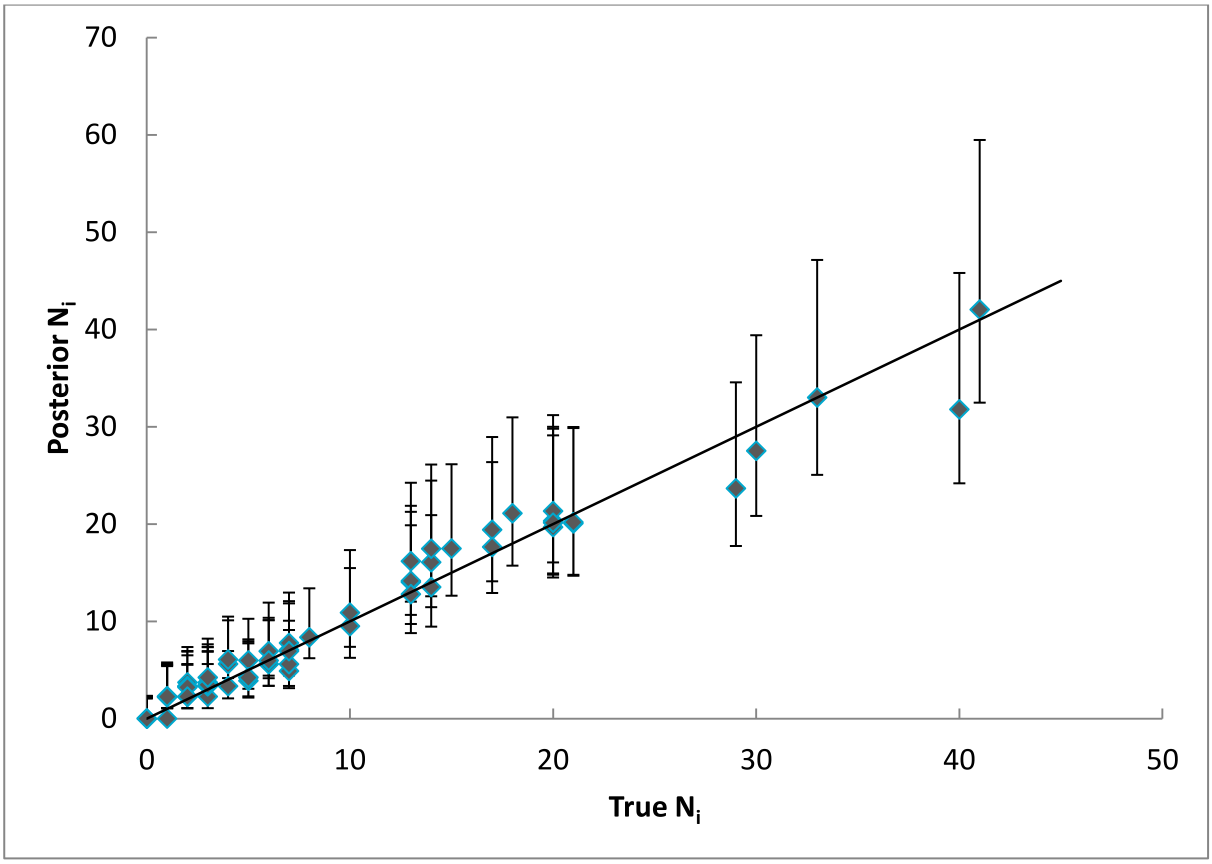

Figure 5-11. Comparison of posterior abundance from Bayesian abundance model with true values for 100 cells. Among these cells, 30 are assumed to be inhabitable with abundance of zero.

In the most complicated situation in the fishery, individual fish often aggregate in certain areas. At a finer spatial scale (e.g., a grid cell with medium size), a random distribution of fish may be more typical. At each gear deployment, abundance within the gear-affected range may change as a result of fish movement.

For this near-real situation, the above scenarios and simulations show that, for presence-only data where zero catch is not recorded, the Bayesian model 4.3 performs quite well. When this model is applied to the worst-case scenario (Scenario 5) where fish exhibit an aggregated distribution between cells and within each cell, local abundance changes at each gear deployment, the results are still fairly good. Hence, this model is used to estimate gear efficiency and abundance for the case study species in the later sections.

5.3.2 ESTIMATION OF FISH DENSITY AND FISHING MORTALITY

Fish density has been assumed to be uniform and random within their distribution range in some of the previous ecological risk assessments (e.g. SESSF). This assumption simplifies the assessment process in data-poor situations but is likely to cause bias in estimates of fishing mortality. It is possible to derive heterogeneous density based on limited survey or observer data, together with the gear efficiency derived in the previous section.

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

$$\boldsymbol{D_{yij}} = \frac{\boldsymbol{c_{yijk}}}{\boldsymbol{a_{yijk} Q_k}}. \qquad (5\text{-}8)$$

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

$$\log(\boldsymbol{D}_{\mathbf{yij}}) = \boldsymbol{\beta_0} + \boldsymbol{f_1}(\boldsymbol{lon}, \boldsymbol{lat}) + \boldsymbol{f_2}(\boldsymbol{year}), \qquad (5\text{-}9)$$

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

To estimate total biomass in a given year, we assumed that the stock distribution area was defined as its core distribution from refined Bioregional Mapping (Heap et al. 2005). The distribution area is stratified into four strata: Core area, Bioreg area, eastern region (< 147 longitude degree), and western region (> 147 longitude degree). The total fishable biomass in year y is then

$$\boldsymbol{B_y} = \sum_{g=1}^{n} \widehat{\boldsymbol{D}}_{\boldsymbol{yg}} \boldsymbol{A_g} \qquad (5\text{-}10)$$

where $\widehat{D}_{yg}$ is the median density predicted by the GAM model above within each stratum g, A_g is the area size in stratum g within the distribution range, and n is the total number of strata (i.e., 4). This method takes heterogeneous density into account, and should be superior to the assumption that individual fish are homogeneously distributed in their distribution range.

Estimating fishing mortality rate

Fishing mortality F in year y by gear (or sub-fishery) k is:

$$\boldsymbol{F_{yk}} = \frac{\sum_g \boldsymbol{a_{ygk}} \widehat{\boldsymbol{D}}_{yg} \mathbf{Q}_k}{\boldsymbol{B_y}} = \frac{\sum_g \boldsymbol{a_{ygk}} \widehat{\boldsymbol{D}}_{yg} \mathbf{Q}_k}{\sum_g \widehat{\boldsymbol{D}}_{yg} \boldsymbol{A_g}} \qquad \textbf{(5-11)}$$

Where a_{ygk} is gear-affected area (e.g., swept area) in year y, stratum g by gear type k, $\widehat{D}_{yg}$ is the median density predicted by the GAM model above within each stratum g, Q_k is the gear efficiency. Note that we use instantaneous fishing mortality rate F here instead of exploitation rate (commonly represented by U) because we have used the fishing effort over the entire year so the biomass is not the peak biomass but the average over the year. This F_y can then be compared with reference points such as F_{MSY} derived from simple life history parameters, such as the natural mortality rate (Zhou et al. 2012b) and methods in the following section.

5.3.3 DEVELOPING SUSTAINABILITY REFERENCE POINTS

Zhou et al. (2012b) developed an empirical relationship between fishing mortality-based reference points and fish life-history traits. Among a range of life-history parameters (LHPs), they focused on natural mortality because there have been extensive theoretical studies on the rule of thumb correlation between F_{msy} and M. However, natural mortality is often calculated from other more easily obtainable parameters based on the theory of life history invariant. These life history parameters include von Bertalanffy growth parameters κ and L_∞ (Pauly 1980; Gislason et al. 2010; Charnov et al. 2012), age at maturity A_{mat} (Jensen 1996), maximum age A_{max} (Hoenig 1983) etc. This means that these more easily available parameters can be reliable predictors for biological reference points. Therefore, in this project, we exclude natural mortality as a predictor but link fishing mortality-based biological reference point F_{BRP} with other LHPs. To our best knowledge, this is the first empirical study attempting to link biological reference points to life history parameters other than natural mortality.

5.3.3.1 Data

The majority of the data used in Zhou et al. (2012b) are re-used here. However, we have added and removed a few species because of data quality. We also re-validated data for some species. No attempt has been made to check natural mortality as it is not used in this analysis.

Our data include both chondrichthyans and teleosts. Again, methods for estimating biological reference points are categorized into three types: F_{msy} from formal stock assessments, F_{proxy} from per-recruit methods and $F_{0.5r}$ from demographic analyses of intrinsic growth rate (Table 5-17). A total of 248 species, with 324 data points, is used in the analysis.

Table 5-17. Number of species and data points included in the analysis.

	Chondrichthyan		Teleost	
Reference point	Species	Data points	Species	Data points
F_{msy}	10	11	75	88
F_{proxy}	4	4	100	131
$F_{0.5r}$	52	79	7	11
Total	66	94	182	230

5.3.3.2 Methods

The LHPs that we investigated were von Bertalanffy growth coefficient (κ), maximum or asymptotic length (L_{max}), and maximum age ($A_{\max}$). These data were sourced from original literature and FishBase. Importantly, where FishBase data were used, stocks were treated separately and the different parameters obtained for each stock, were matched to the same location. We grouped data at class [Osteichthyes (teleosts) and Chondrichthyes] levels to capture major life-history variability and to avoid over-parameterization at species or stock levels. Along with three F_{BRP} categories (Type), we consider these six groups (a matrix composed of taxonomic levels and the type of methods) as multiple populations. The amount of data and their quality vary substantially among these six populations (Table 5-17) but populations share certain similarities in their life-history traits and BRPs. Hence, we again use Bayesian hierarchical modelling to derive robust estimates from such a multilevel structure.

It is important to note that two of the LHPs in this analysis, maximum length $L_{\max}$, and maximum age $A_{\max}$ lie outside the range of most of the data used to generate them (Haddon 2001; Irvine et al. 2012). In addition the growth coefficient κ, is an emergent parameter that describes the rate which a population moves towards its maximum size and cannot be obtained from measurements of individuals. An additional source of model error is the effect of individual variability on the von Bertalanfy growth equation (Sainsbury 1980). Ignoring measurement errors in these variables would result in biased estimates of their effects on F_{BRP}. To obtain unbiased estimates, we specifically incorporated measurement errors in these variables by using an error-in-variable (EIV) model (Fuller 1987; Quinn and Deriso 1999). Hence, the method was referred to as Bayesian Hierarchical Error-in-Variable models (BHEIV).

The scatter plots and smoothing lines show a general relationship between F_{BRP} and LHPs. For example, F_{BRP} and κ exhibits a positive correlation (Figure 5-12) while F_{BRP} and $L_{\max}$ and $A_{\max}$ tend to be negatively correlated (Figure 5-13, Figure 5-14). These plots also indicate that variance may not be normally distributed. Accordingly, we examined the log-transformed data (Figure 5-15, Figure 5-16, and

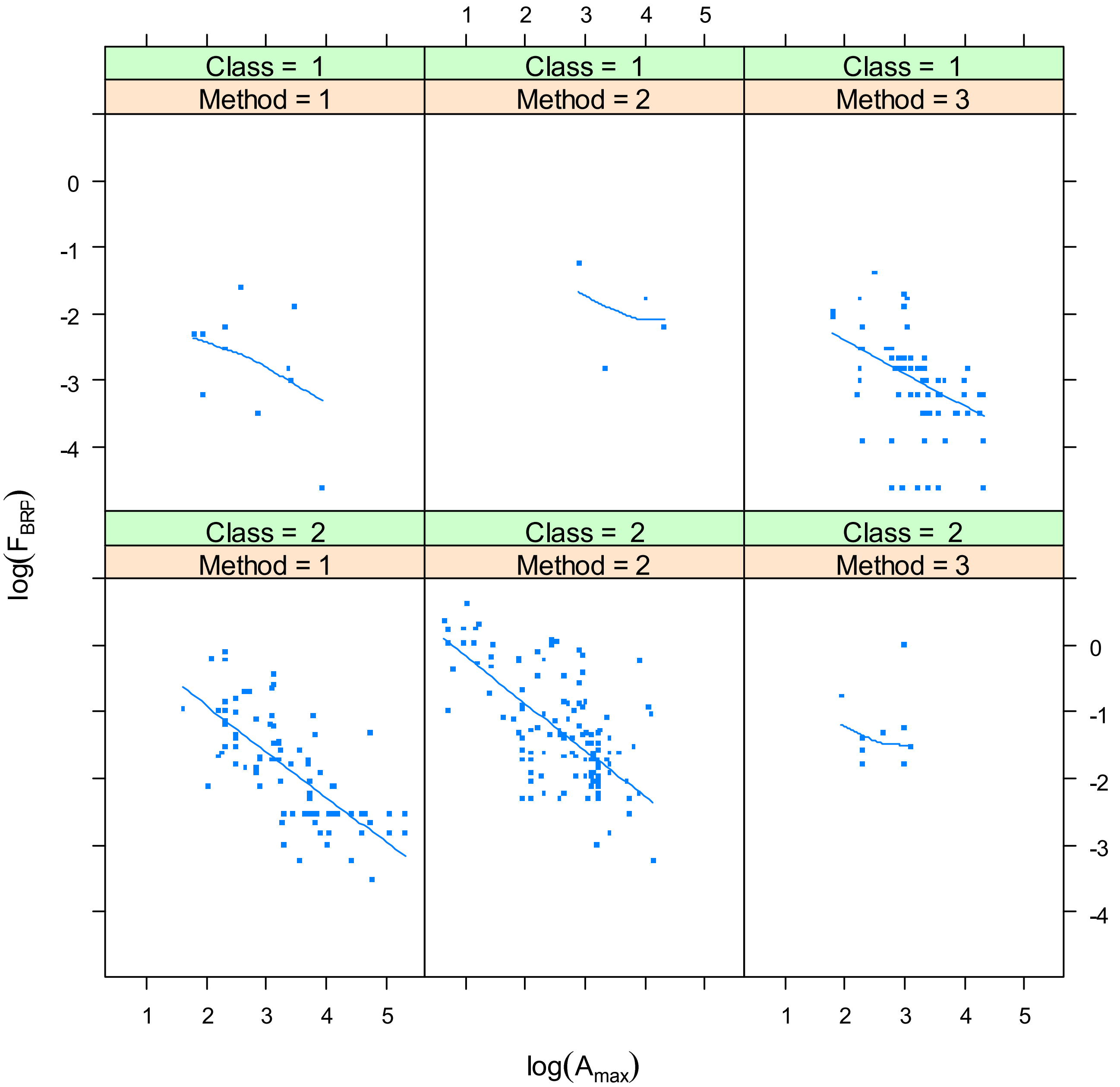

Figure 5-17). This treatment appears to improve the normality of the distribution, therefore we focus on multiplicative error structure models in the report, although we also examined models with additive error structure.

The general model has the form of

$$\log(F_{BRP,t,c,i}) = \beta_0 + \beta_{t,c,x} \log[\mathbf{x}_i \exp(\varepsilon_{\mathbf{x},t,c,i})] + e_{t,c,i} \quad \textbf{(5-12)}$$

where $\mathbf{x}_i$ is a matrix of covariates (composed of one or more of κ, L_{max}, and A_{max} depending on the model evaluated), $\beta_{t,c,x}$ is the parameter for variable x for method type t, and class c. The independent normal random error $e_{\bullet,i}$ has a mean of 0 and variance $\sigma^2_{e_\bullet}$. The symbol • indicates that the heterogeneity may vary between types or classes depending on model specification.

We assumed $\beta_{\bullet,\mathbf{x}} \sim normal(\mu_{\beta_{\bullet,\mathbf{x}}}, \sigma^2_{\beta_{\bullet,\mathbf{x}}})$ where $\mu_{\beta_{\bullet,x}}$ is the prior mean for parameter $\beta_{\bullet,x}$, and $\sigma^2_{\beta_{\bullet,\mathbf{x}}}$ is the variance. These priors have their own hyper-priors, and we assumed $\mu_{\beta_{\bullet,x}} \sim normal(\bar{\mu}_{\beta_x}, \sigma^2_{\bar{\mu}_{\beta x}})$, and $\sigma^2_{\beta_{\bullet,x}} \sim gamma(r = 0.01, \ \ \mu = 0.01)$. The symbol • at the hyper prior level indicates it can be shared either across method, or both method and class depending on the models. Further, we used a normal distribution with a large variance for the hyper-mean, $\bar{\mu}_{\beta_x} \sim normal(0, \ 1000)$. For the measurement error variance, we specified $\sigma^2_{\varepsilon,\mathbf{x}} \sim gamma(r = 0.01, \ \ \mu = 0.01)$. These specifications provide relatively non-informative priors and hyper-priors, as gamma(0.01, 0.01) represents a mean 1 and variance 100. We tested a range of models with alternative priors and used deviation information criteria DIC (Spiegelhalter et al. 2003) as primary criteria for model comparison.

We applied the Gibbs sample implemented using the WinBUGS program to sample parameter vectors from the above posterior distribution. Three Markov chains were constructed based on dispersed initial values and the results of the first 10,000 cycles of each chain were discarded. The results of an additional 30,000 cycles from the three chains were saved for further analysis. We visually examined the chains for each parameter in the model as well as analysed the saved samples by using the CODA package (Best et al. 1996) to ensure that there was no evidence for non-convergence in the MCMC sampling chain.

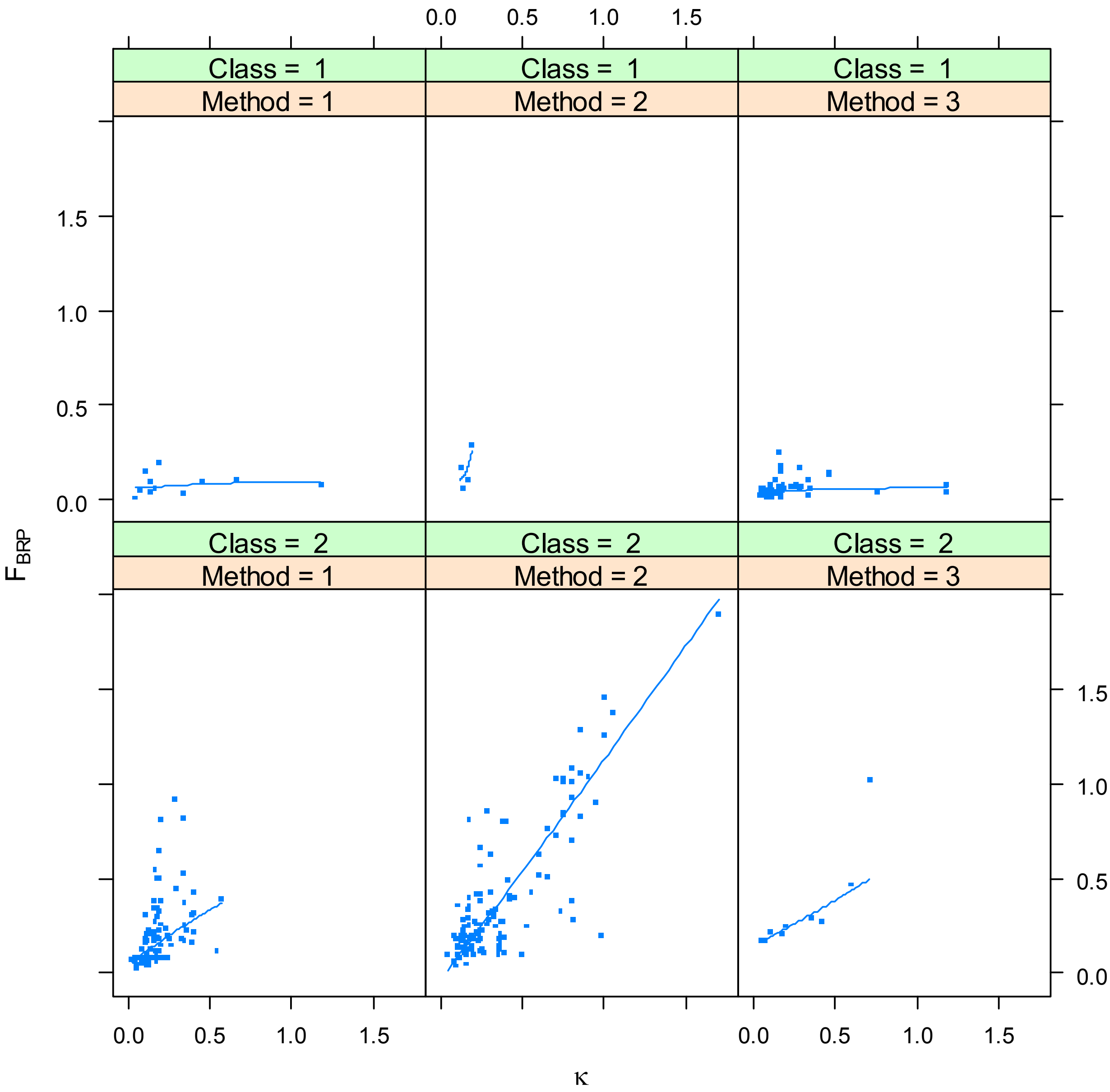

Figure 5-12. Scatter plots and smoothing lines for F_{BRP} and growth rate κ. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

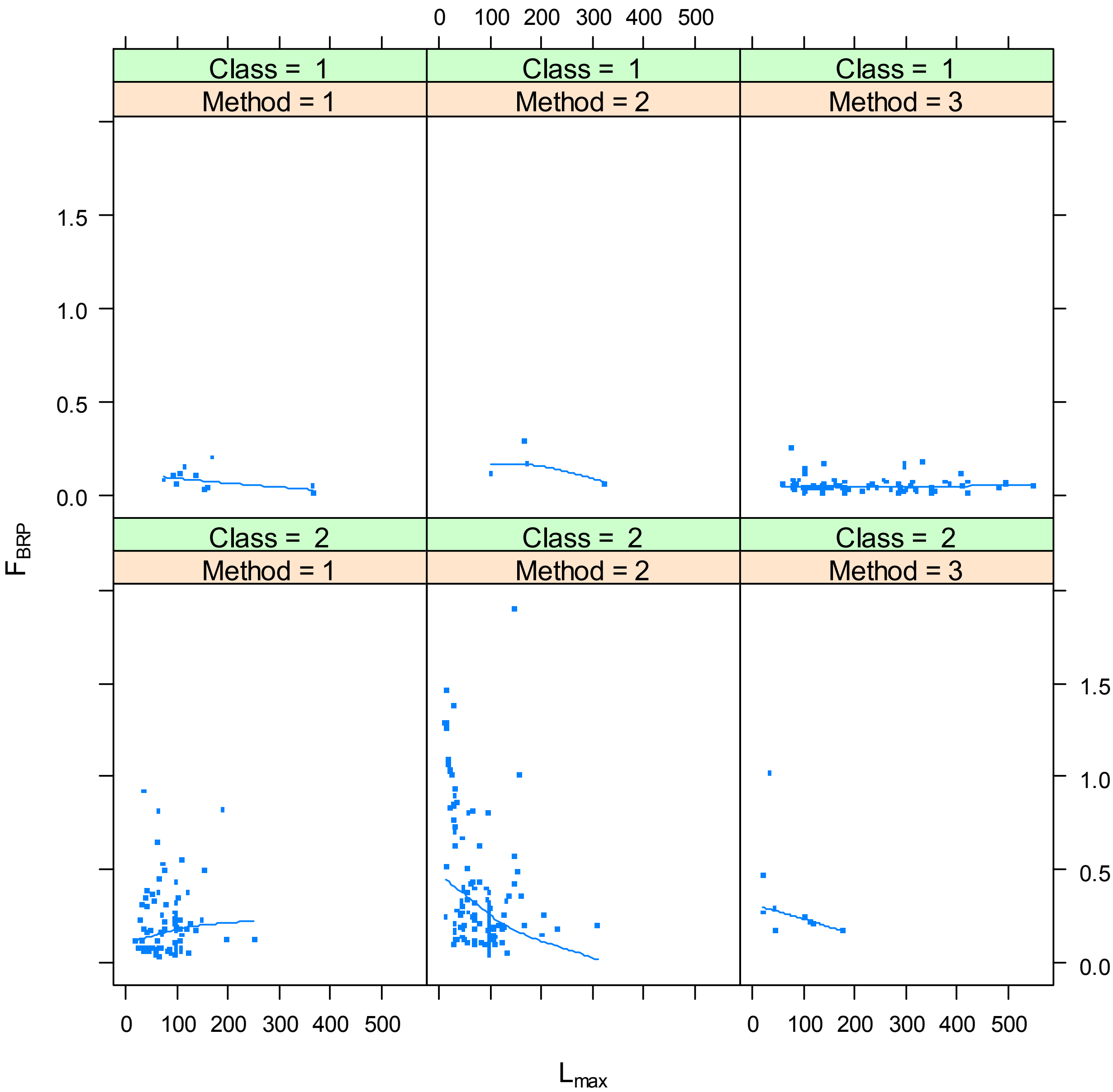

Figure 5-13. Scatter plots and smoothing lines of F_{BRP} and maximum length L_{max}. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

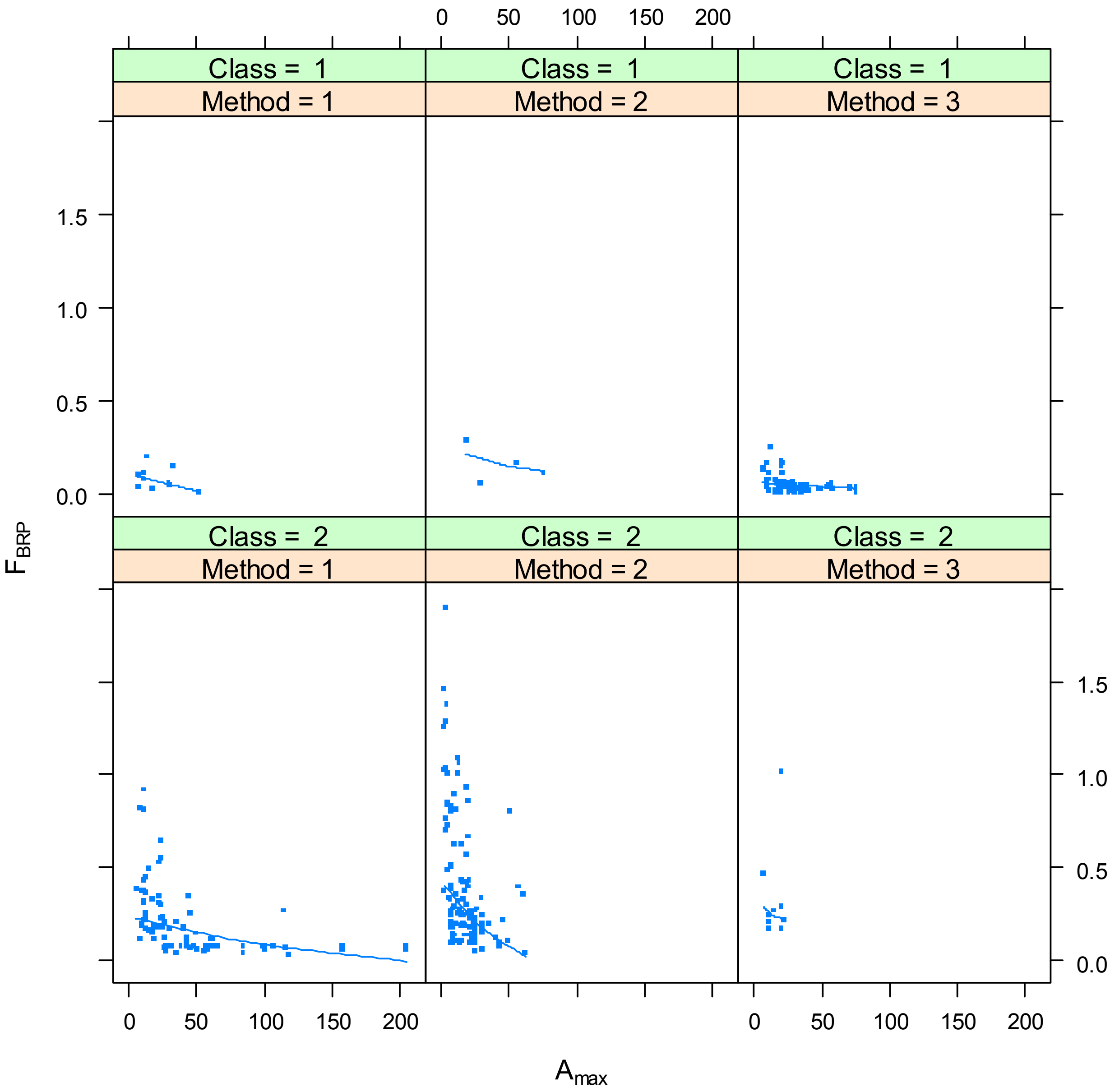

Figure 5-14. Scatter plot of F_{BRP} and maximum age A_{max}. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

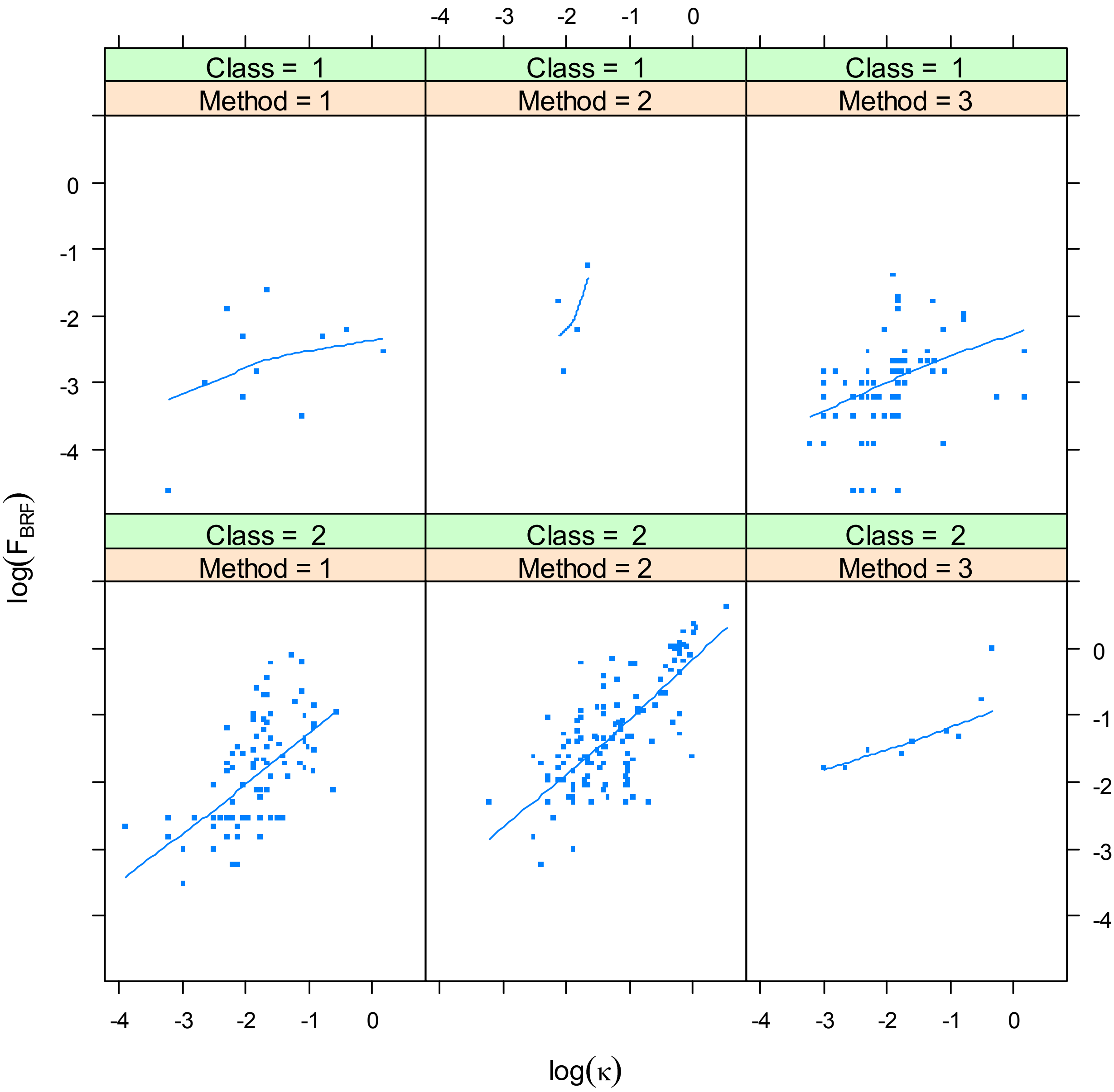

Figure 5-15. Scatter plots and smoothing lines in log scale for F_{BRP} and growth rate k. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

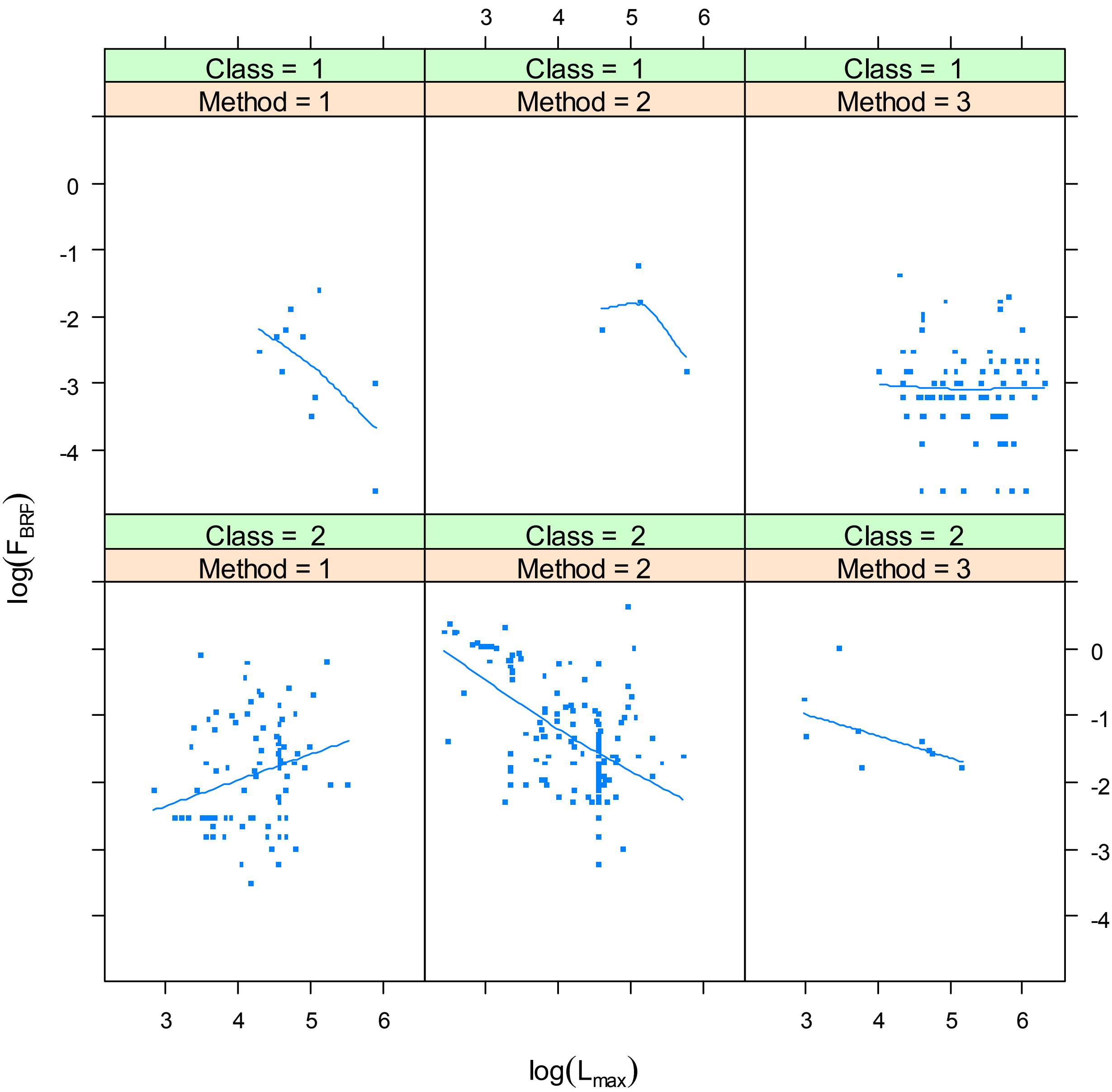

Figure 5-16. Scatter plots and smoothing lines in log scale for F_{BRP} and maximum length L_{max}. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

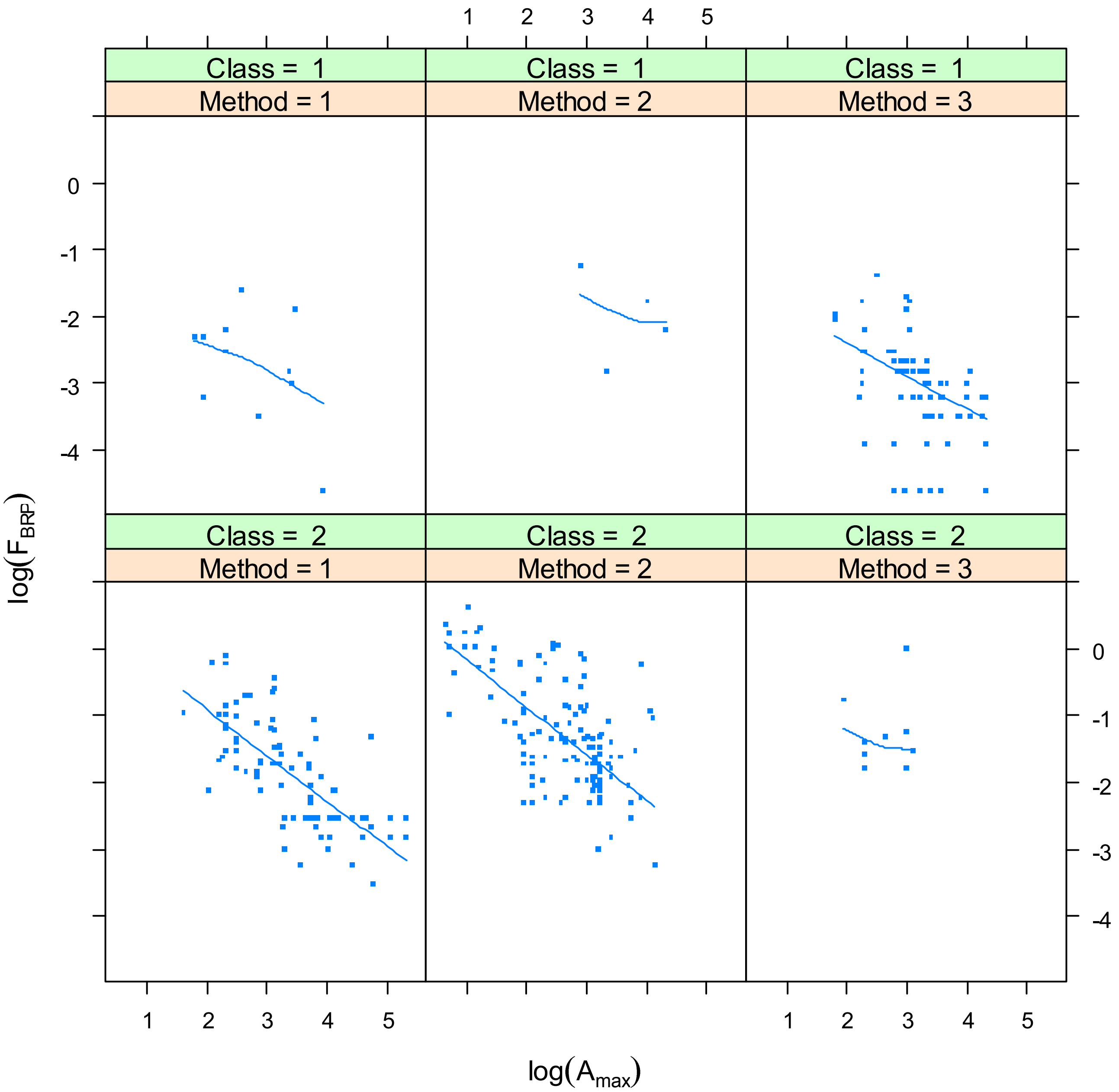

Figure 5-17. Scatter plots and smoothing lines in log scale for F_{BRP} and maximum age A_{max}. Class 1 is chondrichthyan and 2 teleosts; method 1 is F_{msy}, 2 F_{proxy}, 3 $F_{0.5r}$.

5.3.3.3 Results

A range of models with different LHPs and hyper priors are investigated. Table 5-18 lists examples of the models. Most of these models converged quickly, in less than 2000 cycles of the MCMC algorithm. There was no evidence of non-convergence for any model after sufficient cycles. The best model with the lowest DIC has all three LHPs as predictors with a hyper prior mean $\mu_{\beta_{c,\kappa}}$ and $\mu_{\beta_{c,L\max}}$, separated between chondrichthyans and teleosts but $\mu_{\beta_{A\max}}$ shared across both class and type of the method. Interestingly, using κ alone as a predictor (Models 4 and 6 in Table 5-18) is better than many other more complicated models. Also, non-hierarchical model (Model 9 in Table 5-18) is clearly not an option.

The detailed results of the best model are shown in (Table 5-19). The posterior distribution of the estimated parameters shows distinct differences in κ and L_{max} between chondrichthyans and teleosts (Figure 5-18, Figure 5-19) but less clear for the A_{max} (Figure 5-20). Generally, F_{BRP} increases for faster-growing species, but decreases for long-lived (larger A_{max}) species or species with a large body size (larger L_{max}). However, some estimates are not significant. For example, the 95% confidence intervals for $\beta_{1,\bullet,k}$ (growth rate for chondrichthyans) and $\beta_{2,\bullet,Lmax}$ (L_{max} for teleosts), as well as β_0, cover 0. Some of the insignificance is clearly due to too few data points, e.g., $\beta_{1,2,Amax}$ and $\beta_{1,2,Lmax}$ (only 4 data points).

Table 5-18. Comparison Bayesian hierarchical error-in-variable models using deviation information criteria. ***κ*** **is growth rate,** ***L_{max}*** **is maximum length, and** ***A_{max}*** **is maximum age.**

Ranked model	Hyper prior	Parameter and LHPs	ΔDIC
1	$\mu_{\beta_{c,\kappa}}, \mu_{\beta_{c,L\max}}, \mu_{\beta_{A\max}}$	β_0, κ, L_{max}, A_{max}	0.0
2	$\mu_{\beta_{\kappa}}, \mu_{\beta_{L\max}}, \mu_{\beta_{A\max}}$	β_0, κ, L_{max}, A_{max}	77.4
3	$\mu_{\beta_{c,\kappa}}, \mu_{\beta_{L\max}}, \mu_{\beta_{A\max}}, \tau_{\beta_{c,\kappa}}$	β_0, κ, L_{max}, A_{max}	120.5
4	$\mu_{\beta_{\kappa}}$	β_0, κ	158.6
5	$\mu_{\beta_{c,\kappa}}, \mu_{\beta_{c,L\max}}$	β_0, κ, L_{max}, A_{max}	169.0
6	$\mu_{\beta_{c,\kappa}}$	β_0, κ	177.7
7	$\mu_{\beta_{c,\kappa}}, \mu_{\beta_{c,L\max}}, \mu_{\beta_{c,A\max}}$	β_0, κ, L_{max}, A_{max}	201.4
8	$\mu_{\beta_{\kappa}}, \mu_{\beta_{A\max}}$	β_0, κ, A_{max}	229.5
9	non-hierarchical	β_0, κ, L_{max}, A_{max}	233.6
10	$\mu_{\beta_{c,\kappa}}, \mu_{\beta_{c,L\max}}, \mu_{\beta_{A\max}}$	κ, L_{max}, A_{max}	248.7
11	$\mu_{\beta_{L\max}}, \mu_{\beta_{A\max}}$	β_0, L_{max}, A_{max}	285.1
12	$\mu_{\beta_{\kappa}}, \mu_{\beta_{A\max}}$	β_0, κ, A_{max}	348.0

Table 5-19. Posterior statistics of Bayesian hierarchical errors-in-variables model $\log(F_{BRP,t,c,i}) = \beta_0 + \beta_{t,c,\kappa} \log[\kappa_{t,c,i} \exp(\varepsilon_\kappa)] + \beta_{t,c,Lmax} \log[L_{max,t,c,i} \exp(\varepsilon_{Lmax})] + \beta_{t,c,Amax} \log[A_{max,t,c,i} \exp(\varepsilon_{Amax})] + e_i$ (t = type of method, c = class).

Param	Mean	SD	Low 95%CI	Median	Upper 95%CI
β_0	0.09	0.36	-0.46	0.05	0.98
$\beta_{1,1,Amax}$	-0.39	0.16	-0.70	-0.39	-0.07
$\beta_{1,2,Amax}$	-0.29	0.15	-0.56	-0.30	0.03
$\beta_{1,3,Amax}$	-0.42	0.10	-0.64	-0.41	-0.23
$\beta_{2,1,Amax}$	-0.45	0.07	-0.58	-0.45	-0.32
$\beta_{2,2,Amax}$	-0.31	0.07	-0.47	-0.31	-0.17
$\beta_{2,3,Amax}$	-0.28	0.14	-0.53	-0.29	0.03
$\beta_{1,1,k}$	0.10	0.17	-0.25	0.10	0.44
$\beta_{1,2,k}$	0.06	0.23	-0.40	0.07	0.49
$\beta_{1,3,k}$	0.13	0.12	-0.10	0.13	0.37
$\beta_{2,1,k}$	0.40	0.10	0.19	0.41	0.60
$\beta_{2,2,k}$	0.54	0.10	0.32	0.55	0.73
$\beta_{2,3,k}$	0.47	0.13	0.22	0.46	0.73
$\beta_{1,1,Lmax}$	-0.22	0.07	-0.37	-0.22	-0.08
$\beta_{1,2,Lmax}$	-0.14	0.09	-0.31	-0.14	0.04
$\beta_{1,3,Lmax}$	-0.21	0.06	-0.35	-0.21	-0.11
$\beta_{2,1,Lmax}$	0.05	0.06	-0.09	0.06	0.14
$\beta_{2,2,Lmax}$	0.02	0.06	-0.11	0.02	0.12
$\beta_{2,3,Lmax}$	0.02	0.07	-0.13	0.02	0.16

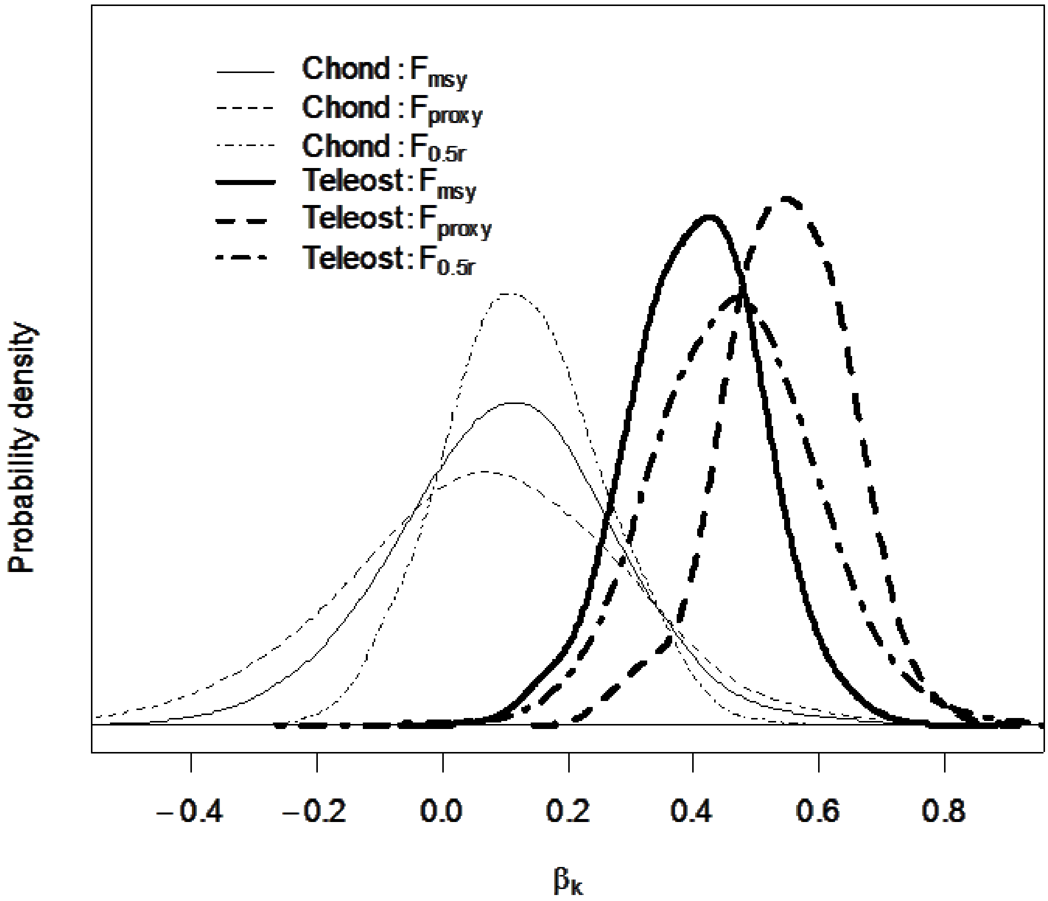

Figure 5-18. Posterior distribution of growth coefficient κ from multiplicative error model.

For some data-poor species, such as the bycatch species, there are no ageing studies, therefore maximum age may not be available. Similarly, maximum length may be poorly estimated. Therefore, presenting the simplest model that requires only a single life history parameter is likely to be the most comprehensive in terms of species coverage. The comparison of DIC suggests that using growth coefficient κ alone is one of the best options (Model 4 in Table 5-18). The posterior $\beta_{\bullet,k}$ are presented in Table 5-20.

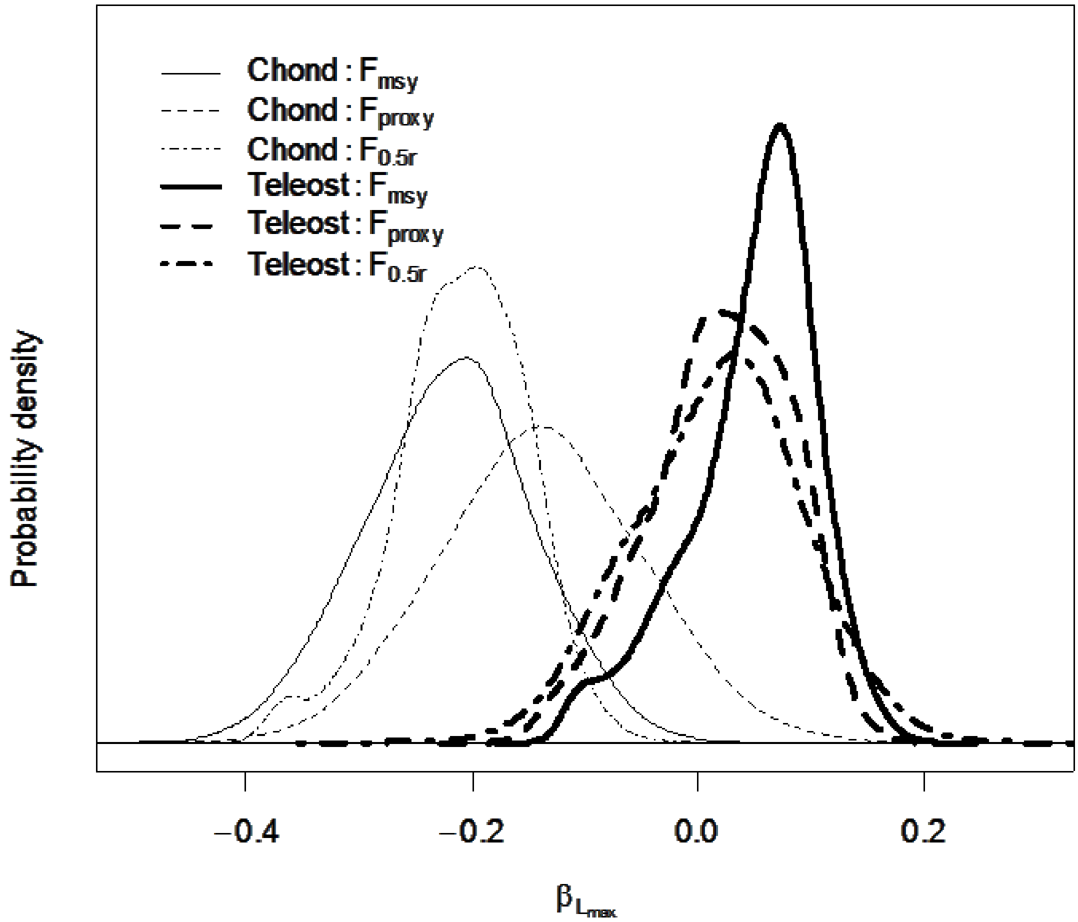

Figure 5-19. Posterior distribution of maximum length coefficient from multiplicative error model.

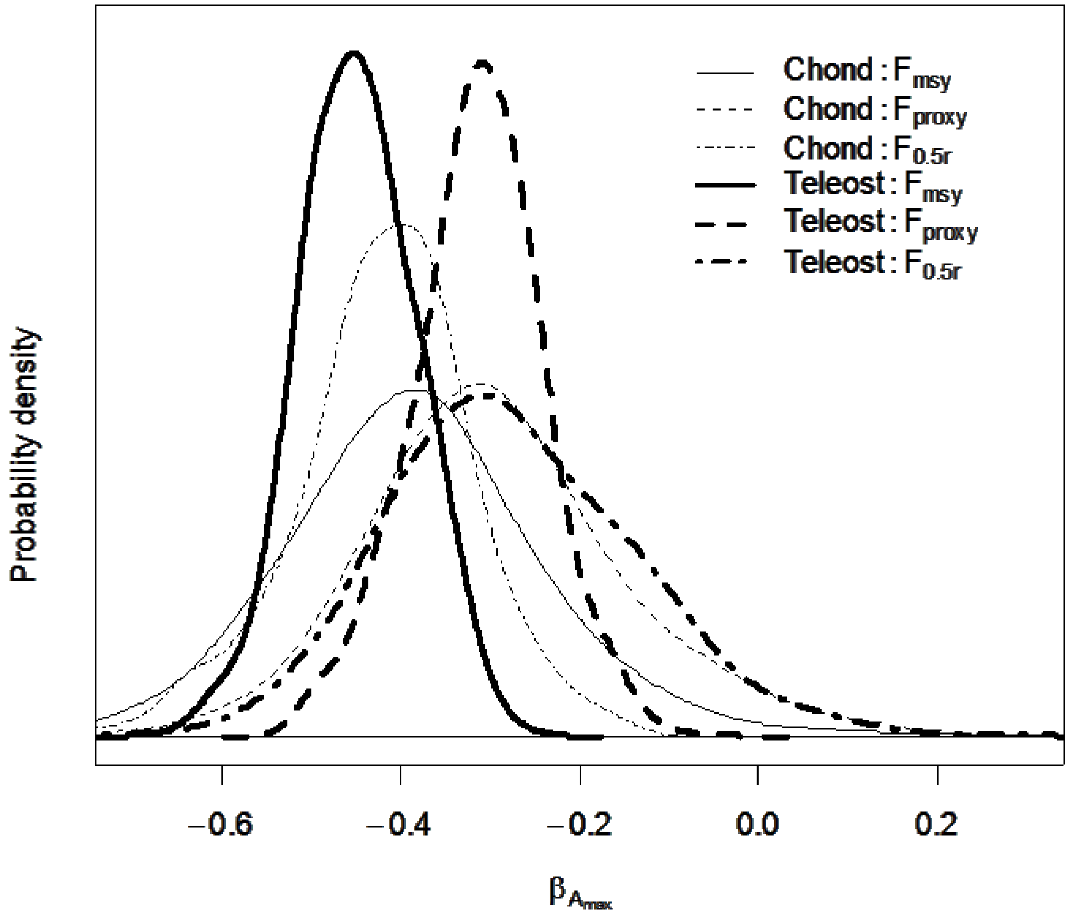

Figure 5-20. Posterior distribution of maximum age coefficient from multiplicative error model.

Table 5-20. Posterior statistics of Bayesian hierarchical errors-in-variables model $\log(F_{BRP,t,c,i}) = \beta_0 + \beta_{t,c,k} \log[\kappa_{t,c,i} \exp(\varepsilon_\kappa)] + e_i$ (t = type of method, c = class).

Class	Type	Param	Mean	SD	Low 95%CI	Median	Upper 95%CI
		β_0	-0.51	0.08	-0.66	-0.50	-0.35
Chondrichthyan	F_{msy}	$\beta_{1,1,k}$	1.14	0.12	0.92	1.13	1.40
Chondrichthyan	F_{proxy}	$\beta_{1,2,k}$	0.82	0.16	0.56	0.81	1.18
Chondrichthyan	$F_{0.5r}$	$\beta_{1,3,k}$	1.16	0.06	1.05	1.16	1.27
Teleost	F_{msy}	$\beta_{2,1,k}$	0.76	0.05	0.65	0.76	0.87
Teleost	F_{proxy}	$\beta_{2,2,k}$	0.67	0.05	0.56	0.67	0.77
Teleost	$F_{0.5r}$	$\beta_{2,3,k}$	0.50	0.09	0.34	0.49	0.71

5.4 Application of cumulative risk assessment methods to selected species

In this section, we apply the methods developed in previous sections to selected fish species in the southeast region.

5.4.1 BIGHT SKATE

5.4.1.1 Gear efficiency

Data source

The Bight Skate, *Dipturus gudgeri*, is an endemic species occurring mainly on the upper continental slope off the south coast of Australia where it is one of the most common skate species taken by temperate demersal fisheries (Daley et al. 2002). This species was chosen as one of the priority species because several fisheries currently impact upon it and it was assessed to be at high risk in the ERAEF assessments for SESS fisheries (Wayte et al. 2006; Zhou et al. 2012c). The key data source used in this study is the combined scientific surveys and fisheries observer database which commenced in1976. Three groups of gear have caught Bight Skate: automatic longline, Danish seine, and various trawls. Many records, particularly prior to 2003 are incomplete, meaning that some information such as gear type, catch, length of trawling or lines, etc. (Daley et al. 2003) was missing. These incomplete records cannot be used and have to be excluded. The cross-sampling method has the capability to estimate parameters from non-random aggregated distribution patterns and varying abundance at each sample occasion, which is common for marine fish. The cost of this power is a need for more than one fishing gear being used to catch the same population—cross sampling with multiple gears at the same time and location. This requirement significantly reduces the number of records. One way to ensure sufficient sample size is to use relatively large time steps and area sizes. In this example, we assume that abundance in 1 × 1 degree grid cell does not significantly change within a 1 year time step. “Not significantly change” means that variation in available abundance within the grid and time frame can be modelled by a Poisson distribution, i.e., the variance is about the same as the mean. However, this assumption can be relaxed, because we show in the simulations that reasonable estimates can be obtained even when the variance is about 50 times of the mean.

Data preparation

First, it is necessary to define and estimate the gear-affected area for each gear deployment (shot). For actively moving gears, such as trawl and seine, this is relative straightforward. We use the follow equations to estimate swept area for trawl and seine:

Trawl: $a = 0.7Lh$

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

Where a is swept area, L is the trawling length or length of the seine net, h is the headrope length, and 0.7 is the adjustment factor when the trawl is towed under the water.

For longline, we define the gear-affected area as a band of the length of the longline with 1 km width, i.e., $a = 1L$.

Catch per unit of effort (CPUE), expressed as c/a, where c is the catch in number of fish, may exhibit a large variability within each grid-year unit. This over-dispersion may violate the Poisson distribution assumption (see below). We test the model sensitivity by including grid-years at three levels of variability: variance (of CPUE) equals or less than the mean, variance is equal or less than 10 times of the mean, and variance is equal or less than 50 times the mean. Incomplete data, the requirement of cross sampling and too large a variance reduce the usable grid-year to less than 25 for the Bight Skate (Figure 5-21).

Most data collected were for trawl gear, while Danish seine was used on only 2 grid-years in 4 shots. There are many overlaps between auto longline and trawl, but Danish seine did not occur in any grid-year where either auto longline or trawl has fished. Hence, we analysed the data in two ways: the first includes only longline and trawl, and the second includes data from all three gear types, even though Danish seine did not overlap with other gears.

Bayesian cross-sampling model

The abundance of Bight Skate in the SESSF region is assumed to have a non-random aggregated distribution. As in the previous method section, the number of fish between unique grid-year units is modelled as

$N_i \sim \text{negbin}(p, r)$,

where unit i can be an unique grid cell or the same grid cell but in a different year. Within each grid-year unit, the local abundance available to each shot is assumed to following a Poisson distribution:

$N2_{ijk} \sim \text{pois}(N_i)$.

Catch data are then modelled as a binomial distribution:

$C_{ijk} \sim \text{binom}(Q_{ik}, N2_{ijk})$.

Weak informative priors are given to p, r, and Q_{ik} as:

$P \sim \text{beta}(1, 1)$
$r \sim \text{lognorm}(0, 0.01)$
$Q_{ik} \sim \text{beta}(1, 1)$.

Although covariates can be incorporated into the model to reduce random effects on parameters, there are insufficient data for Bight Skate because of many pieces of missing information such as depth, bottom type, etc. Hence, the models presented here are generic and in the same configuration as in the simulation studies.

Estimation of gear efficiency

A total of four alternative datasets and their corresponding models are used in this study. All models converge well after only a few thousand iterations. There is no abnormal behaviour of the MCMC process. The posterior of the scale parameter *r* is generally less than 2, indicating the distribution of Bight Skate between grid cells is highly aggregated. However, the four models produce similar results (Table 5-21). Auto longline has an efficiency of about 0.1, while that of trawl is about 0.6. When grid-years with high CPUE variance are included, i.e., V[CPUE] <= 50 E[CPUE], gear efficiencies tend to be underestimated. Consequently, fish density is overestimated.

Interestingly, after including the Danish seine, even though it does not overlap with other gears, the model still can produce acceptable results (Figure 5-22). The restraints imposed by a negative binomial distribution between grid-years and a Poisson distribution within a grid-year allow the model to "borrow strength" from auto longline and trawl and "deduce" sensible parameter spaces. However, Danish seine's intermediate efficiency pulls the Q_{AL} and Q_{TW} towards their mean, which is considered common in mixed models (Gelman and Pardoe 2006; Lockwood et al. 2001).

Table 5-21. Summary of Bayesian posteriors for key parameters of Bight Skate from surveys and observer data.

Var to mean	Para	mean	sd	2.50%	median	97.50%
Var=Mean	Q_{AL}	0.12	0.02	0.08	0.11	0.17
	Q_{TW}	0.60	0.06	0.47	0.60	0.72
	μ	18.60	6.73	9.47	17.39	34.86
	P	0.07	0.03	0.02	0.06	0.15
	r	1.26	0.57	0.47	1.15	2.65
Var=10Mmean	Q_{AL}	0.09	0.02	0.06	0.09	0.13
	Q_{TW}	0.61	0.05	0.51	0.61	0.71
	μ	20.38	5.35	12.25	19.60	32.88
	P	0.08	0.03	0.03	0.07	0.15
	r	1.61	0.66	0.67	1.50	3.21
Var=50Mean	Q_{AL}	0.07	0.01	0.05	0.07	0.09
	Q_{TW}	0.46	0.04	0.39	0.46	0.54
	μ	41.07	9.50	26.19	39.87	63.27
	P	0.03	0.01	0.01	0.03	0.06
	r	1.27	0.40	0.66	1.21	2.21
Var=Mean	Q_{AL}	0.18	0.04	0.10	0.17	0.25
3 gears	Q_{DS}	0.47	0.08	0.32	0.47	0.62
	Q_{TW}	0.58	0.06	0.46	0.58	0.70
	μ	20.78	7.10	11.22	19.45	38.52

Var to mean	Para	mean	sd	2.50%	median	97.50%
	P	0.07	0.03	0.02	0.06	0.15
	r	1.39	0.62	0.54	1.28	2.84

Note: var to mean is the ratio between the CPUE variance and mean CPUE within each grid-year unit. μ is the mean fish density per km^2 for all grid-years.

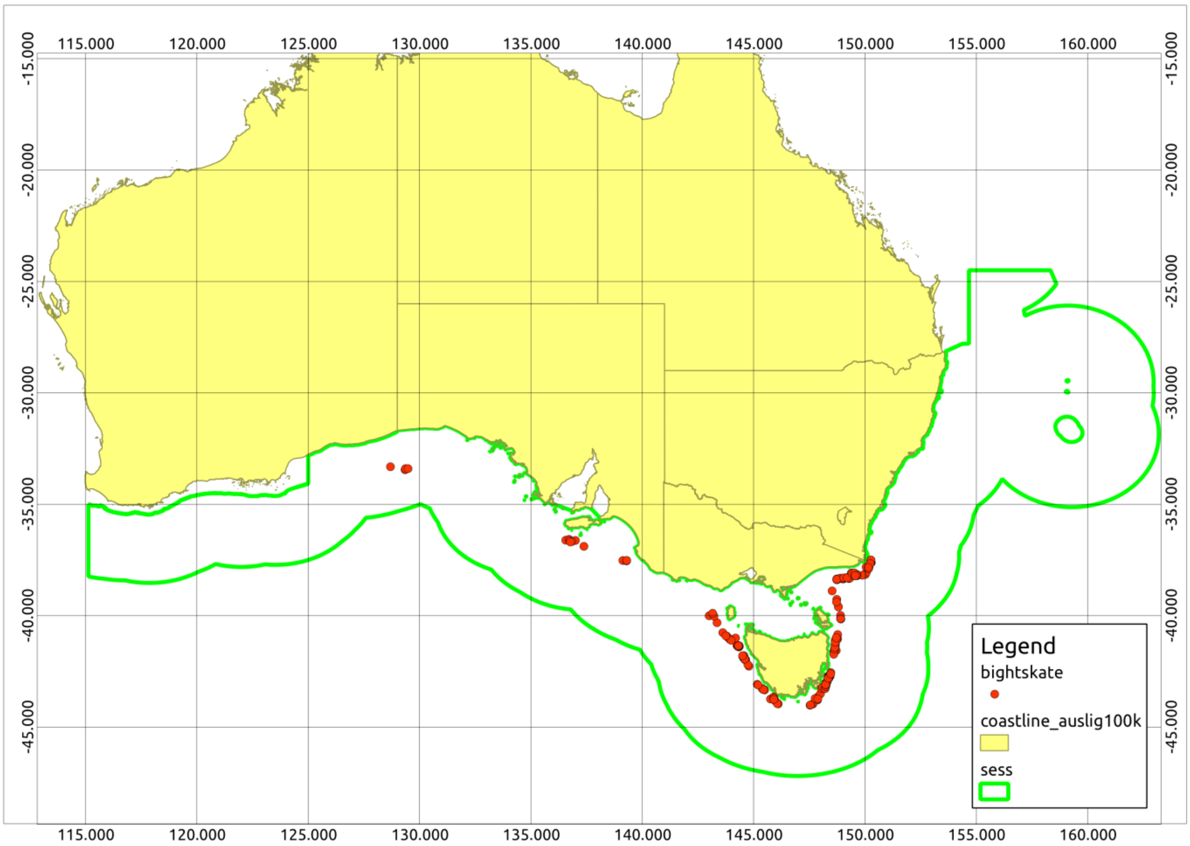

Figure 5-21. Locations of grid cells in SESSF region where data meet the requirements for applying the cross-sampling method for estimating gear efficiency.

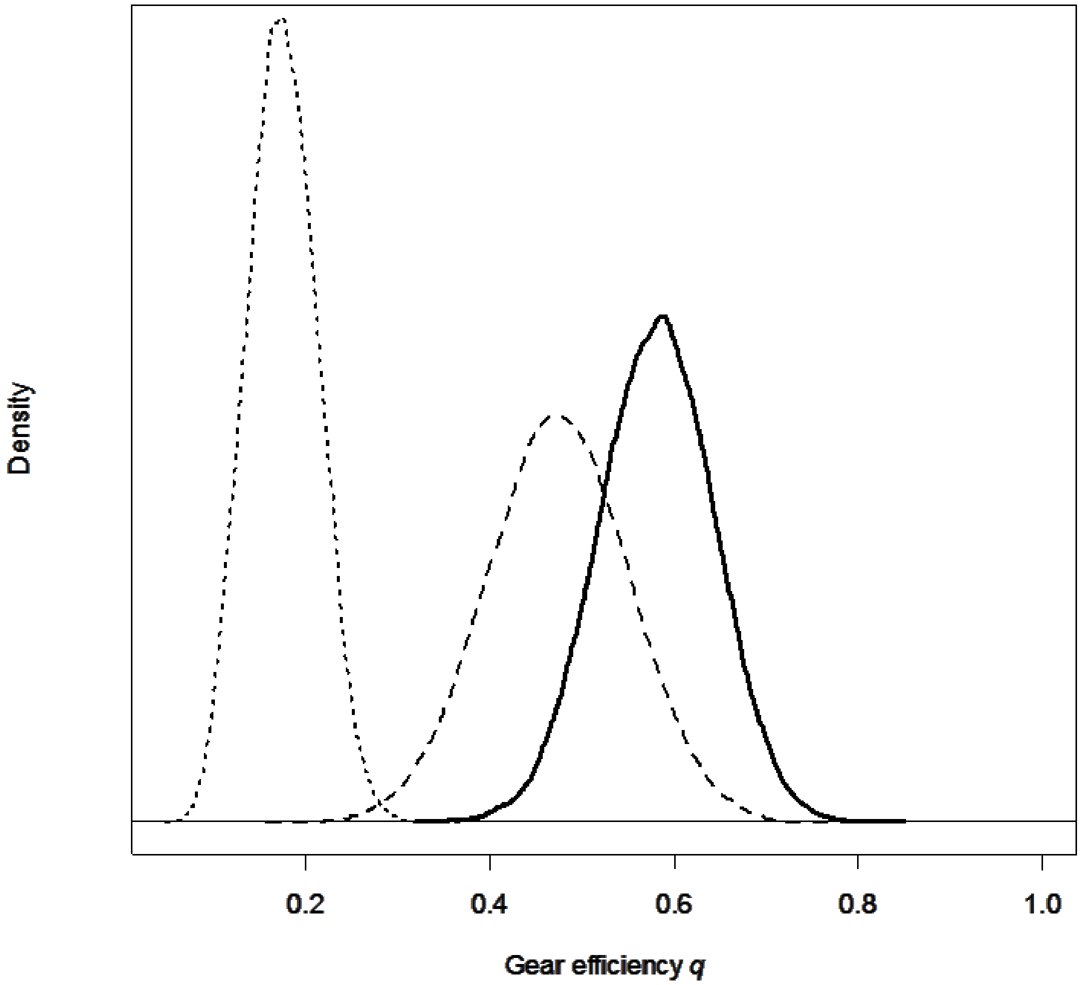

Figure 5-22. Posterior density of gear efficiency parameter for three types of gear. From left to right: Auto Longline, Danish Seine, and Trawl.

5.4.1.2 Distribution and density

Bight Skate has a narrow distribution along the continental slope (Figure 5-23). There are a total of 1485 catch records of Bight Skate from 1984 to 2012 in the survey-observer data. The estimated density (kg/km^2) from observed catch and gear efficiency *Q* ranges from 0.8 to 1663 kg/km^2 (Figure 5-24, Figure 5-25). The data appear to be noisy but the GAM captures the distribution pattern of the data fairly well (Figure 5-26, Figure 5-27).

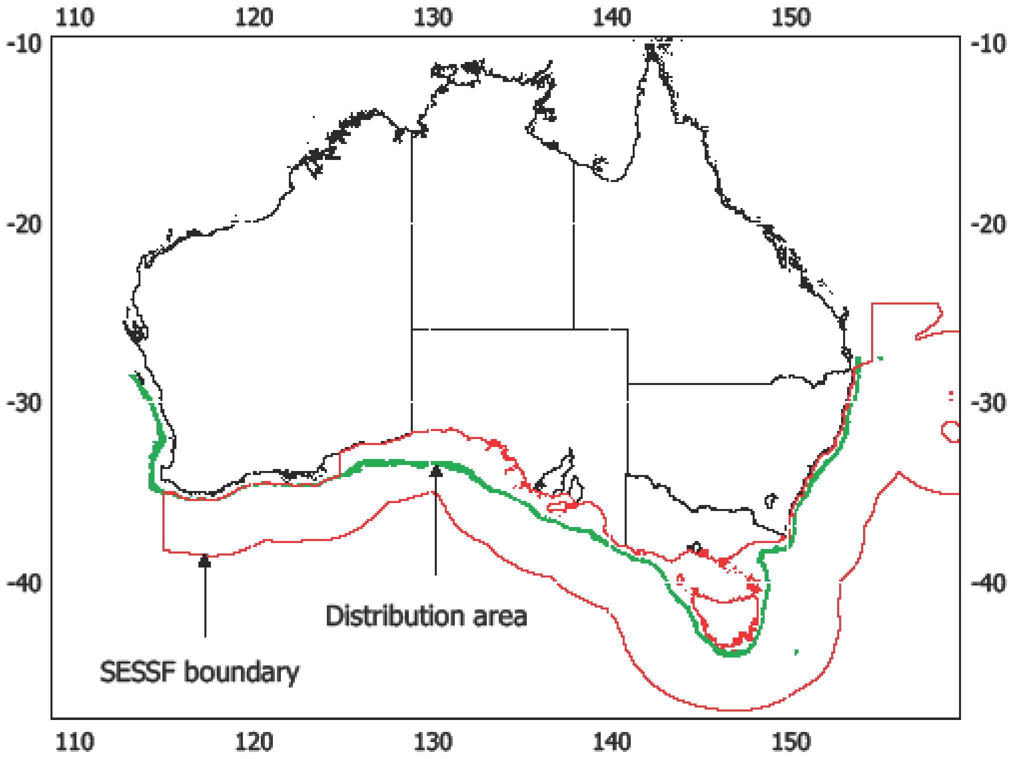

Figure 5-23. Bight Skate distribution range.

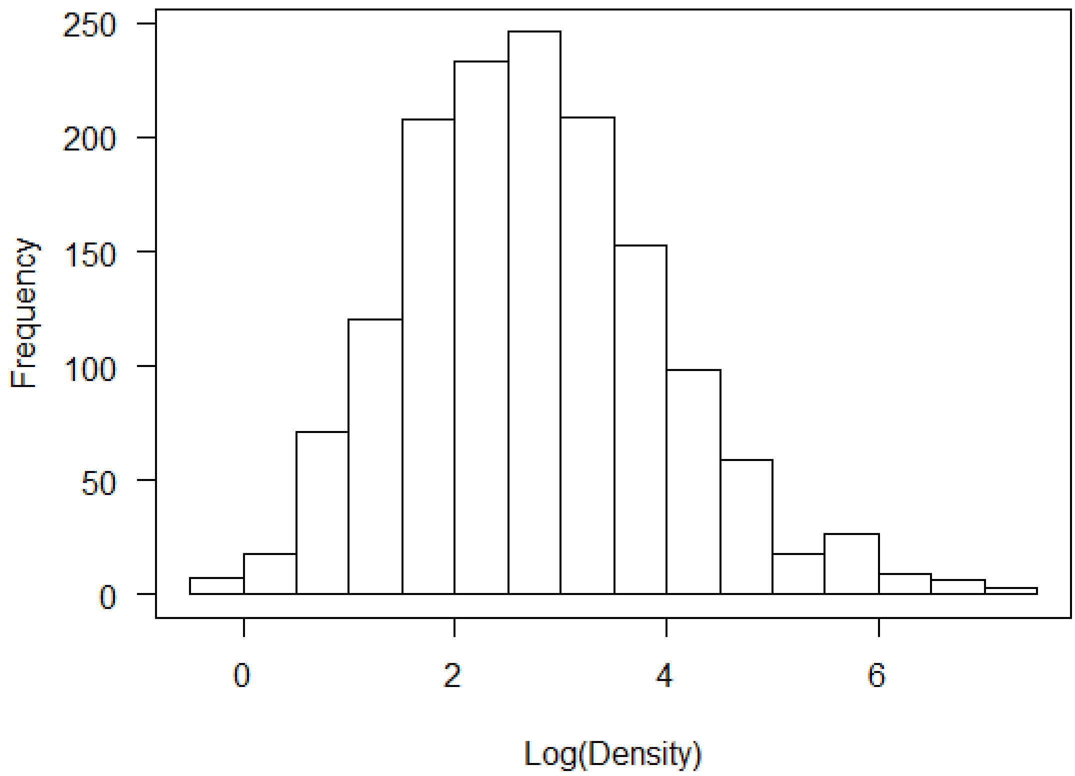

Figure 5-24. Bight Skate density (kg/km^2) in log scale.

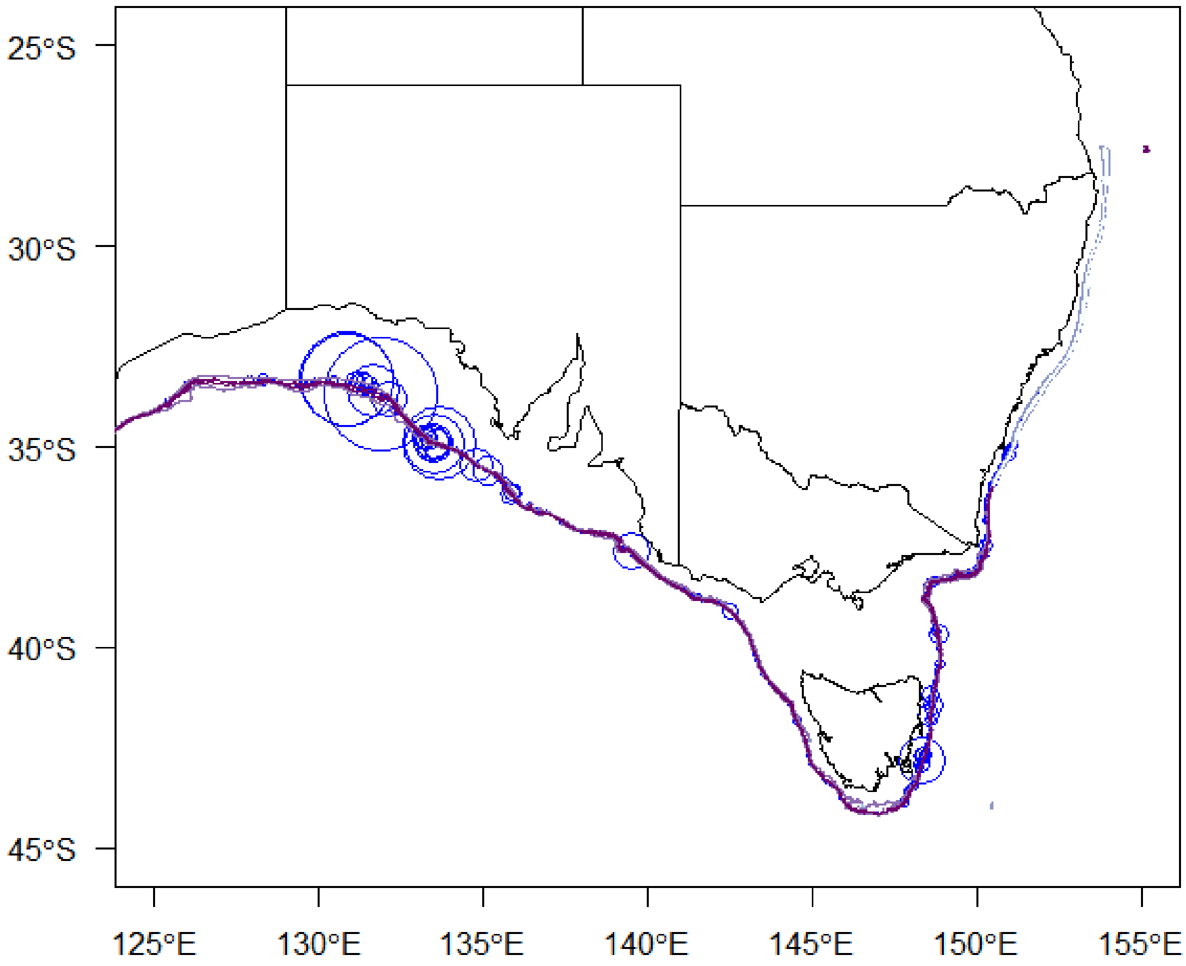

Figure 5-25. Bight Skate relative density from survey-observer data.

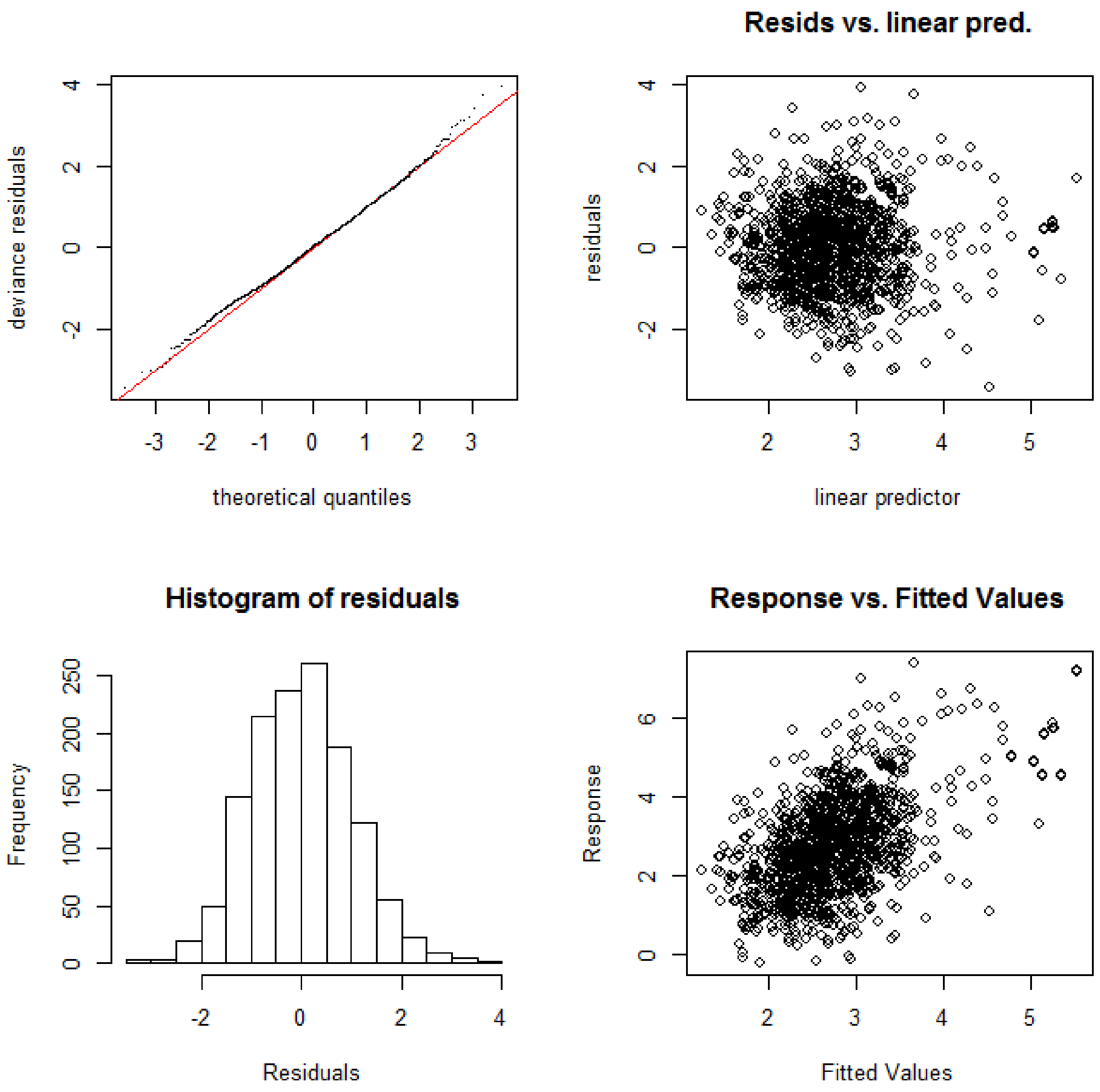

Figure 5-26. Model check for the Bight Skate density GAM model.

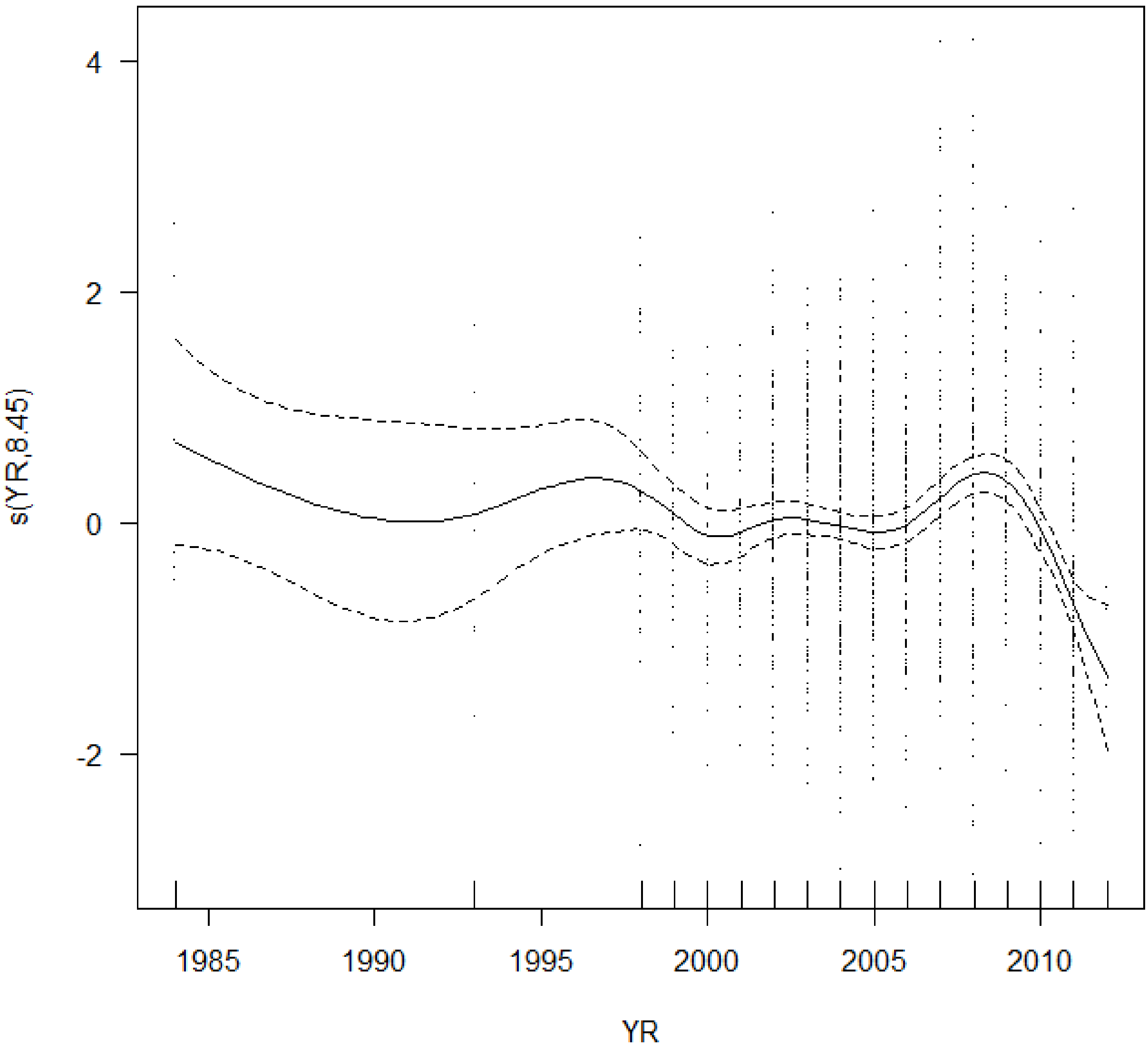

Figure 5-27. Estimated smooth year term for the Bight Skate density GAM model.

The mean densities in Bioreg or Core areas do not vary significantly (Table 5-22). This is also the case for the east and west regions and across the four years examined. The GAM model may have smoothed out the variability in density over space and time, however, the variation for the mean is relatively large.

Table 5-22. Bight Skate density (log scale kg/km^2) in Bioreg area/Core zones and east/west 147^o regions from survey and observer database.

		2007		2008		2009		2010	
Zone	Region	Mean	sd	Mean	sd	Mean	sd	Mean	sd
Bioreg	West 147	3.01	0.75	3.20	0.75	3.14	0.75	2.74	0.75
Core	West 147	2.84	0.50	3.03	0.50	2.97	0.50	2.57	0.50
Bioreg	East 147	2.96	0.37	3.16	0.37	3.10	0.37	2.69	0.37
core	East 147	2.97	0.38	3.16	0.38	3.11	0.38	2.70	0.38

5.4.1.3 Fishing mortality

Commonwealth fisheries

The distribution of Bight Skate overlaps with the effort in the SESS trawl sector, GAB trawl sector, and SESS auto longline sector. There are no catches recorded in AFMA logbooks but this species is recorded in observer data which show an increase in catch per unit effort attributable to improved reporting (Daley et al. 2003, Walker and Gason 2007). It was assessed to be at high risk from these sub-fisheries (Wayte et al. 2006; Zhou et al. 2012b). There are other gear types operating in the SESS area, which may potentially capture Bight Skate (Table 5-23), however, the fishing effort was relatively low for them. To estimate the potential total fishing mortality from Commonwealth fisheries, we applied fishing effort and gear efficiency to modelled density and species distribution area. We assumed gear efficiency Q_{AL} to be the same for all line gears, Q_{DS} same for Danish seine, purse seine, and gillnet, and Q_{TW} same for trawl and dredge. Gear-affected area for each shot was estimated as follows:

Longline: $a = wL$, where w = 1 km and L is the length of the line; Seine: $\pi(L/2\pi)^2 = 0.32$ km^2 (Zhou et al. 2012c); Gillnet: wL, where w = 1 km and L is the length of the net; Trawl: $0.7Lh$, where h is the headrope length and L is the total towed length; Dredge: wL, where w = 2 m and L is the total towed length; Handline: wL, where w = 1 km and L is the length of the line; Jigger, pole, rod and reel: $\pi/4\ L \approx 0.8$ km^2, where L = 1 km; Trotline and trolling: wL, where w = 1 km and L is the length of the line.

For gears that use baits to attract fish, it is difficult to define the distance from the gear within which a fish may likely be caught. For these gears, gear- affected area depends on various factors, including type of bait, soak time, physiological state of the fish (duration of food deprivation), current speed and direction, fish swimming speed, body size, etc. (Løkkeborg et al. 1989, 1995). The active space where the odour concentration is present in over-threshold quantities shrinks with soak time. Within the first hour, the maximum length of the active space for sablefish is 925 m, in 2 h it is 793 m, and in 6 h it is 654 m (Løkkeborg et al. 1995). In a field study using baited gillnets, cod were observed to move directly towards the gear from distances up to 400 m (Kallayil et al. 2003). Nearly 90% of sablefish were hooked within 3 hours of soak time, which corresponds to the leading edge of the plume of about 800 m from the bait (Sigler 2000). In a baited video experiment, the greatest distance of fish attraction was 48-90 m for a

200 mm fish in a current velocity of 0.1- 0.2 m s^{-1} (Ellis and DeMartini 1995). If the current speed is about 0.2 m s^{-1}, bait soaked for 1 hour may have an effective range of attraction of about 480 m for fish of 200-300 mm length (Cappo et al. 2004). Based on these studies, for baited gears we assumed that the gear-affected area was w = 1 km from the gear. Similarly, for minor gears, including handline (HL), dropline (DL), trolling (TL), and fish trap (FP), we assumed that a for each shot was 1 km^2. Within a reasonable range, the delineation of the gear-affected area a is relatively robust in estimating fishing impact, because gear efficiency Q is a relative scaling parameter negatively correlated to a so the effect is mitigated in density or biomass estimation as long as the same a is used in estimating Q and in estimating density or biomass. Furthermore, because effort is very low for many minor gear types (e.g., dredging, handline, jigging, pole, rod and reel, trotline, trolling etc.), fishing mortality caused by them would be small anyway.

Table 5-23. Gear types and effort (number of shots) in Commonwealth fisheries that potentially intersect with Bight Skate distribution area in 2007 to 2011.

Code	Gear	2007	2008	2009	2010	2011	Sum
AL	Auto Longline	1,533	1,467	1,452	1,281	1,405	7,138
BL	Demersal Longline	70	63	60	51	92	336
DG	Dredging			18			18
DL	Drop Line	173	117	119	301	326	1,036
DS	Danish Seine	37	31	43	44	37	192
GN	Gillnet	98	31	118	136	29	412
HL	Handline	5		1		15	21
J	Jigging	6		1			7
LLP	Pelagic Longline	522	668	578	289	349	2,406
PL	Pole		4	2		3	9
PS	Purse Seine		19	7		7	33
RR	Rod And Reel	9	7		3	12	31
TL	Trotline		6			47	53
TR	Trolling	51	21	3	5		80
TW	Trawling	19,849	19,624	18,975	18,966	21,205	98,619
Total		22,353	22,058	21,377	21,076	23,527	110,391

The biggest impact is the otter trawl sector, followed by auto longline (Table 5-24). Other sub-fisheries have minor impacts, mainly due to their low fishing effort. The estimated cumulative F varied between 0.057 in 2010 to 0.063 in 2007.

Table 5-24. Estimated Bight Skate fishing mortality *F* for Commonwealth sub-fisheries (gear type).

Gear	2007	2008	2009	2010
AL	0.010	0.011	0.009	0.008
BL	<0.001	<0.001	<0.001	<0.001
DG			<0.001	
DL	0.001	<0.001	<0.001	0.001
DS	<0.001	<0.001	<0.001	<0.001
GN	0.003	0.001	0.003	0.004
HL	<0.001		<0.001	
J	<0.001		<0.001	
LLP	0.004	0.005	0.005	0.002
PL		<0.001	<0.001	
PS		<0.001	<0.001	
RR	<0.001	<0.001		<0.001
TL		<0.001		
TR	<0.001	<0.001	<0.001	<0.001
TW	0.046	0.042	0.041	0.040
Sum	0.063	0.060	0.059	0.057

State fisheries

The States' jurisdiction extends from coast line to three nautical miles. Bight skate only occurs 160 m and deeper, and mostly deeper than 400 m. The distribution range is generally outside the state waters. Therefore, the impact from state fisheries is minimal.

5.4.1.4 Reference points and sustainability

Bight Skate is a large, slow growing, and long-lived chondrichthyan species. We used three methods to derive sustainability reference points: the first is based on κ, L_{max}, A_{max} as described in section 5.3.1.3, the second is based on κ alone, and the third is based on M (Zhou et al. 2012a). The life history parameters used are growth rate κ 0.1, maximum length L_{max} 245 cm, maximum life span A_{max} 25 years, and annual natural mortality M 0.09. The first method may have over-estimated the F_{msy}, particularly the upper confidence limit (Table 5-25).

Assuming the population dynamics can be described with a logistic surplus population model, we may define limit fishing mortality rate as $F_{lim} = 1.5\ F_{msy}$. Using the mean value in Table 5-25, we obtain a medium $F_{lim} = 0.08$ with lower and upper 95% confidence limits at 0.03 and 0.31. Similarly, $F_{crash} = 2\ F_{msy}$, i.e., medium 0.10, with lower and upper 95% confidence limits at 0.04 and 0.41.

Table 5-25. Estimated F_{msy} for Bight Skate based on three methods.

	Lower 95% CI	Medium	Upper 95% CI
Based on κ, L_{max}, A_{max}	0.02	0.07	0.50
Based on κ	0.03	0.04	0.06
Based M	0.02	0.04	0.05
Mean	0.02	0.05	0.20

Comparing the cumulative fishing mortality rates in Table 5-24 with the estimated reference points, we conclude that Bight Skate were at least at medium risk ($F \geq F_{msy}$) in 2007 to 2010.

5.4.2 DRAUGHTBOARD SHARK

The Draughtboard Shark, *Cephaloscyllium laticeps*, is endemic to southern Australia, found from the Recherche Archipelago in Western Australia to Jervis Bay in New South Wales (Last and Stevens 1994). It is the most common member of the catshark family (Scyliorhinidae) in the region and occurs inshore on the continental shelf to at least 60 m in depth (Daley et al. 2002). The Draughtboard Shark reaches at least 100 cm total length (TL) (possibly 150 cm) with males maturing at about 82 cm. Throughout the year, females lay egg cases of about 13 cm by 5 cm which are attached to seaweed and bottom-dwelling invertebrates by long tendrils (Awruch et al. 2009). The young hatch at about 14 cm TL (Last and Stevens 1994). Tagging studies show this species has high site fidelity for isolated high profile reefs, although movements of up to 300 km have been recorded over long periods (Awruch et al. 2012). This species is a high trophic level predator and spends periods of up to five days sheltering from predators among the reefs after ingesting large prey (Awruch et al. 2012). The main dietary items are reef-associated species including octopus, rock lobster and hermit crabs (Awruch et al. 2012).

This species forms a significant bycatch of the demersal trawl, line and gillnet methods in both Commonwealth and State fisheries and was previously assessed to be not at risk (Zhou et al. 2012b. Analysis of catch per unit effort for this species indicates a decline in abundance by 54% in Bass Strait over approximately 25 years between the mid 1970's and 2000 (Walker et al. 2005). The cause of this decline is unclear but possibly due to changes in fishing practices. In Tasmania, output controls have been implemented to constrain future catches as a precautionary measure (DPIWE 2011).

5.4.2.1 Gear efficiency

From the combined scientific survey and fisheries observer database, we determined that four groups of gear have caught Draughtboard Shark: automatic longline, Danish seine, gillnets, and various trawls. The database contains many incomplete records, which cannot be used and have to be excluded. Again, we used the cross-sampling method to estimate gear efficiency. The spatial resolution is 1 × 1 degree grid cell and the time step is one year. Similar to the Bight Skate, we defined and estimated gear-affected area a for each gear type in one deployment (shot) as follows:

Longline: $a = wL$

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

Gillnet: $a = wL$

Trawl: $a = 0.7Lh$

The assumption and procedures for estimating Q is similar to that used for Bight Skate. That is, aggregated distribution (negative binomial) is assumed for fish between unique grid-year units and random distribution (Poisson) is assumed for fish within each grid-year unit. Catch is modelled as a binomial process. Weak informative priors are given to p, r, and Q_{ik}.

The Bayesian model converged after only a few thousand iterations and there was no abnormal behaviour of the MCMC process. The posterior of the scale parameter r is smaller than 2, indicating the distribution of Draughtboard Shark between grid cells is highly aggregated. For the defined gear-affected area, longline has the lowest efficiency while gillnet has the highest one (Table 5-26).

Table 5-26. Bayesian posteriors gear efficiency *Q* for Draughtboard Shark from surveys and observer data.

Gear	mean	sd	2.50%	median	97.50%
Longline	0.25	0.02	0.22	0.25	0.30
Danish seine	0.47	0.05	0.36	0.47	0.57
Gillnet	0.77	0.04	0.69	0.77	0.84
Trawl	0.46	0.05	0.35	0.46	0.55

5.4.2.2 Density and distribution

Draughtboard Shark lives in relatively shallow water (Figure 5-28). There are a total of 3200 catch records of Draughtboard Shark from 1978 to 2012 in the survey-observer data. The estimated density (kg/km^2) from observed catch and gear efficiency Q ranges from 0.3 to 1756 kg/km^2 (Figure 5-29, Figure 5-30). The data appear to be noisy but the GAM captures the distribution pattern fairly well (Figure 5-31, Figure 5-32).

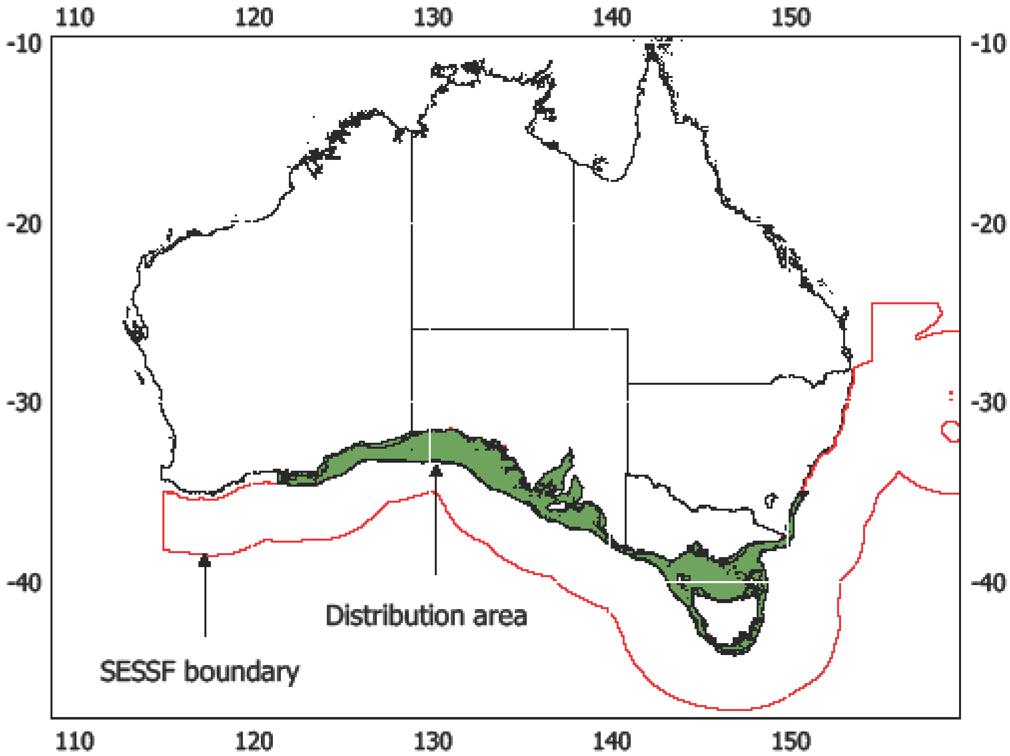

Figure 5-28. Draughtboard Shark distribution range.

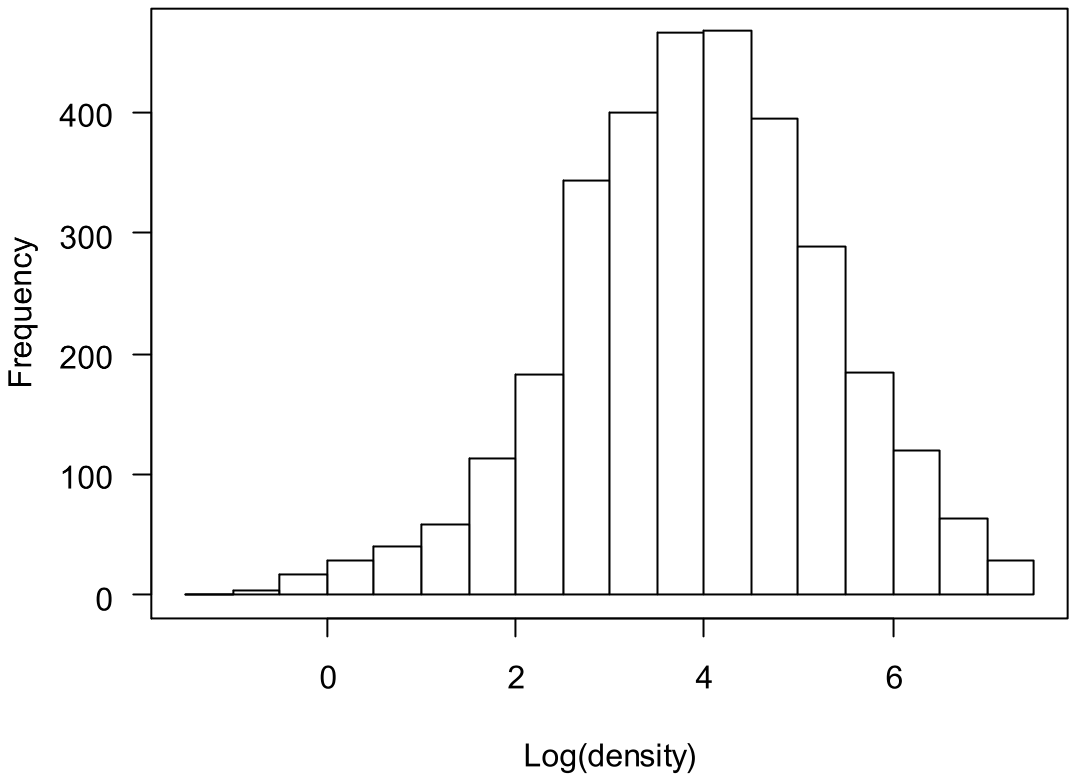

Figure 5-29. Estimated Draughtboard Shark density (kg/km^2) in log scale from survey-observer data.

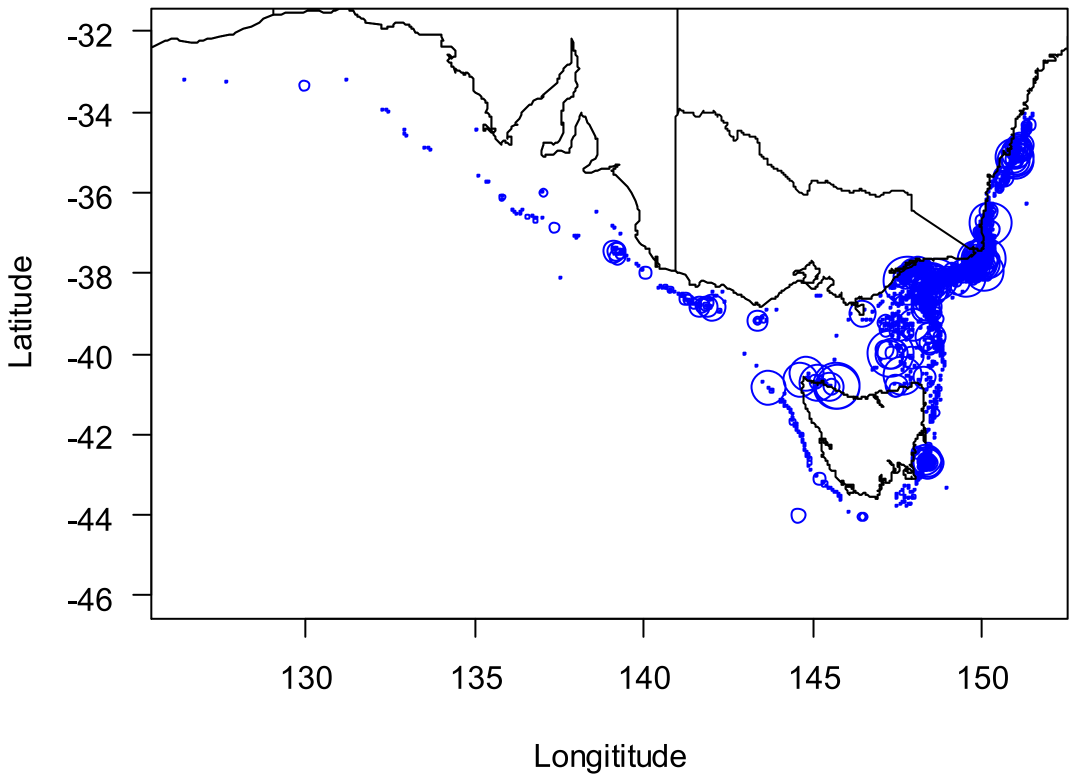

Figure 5-30. Draughtboard Shark relative density from survey-observer data.

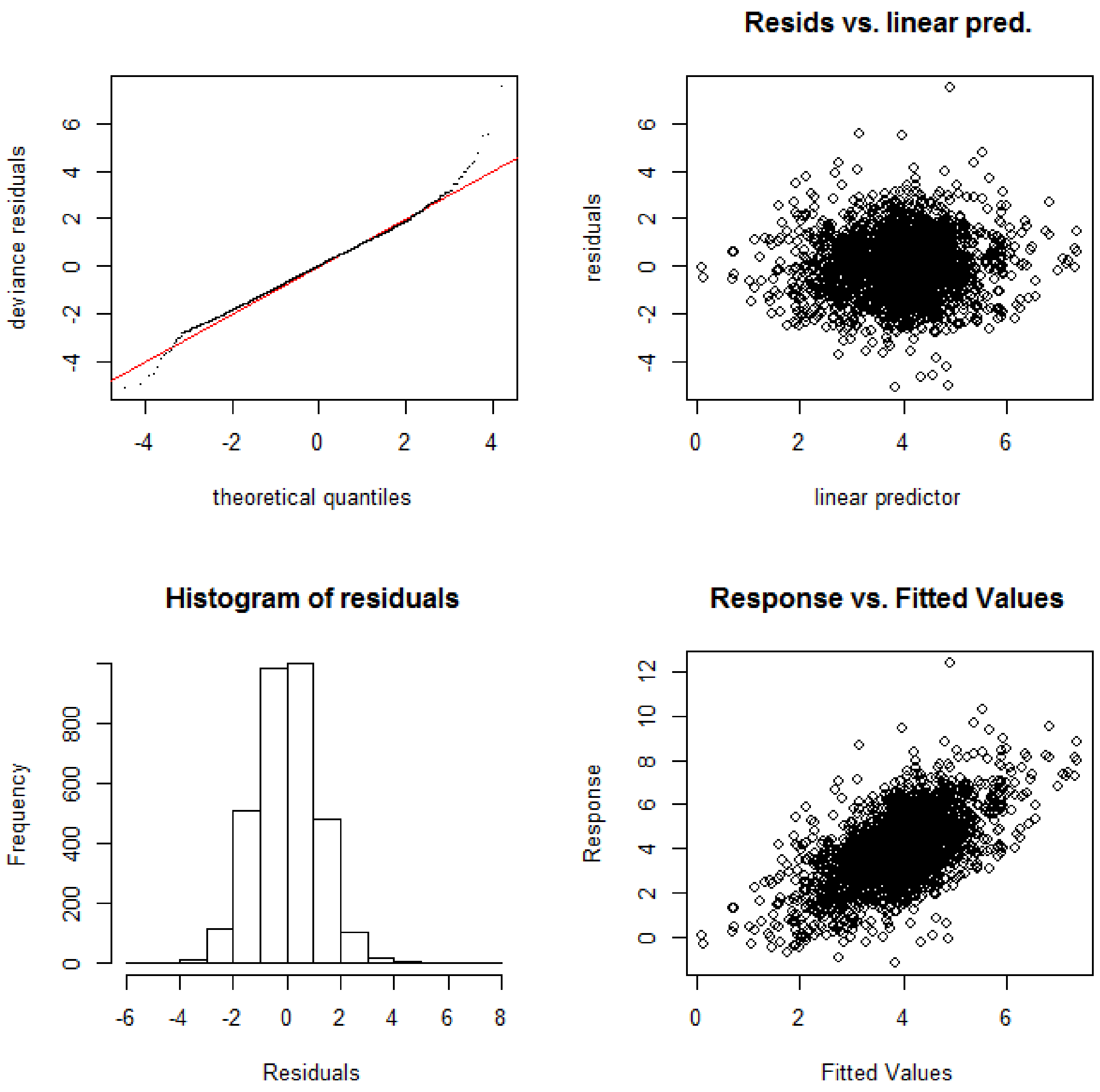

Figure 5-31. Model check for the Draughtboard Shark density GAM model.

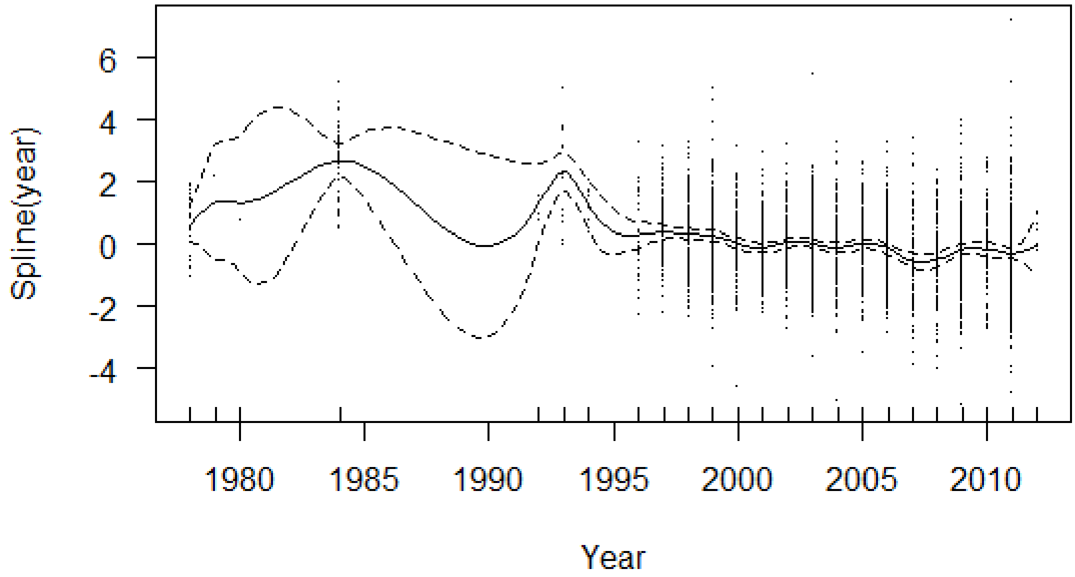

Figure 5-32. Estimated smooth year term for the Bight Skate density GAM model.

5.4.2.3 Fishing mortality of Draughtboard Shark

Commonwealth fisheries

The distribution of Draughtboard Shark is potentially overlapped by the SESS trawl sector, GAB trawl sector, gillnet, and SESS auto longline sector. It was assessed not to be at risk from these sub-fisheries (Zhou et al. 2012b). There are other gear types operating in the SESSF area which may also catch Draughtboard Shark (Table 5-27). The AFMA logbook contains incomplete records of catch. For example, the total catches of Draughtboard Shark in Commonwealth fisheries were 4.0, 13.0, 22.0, and 21.9 tonnes in 2007 to 2010, respectively. In all likelihood these records only represent catches that were retained and sold whereas discards are not normally recorded. To estimate the potential total fishing mortality from Commonwealth fisheries, we applied fishing effort and gear efficiency to modelled density and species distribution area. We assumed gear efficiency Q_{AL} to be the same for all line gears, Q_{DS} for both Danish seine and purse seine, and Q_{TW} for both trawl and dredge. Similar to the Bight Skate, gear-affected area for each shot was estimated as: Longline: $a = wL$, where w = 1 km and L is the length of the line; Seine: $\pi(L/2\pi)^2 = 0.32$ km^2 (Zhou et al. 2012c); Gillnet: wL, where w = 1 km and L is the length of the net; Trawl: $0.7Lh$, where h is the headrope length and L is the total towed length; Dredge: wL, where w = 2 m and L is the total towed length; Handline: wL, where w = 1 km and L is the length of the line; Jigger, pole, rod and reel: $\pi/4\ L \approx 0.8$ km^2, where L = 1 km; Trotline and trolling: wL, where w = 1 km and L is the length of the line.

Table 5-27. Gear types and effort (number of shots) in Commonwealth fisheries that potentially overlap with Draughtboard Shark distribution area in 2007 to 2010.

Code	Gear	2007	2008	2009	2010	Sum
AL	Automatic longline	124	104	114	83	425
BL	Demersal Longline	695	671	892	793	3,051
DG	Dredging			343	407	750
DL	Drop Line	32	36	53	49	170
DS	Danish Seine	6,825	7,462	6,752	7,323	28,362
GN	Gillnet	9,021	9,369	10,020	10,598	39,008
HL	Handline	14	13	3		30
J	Jigging	387	108	146	76	717
LLP	Pelagic Longline	38	21	61	10	130
PL	Pole			1		1
PS	Purse Seine	366	304	442	215	1,327
RR	Rod And Reel	16	5		6	27
TL	Trotline		3			3
TR	Trolling	61	14	4	4	83
TW	Trawling	11,274	11,436	10,307	10,389	43,406
Total		28,853	29,546	29,138	29,953	117,490

The biggest impact is from the gillnet sector, followed by auto longline (Table 5-28). Other sub-fisheries have minor impacts. The estimated cumulative *F* varied between 0.057 in 2010 to 0.063 in 2007.

Table 5-28. Estimated Draughtboard Shark fishing mortality *F* for Commonwealth sub-fisheries (gear type).

Gear	2007	2008	2009	2010
AL	0.001	0.001		<0.001
BL	0.002	0.002	0.003	0.003
DL	<0.001	<0.001		<0.001
DS	0.001	0.001	0.001	0.001
GN	0.035	0.037	0.039	0.042
HL		<0.001		
J	<0.001	<0.001	<0.001	<0.001
LLP	<0.001	<0.001	<0.001	<0.001
PS	<0.001	<0.001	<0.001	<0.001
RR	<0.001	<0.001	<0.001	<0.001
TL		<0.001		
TR		<0.001		<0.001
TW	0.003	0.003	0.003	0.003
Total	0.043	0.044	0.047	0.050

Note: blank cell means no effort for that gear type in that year.

New South Wales ocean fisheries

The NSW has been using a new logbook reporting system since 2009/10 financial year. We obtained data for two financial years: 2009/10 and 2010/11, hence, the data only cover one full calendar year, i.e., 2010. The ocean fisheries extend from about latitude 28°S to 38°S (Figure 5-33). We included fishing effort from Map A to Map J in Figure 5-33 (detailed maps for grid codes were not shown).

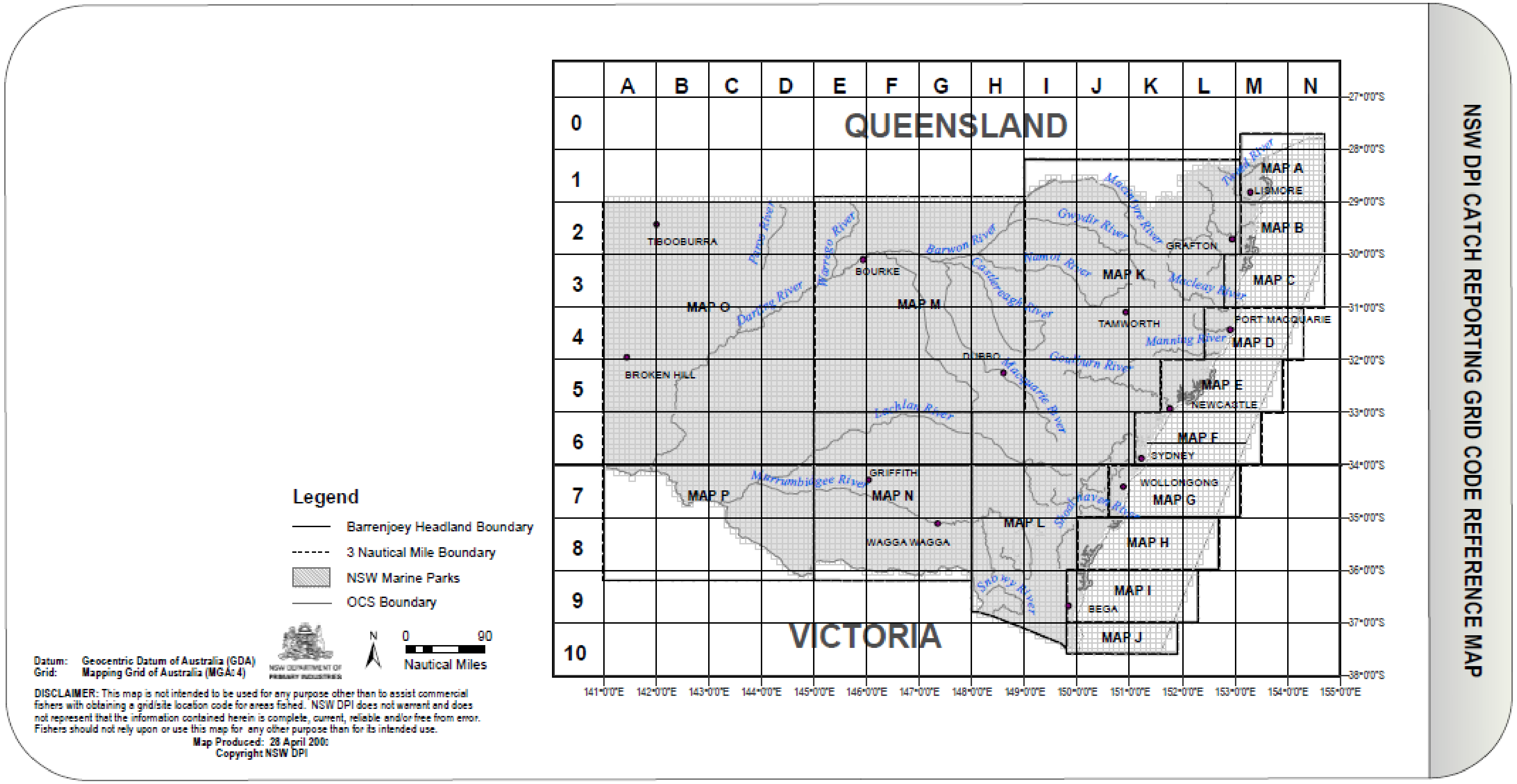

Figure 5-33. New South Wales reference map for fishing report.

In 2010, only three fishing methods were recorded in NSW ocean fishery data: fish trap (FTD), hand gathering (HDG), and jigging (JGG) (Figure 5-34). The numbers of gear deployments were 26, 502, and 106, respectively for the three methods. Hand gathering does not catch Bight Skate. Assuming gear efficiency of Q_{FTD} = 0.47 (similar to Q_{DS}), and Q_{JGG} = 0.09 (similar to Q_{AL}), the estimated total fishing mortality *F* in 2010 is less than 0.0003. In fact, New South Wales fisheries data provided detailed catch in weight for Draughtboard Shark. The total catch in 2010 was 3280 kg, which represents a fishing morality rate of less than 0.0001.

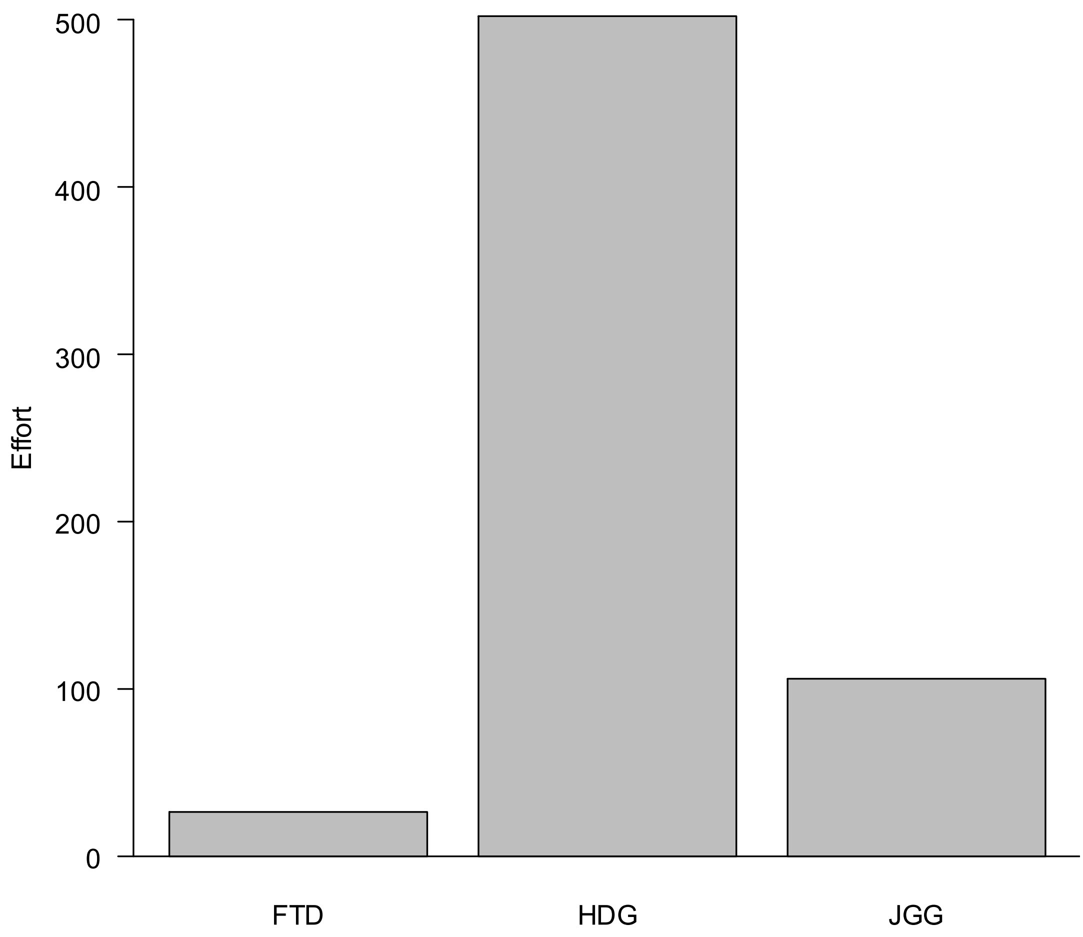

Figure 5-34. Fishing effort (number of shots) in NSW ocean fisheries in 2010. FTD = Fish trap; HDG = Hand gathering; JGG = Jigging (See Table 5-2 for gear codes and effort units).

Victoria ocean fisheries

The Victoria fisheries data contain catches of many individual species or group of species. Five gear types have recorded the catch of Draughtboard Shark (Table 5-29). Of these gear types, prawn trawl has caught the highest number of Draughtboard Shark, and in 2007 had the highest catch. Nevertheless, the catch was small and the estimated fishing mortality rate was less than 0.001 in any year or for any gear type.

Table 5-29. Catch in kilogram of Draughtboard Shark by gear types in Victoria ocean fisheries from 2007 to 2010.

Code	Gear	2007	2008	2009	2010	Sum
N5	Non-shark Monofilament Mesh 125-130mm		14			14
N6	Non-shark Monofilament Mesh > 130mm		37			37
PT	Prawn Trawl (no sweeps attached)	752	305	448	220	1725
RL	Lobster Pots	392	7	5	51	455
SN	Snapper Long Line	15				15
Total		1159	363	453	271	2246

Tasmania fisheries

Tasmania fisheries data also contain catch of many individual species or group of species. Two gear types have recorded the catch of Draughtboard Shark: graball netting and hand line (Table 5-30). However, the catch was small smaller and the estimated fishing mortality rate was less than 0.001 in any year or for any gear type.

Table 5-30. Catch in kilogram of Draughtboard Shark by gear types in Tasmania fisheries from 2007 to 2010.

Code	Gear	2007	2008	2009	2010	Sum
GN	Graball netting	170	267	318.5	173	928
HL	Hand line	12	15	11.8	75	114
Total		182	282	330	248	1042

Cumulative fishing impacts

Jurisdiction	2007	2008	2009	2010
Commonwealth	0.043	0.044	0.047	0.050
States	<0.001	<0.001	<0.001	<0.001
Total	0.043	0.044	0.047	0.050

5.4.2.4 Reference points and sustainability

Draughtboard Shark is a relative fast-growing species of a medium body size. Because the maximum age is not available, we used two methods to derive sustainability reference points: one based on κ as described in section 5.3.1.3 and the other one based on M (Zhou et al. 2012a). The life history parameters used are growth rate $\kappa = 0.36$ and annual natural mortality $M = 0.22$. The growth coefficient κ may be too high, which may have resulted in an over-estimate of the F_{msy} (Table 5-31).

Table 5-31. Estimated F_{msy} for Draughtboard Shark based on two methods.

	Lower 95% CI	Medium	Upper 95% CI
Based on κ	0.17	0.19	0.20
Based M	0.05	0.09	0.13

Comparing the cumulative fishing mortality rate and the reference point F_{msy}, it appears that the total impacts in 2007-2010 were within sustainable level for this species.

5.5 Trade-off between cost and benefit

Unquestionably, conducting ecological risk assessments for effects of fishing and implementing ecosystem-based fishery management will incur some costs. However, it is expected that the long-term benefit will outweigh the costs when using low-cost methods such as those developed in this report. Unfortunately, rigorously analysing the trade-off between cost and benefit is challenging because the process involves explicitly or implicitly weighing the total expected costs against the total expected benefits resulting from the assessment and management and both are very difficult to quantify. For general cost-benefit analysis in other fields, both the benefits and costs are expressed in monetary terms, and are also adjusted for the 'time value' of money in the form of so called "discount rate" (http://www.fao.org/fishery/eaf-net/eaftool/eaf_tool_9/en).

Specifically, when we discuss the assessment of cumulative effects of fishing on species, the potential costs may include: collecting additional data on fisheries operations, biological and fishery information on each bycatch species, and analysing these data qualitatively or quantitatively to infer total impacts from multiple fishing activities. It is possible to estimate the monetary costs for carrying out the entire assessment.

On the other hand, the potential benefits from the assessment can be extensive and difficult to quantify in economic terms alone. For example, FAO lists three major groups of benefits of EAF implementation: ecological benefits, management benefits, and economic benefits (De Young et al. 2008). Benefits related to the assessment of and implementation of cumulative fishing effect may include: healthier marine ecosystems, increased fisheries production, improved fish abundance, reduced impact on threatened, endangered, and protected species, less habitat damage, better integration of management across a range of fisheries, greater societal benefits, better balancing of multiple objectives from multiple users, increased economic return per fish caught, reduced fishing costs and increased net economic returns, positive impacts on food supply in long term, and greater resilience of ecosystem and fisheries. For the resource user, there is one clear benefit from Ecological Risk Assessment: greater security of access to the resource given the increased application of the precautionary principle in Ecosystem-based Fishery Management.

Certainly, there should be a balance between the costs of collecting data for ERA and the benefit returned to the industry and management. The benefit goes beyond industry and management – the Australian community wants information on the impacts on bycatch. Obviously, managing bycatch effectively allows the fishery to meet its obligations under environmental laws. There are various cases where not doing so has resulted in additional conditions imposed on the fishery, e.g. closed areas Such as those for gulper sharks and sea-lions. Therefore demonstrating sustainability can save millions in potential losses that would result from further fishery restrictions. Moreover, managing bycatch species to ensure the maintenance of ecosystem structure and biodiversity is beneficial to sustainable production of target species (Zhou et al. 2011; Garcia et al. 2012).

We have aimed to develop methods that can utilize established data sets, particularly fishery-dependent ones. This has greatly reduced the cost of collecting specific data for ecological risk assessment of fishing effects. For the purpose of assessing cumulative impacts, it is necessary to scope and include as many fisheries as possible. The process of data gathering, understanding, validation, standardisation, comparison, and inclusion in the cumulative assessment has been a challenging task. The data we obtained are typically raw data which might not have been validated; many people hold different types of information; each agency has different formats and purposes. As such, assessing cumulative effects from all fishing activities is time consuming even where sound methods are available for such a job. However, the cumulative impact does not increase linearly when more fisheries are included. Typically, only a few fisheries make up the vast bulk of the mortality to a specific species while the numerous remaining fisheries have only very minor effects. For example, from 2007 to 2010, on average four out of 15 sub-fisheries (gear types) yielded 98% of the total fishing mortality for Bight Skate (Figure 5-35), and five out of 21 fisheries yielded 99% total fishing mortality for Draughtboard Shark (Figure 5-36).

Hence, it is clear that the relationship between cost of research and benefit to the fisheries and environment is not linear. If we can identify major sources of impact, for example, by examine fishing effort and its distribution, before carrying out thorough risk assessment, significant cost and effort could be saved.

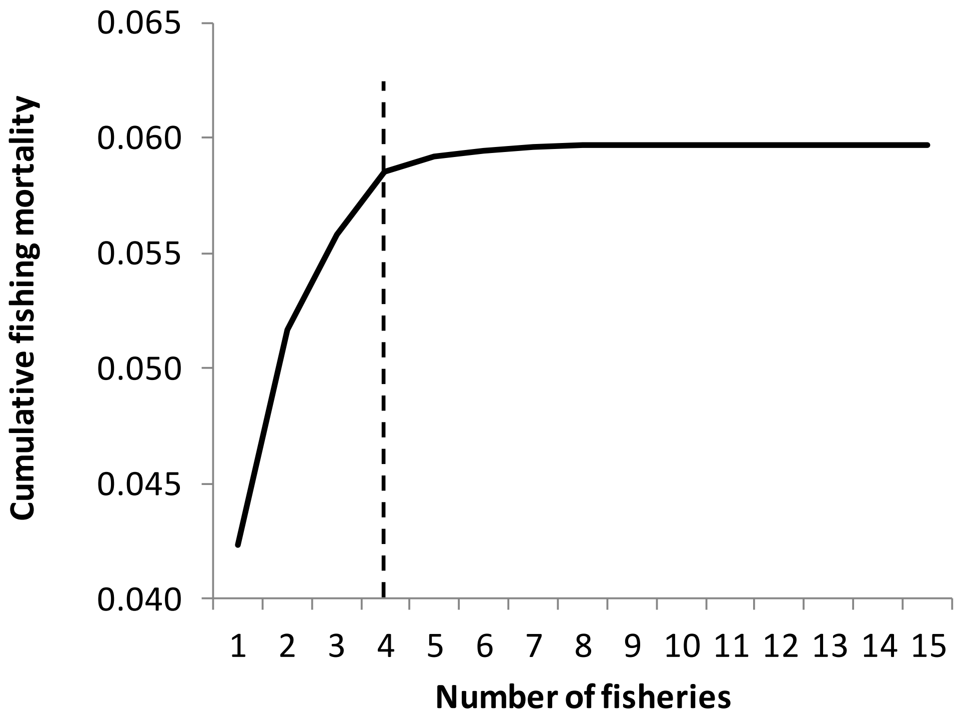

Figure 5-35. Mean cumulative fishing mortality for Bight Skate from 15 sub-fisheries in 2007-2010.

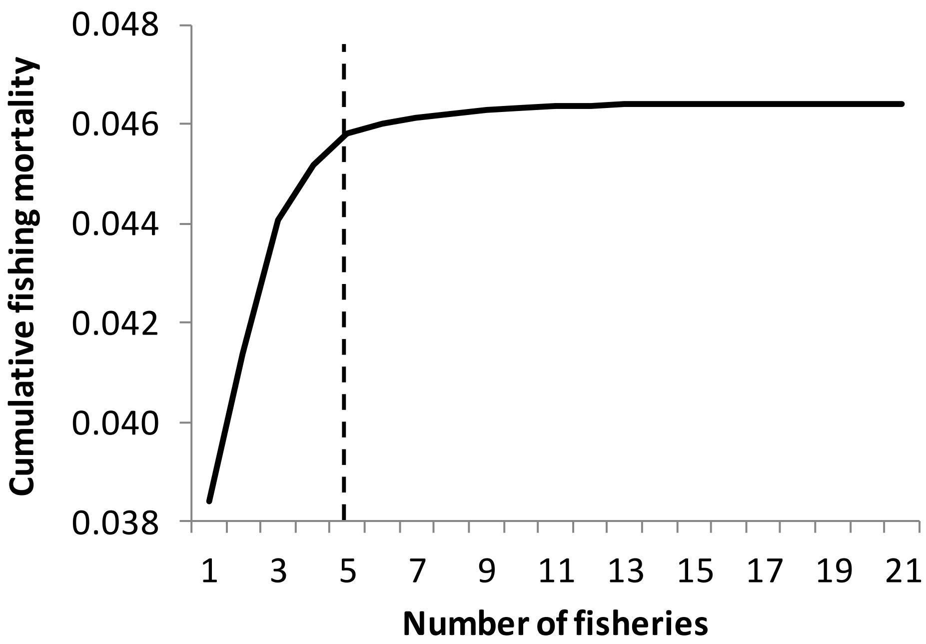

Figure 5-36. Mean cumulative fishing mortality for Draughtboard Shark from 21 sub-fisheries in 2007-2010.

6 Benefits

This project focused on Commonwealth fisheries and used the species in the southeast region as case studies. Hence, the initial beneficiaries of the outputs are Commonwealth fisheries. Other fisheries, such as state fisheries, can benefit from this project as their potential impacts have also been taken into account. Further, any organisation, including State fisheries management agencies, should benefit from the results if they adopt the methods developed in the project, or by adopting the outcomes when implementing management arrangements for overlapping species. Further uptake and benefits require more consistent data collection. The publication of the results is likely to be adopted globally as Australia is currently leading research in this field.

The tools developed from this project will help AFMA to develop more comprehensive and effective ecological risk management for fish species in Commonwealth fisheries. The methods will also be applicable to state-managed fisheries. The project has identified information gaps and data needs, which will contribute to strategic planning for future research and monitoring.

Since this project has been technically successful, the potential impact of the research will improve management practices and efficiency and enhance resource sustainability. Adoption of the outputs may reduce the ecological risks to all fish bycatch species that may be incidentally caught at unsustainable levels.

7 Further Development

In this report, we develop new methods as integrated components of the quantitative methodology for assessing cumulative ecological risk of fishing effects. We apply the methods to selected species, mainly to test their performance and as case studies. We recommend that relevant fishery managers (AFMA and its RAGs and MACs.) critically review these approaches and assess whether they could be applied to a wide range of species and fisheries. If so, these methods are basically ready to be applied to other Commonwealth fisheries and stocks.

Gear efficiency is one of the keys variables that affect fisheries profitability when catching target species; it is also a major factor determining fishing impact when catching non-target species. The cross-sampling method can be applied to many target and non-target species when fishery-dependent or fishery-independent data are available. If a random distribution can be reasonably assumed, there should be sufficient data to allow estimating gear efficiencies for the majority of fish species. For non-randomly distributed populations, observations on gear overlap are essential for such analysis. One of the gaps we identified is insufficient utilizable data to estimate gear efficiency when distribution is non-random. Partial-experiments may be conducted where fishermen using different gears are encouraged to fish in the same location and at the same time.

Determination of gear-affected area will have some effect on estimated fishing density and subsequent population size. While determination of gear-affected area for gear that physically sweeps through the water column seems straightforward, determining the width of swept by the gear may vary from species to species. For example, herding behaviour by bridles and otter boards of demersal trawls are important for some species but less significant for other species (Ramm and Xiao 1995; Fraser et al. 2007; Somerton et al. 2007). It is even more difficult for gear that passively catches fish, such as gillnet, traps, and hook and line. The cross-sampling may have some capability to accommodate bias in the definition of gear- affected area, because efficiency Q is a relative scale that negatively correlates with the size of defined gear-affected area. However, we have not investigated how robust this relationship is. Further research may elucidate these concerns.

We stratified the area of fish distribution into presumably heterogeneous density strata to improve the estimation of population size. One of the decisive factors is the Bioregional mapping data where a higher density of Core range is defined. However, at least for some species (e.g., Bight Skate), survey and observer data do not show significant differences between Core area and Bioreg area. It would be useful to refine the distribution range by incorporating all observed data.

The majority of the data used in this research came from existing databases maintained by CSIRO, including historical scientific surveys, logbook records, observer data, species distribution, habitats, life-history information, etc. These data will continue to be kept in the existing databases. We obtained some additional data from State agencies during the project. These States' data are gear codes and descriptions, limited fishing effort and catch in recent years and confidential information will be erased after the completion of the research.

8 Planned Outcomes

We have presented results of reviewing methods for measuring cumulative fishing effects, scoping a range of data sources that have the potential for utilisation in the assessment, developing innovative methods for assessing cumulative risk, and applying the methods to selected species impacted by many fisheries. We developed quantitative methods that use largely existing data. The main outcomes of the project are quantitative methods for assessing cumulative effects of fishing on species from multiple fisheries and sub-fisheries. More specifically, the key achievements are the development of: innovative methods to estimate multiple gear catchability even when fish have an aggregated distribution pattern; a method to estimate heterogeneous fish density; and models that describe the relationship between sustainability reference points and simple life history parameters other than natural mortality. These methods take data-poor situations and research cost into account where existing data from various sources are integrated for enhanced utilisation, and fishing mortality can be estimated with no time series of catch data. This project also identified data requirements for the estimation of cumulative effects by using the developed methods.

The methods developed in this project can be applied to other species and fisheries beyond those assessed in our case studies. Such an extension of the outcomes can be beneficial to researchers who may carry out similar studies on cumulative effects of fishing for other fisheries.

This research will be useful in fisheries management for both Commonwealth and State fisheries by adopting the methods developed in the project, and/or by adopting its outcomes when implementing management arrangements for overlapping species. The publication of the results is likely to be picked up globally as the outcomes contain several innovative developments. The tools developed from this project will enable AFMA to finalise effective ecological risk management for Commonwealth fisheries. It is anticipated that adoption of the outputs will reduce the ecological risks to all bycatch species that are incidentally caught at unsustainable level. Hence, the research will improve management practices and efficiency and enhance resource sustainability.

Some of the project results have been disseminated through seminars, workshops, and international conferences. For example, a seminar was delivered to multiple management agencies in Canberra in March 2013, presentations were made in CSIRO meetings, in an international workshop in Indonesia, and in an international conference in New Zealand. A manuscript on estimating gear efficiency and fish density has been submitted to a scientific journal for publication. Additional papers are in preparation. Further communications of the results to Australian audiences will be made in the coming years.

9 Conclusion

This project aimed to: review existing methods for measuring cumulative effects of fishing on species; scope data sources available to be included for assessment; develop methods for assessing cumulative risk from multiple fisheries; apply the method to selected Commonwealth fisheries and species; describe the trade-off between research costs and the benefit to the industry.

The project has successfully achieved all these objectives, explained as follows.

We reviewed and discuss a range of methods for the assessment of fishing effects on species. The methods can be generally categorized as qualitative, semi-quantitative, and fully quantitative. Existing qualitative and semi-quantitative methods are appropriate for analysis of single non-cumulative pressure. Some of the qualitative methods have also been applied to cumulative risk assessment. Because these risk assessment methods produce ordinal risk predictions that express ranked order (e.g., low, medium, and high risk score), assessment methods in these categories may encounter unique challenges handling cumulative risks, such as uncertainty analysis. In contrast, quantitative methods use numerical data and mathematical models. They allow mathematical calculation of fishing mortality in the whole assessment process. Hence, it is straightforward to apply quantitative methods in dealing with cumulative effects in an ecological process. The SAFE method has the potential to be extended and improve assessments involving cumulative fishing impacts on species. SAFE involves two major components: estimating fishing mortality based on a specie's distribution and fishing effort distribution as well as gear efficiency, and sustainability reference points based on simple life history traits. Improvement and extension in these areas have been achieved in this report.

We scoped the different data sources and found that a large volume of useful data had been collected by both Commonwealth and State agencies. The resulting historical scientific survey and fishery observer database contains over 886,000 records covering both Commonwealth and State waters. These data are particularly valuable for estimating bycatch species distribution, density, and gear efficiency. Most species, but not all, may have enough data for quantitative risk assessment of cumulative fishing effects. Furthermore, some data contain obvious errors, indicating that they are raw and unverified data. Continuous data collection and validation are essential.

The Bioreg Database contains spatial distribution ranges for the majority of fish species in Australian oceans. The distribution ranges have been stratified into Core areas and Bioreg areas of different densities. It is possible to refine this information by additional observed catch and to further stratify into geographic regions.

More than 130 fisheries or gear types have been used in Commonwealth fisheries and the State fisheries in New South Wales, Tasmania, and Victoria. It is a challenging task to understand, check, standardise, and integrate data from various sources, because each agency collects different types of information, uses different codes, terms, units, formats, etc., in addition to many obvious errors. Nevertheless, these fishery data allow assessment of cumulative fishing effects on each species. Analyses on many other species besides those in this case study can be carried out in the future.

The level of risk imposed on each species by each fishery (i.e., type of gear) largely depends on spatial overlap between species distribution and fishing effort distribution, as well as efficiencies of particular gear types catching the species. In the previous SAFE studies, it was often assumed that individuals of the studied population are homogeneously distributed within their distribution range. Further, three levels of catchability *Q* (0.33, 0.67, and 1.0) were typically assumed for each species based on their size and behaviour (Walker 2005; Zhou et al. 2011). Sustainable reference points were typically derived from natural mortality rate which in turn was estimated from other life history parameters.

In this project, we developed new methods to improve these three areas. We developed statistical models to estimate fishing gear efficiency and abundance. The models can be applied to situations where fish have either a random or aggregated distribution pattern and where local abundance may be fixed or changing. When fish are non-randomly distributed, it is necessary to apply the cross-sampling method that requires multiple gears fishing at the same location and time. The new cross-sampling method has the capability of estimating catchability of multiple gears on non-randomly distributed population. To estimate heterogeneous density, we utilized all available data, including both scientific surveys and fishery observations. The estimated gear efficiency enables abundance estimation and modelling by using a general additive model. Consequently, fishing mortality for each fishery, sub-fishery, or gear type can be derived and cumulative impact from multiple stressors on each species can be summarized.

A species' capacity to withstand fishing pressure directly depends on its life history traits. Using data from 248 species worldwide, we built a Bayesian error-in-variable model to link fishing mortality-based reference point, FBRP, to one to three simple life history parameters: growth coefficient, maximum length, and maximum age. The best model is to include all of these three parameters, but when not all data are available, using growth coefficient alone can reasonably predict sustainable reference point. Chondrichthyes and teleosts exhibit different levels of sustainability, which should be considered in ecological risk management. This appears to be the first study that links fishing mortality-based reference points to life history parameters other than natural mortality. This analysis eliminates the step of estimating natural mortality from other life history parameters and should reduce the uncertainty and increase the applicability to data-poor species.

We identified data needs during the process of data collection, method development, and modelling. For example, improving species distribution range is important. Bioregional mapping data (e.g., Heap et al. 2005) is currently used to define species distribution range. It is possible to incorporate observed catch locations to improve Bioregional mapping data.

Although catch data are not essential for applying quantitative method for assessing cumulative fishing impacts, information on catch of bycatch species can be very useful. This includes catch (both weight and number), gear type, effort unit, location, time, etc. Other information, such as habitat type, depth, could be useful to enhance the modelling. Of course, scientific surveys may provide the best fishery-independent data. Observer data from fishing vessels can be a more cost-effective approach.

Field experiments have been the traditional way to study gear efficiency. Although we have developed the cross-sampling method to estimate gear efficiency using fishery data, not all gears and species have the necessary gear-overlap data (i.e., different gears fish at the same location and time). It would be very valuable to conduct a collaborative research experiment in which fishermen using different gears are encouraged to target the same populations and record the catch of each species.

Our methods avoid the stock assessment approaches that require time series of catch and effort data, as well as other auxiliary information. Nevertheless, accurate life history data is important for estimating sustainability reference points. In particular, growth coefficient, maximum length, and maximum age are the basic parameters, besides natural mortality rate. This highlights a need for more basic biological research, particularly ageing studies for bycatch fish species.

The costs of cumulative ecological risk assessment involve data collection and integration from a range of sources. However, cumulative impact does not increase linearly with the number of fisheries included. A handful of fisheries often result in a large fraction of mortality to specific species while many other fisheries have very minor effect. This means that the relationship between cost of research and benefit to the fisheries and environment is nonlinear. Considering the trade-off between costs and benefits, we suggest identifying major sources of impact before carrying out thorough risk assessment.

10 References

AFMA. 2011. Review of AFMA's arrangements for obtaining and using scientific and economic information and advice. Draft Report of the Expert Panel, 11 May 2011.

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

Astles, K.L., M.G. Holloway, A. Steffe, M. Green, C. Ganassin, P.J. Gibbs (2006). An ecological method for qualitative risk assessment and its use in the management of fisheries in New South Wales, Australia. Fisheries Research 82: 290–303.

Awruch, C. A., Frusher, S. D., Stevens, J. D. and Barnett, A. 2012. Movement patterns of the draughtboard shark *Cephaloscyllium laticeps* (Scyliorhinidae) determined by passive tracking and conventional tagging. Journal of Fish Biology 80: 1417–1435.

Awruch, C.A., Pankhurst, N. W., Frusher, S.D., Stevens, J.D. 2009. Reproductive seasonality and embryo developmentin the draughtboard shark *Cephaloscyllium laticeps*. Marine and Freshwater Research 60: 1265–1272.

Astles, K.L., Gibbs, P.J., Steffe, A.S., Green, M. 2009. A qualitative risk-based assessment of impacts on marine habitats and harvested species for a data deficient wild capture fishery. Biological Conservation 142: 2759–2773.

von Bertalanffy, L. 1938. A quantitative theory of organic growth. Human Biology 10: 181–213.

Best, N., Cowles, M.K., and Vines, K. 1996. CODA Convergence Diagnosis and Output Analysis Software for Gibbs Sampling Output. (MRC Biostatistics unit, Cambrdge, UK.).

Beierle, T. C. 2002. The quality of stakeholder-based decisions. Risk Analysis, 22: 739-749.

Borgström, R., Plahte, E., 1992. Gillnet selectivity and a model for capture probabilities for a stunted brown trout (Salmo trutta) population. Canadian Journal of Fisheries and Aquatic Sciences 49, 1546–1554.Fletcher, W. J. (2005). The application of qualitative risk assessment methodology to prioritise issues for fisheries management. ICES Journal of Marine Science, 62:1576-1587.

Bulman, C, Daley, R, Stevenson, D., Hobday, A., Sporcic, M. and Fuller, M. 2008. Ecological Risk Assessment for the Effects of Fishing: Report for Demersal Longline Sub-fishery of the Heard and McDonald Islands Fishery. Report for the Australian Fisheries Management Authority, Canberra.

Burgman, M. A. 2005. Risks and Decisions for Conservation and Environmental Management. Cambridge University Press, Cambridge, England.

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

Charnov, E.L., Gislason, H., and Pope, J.G. 2012. Evolutionary assembly rules for fish life histories. Fish and Fisheries . DOI: 10.1111/j.1467-2979.2012.00467.x.

Daley, R., Dowdney, J., Bulman, C, Sporcic, M., Fuller, M., Ling, S., Milton, D., and Hobday, A. 2007. Ecological Risk Assessment (ERA) for the Effects of Fishing: Report for the purse seine sub-fishery of the Small Pelagic Fishery. Report for the Australian Fisheries Management Authority. Canberra, Australia.

Daley, R. K., Stevens, J. D., Last, P. R., Yearsley, G. 2002. Field Guide to Australian Sharks and Rays. CSIRO Publishing.

Daley, R. K., Stevens, J. D. and Last, P. R. 2003. Preparation of a field guide to sharks and rays caught by Australian fisheries. Final Report to the Fisheries Research and Development Corporation for Project 1000/105. CSIRO Marine and Atmospheric Research, Hobart.

De Young, C., Charles, A., Hjort, A. 2008. Human dimensions of the ecosystem approach to fisheries: an overview of context, concepts, tools and methods. FAO Fisheries Technical Paper. No. 489. Rome, FAO. 2008. 152p.

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

DPIWE. 2011. Sea Fishing and Aquaculture. Tasmania: Department of Primary Industries, Parks, Water and Environment. Available at http://www.dpipwe.tas.gov.au (last accessed 13 April 2011).

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

Evans, R. and Molony, B. W. 2010. Ranked Risk Assessment for Bycatch in Multiple Fisheries: a Bioregional Risk Assessment Method. Fisheries Research Report No. 212. Department of Fisheries, Western Australia. 88pp.

Fletcher, W.J., Chesson, J., Fisher M., Sainsbury, K.J., Hundloe, T., Smith, A.D.M. and B. Whitworth. 2002. National ESD Reporting Framework for Australian Fisheries: The 'How To' Guide for Wild Capture Fisheries. FRDC Project 2000/145, Canberra, Australia.

Fletcher, W.J. 2005. The application of qualitative risk assessment methodology to prioritize issues for fisheries management. ICES J. Mar. Sci. 62, 1576–1587.

Fletcher, W.J. 2010. Planning processes for the management of the tuna fisheries of the Western and Central Pacific Region using an Ecosystem Approach. Forum Fisheries Agency, Honiara, Solomon Islands. Faciliator's Version 6.1 January 2010.

Fletcher, W.J., Shaw, J., Gaughan, D.J. and Metcalf, S.J. 2011 Ecosystem Based Fisheries Management case study report – West Coast Bioregion. Fisheries Research Report No. 225. Department of Fisheries, Western Australia. 116pp.

Fletcher, W.J., Guaghan, D.J., Metcalf, S.J., and Shaw, J. 2012a. Using a regional level, risk-based framework to cost effectively implement ecosystem-based fisheries management. In: G.H. Kruse, H.I. Browman, K.L. Cochrane, D. Evans, G.S. Jamieson, P.A., Livingston, D. Woodby, and C.I. Zhang (eds.) Global Progress in Ecosystem-Based Fisheries Management. Alaska Sea Grant, University of Alaska Fairbanks, 129-146.

Fletcher, W.J. 2012b. National Application of Sustainability Indicators for Australian Fisheries- Part 2: Ecosystem based frameworks for aquaculture, multi-fishery and international applications. FRDC Report – Project 2000/145 Part 2. Fisheries Research Report No 235 Department of Fisheries, Western Australia.

Fletcher, W.J. and Santoro, K. (eds). 2012c. Status Reports of the Fisheries and Aquatic Resources of Western Australia 2011/12: The State of the Fisheries. Department of Fisheries, Western Australia.

Fock, H. 2011. Integrating multiple pressures at different spatial and temporal scales: A concept for relative ecological risk assessment in the European marine environment. Human and Ecological Risk Assessment, 17: 187-211.

Fraser, H. M., Greenstreet, S. P. R., and Piet, G. J. 2007. Taking account of catchability in groundfish survey trawls: implications for estimating demersal fish biomass. ICES Journal of Marine Science, 64: 1800–1819.

Fuller, W.A. 1987. Measurement Error Models. John Wiley and Sons Inc., New York.

Garcia, S.M., J. Kolding, J. Rice, M.-J. Rochet, S. Zhou, T. Arimoto, J. E. Beyer, L. Borges, A. Bundy, D. Dunn, E. A. Fulton, M. Hall, M. Heino, R. Law, M. Makino, A. D. Rijnsdorp, F. Simard, A. D. M. Smith. 2012. Reconsidering the consequences of selective fisheries. Science 1045-1047.

Gelman, A. and Pardoe, I. 2006. Bayesian measures of explained variance and pooling in multilevel (hierarchical) models. Technometrics 48: 241-251.

Gislason, H., Daan, N., Rice, J.C., and Pope, J. G. 2010. Size, growth, temperature and the natural mortality of marine fish. Fish and Fisheries 11: 149-158.

Haddon, M. 2001. Modelling and Quantitative Methods in Fisheries. New York, NY: Chapman & Hall.

Hobday, A.J., Bulman, C., Williams, A., Fuller, M. 2011. Ecological risk assessment for effects of fishing on habitats and communities FRDC report 2009/029.

Hayes, K. R. 2011. Uncertainty and uncertainty analysis methods. Technical report, CSIRO Division of Mathematics, Informatics and Statistics, Hobart, Australia, 136pp.

Hayes, K.R., Hosack, G.R., Zhou, S. In review. Risk assessment methods for Ecosystem Based Fishery Management.

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

Hobday, A. J., A. D. M. Smith, H. Webb, R. Daley, S. Wayte, C. Bulman, J. Dowdney, A. Williams, M. Sporcic, J. Dambacher, M. Fuller and T. Walker. 2007. Ecological Risk Assessment for the Effects of Fishing: Methodology. Report R04/1072 for the Australian Fisheries Management Authority, Canberra.

Hobday, A. J., A. D. M. Smith, I. C. Stobutzki, C. Bulman, R. Daley, J. M. Dambacher, R. A. Deng, J. Dowdney, M. Fuller, D. Furlani, S. P. Griffiths, D. Johnson, R. Kenyon, I. A. Knuckey, S. D. Ling, R. Pitcher, K. J. Sainsbury, M. Sporcic, T. Smith, C. Turnbull, T. I. Walker, S. E. Wayte, H. Webb, A. Williams, B. S. Wise, and S. Zhou. 2011. Ecological risk assessment for the effects of fishing. Fisheries Research 108: 372-384.

Irvine, S. B., Daley, R. K., Graham, K. J. and Stevens, J. D. 2012. Biological vulnerability of two exploited sharks of the genus *Deania* (Centrophoridae). Journal of Fish Biology 80: 118 –1206.

Hoenig, J.M. 1983. Empirical use of longevity data to estimate mortality rates. Fishery Bulletin 82: 898–903.

Jensen, A.L. 1996. Beverton and Holt life history invariants result from optimal tradeoff of reproduction and survival. Canadian Journal of Fisheries and Aquatic Sciences 53, 820-822.

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

Kynn, M. 2008. The heuristics and biases bias in expert elicitation. Journal of the Royal Statistical Society Series A, 171: 239-264.

Last, P., Lyne, V., Yearsley, G., Gledhill, D., Gomon, M., Rees, T., White, W., 2005. Validation of the national demersal fish datasets for the regionalization of the Australian continental slope and outer shelf (>40 m depth). Report for Australia's National Oceans Office, 2005, CSIRO, Hobart. <http://www.environment.gov.au/coasts/mbp/publications/general/nmb-fish-report.html>.

Lockwood, J.R., Roeder, K, and Devlin, B. 2001. A Bayesian hierarchical model for Allele frequencies. Genetic Epidm. 20: 17-33.

Løkkeborg, S., Bjordal, A., and Ferno, A. 1989. Responses of cod (Gadus morhua) and haddock (Melanogrammus aeglefinus) to baited hooks in the natural environment. Can. J. Fish. Aquat. Sci. 46: 1478–1483.

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

Martin, J., Royle, J.A., Mackenzie, D.I., Edwards, H.H., Kery, M., and Gardner, B. 2011. Accounting for non-independent detection when estimating abundance of organisms with a Bayesian approach. Methods in Ecology and Evolution doi: 10.1111/j.2041-210X.2011. 00113.x

Pauly, D. 1980. On the interrelationships between natural mortality, growth parameters, and mean environmental temperature in 175 fish stocks. J. Cons. Int. Explor. de la Mer 39: 75–284.

Pears, R.J., Morison, A.K., Jebreen, E.J., Dunning, M.C., Pitcher, C.R., Courtney, A.J., Houlden, B. and Jacobsen, I.P. 2012. Ecological risk assessment of the East Coast Otter Trawl Fishery in the Great Barrier Reef Marine Park: Technical report, Great Barrier Reef Marine Park Authority, Townsville.

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

Quinn, T. J., and Deriso, R.B. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.Royle, J.A., Nichols, J.D. & Ke´ry, M. 2005. Modelling occurrence and abundance of species when detection is imperfect. Oikos, 110, 353–359.

Ramm, D. C. and Xiao, Y. 1995. Herding in groundfish and effective path width of trawls. Fisheries Research, 24: 243-259.

Royle, J.A. 2004. N-mixture models for estimating population size from spatially replicated counts. Biometrics, 60, 108–115.

Sainsbury, K. J. 1980. Effect of individual variability on the von Bertalanffy growth equation. Canadian Journal of Fisheries and Aquatic Sciences 37, 241–247.

Scandol, J., Ives, A.R., Lockett, M.M., 2009. Development of national guidelines to improve the application of risk-based methods in the scope, implementation and interpretation of stock assessments for data-poor species. FRDC Project No. 2007/016. Canberra, Australia.

Sharp, B. R. amd Parker, S. J. and Smith, N. 2009. An impact assessment framework for bottom fishing methods in the CAMLR convention area. CCAMLR Science, 16: 195-210.

Sigler, M.F. 2000. Abundance estimation and capture of sablefish (Anoplopoma fimbria) by longline gear. Can. J. Fish. Aquat. Sci. 57: 1270–1283.

Smith, A.D.M.., A.J. Hobday, H. Webb, R. Daley, S. Wayte, C. Bulman, J. Dowdney, A. Williams, M. Sporcic, J. Dambacher, M. Fuller, D. Furlani, S. Griffiths, R. Kenyon, and T. Walker. 2007. Ecological Risk Assessment for the Effects of Fishing: Final Report R04/1072 for the Australian Fisheries Management Authority, Canberra.

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

Somerton, D. A., Munro, P. T. and Weinberg, K. L. 2007. Whole-gear efficiency of a benthic survey trawl for flatfish. Fisheries Bulletin, 105:278-291.

Spiegelhalter, D., Thomas, A., Best, N., Lunn, D. 2003. WinBUGS User Manual, V.1.4. (MRC Biostatistics Unit, Cambridge, U.K.)

Stobutzki, I., Miller, M. and Brewer, d. 2001. Sustainability of fishery bycatch: a process for assessing highly diverse and numerous bycatch. Environmental Conservation 28: 167-181.

Walker, T. 2005. Management measures. In: J.A. Musick and R. Bonfil (eds.). Management techniques for elasmobranch fisheries. FAO Fishereis Techinical Paper 474: 216-242.

Walker, T. I., Hudson, R. J., Gason, A. S. 2005. Catch evaluation of target, by-product,and by-catch species taken by gillnets and longlines in the shark fishery of south-eastern Australia. Journal of Northwest Atlantic Fishery Science: 35, 505–530

Wayte, S., Dowdney, J., Williams, A., Bulman, C., Sporcic, M., Fuller, M., Smith, A. (2006) Ecological Risk Assessment for the Effects of Fishing: Report for the otter trawl sub-fishery of the Commonwealth trawl sector of the Southern and Eastern Scalefish and Shark Fishery. Report for the Australian Fisheries Management Authority, Canberra.

Wenger, S.J., and Freeman, M.C. 2008. Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. Ecology 89: 2953–2959.

Wood, S.N. 2006. Generalized Additive Models: An Introduction with R. CRC/Chapman & Hall.

Zhou, S., A.D.M. Smith, M. Fuller. 2011. Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. Fisheries Research 112: 168-178.

Zhou, S., and S. Griffiths. 2008. Sustainability assessment for fishing effects (SAFE): A new quantitative ecological risk assessment method and its application to elasmobranch bycatch in an Australian trawl fishery. Fisheries Research, 91: 56-68.

Zhou, S., Fuller, M., and Daley, R. 2012c. Sustainability assessment of fish species potentially impacted in the Southern and Eastern Scalefish and Shark Fishery: 2007-2010. Report to the Australia Fisheries Management Authority, Canberra, Australia. June 2012.

Zhou, S., Milton, D. A., and Fry, G. C. 2012a. Integrated risk analysis for rare marine species impacted by fishing: sustainability assessment and population trend modelling. ICES Journal of Marine Science, 69: 271–280.

Zhou, S., S.P. Griffiths, and M. Miller. 2009. Sustainability assessments for fishing effects (SAFE) on highly diverse and data-limited fish bycatch in a tropical Australian trawl fishery. Marine and Freshwater Research, 60, 563-570.

Zhou, S., A.D.M. Smith, A.E. Punt, A.J. Richardson, M. Gibbs, E.A. Fulton, S. Pascoe, C. Bulman, P. Bayliss, and K. Sainsbury. 2010. Ecosystem-based fisheries management requires a change to the selective fishing philosophy. Proceedings of the National Academy of Sciences 107: 9485-9489.

Zhou, S., Yin, S., Thorson, J.T., Smith, A.D.M., Fuller, M. 2012b. Linking fishing mortality reference points to life history traits: an empirical study. Canadian Journal of Fisheries and Aquatic Science 69: 1292–1301.

11 Appendix 1: Staff list

Alistair Hobday, CSIRO Hobart

Cathy Bulman, CSIRO Hobart

Doug Ferrell, Industry and Investment New South Wales

Mike Fuller, CSIRO Hobart

Paul Ryan, AFMA

Ross Daley, CSIRO Hobart

Shijie Zhou, CSIRO Brisbane

Tony Courtney, Queensland Department of Agriculture, Fisheries and Forestry

12 Appendix 2: Modelling multiple fishing gear efficiencies and abundance for aggregated populations using fishery data

Shijie Zhou[1*], Neil L. Klaer[2], Ross M. Daley[2], Zhengyuan Zhu[3], Michael Fuller[2], Anthony D.M. Smith[2]

[1]CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, P.O. Box 2583, Brisbane, QLD 4001, Australia

[2]CSIRO Marine and Atmospheric Research and Wealth from Oceans Flagship, GPO Box 1538, Hobart, TAS 7001, Australia

[3]Iowa State University, Department of Statistics, Ames, IA 50011, USA

12.1Abstract

1. Fish and wildlife often exhibit an aggregated distribution pattern while local abundance changes constantly due to movement. Estimating population density or size and survey detectability (i.e., gear efficiency in a fishery) for such elusive species is technically challenging.

2. We extend abundance and detectability (N-mixture) methods to deal with this difficult situation, particularly for application to fish populations where gear efficiency is almost never equal to one. The method involves a mixture of statistical models (negative binomial, Poisson, and binomial functions) at two spatial scales: between-cell and within-cell. The innovative approach is to use more than one fishing gear to simultaneously catch (sample) the same population in each cell at the same time step. We carried out computer simulations on a range of scenarios and estimated the relevant parameters using a Bayesian technique. We then applied the method to a demersal fish species, Tiger Flathead, to demonstrate its utility.

3. Simulation results indicated that the models can disentangle the confounding parameters in gear efficiency and abundance and the accuracy generally increases as sample size increases. A joint negative binomial-Poisson model using multiple gears gives the best fit to Tiger Flathead catch data, while a single gear yields unrealistic results.

4. This cross-sampling method can evaluate gear efficiency cost effectively using existing fishery catch data or survey data. More importantly, it provides a means for estimating gear efficiency for

gear types (e.g., gillnets, traps, hook and line, etc.) that are extremely difficult to study by field experiments.

Keywords: catchability, catch efficiency, detection, biomass, fishing gear, negative binomial, aggregated distribution

12.2Introduction

Estimating abundance is essential for sound management of wildlife and fisheries. For species that cannot be sampled easily, measurements of abundance are highly dependent on reliable estimates of detectability. In a fishery, detectability is always a difficult issue, because fishing gears typically catch only a fraction of the fish that reside within the affected area in each gear deployment. The quantity that links the catch to the true abundance *N* (or biomass) available to the gear at each gear operation (shot) is called gear efficiency *Q* (also referred to as fishing power, catch efficiency, or probability of catching fish). Gear efficiency is essentially the same as detectability in ecology, which is so-called imperfect detection (Archaux et al. 2012; Bailey et al. 2007; Conn and Cooch 2009; Zhou and Griffith 2007a). When we consider the true population size of the whole fish stock, this quantity is referred to as the catchability coefficient or simply catchability (*q*). Catchability is a combination of both gear efficiency (*Q*) and stock availability, where fish availability for a fishing operation is affected by the distribution of the entire fish stock by time, area and depth. Estimating gear efficiency is necessary when deriving absolute abundance estimates from catch data, refining estimates of catchability in stock assessment models, or estimating relative fishing impact on bycatch species (Somerton et al. 1999; Zhou et al. 2011a).

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

Estimating gear efficiency is even more difficult for other gear types, such as hook and lines, seine, gillnets, and traps. Studies on these gear types often focus on relative selectivity rather than efficiency (Borgström and Plahte 1992; Prchalová et al. 2009). Selectivity is a relative scale and a component of overall gear efficiency. Absolute abundance estimates using these gear types are rare.

Mathematical methods for estimation of catchability and abundance have also been developed. A widely adopted traditional method is the so-called depletion method (Hilborn and Walters 1992; Bez et al. 2010; Zhou et al. 2011b). Converting catchability *q* to gear efficiency *Q* requires known stock distribution range and the size of gear-affected area, under the assumption of homogeneous density. In addition to many other assumptions, this method can only be applied when the population is experiencing a “depletion” process due to fishing, i.e., the catch rate (catch per unit of effort) significantly declines over time. This method can be ideally applied to fisheries with a high fishing intensity, short fishing season, or small distribution area. However, this method does not suit for many fisheries where catch rates lacks a depletion trend.

Recently, statistical methods have been developed to estimate gear efficiency and abundance from repeated catch data by assuming a random spatial distribution pattern and random catch process (Trenkel and Skaug 2005). A randomly distributed population is typically modelled using a Poisson distribution, and is a special case in ecology, which may be appropriate when the studied area is reasonably small. Because the Poisson distribution has only one parameter, estimation is straightforward. A common and more difficult situation in ecology is aggregated distribution which leads to over-dispersed count data. Quasi-likelihood or conditional negative binomial models have been proposed to handle spatial heterogeneity in animal densities (Ver Hoef and Boveng 2007). In fisheries research, these models have been applied to well-designed paired survey data to analyse the ratio between two catchabilities resulting from change in survey protocols (e.g., change in vessel or gear) (Pelletier 1998; Cadigan and Dowden 2010; Cadigan and Bataineh 2012; Miller 2013). The parameter of interest in these studies is the ratio of pair means, reducing the number of parameters from multiple individual efficiencies. Because in the designed surveys trawls are fished close together it is reasonable to assume that each trawl encounters the same density of fish and differences in catches are primarily related to differences in gear selectivity or vessel fishing efficiency (Gardner et al. 2010; Cadigan and Bataineh 2012). These studies used maximum likelihood estimate, which rely on asymptotic arguments and has been recognized to result in badly biased and inconsistent estimates, particularly for variances and when sample size is small (Cadigan and Bataineh 2012).

Outside fisheries science, there have been recent advances in ecology to estimate animal abundance and survey detectability. These methods (so called N-mixture models) have been applied in terrestrial populations such as birds (Royle 2004; Wenger and Freeman 2008; Dail and Madsen 2011; Martin et al. 2011). It has been demonstrated that estimating detectability and abundance from repeated observations is possible when the animals are randomly distributed (i.e., modelled by a Poisson distribution) within the study area and the abundance does not change randomly at each observation. Both detectability and over-dispersion in aggregated populations have been considered in some studies. However, for studies that use both Poisson and negative binomial models, the latter is often not supported and its results unrealistic (Royle 2004; Joseph et al. 2009; Dail and Madsen 2011). Also, most studies that use negative binomial models have focused on datasets that are not highly overdispersed (see Lloyd-Smith 2007). Furthermore, animals often move within a studied area, causing local abundance to change even in a relatively short time. However, constant abundance at each site is assumed in many studies, or more complicated models are built that include additional parameters such as probabilities of migration, recruitment and survival (Dail and Madsen 2010; Gardner et al. 2010).

This paper arises from a research project on data poor species where we needed to estimate gear efficiency for a range of gear types while we had no funding to carry out field experiments specifically designed for such a purpose. However, we have plentiful historical data from fishery logbook and from fishery-independent surveys that were designed for other purposes. Unfortunately, recorded catch in each shot exhibits huge variations, indicating a highly patchy distribution pattern. We applied various methods from the literature including those cited in this paper. Either the model failed to converge or produced unrealistic results (e.g., very low or very high gear efficiency and similar across gear types). Clearly, it is challenging to estimate *Q* and *N* for an aggregated population with a varying local abundance at each sampling occasion, which is generally the case for fish species. In the end, we combined data from multiple fishing gears within a single model and used Bayesian technique to simultaneously estimate several parameters, including gear efficiency for multiple gear types, population size at each location, mean density, and the over-dispersion parameter. Encouraged by the realistic results, we carried out a range of simulations to validate and fine tune this method. We further found that only models that take over-dispersion into account (e.g., negative binomial) can handle data of high variance, and using more than one gear type has an advantage over single gear in the complicated situation where population exhibits a highly aggregated distribution and local abundance constantly changes over time.

12.3 Materials and methods

The method for estimating gear efficiency (detectability in ecology, or catchability in some literature) and abundance (or density) involves two modules (Royle 2004; Wenger and Freeman 2008; Martin et al. 2011). The first component describes the distribution pattern of fish over the spatial range where fishing or surveys have taken place. The second component is to catch (sample) fish from such a population distribution pattern.

Distribution process

Population distribution falls into two general patterns, a random distribution and an aggregated distribution. In ecology, random distribution is typically modelled by a Poisson distribution (PS) while the aggregated distribution is modelled by a negative binomial distribution (NB). The Poisson distribution is relatively simple, only involves one parameter, and the mean population size equals its variance. First, a stock area is divided into multiple, equal-sized cells. If the number of individuals in cell *i* is N_i, the probability density mass function of the Poisson distribution is:

$$f_{Pois}(N_i;\lambda) = \frac{\lambda^{N_i}}{N_i!}e^{-\lambda} \qquad \text{(eqn 1)}$$

where λ is mean population size. However, an aggregated distribution is considered more common in ecology and is certainly typical for fish species. Let us assume that individuals of a particular species are distributed in an aggregated pattern in the study area. We used a negative binomial distribution to describe the spatial distribution of aggregated populations. The number of individuals N_i in cell *i* can be described by one of the parameterizations of the NB probability density function, for example (Pollard 1977):

$$f_{NB}(N_i \mid p,r) = \frac{\Gamma(N_i + r)}{\Gamma(r)\times N_i!}p^r(1-p)^{N_i}, \qquad \text{(eqn 2)}$$

where the shape parameter *r* describes the extent of aggregation (overdispersion) and $r > 0$. As $r \rightarrow \infty$, the negative binomial converges in distribution to the Poisson so the variance approaches the mean. Parameter *p* is between 0 and 1. The mean is $\mu = r(1 - p)/p$ and the variance is $\sigma^2 = r(1 - p)/p^2$. When the cell size is relatively large, fish may also exhibit different distribution patterns, either random or aggregated with a lower level of overdispersion than the between-cell pattern.

The catch process

Given an individual fish present in cell *i*, there are two outcomes when fishing gear encounters it: caught or not caught. Hence, it is natural to assume that the number of fish of a particular species caught, C_{ijk}, in cell *i*, at sample time *j* by gear type *k*, follows a binomial distribution:

$$C_{ijk} \sim Bin(Q_k, n_{ijk}), \qquad \text{(eqn 3)}$$

where Q_k is the probability of being caught (i.e., gear efficiency or detectability) by gear type *k*, and n_{ijk} is the available fish within gear-affected area in sampling time *j* by gear type *k*:

$$n_{ijk} \sim Pois\left(a_k \frac{N_i}{A}\right) \qquad \text{(eqn 4)}$$

where a_k is gear-affected (swept) area by gear type *k*, $D_{ijk} = N_i/A$ is the density, *A* is the area size of each cell, and N_i is the number of fish in cell *i* from previous equations. Note here we assume local abundance n_{ijk} is a random variable that may change at every time step *j* and by gear type *k*. Gear efficiency Q_k may depend on many factors, such as fish size, vessel characters, time of fishing, weather, habitat, etc. If data for some of these variables are available and including them is desired, it is trivial to incorporate them in the model, e.g., by using a logistic function (MacKenzie et al. 2002; Zhou et al. 2011b):

$$Q_k = \frac{1}{\exp[-(a + \mathbf{bX})] + 1} \qquad \text{(eqn 5)}$$

where vector **X** could be fish length, water depth, habitat type, etc., and *a* and ***b*** are the model parameters. In this paper, we did not include fish length because it is not our interest and we do not have the data for most species. We exploited water depth and habitat types for some species, but opted not to report it because our interest is the overall gear efficiency for each species and because the result from eqn 5 would not be applied to other locations where only catch data are available.

Equations (3) and (4) indicate that Q_k and a_k are negatively correlated within a reasonable spatial range, as observed catch C_{ijk} is fixed. Assuming a larger a_k will result in a relatively smaller Q_k. Because in aquatic environments the size of cells is often large, abundance available to be caught within a gear affected area may change even when repeated samples are taken during a short time period in the same cell. Hence, Equation (4) allows varying n_{ijk} at each sampling time *j*. If the catch is relatively large, after each time step *j* (which is generally short within a fishing season) the number of fish in each cell is reduced due to catch removal:

$$N_{i,j+1} = N_{i,j} - \sum_k C_{ijk} \qquad \text{(eqn 6)}$$

Again, because our major focus was gear efficiency and not population dynamics, it was unnecessary to consider how population changes from month to month through birth and death. Instead, we directly estimated abundance N_i at each cell and each month and there was no assumption about the continuity of the population beyond a monthly time step.

In real fishery data, catch is recorded either as weight or counts, or both. Discrete statistical distributions, such as Poison and binomial, are typically applied to count data. If weight is used in the analysis, the unit chosen may have a dispersion issue which will affect the variance estimate but not the point estimate (Zhou et al. 2007b). For serious application, it may be worth correcting the dispersion parameter when weight is used (Zhou et al. 2007b). Alternatively, weight can be converted to numbers before modelling.

Simulation

Unlike many terrestrial studies where animals (e.g. birds) are observed at point locations, fishing operations stretch over a varying extent of water (gear-affected area). Practically, we divided a studied area into multiple cells with the same size and shape. Several scenarios regarding fish distribution pattern, movement, and catch process were tested. Two types of distributions were considered: random and aggregated. Further, the two types of distributions were applied at both between-cell level and within-cell level. We also considered two types of fish movements: no movement (fixed local abundance) and random movement within a cell between each sampling occasion. The catch process involved either a single fishing gear or two different gear types. We tested two removal processes: no reduction in abundance (similar to sampling-with-replacement) and reduction in abundance (sampling-without-replacement). In the former case, the abundance in each cell was assumed to remain the same after catch removal. This is the case when the catch in each shot is relatively small compared to the total abundance in the cell. In the latter case, the total number of fish in each cell was reduced by each capture.

In this paper, we only report scenarios involving aggregated distributions across cells, which is more common in fish and wildlife distribution. Parameter estimation for random distributions across cells is relatively simple and easy and we did not include the results in this paper. Because our main interest was gear efficiency and abundance at the time of fishing, we assumed no birth, natural mortality, immigration or emigration during the short monthly study period. The following three scenarios were included in the paper.

Scenario 1: Fish were assumed to follow an aggregated distribution across cells. In addition, fish were assumed to move randomly within each cell so the abundance at the sampling location (which is smaller than the cell size) varied at each sampling time for each gear type. The total abundance did not change with catch removal (sampling-with-replacement). One or two gear types were used and the number of samples per cell per gear were 1, 2, or 4.

Scenario 2: in addition to Scenario 1, fish were assumed to aggregate within each cell. This is what we consider more common in the real world when the cell is sufficiently large.

Scenario 3: in addition to Scenario 2, the total abundance declined with each catch removal (sampling-without-replacement).

Data generation: The studied area was divided into 100 cells with a mean abundance of 1000 fish per cell (Table 1). We used a negative binomial distribution and Poisson distribution with known parameters to generate both between-cell and within-cell abundance. In addition, the Poisson distribution was used to generate random movement within each cell so the local abundance at sampling site varied at each sample time for each gear type. There were two types of gears, gear A and gear B, with efficiency $Q_A = 0.3$ and $Q_B = 0.7$. In principle, this could also be two different vessels with the same gear type but different gear efficiencies. One or two gear types were used to catch the varying population in each cell. We assumed gear-affected area $a_k = 0.1\,A$ for both gear types (i.e., each shot swept 10% of the area). Each cell was sampled 1, 2, or 4 times by each of the two gears.

Application to Tiger Flathead

Tiger Flathead (*Neoplatycephalus richardsoni*) are caught in the Australian Southern and Eastern Scalefish and Shark Fishery (SESSF). We used fishery logbook data from 2000 to 2012. Since our main interest here was about average gear efficiency, to demonstrate the approach of using multiple gears (cross-sampling), we excluded some cells where catches were extremely variable within a monthly time scale. Three gear types overlap in some grids and have caught Tiger Flathead: longline, gillnet, and trawls. Another gear, Danish seine, is also used to catch Tiger Flathead. However, in our data there is no grid where Danish seine overlaps with any other gear types. For the purpose of demonstrating the cross-sampling method, we opted to exclude this gear type in the analysis. The spatial grid has a 1 degree latitude by 1 degree longitude resolution and the time step is a month. We included a total of 218 unique spatial-temporal grid-month cells and 699 data points in the analysis. Out of these grid-month cells, 31 have more than one gear types. The number of samples (shots) used in for the analysis were 176, 451, and 72 taken by longline, gillnet, and trawl, respectively. The mean catch per shot is 8.5 with a variance of 264.8, i.e., a variance to mean ratio of 31.2.

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

Longline and gillnet: $a = wL$

Trawl: $a = 0.7Lh$

where a is the gear-affected area (swept area), L is the length of longline, gillnet, or trawling length in km, w is the width in km along the length of the gear within that range fish can be affected (i.e., width of the swept area for trawl), h is the headrope length, and 0.7 is the spread factor when the trawl is towed under the water (Milton et al. 2007; Pezzuto et al. 2008). For longline and gillnet, it is difficult to define the range of the gear (i.e., $0.5w$) within which a fish may be likely to be caught. Based on the literature (see Discussion), we assumed that the gear-affected area was w = 1 km for these gears.

Parameter estimation

Fish distribution was modelled at between-cell and within-cell levels. Hence, the models involved two layers. In this paper we report the following model combinations:

NB-OM: a negative binomial function (eqn 1) for between-cell distribution but no model (omitted) for within-cell variation;

NB-PS: a negative binomial function for between-cell distribution and a Poisson function for within-cell distribution;

PS-PS: a Poisson function for both between- and within-cell distributions.

Fish distribution and catch processes were modelled using a Bayesian framework. Because NB parameter *p* and gear efficiency *Q* can only take values between 0 and 1, a non-informative beta function Beta(1,1) was used as a prior distribution, which is a flat line between 0 and 1. For the NB shape parameter which is positive, we assume a log-normal prior distribution, i.e., $f(r) \sim \log-normal(mean = 0, SD = 10)$. Similarly, $f(\mu) \sim \log-normal(mean = 1, SD = 10)$ was used for the Poisson mean prior.

WinBUGS software was used to estimate parameters in the high dimensional models. For both simulation and application to real fish data, we ran three Markov Chain Monte Carlo (MCMC) simulations with varying initial values. Convergence was assessed by visual examination of chain trajectories and by the Gelman-Rubin statistic Rhat. MCMC was allowed to continue for sufficient iterations after convergence before an additional 30,000 iterations were kept for parameter inferences. The joint posteriors were evaluated by relative error (RE, or mean relative error MRE when there are multiple parameters such as predicted catch) and mean absolute relative error (MARE):

$$RE_{\theta} = \frac{\hat{\theta}_{Post} - \theta_{True}}{\theta_{True}},$$

where θ is either median *Q*, μ, or *r*. For abundance N_i in each cell,

$$MARE_N = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{N}_{i,Post} - N_{i,True}}{N_{i,True}}\right|$$

where *n* is the number of cells. A similar formula was used for evaluating predicted catch for the real Tiger Flathead data because true parameters regarding *Q*, μ, *r*, and fish density are unknown.

12.4 Results

Simulations

The data generation process produced a “true abundance” in each of the 100 cells. The mean number of fish was 938 (ranging from 42 to 2,694), and the variance was 389,628. The shape parameter *r* was 2.26. Hence, the population was over-dispersed with a variance to mean ratio of 415.

Scenario 1: We focused on the NB-OM model in this scenario because an aggregated distribution occurs between-cells but not within-cell. In all cases, using two gears results in smaller biases than using a single gear. With only one sample per gear per cell, bias can be very high, particularly when only one low efficiency gear is used (e.g., Q_A = 0.3). Bias in parameters *Q*, μ, and N_i decreases as the number of sample increases (Table 2). Low bias can be achieved with as few as 2 samples per gear and per cell per time step (e.g., RE[Q] = 0.03 and ER[μ] = 0.04). Sample size has little effect on the bias of the shape parameter, which is typically underestimated by 10% (population is more aggregated than the true pattern). Correlation between the two primary parameters of interest, Q and μ, is moderately low (between 0.11 and 0.37). The model not only has the capability of estimating mean population size μ but can also estimate abundance in each cell (Figure 1). However, using one gear with low efficiency may result in large bias.

We also tested NB-PS and PS-PS models in this scenario (see the bottom of Table 2). Including a Poisson function for within-cell distribution does not improve the results. In fact, it produces slightly higher biases in RE[Q] and ER[μ]. For the PS-PS model, the three MCMC chains did not mix well even after one million iterations. What is more problematic is that the Q values continue to decline to close to zero. However, a Poisson model can produce accurate results when the between-cell distribution is assumed to be random (result not included).

Many studies have attempted to calibrate gear efficiency by estimating the ratio between two gear types. Our study shows an interesting result: the posterior Q_B/Q_A ratio is very stable and accurate across all models when both gears are used. This high accuracy is true even for the PS-PS model (the numbers in Table 2 were rounded to 0.01) and the NB-OM models where individual Q is extremely biased.

Scenario 2: This is a difficult situation where fish are assumed to have an aggregated distribution pattern both between and within cells and are allowed to move randomly between each sampling. The NB-PS model is used in this case to allow extra flexibility of capturing variation within cells. Again, in all cases, using two gears results in smaller biases than using a single gear, especially when that gear has a low efficiency (gear A). Although bias decreases as sample size increases, it appears that 4 samples per gear per cell are required to achieve a good accuracy in Q, μ, and N_i (Table 3, Figure 2). Again, the ratio between Q_B/Q_A is accurate even when other parameters are very biased. Using only one gear may result in large bias in Q, μ, and N_i when the efficiency is low (i.e., gear A). The NB-OM model performs poorly in this case, resulting in very large biases in Q, μ, and N_i (bottom of Table 3).

Scenario 3: Recall that this scenario assumes that the cell size is relatively small so catch removal reduces the total abundance within each cell. The NB-PS model produces lower biases than in Scenario 2 (Table 4, Figure 3). Removing fish at each sampling may provide additional contrast in the catch data. With 4 samples per gear, the posterior Q, μ, and N_i can be highly accurate. The simplified NB-OM model also yields realistic results, although not as good as the NB-PS model (Table 4 bottom).

Application to Tiger Flathead

We tested a number of models, including NB-PS, NB-OM, PS-PS, with multi-gear data or single-gear data. Models using multiple gears converged quickly (often less than 3000 iterations) and there was no abnormal behaviour of the MCMC (estimation) process.

The NB-PS model fitted to multi-gear catch data quite well (Figure 4). The NB-OM model over- or under-predicted many catches. Visually, the PS-PS model also predicted the catch well. However, mean relative error MRE[C] and mean absolute relative error MARE[C] in catch increase from the NB-PS model to the PS-PS one: 0.08 and 0.38 for NB-PS, 0.12 and 0.46 for NB-OM, and 0.31 and 0.59 for PS-PS, respectively. The positive MRE[C] indicates that all models tend to over-predict the catch. Clearly, among the three models, PS-PS has the highest bias. More problematically, the posterior density from the PS-PS model shrunk toward the middle of the range (Figure 5), in contrast to the heavily skewed catch distribution (Figure 4). This was expected and also observed in simulated data (not shown). Because the Poisson distribution cannot account for over-dispersion, it over-estimates low true values and under-estimates high true values.

All three models showed that significant differences in gear efficiency Q exist among gear types (Table 5). Trawl was the most effective gear, while gillnet was the least effective. The low values for longline and gillnet may reflect the large gear-affected area assumed in calculating catch per swept area and possible low efficiency of using bait to attract Tiger Flathead. The posterior of the scale parameter r was about 2, indicating the distribution of Flathead between grid cells was highly aggregated.

Single gear catch data resulted in unrealistic estimates, particularly for the parameters of most interest: Q and μ (Table 5). This further supports the simulation results on the advantage of the cross-sampling approach using multiple gears.

12.5 Discussion

We extended the class of abundance and detectability models (N-mixture models) to fishery data by simultaneously modelling between-cell and within-cell distributions of an aggregated population. Through simulations and real fishery data, we compared alternative models using single or multiple fishing gears to sample the population. The results show that it is possible to estimate gear efficiency and fish abundance using fishery-dependent catch data where distribution can be highly patchy and local abundance can change from sampling to sampling (we also analysed other species using fishery-independent survey data but did not include in this paper to save space). When the population has an aggregated distribution between- and within-cells, a two layers model involving a negative binomial and a Poisson function can produce accurate estimates with sufficient sample sizes. More importantly, we demonstrated that a cross-sampling approach that uses multiple gears has an advantage over single gear and can yield lower biases in key parameters than single gear. Individual component of our approach, such as the use of a mixture of the Poisson (or negative binomial) distribution with a binomial catch process, and a Bayesian approach, are not new. It is the cross-sampling approach – using multiple gears to sample the same population, modelling the population at two levels (between- and within-cell), and analysing the data with a Bayesian approach – which provides the original element of this paper for estimating abundance and detectability for situations typical of aquatic environments.

Wildlife may exhibit various distribution patterns and the local population size may frequently change over time. There are extensive studies on randomly distributed populations with constant local population sizes (e.g., breeding birds), and statistical methods have been developed to estimate both abundance and detectability (MacKenzie and Kendall 2002; Royle et al. 2005; Martin et al. 2011; Wenger and Freeman 2008). Similar studies in fisheries generally focus on gear research in relatively small areas or surveys using two types of gears together to compare their relative efficiencies (Trenkel and Skaug 2005; Gardner et al. 2010; Cadigan and Bataineh 2012; Miller 2013). Data collected from carefully designed surveys may have a lower variability than fishery-dependent data. However, random distribution patterns are the exception for most groups of animals, while aggregated distributions are typical. In the aquatic environment, aggregated distributions may result from habitat variations and animal behaviour. Further, individuals in the population frequently migrate and disperse. As such, local abundance at sampling sites may change even within relatively short time frames. It is difficult to sample and estimate population size for such an elusive population with an aggregated spatial distribution and varying local abundance. The difficulty has been observed in species we analysed, including Tiger Flathead in this paper.

By contrast, when more than one gear type with different fishing efficiencies was used, the cross-sampling method performed rather well. The power of the cross-sampling method benefits from a combination of applying two or more contrasting gears, parametric statistical models (i.e., the negative binomial distribution for across-cell abundance, the Poisson distribution for within-cell abundance, and the binomial distribution to represent the catch process), combined with a Bayesian approach. Contrasting catch patterns from multiple gear types may provide the key in separating the confounding parameters. A similar effect was found in estimating parameters for aggregated elusive populations using detection and non-detection data (Zhou and Griffiths 2007a).

A more complicated situation than the Scenarios we examined is when scientific surveys or fishing operations take place in locations not occupied by a species. This situation results in more zero catch events than are modelled by the Poison or negative binomial distributions (Equations 1 and 2). When zero catch data are collected, it is logical to use zero-inflated distribution models, such as the zero-inflated Poisson (ZIP) or the zero-inflated negative binomial distribution (ZINB). We also conducted simulations using ZIP and ZINB and achieved similar results. However, we opted not to include this scenario as the main purpose of this paper is to introduce the cross-sampling method.

We presented empirical results for Tiger Flathead captured by three gear types. There is no reference for direct comparison of gear efficiency for this species, as this is a difficult parameter to estimate and is traditionally obtained from field experiments. Estimated trawl efficiency varies greatly among different studies and species. For example, Hoffman et al. (2009) used hydro-acoustic and trawl data to estimate the catch efficiency of a demersal trawl catching Atlantic croakers *Micropogonias undulatus* and White perch *Morone Americana*. They found that the gear efficiency estimates ranged from 0.18 to 1.26 for Atlantic croakers and from 0.11 to 0.60 for white perch. Doray et al. (2010) used the ratio of trawl catches and acoustic densities to estimate gear efficiency for hake and other species, and derived very low *Qs* ranging from 0.022 to 0.18. Trenkel and Skaug (2005) applied statistical models to estimate trawl efficiency for several groundfish species based on small-scale repetitive hauls. Their results vary between 0.05 and 0.42. Dickson (1993) compared trawl gear efficiency for catching cod (*Gadus morhua*) and haddock (*Melanogramrnus aeglefinus*) and found that gear efficiency typically ranged from 0.1 to 0.8 for different size groups. When no information is available for gear efficiency, it is often assumed that $Q = 1$ or $Q = 0.5$ (Pauly 1979; Somerton et al. 1999; Pope et al. 2000). Similarly, $Q = 0.33$, 0.67, and 1.0 has been used in assessment of bycatch species (Zhou etal. 2011a). We believe that the method described here provides more realistic estimates than the default assumptions. There is essentially no study on gear efficiency for other gear types, including longline and gillnet.

Defining gear-affected area can be a difficult issue for gears that do not physically sweep an area, e.g., using baits to attract fish. For these gear types, gear-affected area depends on various factors, including type of bait, soak time, physiological state of the fish (duration of food deprivation), current speed, fish swimming speed, body size, etc. (Løkkeborg et al. 1989, 1995). The active space where the odour concentration is present in super-threshold quantities shrinks with soak time. Within the first hour, the maximum length of the active space for sablefish is 925 m, in 2 h is 793 m, and in 6 h is 654 m (Løkkeborg et al. 1995). In a field study using baited gillnet, cod were observed to move directly towards the gear from distances up to 400 m (Kallayil et al. 2003). Near 90% of sablefish were hooked within 3 hours of soak time, which corresponds to the leading edge of the plume of about 800 m from the bait (Sigler 2000). In a baited video experiment, the greatest distance of fish attraction was 48-90 m for a 200 mm fish in a current velocity of 0.1- 0.2 m s^{-1} (Ellis and DeMartini 1995). If the current speed is about 0.2 m s^{-1}, 1 hour soaks of baits may have an effective range of attraction of about 480 m for fish of 200-300 mm length (Cappo et al. 2004). Based on these studies, for baited gears we assumed that the gear-affected area was $w = 1$ km from the gear. Within a reasonable range, the delineation of gear-affected area a is relatively robust in estimating fish density, because gear efficiency Q is a relative scaling parameter negatively correlated to the defined dimension of a so the effect is mitigated in density or biomass estimation as long as the same a is used in estimating Q and the total abundance. It would be very helpful to test sensitivity of gear-affected area in future studies.

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

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

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

One of the major applications of the method is to derive average gear efficiency for each gear type and each species. This method uses readily available commercial logbook data or observer data and historical surveys, which avoids costly field experimental approaches. We have not explored the effects of many factors that possibly influence gear efficiency, including fish size, fishing season and time, habitat, and other environmental conditions (Arreguin-Sanchez 1996). However, these variables can be incorporated into the model as covariates if data are available and inclusion is deemed appropriate.

Acknowledgements

We thank Geoff Hosack and Alistair Hobday for constructive comments and suggestions on the earlier versions of the paper. The project was jointly funded by the Fisheries Research and Development Corporation (FRDC Project 2010/044 and Project 2011/029) and CSIRO.

References

Archaux, F., Henry, P.Y. & Gimenez, O. (2012) When can we ignore the problems of imperfect detection in comparative studies? *Methods in Ecology and Evolution*, 3, 188–194.

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

Bailey, L.L., Hines, J.E., Nichols, J.D. & MacKenzie, D.I. (2007). Sampling design trade-offs in occupancy studies with imperfect detection: examples and software. *Ecological Applications*, 17, 281–290.

Bez, N., De Oliveira, E. & Duhamel, G. (2010). Repetitive fishing, local depletion, and fishing efficiencies in the Kerguelen Islands fisheries. *ICES Journal of Marines Science*, 63, 532-542.

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

Cadigan, N.G. & Dowden, J.J. (2010). Statistical inference about the relative efficiency of a new survey protocol, based on paired-tow survey calibration data. *Fishery Bulletin*, 108, 15-29.

Fletcher, W. J. (2005). The application of qualitative risk assessment methodology to prioritise issues for fisheries management. *ICES Journal of Marine Science,* 62, 1576–1587.

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

Conn, P.B. & Cooch, E.G. (2009) Multi-state capture–recapture analysis under imperfect state observation: an application to disease models. *Journal of Applied Ecology*, 46, 486–492.

Dail, D. & Madsen, L. (2011). Models for estimating abundance from repeated counts of an open metapopulation. *Biometrics*, 67, 577–587.

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

Doray, M., Mahévas, S. & Trenkel, V.M. (2010). Estimating gear efficiency in a combined acoustic and trawl survey, with reference to the spatial distribution of demersal fish. *ICES Journal of Marine Science*, 67: 668-676.

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

Gardner, B., Reppucci, J., Lucherini, M. & Royle, J.A. (2010). Spatially explicit inference for open populations: estimating demographic parameters from camera-trap studies. *Ecology*, 91, 3376–3383.

Hilborn, R. & Walters, C. J. (1992). 'Quantitative Fisheries Stock Assessment: Choice, Dynamics, and Uncertainty.' (Chapman & Hall: NewYork.)

Hoffman, J.C., Bonzek, C.F. & Latour, R.J. (2009). Estimation of bottom trawl catch efficiency for two demersal fishes, the Atlantic Croaker and White Perch, in Chesapeake Bay. *Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science*, 1, 255–269,

Joseph, L.N., Elkin, C., Martin, T.G. & Possingham, H.P. (2009). Modeling abundance using N-mixture models: the importance of considering ecological mechanisms. *Ecological Applications*, 19, 631–642.

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

Lloyd-Smith, J.O. (2007) Maximum likelihood estimation of the negative binomial dispersion parameter for highly overdispersed data, with applications to infectious diseases. PLoS ONE 2(2): e180. doi:10.1371/journal.pone.0000180.

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

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

MacKenzie, D.I. & Kendall, W.L. (2002). How should detection probability be incorporated into estimates of relative abundance? *Ecology*, 83, 2387–2393.

MacKenzie, D. I., Nichols, J.D., Lachman, G.B., Droege, S., Royle, J.A. & Langtimm, C.A. (2002). Estimating site occupancy rates when detection probabilities are less than one. Ecology 83: 22482255.

Martin, J., Royle, J.A., Mackenzie, D.I., Edwards, H.H., Kery, M. & Gardner, B. (2011). Accounting for non-independent detection when estimating abundance of organisms with a Bayesian approach. *Methods in Ecology and Evolution*, 2, 595–601.

Miller, T.J. (2013). A comparison of hierarchical models for relative catch efficiency based on paired-gear data for U.S. Northwest Atlantic fish stocks. *Canadian Journal of Fisheries and Aquatic Science*. 10.1139/cjfas-2013-0136.

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

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

Pelletier, D. (1998). Intercalibration of research survey vessels in fisheries: a review and an application. *Canadian Journal of Fisheries and Aquatic Science*, 55, 2672-2690.

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

Pollard, J.H. (1977). A handbook of numerical and statistical techniques with examples mainly from the life sciences. Cambridge University Press, Cambridge.

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

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

Royle, J.A. (2004). N-mixture models for estimating population size from spatially replicated counts. *Biometrics*, 60, 108–115.

Royle, J. A., Nichols, J. D. & Kery, M. (2005). Modeling occurrence and abundance of species when detection is imperfect. *Oikos*, 110, 353–359.

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

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

Trenkel, V.M. & Skaug, H.J. (2005). Disentangling the effects of trawl efficiency and population abundance on catch data using random effects models. *ICES Journal of Marine Science*, 62, 1543-1555.

Ver Hoef, J. M. & Boveng, P. L. (2007). Quasi-Poisson vs. negative binomial regression: how should we model overdispersed count data? *Ecology*, 88: 2766–2772.

Wenger, S.J. & Freeman, M.C. (2008). Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. *Ecology*, 89, 2953–2959.

Zhou, S. & Griffiths, S. (2007a). Estimating abundance from detection-nondetection data for randomly distributed or aggregated elusive populations. *Ecography*, 30, 537–549.

Zhou, S., Dichmont, C., Burridge, C.Y., Venables, W.N., Toscas, P.J. & Vance, D. (2007b). Is catchability density-dependent for schooling prawns? *Fisheries Research*, 85, 23–36.

Zhou, S., Smith, A.D.M. & Fuller, M. (2011a). Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. *Fisheries Research*, 112, 168–178.

Zhou, S., Punt, A.E., Deng, R. & Bishop, J. (2011b). Estimating multifleet catchability coefficients and natural mortality from fishery catch and effort data: comparison of Bayesian state–space and observation error models. *Canadian Journal of Fisheries and Aquatic Sciences*, 68, 1171–118.

Table 1. Summary of the simulation and modelling process for Scenarios 1 to 3 (S1, S2, S3). NB = negative binomial, OM = omitted, PS = Poisson, Bin = binomial, C = catch, a = gear-affected area, A = area size of a cell.

	Data generation	Modelling
Number of cells	100	100
Mean fish per cell	μ = 1000	$\hat{\mu} = \frac{r(1-\hat{p})}{\hat{p}}$
Distribution between cells	$N_i \sim \mathrm{NB}(1000,2)$	NB: $\hat{N}_i \sim \mathrm{NB}(\hat{p},\hat{r})$
Distribution within cell	S1: NA S2: $N_{ij} \sim NB(N_i, r=50)$ S3: $N_{ij} \sim NB(\mu = N_{ij-1} - C_{ij-1}, r=50)$	OM: NA PS: $\hat{N}_{ij} \sim Pois(\hat{N}_i)$ PS: $\hat{N}_{ij} \sim Pois(\hat{\mu} = \hat{N}_{ij-1} - C_{ij-1})$
Gear type	2	2
Gear efficiency	0.3, 0.7	$\hat{Q}_A$, $\hat{Q}_B$
Samples per gear per cell	1,2,4	1,2,4
Catch process	$C_{ijk} \sim Bin[Q_k, n_{ijk} = Pois(N_{ij})a_k / A]$	$C_{ijk} \sim Bin[\hat{Q}_k, \hat{n}_{ijk} = Pois(\hat{N}_{ij})a_k / A]$

Table 2. Posterior gear efficiency, bias in key parameters, and correlation between gear efficiency and mean abundance from Scenario 1. LCI and UCI are the lower and upper 95% CI. RE: relative error, MARE: mean absolute relative error. The true values are: Q_A = 0.30, Q_B = 0.71, μ = 938, and r = 2.26.

Model	Sample per gear	Gear number	Gear	Efficiency Q						RE[μ]	RE[r]	MARE[N]	Corr[Q,μ]
				Mean	SD	LCI	Median	UCI	RE[Q]				
NB-OM	1	1	A	0.90	0.02	0.85	0.90	0.93	1.95	-0.67	-0.13	0.66	-0.21
	1	1	B	0.93	0.01	0.90	0.93	0.96	0.31	-0.25	-0.09	0.24	-0.11
	1	2	A	0.39	0.01	0.37	0.39	0.41	0.29	-0.24	-0.10	0.24	-0.23
	1	2	B	0.92	0.02	0.87	0.93	0.96	0.30	-0.24	-0.10	0.24	-0.26
NB-OM	2	1	A	0.67	0.02	0.61	0.67	0.71	1.22	-0.55	-0.13	0.55	-0.34
	2	1	B	0.74	0.02	0.70	0.74	0.77	0.04	-0.05	-0.11	0.13	-0.32
	2	2	A	0.31	0.01	0.30	0.31	0.34	0.03	-0.04	-0.11	0.13	-0.31
	2	2	B	0.74	0.02	0.70	0.73	0.79	0.03	-0.04	-0.11	0.13	-0.33
NB-OM	4	1	A	0.52	0.02	0.49	0.52	0.57	0.73	-0.43	-0.14	0.42	-0.37
	4	1	B	0.70	0.01	0.68	0.70	0.73	-0.02	0.01	-0.10	0.13	-0.33
	4	2	A	0.30	0.01	0.29	0.30	0.32	<0.01	-0.01	-0.10	0.14	-0.22
	4	2	B	0.71	0.02	0.68	0.71	0.75	-0.01	-0.01	-0.10	0.14	-0.23
NB-PS	4	2	A	0.33	0.01	0.31	0.33	0.35	0.08	-0.09	-0.10	0.14	-0.24
	4	2	B	0.78	0.02	0.74	0.78	0.81	0.08	-0.09	-0.10	0.14	-0.25
PS-PS	4	2	A	0.01	<0.01	<0.01	0.01	0.01	-0.98	54.96		108.88	-0.97
	4	2	B	0.01	<0.01	0.01	0.01	0.01	-0.98	54.96		108.88	-0.97

Table 3. Posterior gear efficiency, bias in key parameters, and correlation between gear efficiency and mean abundance from Scenario 2.

Model	Sample per gear	Gear number	Gear	Efficiency Q Mean	SD	LCI	Median	UCI	RE[Q]	RE[μ]	RE[r]	MARE[N]	Corr[Q,μ]
NB-PS	1	1	A	0.87	0.03	0.81	0.88	0.92	1.92	2.40	-0.23	0.66	-0.30
	1	1	B	0.93	0.02	0.88	0.93	0.96	0.34	6.46	-0.15	0.27	-0.19
	1	2	A	0.38	0.01	0.35	0.38	0.40	0.25	-0.21	-0.14	0.23	-0.29
	1	2	B	0.88	0.03	0.83	0.88	0.93	0.25	-0.21	-0.14	0.23	-0.31
NB-PS	2	1	A	0.53	0.03	0.48	0.53	0.58	0.76	-0.51	-0.16	0.50	-0.45
	2	1	B	0.47	0.02	0.45	0.47	0.51	-0.33	0.29	-0.12	0.31	-0.43
	2	2	A	0.24	0.01	0.22	0.24	0.26	-0.21	-0.20	-0.09	0.21	-0.50
	2	2	B	0.55	0.03	0.50	0.54	0.59	-0.22	-0.20	-0.09	0.21	-0.52
NB-PS	4	1	A	0.82	0.02	0.77	0.82	0.86	1.73	-0.67	0.00	0.66	-0.31
	4	1	B	0.88	0.02	0.85	0.88	0.91	0.26	-0.28	-0.04	0.27	-0.18
	4	2	A	0.29	0.01	0.27	0.29	0.31	-0.04	-0.05	-0.05	0.09	-0.38
	4	2	B	0.67	0.02	0.63	0.67	0.72	-0.04	-0.05	-0.05	0.09	-0.39
NB-OM	4	2	A	0.10	<0.01	0.10	0.10	0.10	-0.67	26.69	-0.09	1.80	-0.07
	4	2	B	0.23	<0.01	0.23	0.23	0.24	-0.67	26.69	-0.09	1.80	-0.08

Table 4. Posterior gear efficiency, bias in key parameters, and correlation between gear efficiency and mean abundance from Scenario 3.

Model	Sample per gear	Gear number	Gear	Efficiency Q Mean	SD	LCI	Median	UCI	RE[Q]	RE[μ]	RE[r]	MARE[N]	Corr[Q,μ]
NB-PS	1	1	A	0.89	0.02	0.84	0.89	0.93	1.98	-0.67	-0.15	0.67	-0.25
	1	1	B	0.94	0.01	0.91	0.94	0.96	0.35	-0.26	-0.07	0.25	-0.07
	1	2	A	0.39	0.01	0.37	0.39	0.41	0.31	-0.25	-0.07	0.24	-0.14
			B	0.93	0.02	0.89	0.93	0.96	0.33				-0.16
NB-PS	2	1	A	0.53	0.01	0.51	0.53	0.56	0.76	-0.41	-0.10	0.41	-0.19
	2	1	B	0.80	0.02	0.75	0.80	0.84	0.14	-0.12	-0.09	0.12	-0.23
	2	2	A	0.34	0.01	0.32	0.34	0.36	0.14	-0.12	-0.09	0.12	-0.21
			B	0.79	0.02	0.75	0.79	0.83	0.13				-0.22
NB-PS	4	1	A	0.36	0.02	0.33	0.36	0.39	0.20	-0.14	-0.10	0.15	-0.47
	4	1	B	0.71	0.02	0.68	0.71	0.74	0.01	-0.02	-0.09	0.03	-0.19
	4	2	A	0.30	0.01	0.29	0.30	0.31	<0.01	<0.01	-0.09	0.03	-0.12
			B	0.70	0.01	0.68	0.70	0.72	<0.01				-0.13
NB-OM	4	2	A	0.29	0.01	0.27	0.29	0.30	-0.04	0.04	-0.09	0.05	-0.19
			B	0.67	0.02	0.64	0.67	0.70	-0.04				-0.20

Table 5. Posterior gear efficiency, mean density, and negative binomial parameters *p* and *r* for six models fitted to Tiger Flathead catch data. The subscripts for gear type are: LL = longline, GN = gillnet, and TW = trawl.

Model	Param	Mean	SD	LCI	Median	UCI	Corr[Q,μ]
NB-PS	Q_{LL}	0.032	0.002	0.028	0.032	0.036	-0.45
3 gears	Q_{GN}	0.010	0.001	0.009	0.010	0.011	-0.51
	Q_{TW}	0.840	0.026	0.786	0.842	0.888	-0.25
	μ	63	4	55	62	72	
	r	2.0	0.2	1.6	2.0	2.5	
	p	0.032	0.004	0.025	0.032	0.039	
NB-OM	Q_{LL}	0.017	0.001	0.014	0.017	0.020	-0.63
3 gears	Q_{GN}	0.006	<0.001	0.005	0.006	0.006	-0.67
	Q_{TW}	0.505	0.020	0.463	0.506	0.542	-0.44
	μ	110	9	93	109	129	
	r	2.1	0.2	1.7	2.1	2.5	
	p	0.019	0.002	0.014	0.019	0.024	
PS-PS	Q_{LL}	0.014	0.001	0.012	0.014	0.015	-0.79
3 gears	Q_{GN}	0.005	<0.001	0.004	0.005	0.005	-0.76
	Q_{TW}	0.69	0.03	0.63	0.69	0.75	-0.77
	μ	141	7	128	141	154	
NB-PS	Q_{LL}	0.828	0.030	0.760	0.831	0.879	-0.61
Longline	μ	1.4	0.3	1.0	1.4	2.1	
	r	49.4	130.4	4.1	18.8	333.9	
	p	0.906	0.084	0.688	0.930	0.997	
NB-PS	Q_{GN}	0.564	0.022	0.518	0.565	0.606	-0.20
Gillnet	μ	0.7	0.1	0.6	0.7	0.9	
	r	217.0	733.1	9.1	45.1	1550.0	
	p	0.979	0.020	0.924	0.985	1.000	
NB-PS	Q_{TW}	0.345	0.043	0.272	0.339	0.433	-0.59
Trawl	μ	301	60	203	295	433	
	r	1.6	0.4	0.9	1.5	2.5	
	p	0.005	0.002	0.003	0.005	0.009	

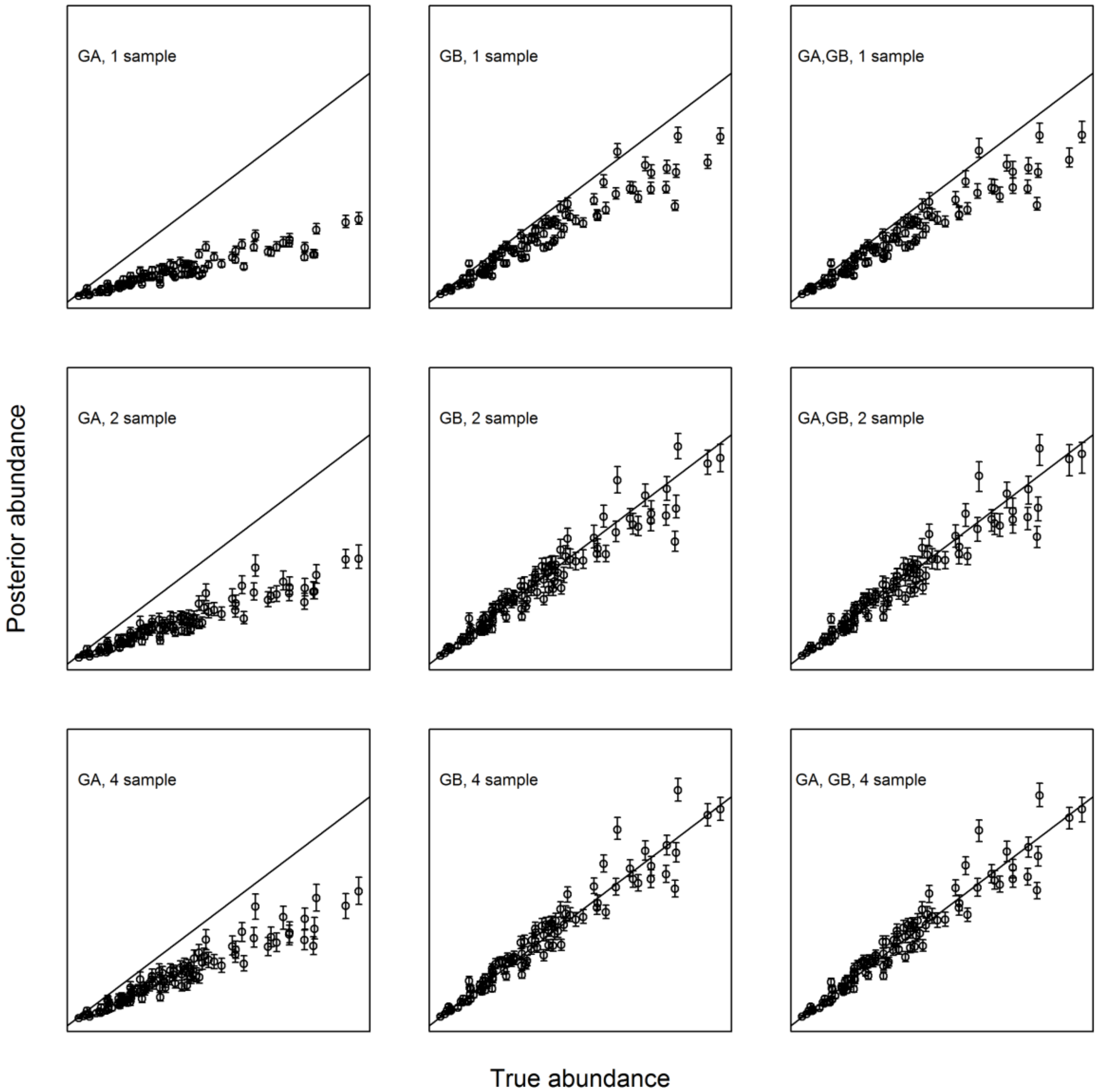

Figure 1. Posterior abundance (with 95% CI) and the true abundance in each cell from simulated Scenario 1. The straight line is where posterior abundance equals the true abundance. Fish are assumed to follow a negative binomial distribution between cells but not within cells. Random movement is assumed within each cell between each sampling. GA and GB are gear A and B, sampl is the number of samples per gear per grid.

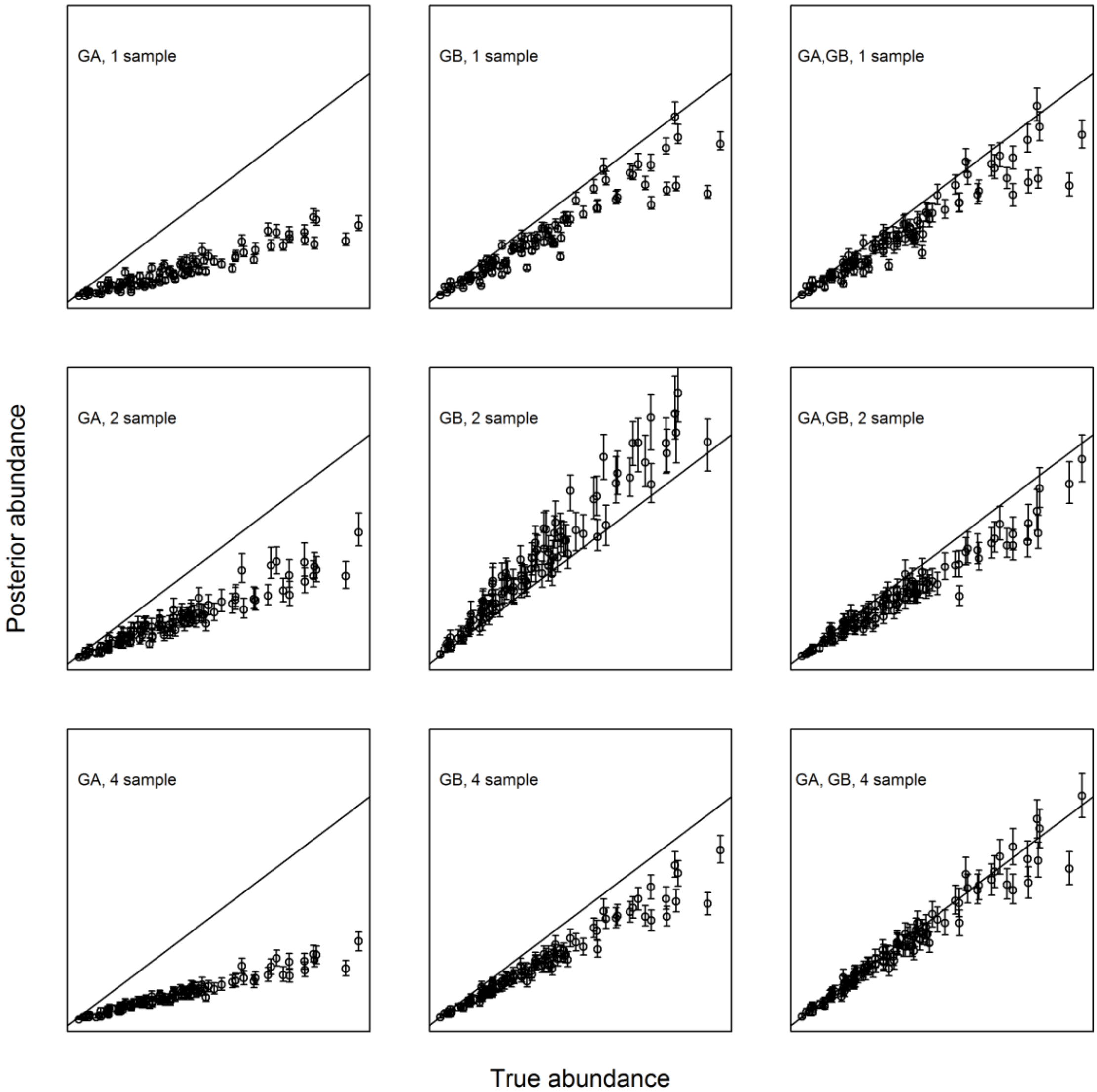

Figure 2. Posterior abundance (with 95% CI) and the true abundance in each cell from simulated Scenario 2. Fish are assumed to follow a negative binomial distribution both between and within cells. Further, random movement is assumed within each cell between each sampling. GA and GB are gear A and B, sampl is the number of samples per gear per grid.

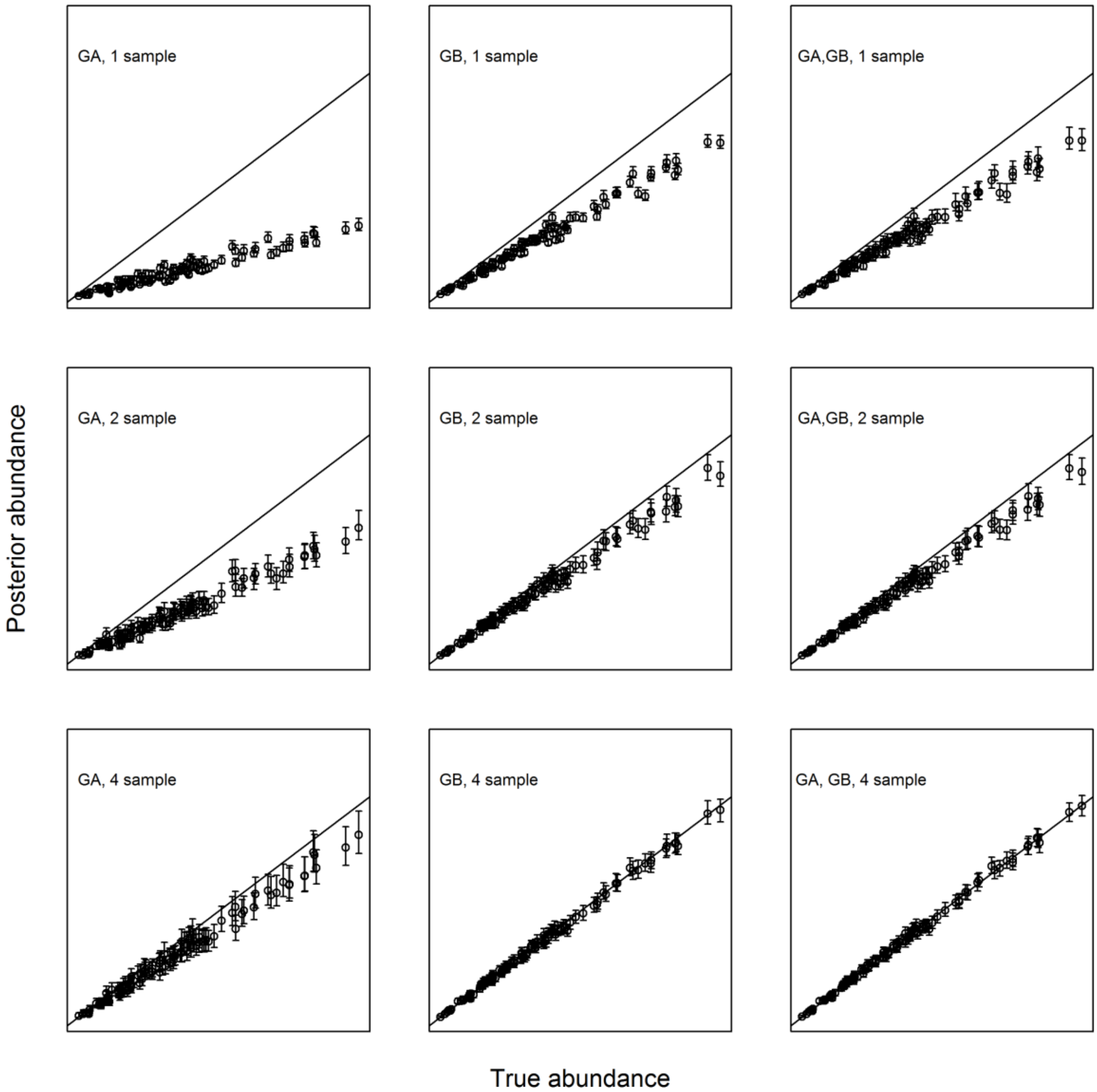

Figure 3. Posterior abundance (with 95% CI) and the true abundance in each cell from simulated Scenario 3. Fish are assumed to follow a negative binomial distribution both between- and within-cells. Further, random movement is assumed within each cell at each sampling and the total abundance declines by removal of each catch (sampling without replacement). GA and GB are gear A and B, sampl is the number of samples per gear per grid.

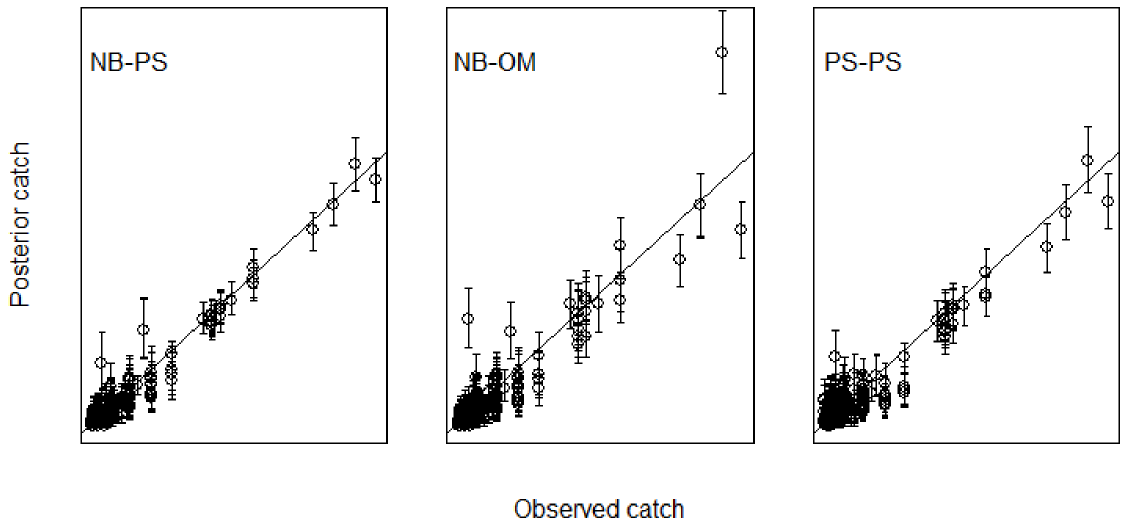

Figure 4. Comparing three models performance for Tiger Flathead catch data. The error bar is the 95%CI. NB-PS: negative binomial for modelling between-grid distribution and Poisson for modelling within-grid distribution; NB-OM: negative binomial for modelling between-grid distribution while within-grid distribution is not modelled (omitted); PS-PS: Poisson for modelling both between- and within-grid distributions. The straight line is where posterior catch equals observed catch.

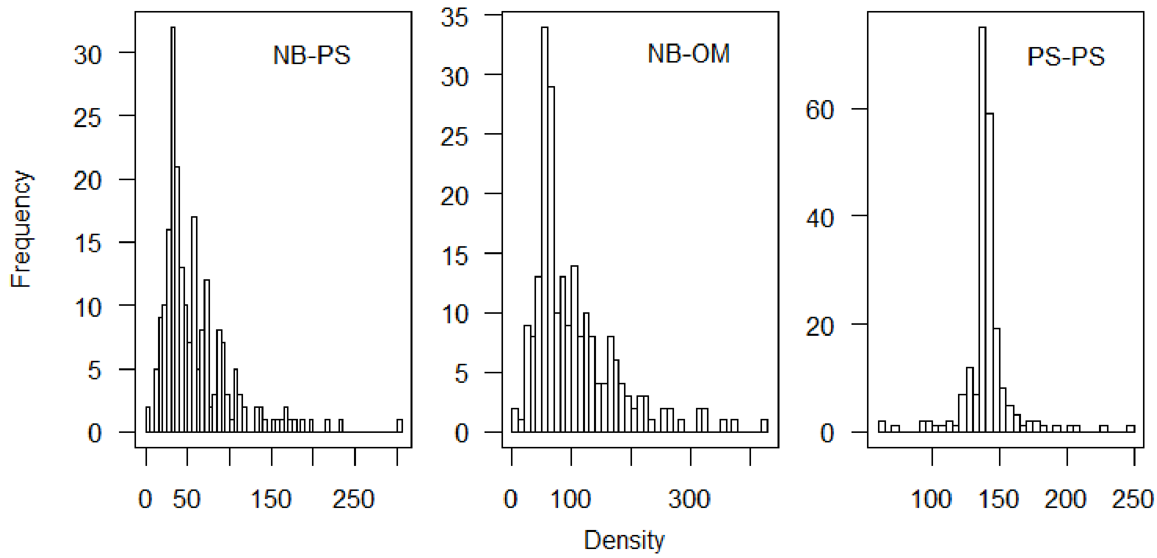

Figure 5. Frequency distribution of posterior Tiger Flathead density in 218 grids from three models. NB-PS: negative binomial for modelling between-grid distribution and Poisson for modelling within-grid distribution; NB-OM: negative binomial only for modelling between-grid distribution; PS-PS: Poisson for modelling both between- and within-grid distributions.

CONTACT US

t 1300 363 400
+61 3 9545 2176
e enquiries@csiro.au
w www.csiro.au

YOUR CSIRO

Australia is founding its future on science and innovation. Its national science agency, CSIRO, is a powerhouse of ideas, technologies and skills for building prosperity, growth, health and sustainability. It serves governments, industries, business and communities across the nation.

FOR FURTHER INFORMATION

Marine and Atmospheric Research
Shijie Zhou
t +61 7 3833 5968
e Shijie.zhou@csiro.au