Fisheries New Zealand

Tini a Tangaroa

Low Information Stock Status Assessment

New Zealand Fisheries Assessment Report 2020/05

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TABLE OF CONTENTS

EXECUTIVE SUMMARY **1**

1. INTRODUCTION **2**

2. SCOPE OF THE PROJECT **5**

3. INTEGRATED ASSESSMENTS **12**

3.1 Eastern tarakihi 12

3.2 Snapper SNA 7 (Tasman Bay/Golden Bay) 13

3.3 Elephant fish ELE 3 14

3.4 Red gurnard GUR 3 15

3.5 Giant stargazer STA 3 and STA 4 24

4. COMMERCIAL FISHERIES DATA PREPARATION **26**

4.1 Data extract 26

4.2 Dataset characteristics 29

5. LIKELIHOOD-BASED CLUSTERING OF COMMERCIAL FISHING DATA (FLEET CHARACTERISATION) **31**

5.1 Data 31

5.2 Data processing 33

5.3 Methods 35

5.3.1 Finite Mixture Models 35

5.3.2 EM Algorithm and Model Selection 36

5.3.3 Application 36

5.4 Results 37

5.4.1 Model selection 37

5.4.2 Primary Model and Resulting Clusters 39

5.5 Discussion of clustering 44

6. SURFACES OF FISH DENSITY **45**

6.1 Available survey data 45

6.2 Available covariate data 53

6.3 Density surface fitting 57

6.4 Biomass predictions within and outside survey areas 65

6.5 Biomass predictions in comparison to integrated assessments 70

7. ESTIMATING GEAR EFFICIENCY FROM CATCH DATA **79**

7.1 Statistical model structure 79

7.2 Applications to simulated and actual data 80

7.3 Current limitations and future enhancements 84

8. eSAFE **85**
8.1 The basic concept of SAFE 85
8.2 Estimating gear efficiency from catch data 86
8.3 Estimating relative density, biomass, catch and fishing mortality 87
8.4 Deriving biological reference points and comparing with estimated fishing mortality rate 89
8.5 New Zealand fisheries data and survey data 89
8.6 Results 89
8.6.1 Gear efficiency 89
8.6.2 Relative biomass, relative catch and fishing mortality 90
8.7 Discussion of eSAFE 102
9. OCOM **103**
9.1 Catch data and life-history parameters 103
9.2 Catch-only methods 105
9.3 Incorporating cpue data into OCOM 108
9.4 Results 109
9.5 Discussion of OCOM and OCOM with CPUE 129
10. COMPARISONS OF RESULTS FOR BIOMASS AND EXPLOITATION BETWEEN FULLY INTEGRATED ASSESSMENTS AND GAM FITS, ESAFE AND OCOM **130**
11. DISCUSSION **135**
11.1 Density surfaces 135
11.2 Moving from relative density surfaces to estimates of absolute abundance 136
11.3 Catchability 137
11.4 Reference points 139
11.5 Catch only methods 139
12. ACKNOWLEDGMENTS **140**
13. REFERENCES **140**
APPENDIX 1: INTEGRATED ASSESSMENT DATA TABLES **146**
APPENDIX 2: COMMERCIAL FISHERIES DATA: ESTIMATED CATCH AND ALLOCATED LANDINGS; KNOWN AND UNKNOWN SPECIES CODES **152**
APPENDIX 3: LIKELIHOOD-BASED CLUSTERING: ADDITIONAL FIGURES AND R-SCRIPT **166**
APPENDIX 4: AVAILABLE SURVEY DATA **170**
APPENDIX 5: GAM DENSITY SURFACE FITS: ADDITIONAL RESULTS **172**
APPENDIX 6: ESAFE: ADDITIONAL FIGURES **187**
APPENDIX 7: CATCH ONLY METHODS: ADDITIONAL TABLES AND FIGURES **190**

EXECUTIVE SUMMARY

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It is difficult to assess low information stocks using traditional stock assessment methods. In New Zealand waters, many low information inshore finfish stocks do not currently have an adequate assessment of stock status and it is not known if current catches are sustainable. The overall objective of this research was to develop and implement a low information stock status assessment model using/ spatially explicit catch, abundance, and harvest rate estimates for inshore finfish stocks.

GAMs (Generalized Additive Models) making use of New Zealand research trawl survey data and environmental covariates were used to determine the spatial extent of stocks, and their relative spatial density. Detailed catch data were extracted from the Fisheries New Zealand catch database. Method development used seven stocks, chosen to include a range of current information states (i.e., from very low information stocks with unknown status, to stocks with higher levels of information and relatively well estimated status). The primary method under investigation called for the species density surfaces to be scaled to absolute levels using coefficients of catchability. Other assessment methods investigated included a spatially explicit risk assessment model known as eSAFE (enhanced Sustainability Assessment for Fishing Effect), and a catch only method OCOM (Optimised Catch Only Method). Where possible results were also compared to those from integrated stock assessment models.

Density surfaces were constructed using a time series of trawl survey data. The biomass estimates from this method were within the range of the biomass estimates from the surveys, for all species except for giant stargazer in the East Coast South Island (ECSI) surveys and tarakihi in the East Coast North Island (ECNI) surveys. New Integrated stock assessments were completed for red gurnard and elephant fish. For those stocks that could be compared to an integrated stock assessment (elephant fish, red gurnard, snapper and tarakihi), biomass estimates were similar to the estimates of vulnerable biomass over an equivalent area.

Using all survey data combined, and using long term averages of environmental covariates, an average density surface could be produced. Reducing the number of survey years produced results that tracked survey relative biomass or assessment vulnerable biomass to a limited extent, but at the expense of a lack of robustness in results.

Final year biomass results and fishing mortality (F) as a ratio of the F that would give maximum sustainable yield (F_{MSY}) from eSAFE and OCOM showed varying levels of consistency with outcomes from the integrated assessments.

Methods to estimate gear efficiency were included as a part of the eSAFE approach, but this did not include estimation of the research survey gear efficiency. Insufficient progress was made in independently estimating the survey catchability, so surfaces of relative abundance could not be converted to surfaces of absolute abundance for comparison with area specific removals.

Ideas and recommendation for further development of the methods, and refinement of the estimates, are provided.

1. INTRODUCTION

It is difficult to assess low information stocks using traditional stock assessment methods. In New Zealand waters, many low information inshore finfish stocks do not currently have an adequate assessment of stock status and it is not known if current catches are sustainable.

Recent developments in spatially explicit risk assessment potentially allow for the evaluation of stock status assessments for low information stocks. Such methods might allow a more formal evaluation of the data, and the uncertainty in estimating the status of stocks, than qualitative or semi-quantitative assessments, and may be more suitable for situations where there is inadequate information for a conventional (integrated) stock assessment.

The overall objective of this research was to develop and implement a low information stock status assessment model using spatially explicit catch, abundance, and harvest rate estimates for inshore finfish stocks. The specific objectives were to:

1. Develop a low information stock status assessment model that estimates stock status from spatially explicit harvest rate estimates for inshore finfish species informed by research survey data, research observations, catch and effort data, and estimates of life history parameters.
2. Implement the model on selected inshore finfish stocks in the South Island of New Zealand to estimate spatially explicit estimates of catch, abundance, and harvest rate to estimate their stock status.
3. To evaluate the model and the resulting estimates for the selected low information finfish stocks in providing suitable scientific advice on their status.

From the beginning, it was envisaged that the project would require iterative development of spatially explicit tools and methods in order to develop an operational assessment method. In particular, under Objective 1, the project was tasked with delivering:

(a) Methods for estimating the spatial and temporal domain for the specific fish stocks, and population components (e.g., vulnerable biomass, spawning stock biomass).
(b) Methods for determining the species-specific catchability estimates (q) of research surveys, so that these can be applied to relative abundance estimates to determine spatially explicit absolute abundance.
(c) Methods to categorise fisheries groups that reflect common gear configurations and patterns of vessel or other fisher behaviour that may affect catch rates, including spatial and temporal considerations, in order to better inform (reduce bias in) stock distribution and catch estimates.
(d) Methods for determining spatially explicit catch (removal) estimates for the selected stocks for each fisheries group, including reported catch, and consideration of discards and other incidental mortality.
(e) Methods for determining species and stock specific utilisation and sustainability harvest rate targets and thresholds from life history characteristics that can be applied to the selected stocks.
(f) Methods for calculating the exploitation rate and stock status for each stock-fleet component, and overall, relative to thresholds and targets for the selected stocks, including explicit consideration of uncertainty bounds.
(g) Methods for reporting the stock status for the selected stocks once the calculations are complete.

Under Objective 2, the project was asked to deliver:

(a) An appropriate list of fish stocks for which status will be estimated. This will include a range of stocks of current information states (i.e., from very low information stocks with unknown status to stocks with higher levels of information and well estimated status) and will be determined in consultation with Fisheries New Zealand.
(b) Spatially explicit relative abundance estimates for the selected stocks, including explicit specification of the underlying assumptions and the associated uncertainty estimates.
(c) Estimates of research survey stock catchability estimates q, including uncertainly estimates.
(d) Categories of fisheries groups, and spatially explicit estimates of removals for each fisheries group.
(e) Estimates of stock-specific utilisation and sustainability harvest rate targets and thresholds.
(f) Estimates of stock status relative to the thresholds and targets.
(g) Stock status reports.

The different aspects of the project, from relative density estimation to estimates of stock utilisation relative to targets and thresholds, are referred to overall in this report as the 'LSP stock assessment approach' (after the project code number LSP2017-02).

For the LSP method to be of value it will need to be applicable to stocks that are genuinely data poor, not just higher information "best-case" stocks. However, for a new approach to be effectively evaluated, the stock selection needed to include some cases where good quantitative stock status information exists, against which the method could be compared. Section 3 summarises conventional, integrated stock assessments, two of which were developed under this project, the results of which could be contrasted with those of the LSP methods.

Determining the spatial extent of stocks, and their relative spatial density (objectives 1a and 2b), was central to the approach. Although new approaches to analysing such data continue to be made available, the project focused on the use of a relatively conventional and well-understood method, GAMs (Generalized Additive Models), analysing the New Zealand research survey data and environmental covariates. This work, including ground-truthing against survey estimates of relative biomass, and against the results from the available integrated assessments, is detailed in Section 6.

Much of the recent work on spatially explicit risk assessment and evaluation of stock status has been conducted by CSIRO, and the project included CSIRO in the project team. CSIRO had developed the eSAFE (enhanced Sustainability Assessment for Fishing Effect) method which, as the name suggests, built on the SAFE method originally developed for bycatch assessment. The enhancements in eSAFE include use of non-uniform fish stock density and estimates of species- and gear-specific catch efficiency. The method, described in Section 8, produced spatially explicit, stock-specific exploitation rates (Objectives 1e,f and 2d,e).

The eSAFE method relies on comparisons of spatially explicit catch rates across different fleets. The default, broad brush, fleet characterisation is based on gear type. However, to enhance eSAFE, or any alternative LSP approach, work to categorise fisheries groups using methods developed from mixture-based clustering with covariates was undertaken (objectives 1c and 2d). The outcomes of this work are summarised in Section 5.

The fleet clustering and LSP methods require high quality, spatially explicit catch and effort data. Details of the data preparation are provided in Section 4.

One alternative to the LSP and eSAFE spatially explicit approaches to data poor stocks are catch only methods. To enable a broader comparison of results, the OCOM (Optimised Catch Only Method) developed by CSIRO was also applied to the stocks. This research included methodological development of OCOM which is summarised, along with results, in Section 9.

The estimation of trawl survey catchability (q) was a central issue in applying the LSP stock assessment approach (objectives 1b and 2c). Catchability allows conversion from relative biomass to absolute biomass, and is composed of three elements: vulnerability, vertical availability, and areal availability (Francis 1989). It is possible to estimate gear efficiency (a combination of vulnerability and vertical availability) within the eSAFE approach by comparing the spatial catch rates across multiple gears, given the underlying spatial density distribution of species (estimated outside of eSAFE, using the GAMs). Section 7 also details the research performed on an improved analytical method to estimate the gear efficiency.

The final discussion (Section 11) considers future work that could refine methodological steps taken so far, or establish empirically based estimates of q for New Zealand stocks, as well as other lessons learnt of value to the LSP approach.

2. SCOPE OF THE PROJECT

Under Specific Objective 2, it was requested that the methods developed under Specific Objective 1 be applied to at least six inshore finfish stocks from the South Island of New Zealand. The focus was expected to be on stocks surveyed by the East Coast South Island (ECSI) or possibly West Coast South Island (WCSI) inshore trawl survey series (e.g., Beentjes et al. 2016, Stevenson & MacGibbon, 2018). A summary of stocks considered, including the decision on whether-or-not to include them in the project, and the reasoning behind that decision is given in Table 2.1. The stocks given priority were ELE 3 (elephant fish), GUR 3 (red gurnard), RSK 3 (rough skate), SNA 7 (snapper), SPE 3 (sea perch), STA-GIZ 3 (giant stargazer) and TAR-NMP 1-3 (tarakihi). A significant factor in the selection of these seven stocks was the availability (or potential availability) of a fully quantitative assessment for comparison against the LSP method. One stock was given secondary priority, RCO 3 (red cod). Those rejected (for this phase) were BAR 1 (barracouta), BCO 3 (blue cod) and SPD 3 (spiny dogfish). Figure 2.1 shows the fisheries management areas of the species chosen, highlighting those of the stock being considered.

Table 2.1: Stocks considered for inclusion in the project. ELE 3: Elephant fish (*Callorhinchus milii*) in FMAs 3&4; GUR 3: Red gurnard (*Chelidonichthys kumu*) in FMAs 3, 4, 5 & 6; RSK 3: Rough skate (*Zearaja nasuta*) in FMAs 3, 4, 5 & 6; SNA 7: Snapper (*Chrysophrys auratus*) in FMA 7; SPE 3: Sea perch (*Helicolenus barathri*) in FMA 3; STA 3: Giant stargazer (*Kathetostoma giganteum*) in FMA 3; TAR 1-3: Tarakihi (*Nemadactylus macropterus*) in FMAs 1, 2, 3 and 7(Eastern Cook Strait); RCO 3 (*Pseudophycis bachus*) in FMAs 3, 4, 5 & 6; BAR 1: Barracouta (*Thyrsites atun*) in FMAs 1, 2 & 3; BCO 3: Blue cod (*Parapercis colias*) in FMA 3; SPD 3: Spiny dogfish (*Squalus acanthias*) in FMA 3.

Stock	Status	Can be compared to integrated stock assessment?	Commentary	Challenges
ELE 3	Included	Earmarked for attempted integrated assessment during LSP project	Depth range within survey depth range Target species of ECSI survey (2 phase design to improve CVs) Not migratory and stays near seabed Survey biomass CVs reasonable (in most years) Management area ELE 3 covers both FMA3 and FMA4 but elephant fish considered virtually absent in FMA4 Bayesian surplus production model has been fitted previously	Biomass CV can be high Suspected productivity change in early 2000s Seasonal changes in distribution expected
GUR 3	Included	Earmarked for attempted integrated assessment during LSP project	Depth range within survey depth range. Not migratory; doesn't aggregate Stays near bottom Good survey biomass CVs and high % occurrence	May be some discarding of small fish

Stock	Status	Can be compared to integrated stock assessment?	Commentary	Challenges
RSK 3	Included	No	Stays near bottom Important to include a ray species	Mixed species commercial landings code used (SKA; may include some smooth skate also)
SNA 7	Included	Yes	None on ECSI (not enough to worry about). WCSI survey largely catches SNA in Tasman Bay and Golden Bay Depth range within survey depth range. New inshore stratum for SNA 7 recently added to WCSI survey Valuable species	Recreational catch approx. ½ commercial catch SNA 7 fish may migrate into SNA 8 management area Very low catchability to surveys has been estimated; suggested to be strong swimmers
SPE 3	Included	No	Stays near bottom Good survey biomass CVs and high % occurrence	Code includes more than one species, although species may separate by depth Can live beyond survey depth range (but most common within survey depth range); may have to model down to around 1000 m
STA 3	Included	Earmarked for attempted integrated assessment during LSP project	Believed not migratory Stays near bottom Good survey biomass CVs and high % occurrence There has been a preliminary stock assessment (STA 7, see Manning 2008a)	Can live beyond ECSI survey depth range, to around 600 m (but most common within survey depth range) Live weight catch data may be inaccurate as fish usually headed and gutted

Stock	Status	Can be compared to integrated stock assessment?	Commentary	Challenges
TAR (1-3)	Included	Yes	Reasonable survey biomass CVs and high % occurrence Depth range within survey depth range Distribution seems quite stable over time Often in top five species caught/landed	Big stock range and ECSI survey only catches younger ages Larger/older fish move out of the ECSI survey area
RCO 3	Reserve list	No (last assessment 1999)	One of the target species for the ECSI survey Important prey species for mega fauna In-season management currently being applied	Highly variable recruitment Survey sees the fish (i.e., a strong year class) after the commercial fleet Survey biomass CVs can be very large Seasonal migration inshore/offshore Some discarding of small fish suspected
BAR 1	Rejected	No	Depth range within survey depth range Good survey biomass CVs and very high % occurrence Video footage suggests poor endurance in front of trawls, so vulnerability could be high	Highly migratory, (fish tagged off South Island caught off North Island). The survey is at a time when adults are migrating so adult proportion in the survey area may be variable Schooling Uses whole water column (but acoustic data suggest most near bottom) Fishers may actively avoid BAR (low value)
BCO 3	Rejected	No		Poorly represented in trawl surveys (live in shallower waters on rough ground). Pot surveys have been preferred over trawl

Stock	Status	Can be compared to integrated stock assessment?	Commentary	Challenges
				Biomass CVs from trawl surveys can be very high, and % occurrence low
SPD 3	Rejected	No	Reasonable survey biomass CVs and very high % occurrence	Believed to be highly migratory/mobile Stock structure especially uncertain. Forms size and sex specific aggregations Found in mid water as well as near bottom Can live beyond survey depth range (but most common within survey depth range) Some wide-spread changes in abundance noted in the 1990s, although these could not be explained by year class strengths Annual catchability expected to vary considerably Legal and illegal discarding takes place

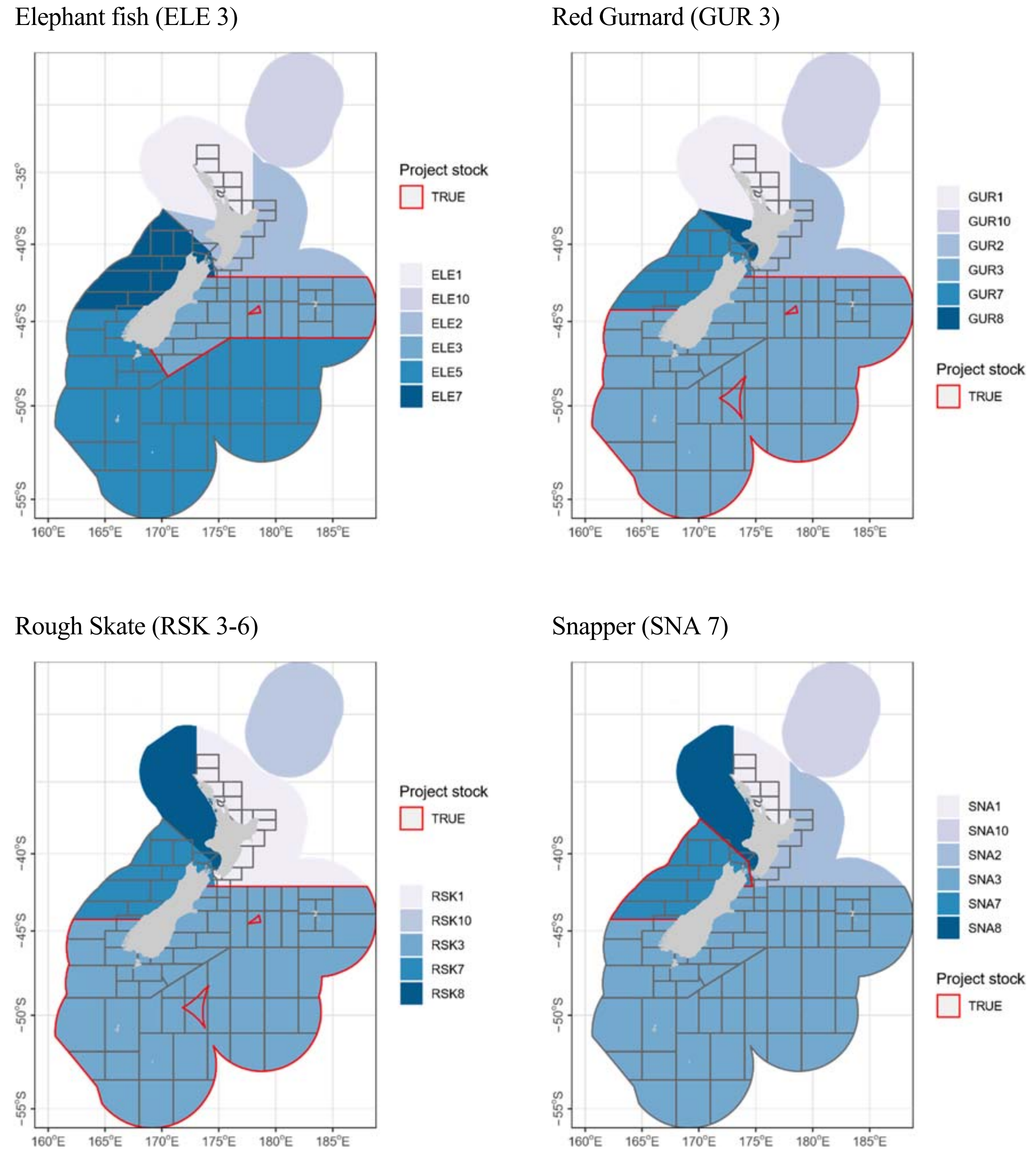
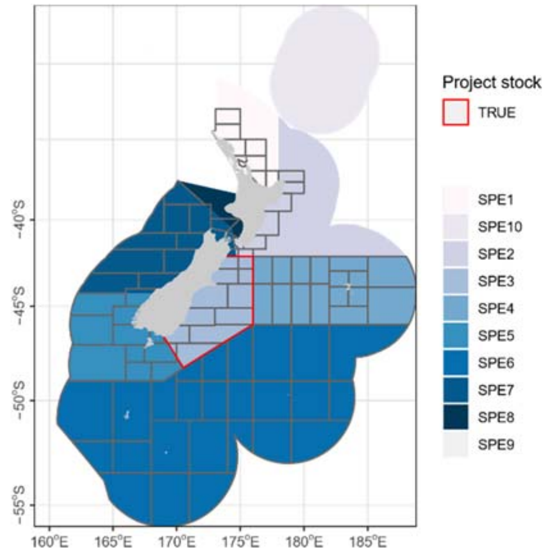
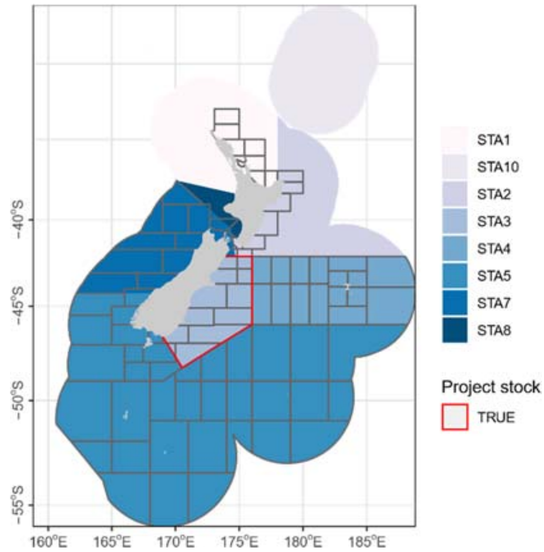


Figure 2.1: FMAs for species that have at least one stock included in the project (outlined in red).

Sea Perch (SPE 3)



Giant Stargazer (STA-GIZ 3)



Tarakihi (TAR-NMP 3)

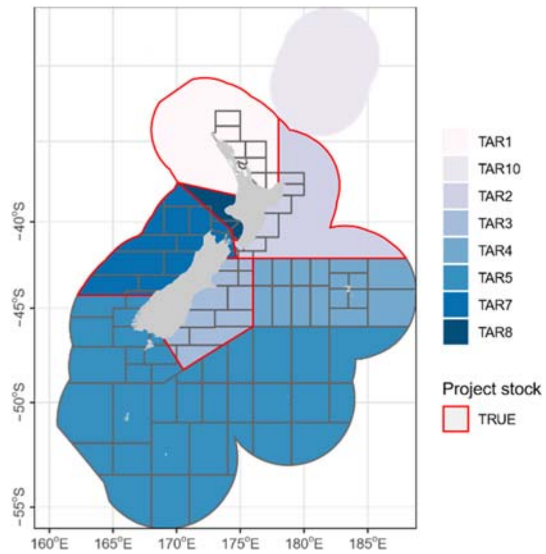


Figure 2.1 (cont): FMAs for species that have at least one stock included in the project (outlined in red).

3. INTEGRATED ASSESSMENTS

A key component of the evaluation of various LSP approaches is the comparison of the results with estimates of stock biomass, yields and current fishing mortality rates from other stock assessments. Although the true stock size and status remain unknown, integrated assessment were assumed to provide the best available estimates. Comprehensive stock assessments were available for a limited number of southern inshore finfish stocks, including snapper in SNA 7 (Langley 2018a) and eastern tarakihi (eastern TAR 1, TAR 2, TAR 3 and eastern TAR 7) (Langley 2018b and Langley 2019). Both stock assessments were conducted using a statistical age structured population model implemented in Stock Synthesis (Methot & Wetzel 2013).

The results of a preliminary stock assessment were also available for the main elephant fish (ELE 3) stock (Fisheries New Zealand 2018). The assessment was not adopted by the Inshore Fisheries Assessment Working Group as it was not considered sufficiently robust for the purpose of formulating management advice. Nonetheless, the results were consistent with the main sets of abundance indices incorporated in the assessment model, suggesting that the model may provide a general indication of the overall magnitude of the stock.

These three stock assessments each incorporated a time series of biomass estimates and length and/or age composition data from the southern inshore trawl surveys (ECSI and WCSI). Thus, the results are likely to provide a useful comparison with the results from other assessment approaches that utilise these trawl survey data. Hence, these three stocks were readily selected as candidates for applying the assessment methodologies proposed under the LSP project. During the initial planning phase, other potential candidate stocks were also selected based on the utility of the available trawl survey data. Several of those stocks were also identified as having sufficient data available to potentially develop a more comprehensive stock assessment model, specifically red gurnard in GUR 3 and giant stargazer (STA 3 and STA 4).

This section presents a brief summary of the relevant results from the stock assessments of eastern tarakihi, SNA 7 and ELE 3. A more detailed summary of the results from the preliminary stock assessment modelling for GUR 3 and giant stargazer is also presented.

3.1 Eastern tarakihi

The stock assessment of eastern tarakihi encompasses the coastal waters off the entire eastern coast of mainland New Zealand (Langley 2018b and Langley in prep). The Canterbury Bight/Pegasus Bay area is assumed to represent the main nursery ground for juvenile tarakihi. Fish tend to disperse northwards from the nursery area following the onset of sexual maturity at about 5 years of age.

The east coast South Island *RV Kaharoa* trawl survey monitors the abundance and age composition of tarakihi within the Canterbury Bight/Pegasus Bay area. The model does not explicitly represent the spatial structure of the population. Rather, the regional differences in the population age structure are accommodated in the assessment model through differences in the age-specific selectivity functions estimated for the individual (spatially defined) fisheries and the ECSI trawl survey. For the winter (and summer) ECSI trawl surveys, the model estimates full selectivity at 2–4 years of age and low selectivity for fish older than 5 years. Thus, a relatively small proportion of the total stock biomass is indexed by the trawl survey (vulnerable biomass) (see Table A1, Appendix 1). The assessment model estimates a catchability coefficient (q) of 0.172 for this component of the biomass (derived based on the swept area between the doors).

The assessment model is initiated in 1975 assuming an exploited, equilibrium age structure. The stock is estimated to be in a depleted state in 1975 which is consistent with the large reported catches during the preceding years. Equilibrium yield (at fishing mortality giving 40% virgin biomass, $F_{SB40\%}$) for the stock is estimated to be 4165 t (s.e. 88 t). The time-series of estimated annual biomass derived from the assessment model is presented in Table A1 (Appendix 1).

3.2 Snapper SNA 7 (Tasman Bay/Golden Bay)

Most of the SNA 7 catch is taken from Tasman Bay and Golden Bay during spring-summer (November-March). The fisheries developed from the late 1940s and large catches were taken during the 1960s and 1970s. Since the late 1980s, catches have been relatively low and constrained by the TACC. The stock assessment incorporates data from multiple sources. The most influential data are age composition data from commercial fisheries (from early and more recent periods), a biomass estimate from a 1987 tagging programme and a time-series of CPUE indices from 1989–2016. The assessment estimates that the stock was heavily depleted by the early 1980s and remained at a low level during the 1990s and 2000s. The stock biomass increased considerably from 2009 following the recruitment of an exceptionally large year class.

The *Kaharoa* west coast South Island trawl survey also encompasses the Tasman Bay/Golden Bay area. The survey occurs in March-April coinciding with the time that snapper disperse from the Tasman Bay/Golden Bay area. Snapper biomass estimates from the trawl survey were very low during the 1990s and 2000s. The trawl survey biomass estimates increased considerably from the early 2010s. For comparative purposes, the time series of biomass estimates was included in the model data sets but was not included in the model estimation procedure. The relative trend in survey biomass estimates is consistent with the trend in stock biomass, including the large increase in biomass from 2009. Age composition data from the recent trawl survey are also consistent with the age composition data from commercial fisheries and reveal the presence of another strong year class recruiting to the fisheries.

The stock assessment model estimates a catchability coefficient of 0.041 for the trawl survey biomass estimate (swept area between the doors). The relatively low catchability coefficient may be attributable to the timing of the trawl survey; a significant proportion of the snapper biomass may have dispersed from the trawl survey area at the time of the survey. The vulnerability of snapper to the research trawl gear may also be low due to the relatively short duration of the trawls.

The average equilibrium yield (at $F_{SB40\%}$) for SNA 7 is estimated to be 737 t (95% confidence interval 590–857). The time series of biomass estimates from the assessment model is presented in Table A2 (Appendix 1).

3.3 Elephant fish ELE 3

A preliminary stock assessment for ELE 3 was presented to the Southern Inshore Stock Assessment Working Group (SINSWG) in March-April 2016 (see Fisheries New Zealand 2018). The model incorporated the entire catch history from the fisheries (from 1930), including a considerable allowance for underreporting of the catch prior to the introduction of the QMS, and an assumed level of catch discarding throughout the history of the fisheries. The model included two sets of abundance indices: biomass estimates from the *Kaharoa* winter east coast South Island trawl survey (to 2014) and CPUE indices from the ECSI inshore trawl fishery. Both sets of indices indicate that abundance of elephant fish was considerably higher (approximately double) in the more recent period (2007–2014) compared to the early 1990s.

There are limited data available to characterise the length composition of the commercial catch of elephant fish and inform the model regarding the selectivity of the commercial fisheries (primarily trawl and set net). There is also considerable variability in the time-series of length composition data from the trawl survey. Biomass estimates from the trawl survey are also relatively imprecise due to the variable distribution of elephant fish within the survey area. More recent trawl surveys have been extended to include the shallower areas of Canterbury Bight and Pegasus Bay (10–30 m) with the intention of improving the utility of the survey for monitoring elephant fish abundance. However, the trawl survey biomass estimates from the expanded area are also highly variable and imprecise. The stock assessment modelling was also limited by the lack of robust estimates of the key biological parameters for elephant fish, particularly reliable estimates of growth and natural mortality.

The assessment model was only able to fit the increase in CPUE indices and trawl survey biomass through estimating variation in recruitment from 1990 onwards; recruitment was estimated to be considerably higher than the equilibrium level and fluctuated over a 5–7-year cycle. The model could provide a reasonable fit to the CPUE indices although the fit to the trawl survey biomass estimates was poor, reflecting the higher variability and relatively low precision of the biomass estimates. The limited length data available from the trawl survey were not consistent with the magnitude of the variation in estimated annual recruitments.

Given the uncertainties in the assessment model, there was concern regarding the reliability of the estimates of recent stock status. The SINSWG concluded that the "*preliminary model produced plausible biomass trajectories, but uncertainty about productivity and fits to commercial length data precluded acceptance of the model as a reliable estimator of current stock status*".

Despite these limitations, it appears that the assessment model may provide a reasonable estimate of the overall scale of the stock biomass (see Appendix 1, Table A3) which will be of some utility in the evaluation of the results from the range of LSP approaches applied to the stock. However, estimates of equilibrium yields are considered to be unreliable. The model estimates of the catchability coefficient for the trawl survey biomass estimates (based on swept area between doors) were low (0.035 or 0.055 depending on selectivity assumptions). The low catchability coefficients may partly reflect the areal availability of the species as for a large proportion of the survey time series the survey did not include the area less than 30 m in depth that accounts for a high proportion of the total elephant fish catch, especially during spring-summer.

3.4 Red gurnard GUR 3

For this study, a preliminary assessment model was developed for GUR 3. The model has yet to be reviewed by the SINSWG and, consequently, the results are not intended to be applied to provide estimates of current stock status for management purposes.

The model was implemented in Stock Synthesis (V3.30.12) and incorporated the entire catch history from 1931–2018 (where 2018 denotes the 2017–18 fishing year). Annual catches prior to 1983 were collated from Francis & Paul (2013)[1]. Unreported catches were assumed to represent an additional 20% of the annual reported catch for the period prior to the introduction of the QMS (1986–87) and 10% of the annual reported catch in subsequent years. Annual catches increased from the 1940s to reach a peak in the early 1960s and then tended to decline to a relatively low level in the 1980s (Figure 3.1). There was a general increase in catch since the late 2000s. Most of the red gurnard catch is taken by the inshore bottom trawl fishery and all catches were allocated to a single fishery within the model.

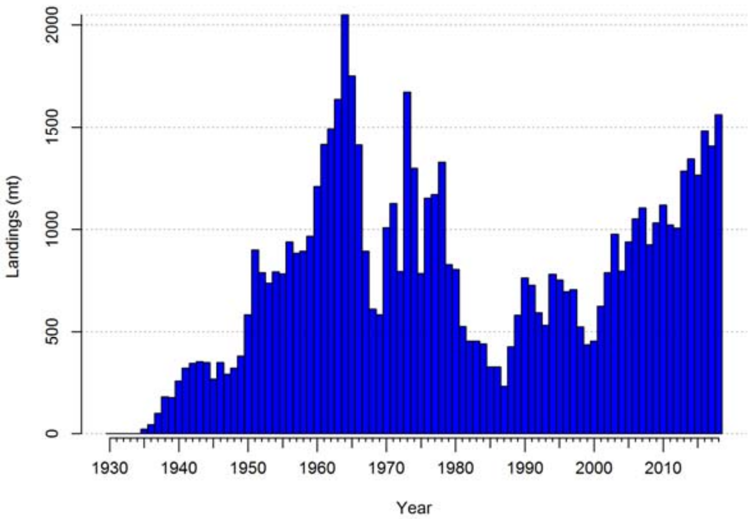


Figure 3.1: Annual catches included in the red gurnard (GUR 3) model.

The model partitioned the population by year, sex, and 10 age classes (1–9, 10+) included within a single region. Biological parameters incorporated in the model are presented in Table 3.1. Five sets of abundance indices were included in the stock assessment model (Table 3.2). Trawl CPUE indices were available from two discrete periods (Table 3.2). The *Kaharoa* winter trawl surveys were included as two separate series depending on the spatial extent of the survey; the entire series encompassed the 30–400 m depth range, while a subset of the surveys also included the shallower area of the Canterbury Bight and Pegasus Bay (10–400 m).

Length compositions for male and female red gurnard were available for each trawl survey, while age compositions were available for three 30–400 m winter trawl surveys (Table 3.2). In the model likelihood formulation, each length composition was assigned an Effective Sample Size (ESS) of 10 and the three age compositions were assigned an ESS of 20.

For each survey, a length-based selectivity function was parameterised using a double normal function, with the upper limb of the function constrained to achieve full selection of the largest length classes

[1] The same data are incorporated in Fisheries New Zealand plenary reports.

(approximating a logistic function). The parameters for the length at peak selectivity and the width of the ascending limb were estimated. Full selection was estimated at about 20 cm for the three sets of surveys, although the wider area winter 10–400 m survey selected smaller fish than the 30–400 m surveys (Figure 3.2).

No length or age composition data were available from the commercial fisheries. It is understood that red gurnard less than 25–30 cm have very limited commercial value and, hence, it is considered that small fish are unlikely to have been caught and/or landed in any significant quantities. On that basis, the commercial fisheries, and the corresponding sets of CPUE indices, were assumed to have a knife edge selectivity at a length of 30 cm.

Annual recruitments were derived from a Beverton-Holt spawner-recruitment relationship (SRR) with an assumed steepness of 0.85 (Table 3.1). Annual deviates from the SRR were estimated for the period for which abundance and composition data were available (1985–2016).

Table 3.1. Biological parameters for red gurnard included in the assessment model.

Parameter	**Initial value**	**Estimated**	**Reference**
M Female	0.29	No	Sutton 1997
M Male	0.35	No	Sutton 1997
Maturity OGIVE	0.5 at 2yr; 1.0 at 3–10 yr	No	Fisheries New Zealand 2018
Length-wt	a = 5.3e-06, b = 3.19	No	Stevenson 2000
Growth Female	*Lage1* = 19.4 k = 0.44 *Lmax* = 48.2	No	Sutton 1997
Growth Male	*Lage1* = 19.4 k = 0.49 *Lmax* = 42.2	No	Sutton 1997
CV length-at-age	0.1	No	
R0 (ln)	8 (Stdev 10)	Yes	
SRR Steepness	0.85	No	
SigmaR	0.6	No	
RecDev	1985–2016	Yes	

Table 3.2. Summary of abundance indices included in the GUR assessment model. The selectivity function associated with each index in the model is shown in Figure 3.2.

Index	Period	N obs	CV	Auxiliary data	Reference[1]	Selectivity function
CPUE_BT	1990–2014	25	0.30	-	Plenary 2018	BT
CPUE_BT_Old	1963-1973	11	0.40	-	Sullivan 1981	BT
TrawlSurvey_Winter30-400 m	1991-2018	12	0.25-0.35	Length comps	Plenary 2018	TS1
				Age comps (3)	Sutton (1997)	
TrawlSurvey_Winter10-400 m	2007-2018	5	0.15-0.27	Length comps	Plenary 2018	TS2
TrawlSurvey_Summer	1997-2001	5	0.13-0.34	Length comps	Plenary 2018	TS3

1: For 'Plenary 2018' see Fisheries New Zealand 2018

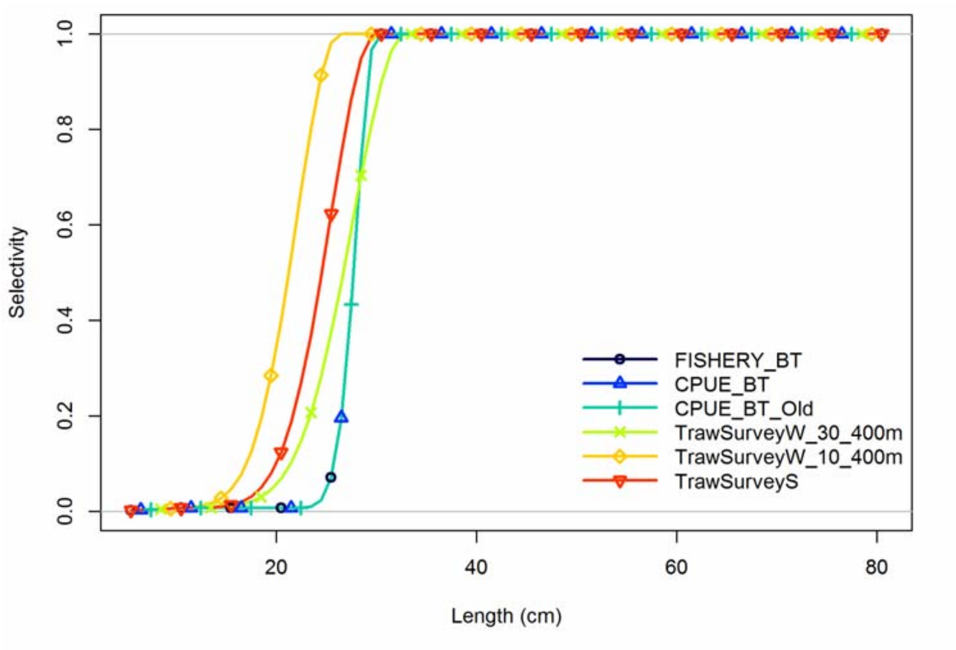


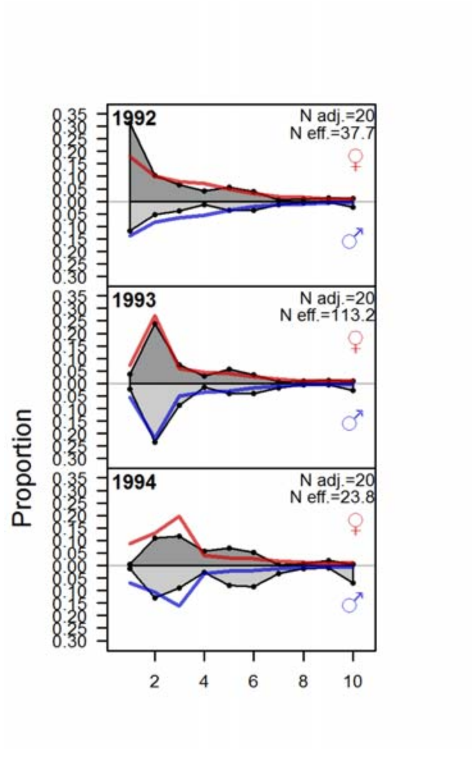
Figure 3.2: Length based selectivity functions for each trawl survey and the fisheries from the assessment model.

The assessment model provided a good fit to the three winter 30–400 m trawl survey age compositions (Figure 3.3). The model also approximated the structure of the length composition data from each survey series (Figure 3.4) although the fit to the individual length compositions was relatively poor. The model also underestimated the higher proportion of larger male fish observed in the deeper portion of the survey area (30–400 m). This bias is less evident from the trawl surveys that encompassed the broader depth range (10–400 m) (Figure 3.4).

The recent set of CPUE indices represent the most comprehensive series of relative abundance indices included in the model. The model provides a good fit to these data with the exception of the three most recent years (2012–2014) which are over-estimated (Figure 3.5). The poor fit in those years is likely to be attributable to a conflict with the recent winter 30–400 m trawl survey biomass estimates which indicate that the stock has increased to a greater extent since the early 1990s (compared to the CPUE indices) (Figure 3.6).

The other sets of abundance indices are less influential in the model as they span a relatively short time period. The model underestimates the general decline in five summer (30–400 m) trawl survey biomass estimates (Figure 3.7) as the decline is moderated by a lesser decline in the CPUE indices during the same period (late 1990s). There is limited contrast in the winter 10–400 m trawl survey biomass estimates (Figure 3.8). The model has limited flexibility to fit the early CPUE indices (1960s–early 1970s) (Figure 3.9) due to the assumption of equilibrium recruitment for the period prior to 1985 (Figure 3.10).

Since 2000, recruitment is estimated to have been considerably higher than during the 1980s and 1990s (Figure 3.10). Correspondingly, biomass is estimated to have increased during the early 2000s (Figure 3.11) consistent with the increase in the CPUE indices and trawl survey biomass estimates in the 2000s compared with the early 1990s.



Age (year)

Figure 3.3: Observed (grey polygons) and predicted (lines) female and male age compositions from three winter 30–400 m trawl surveys.

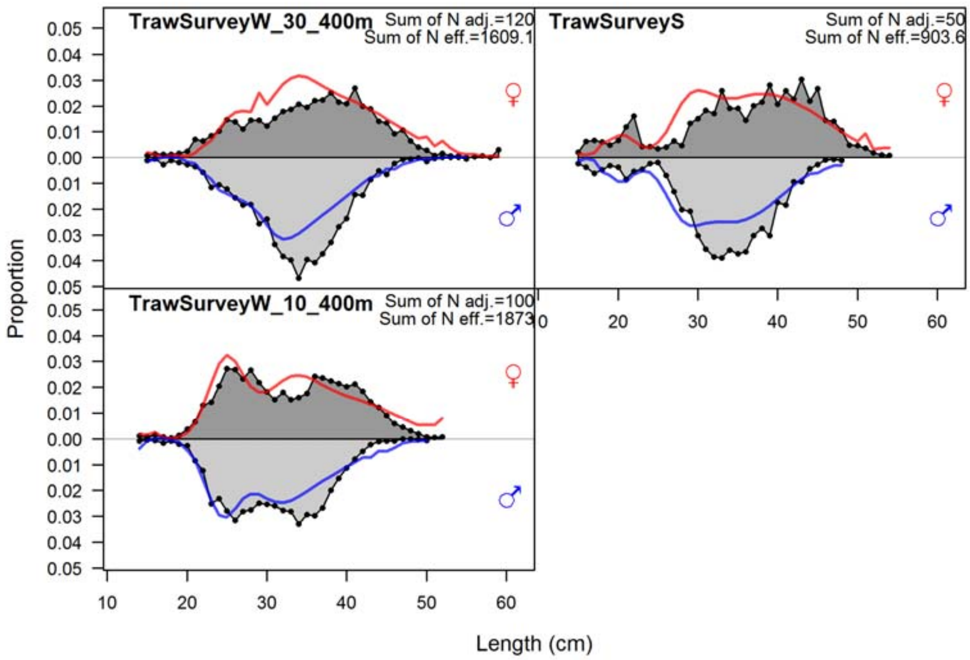


Figure 3.4: Aggregated observed (grey polygons) and predicted (lines) female and male length compositions from the three sets of trawl surveys included in the GUR 3 model.

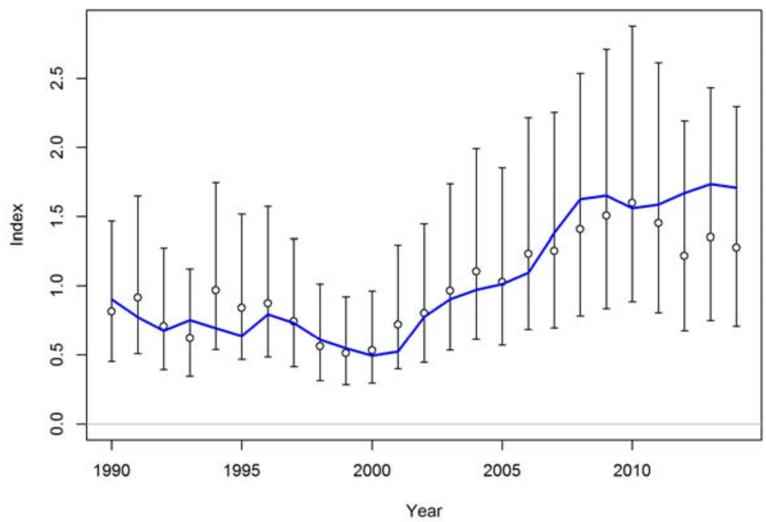


Figure 3.5: The fit to the recent series of CPUE indices (points and 95% confidence interval) from the GUR 3 assessment model.

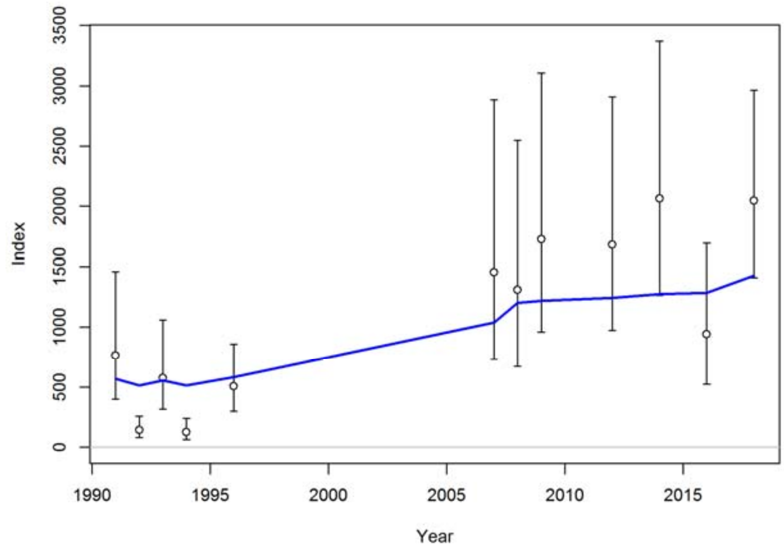


Figure 3.6: The fit to the winter 30–400 m trawl survey biomass estimates (points and 95% confidence interval) from the GUR 3 assessment model.

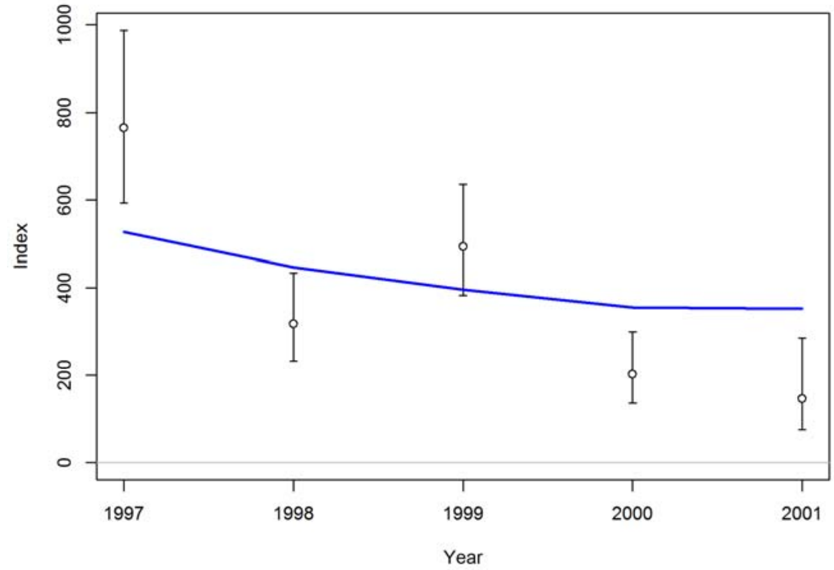


Figure 3.7: The fit to the summer 30–400 m trawl survey biomass estimates (points and 95% confidence interval) from the GUR 3 assessment model.

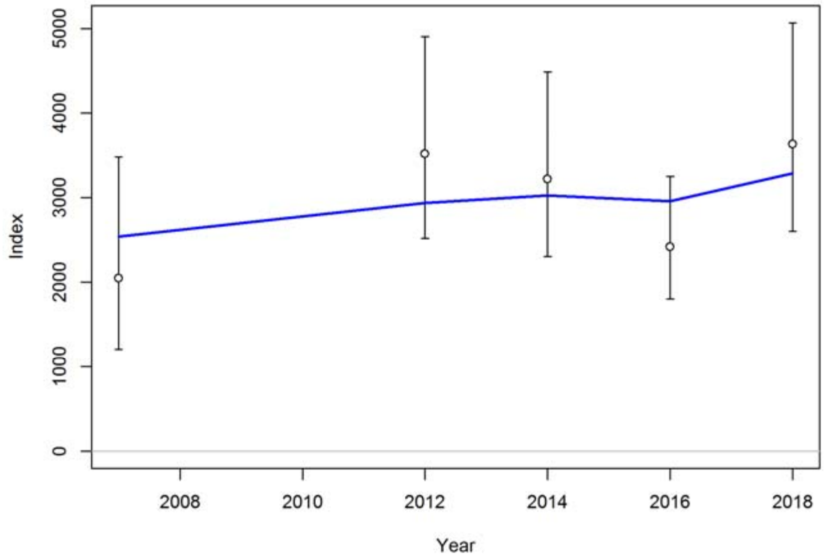


Figure 3.8: The fit to the winter 10–400 m trawl survey biomass estimates (points and 95% confidence interval) from the GUR 3 assessment model.

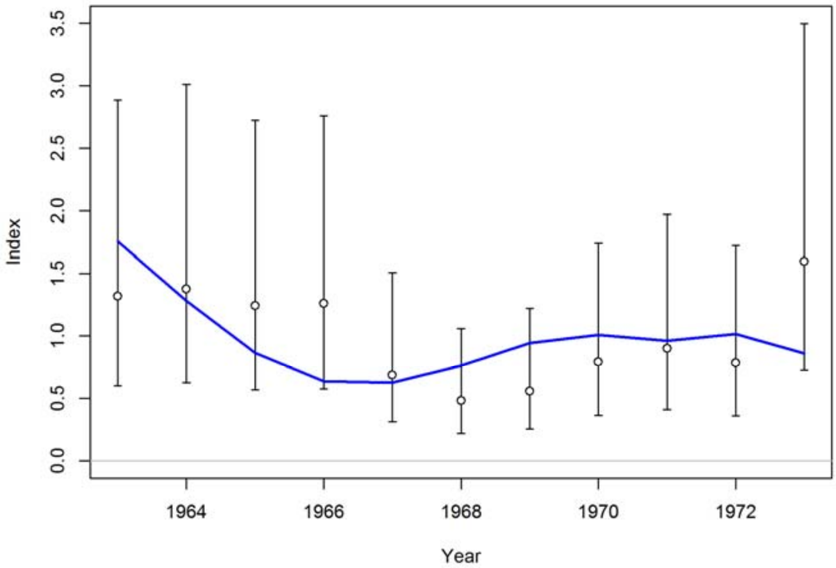


Figure 3.9: The fit to the early CPUE indices (points and 95% confidence interval) from the GUR 3 assessment model.

The assessment model estimated that the stock had been depleted to a very low level in the 1960s and 1970s. Large catches were taken during that period and, correspondingly, estimates of fishing mortality were exceptionally high (exceeding 1.0 in some years). During the earlier period of the model, the level of depletion is determined from the accumulated level of catch relative to the equilibrium levels of recruitment and yields. Depletion will be poorly estimated if historical catches are poorly determined and/or actual recruitments deviate considerably from equilibrium (average) levels. Both these factors are likely to have influenced the estimates of depletion during the earlier period of the model and, as such, the level of depletion in the 1960s may be overestimated. To address this issue, an alternative model was formulated that initiated the stock in 1980 and estimated the initial level of fishing mortality. The alternative model estimated a higher level of biomass in 1980 compared to the full catch history model (Figure 3.12) and estimated more plausible levels of fishing mortality at that time (F = 0.49 compared to 1.15). The biomass trajectories from the two models converged in the early 1990s, influenced by the differing trends in recruitment estimated during the late 1980s (see Appendix 1 Table A4).

Estimates of equilibrium yields (at $F_{SB40\%}$) are very similar for the full catch history model (938 t) and the model commencing in 1980 (934 t). Estimates of recent levels of fishing mortality are also very similar.

The model estimates three catchability coefficients for the trawl survey biomass estimates (based on swept area between doors): a relatively high coefficient (0.422) for the winter 10–400 m biomass estimates and lower coefficients for the 30–400 m winter (0.196) and summer (0.192) biomass estimates. The lower catchability coefficients for the 30–400 m biomass estimates is consistent with the areal availability of red gurnard to the respective surveys.

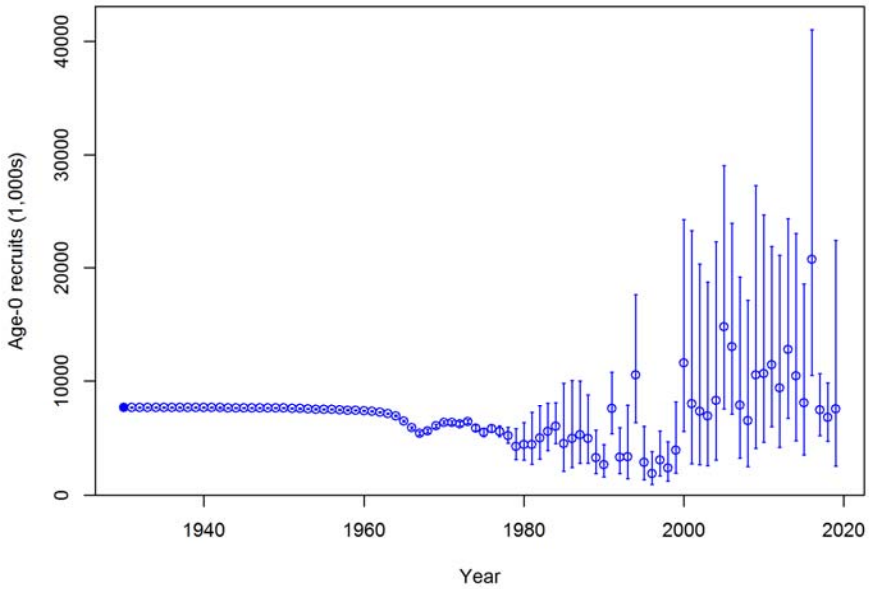


Figure 3.10: Estimates of annual recruitments (and 95% confidence interval) from the GUR 3 assessment model.

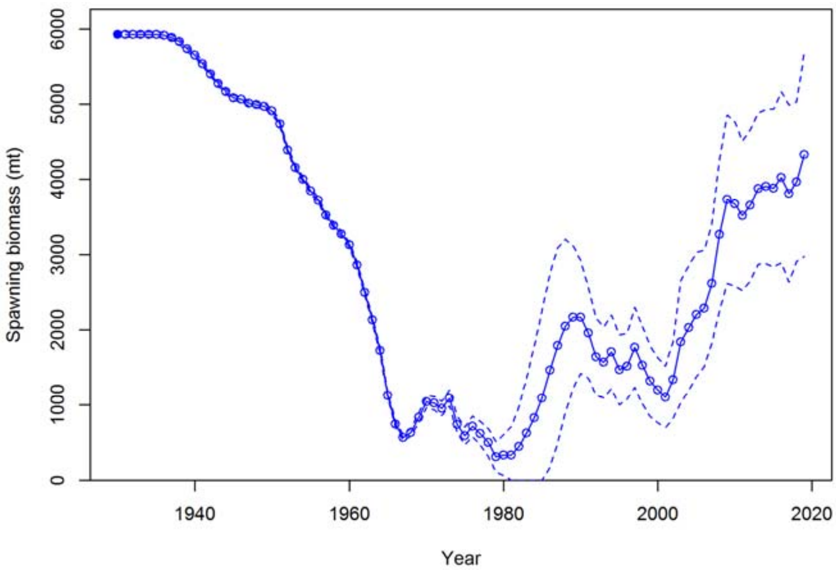


Figure 3.11: Estimates of spawning biomass (mature, female biomass) (and 95% confidence interval) from the GUR 3 assessment model.

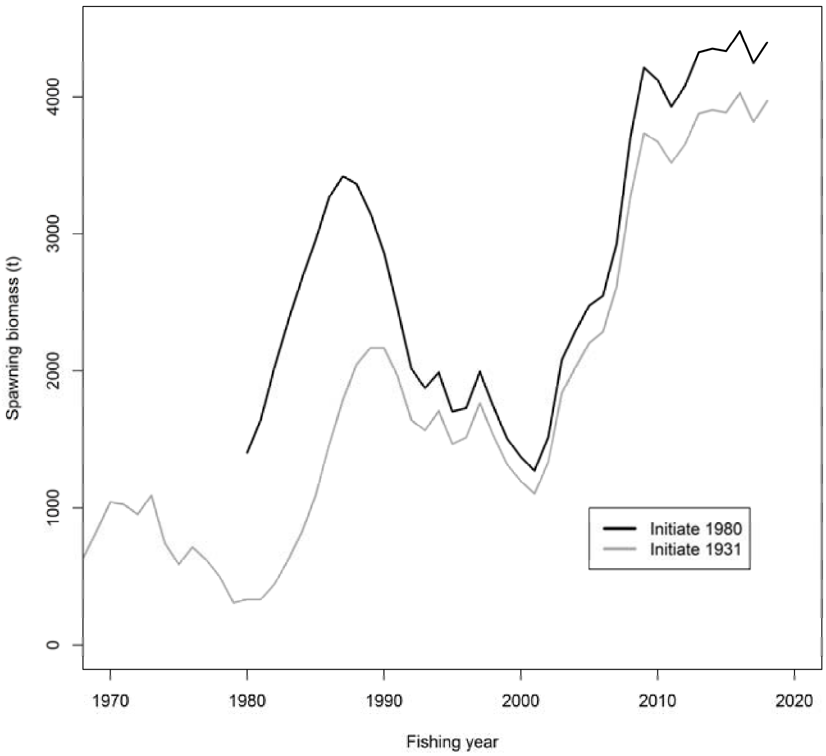


Figure 3.12. A comparison of the biomass trajectories for GUR 3 assessment models that included the entire catch history (initiate 1931) and an alternative model commencing in 1980.

3.5 Giant stargazer STA 3 and STA 4

STA 3 was selected as a potential candidate for the development of a stock assessment model due to the availability of a time-series of CPUE indices from the STA 3 inshore trawl fishery and the relatively high precision of the time-series of biomass estimates from the winter ECSI trawl survey.

The length composition data from the ECSI trawl survey is predominantly composed of 25–50 cm fish. The available growth estimates indicate that these fish are likely to be about 2–5 years of age, while sexual maturity is estimated to occur at about 6–7 years of age. This suggests that the trawl survey is primarily monitoring the sub-adult component of the population.

The distribution of giant stargazer extends across the Chatham Rise (STA 4) — the western Chatham Rise is contiguous to the eastern boundary of STA 3. Giant stargazer sampled from the *RV Tangaroa* Chatham Rise trawl survey are generally larger than 40 cm in length and encompass the upper length range of giant stargazer, up to about 80 cm in length. Most of the female fish sampled from the trawl survey are larger than 50 cm, indicating that the survey is primarily sampling the adult portion of the population.

The comparative length compositions from the two trawl surveys may indicate that the ECSI trawl survey area (essentially STA 3) encompasses a nursery area for a stock whose total distribution extends over a wider area including the Chatham Rise (STA 4). The idea is supported by the fact that within STA 3, giant stargazer catch rates by the inshore trawl fishery are highest in depths greater than 75 m.

A stock assessment model was configured based on the stock hypothesis that STA 3 and STA 4 represent a single biological stock. Biological parameters for the model were sourced from the Plenary report (Fisheries New Zealand 2018). The model incorporated the summer and winter (30–400 m) east coast South Island trawl survey biomass estimates and the time-series of *Tangaroa* trawl survey biomass estimates. The model estimated selectivities for each survey series based on the length composition data from the respective survey. The model provided a reasonable fit to the length composition data from each trawl survey.

Annual catches were compiled separately for STA 3 and STA 4. Catches in both areas were very low prior to about 1980. These two areas were defined as separate fisheries within the model and the selectivity of each fishery was assumed to be equivalent to the trawl survey selectivity in the respective fish stock area. The CPUE indices from the STA 3 fisheries were also assumed to have an equivalent selectivity to the ECSI trawl surveys.

The abundance indices from the time series of trawl surveys and the CPUE indices indicate that the stock has remained relatively stable since the early 1990s. The model provided a reasonable fit to each set of abundance indices. However, due to the lack of contrast in the abundance indices, along with moderately stable catches, the overall size of the stock was poorly determined by the model (Figure 3.13). Consequently, the model was not considered sufficiently robust for the evaluation of the LSP methodology, especially given that the spatial domain of the model extended well beyond the area monitored by the ECSI inshore trawl survey with large differences in the length structure of the fish sampled from the two surveys. Detailed results of the preliminary modelling are not presented.

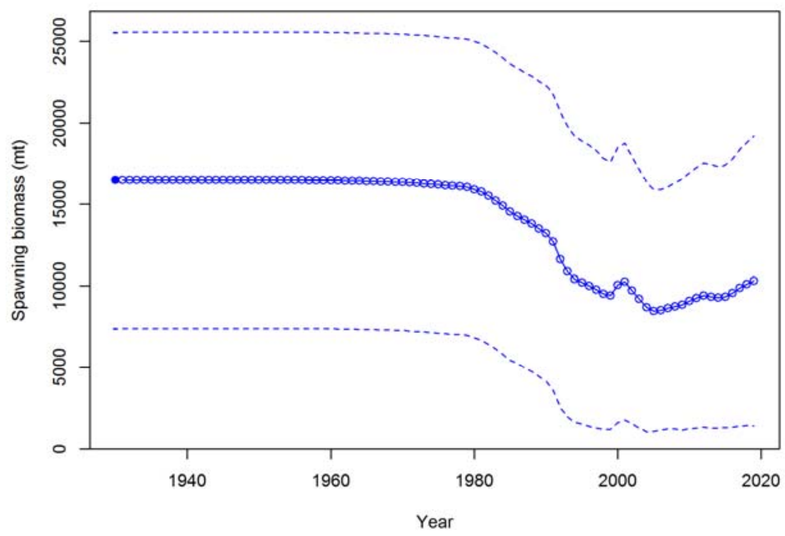


Figure 3.13. Estimated annual spawning (mature, female) biomass (and 95% confidence interval) for giant stargazer from a preliminary model encompassing STA 3 and STA 4 fish stock areas.

4. COMMERCIAL FISHERIES DATA PREPARATION

Fishing effort and associated catch data were requested in a 'wide' format, with one row per fishing event and columns for the catch per species. To cluster fishing effort into fishery units, data were required for all species caught. Likewise, to estimate catchability, data were required for all fishing events in the areas of interest not just those catching the study stocks.

4.1 Data extract

To limit the data extract to fishing events using fishing methods relevant to the stocks of interest, all trips (see Ministry of Fisheries 2010, p.9) that had landings of the study stocks were identified. The allocated landings (Starr 2007) of the species of interest (ELE, GUR, RCO, RSK, SNA, SPE, STA, TAR) from these trips were summed by method. Methods where total allocated landings since 1989 exceeded 500 t were selected as the fishing methods for inclusion in the data extract (Table 4.1).

All fishing events using the selected methods and occurring from 1 October 2007 to 30 September 2018 in the statistical areas composing the Quota Management Areas of interest, were extracted (see Figure 2.1 Section 2). The spatial selection was based on statistical areas as this is the finest spatial resolution available for some fishing events. Where an event had a start latitude/longitude recorded this information was used to assign the event to a statistical area. To match the spatial selection used in the east coast tarakihi stock assessment, only the inshore statistical areas are included for Fisheries Management Areas (FMAs) 1 and 2 (the spatial extent of the east coast tarakihi stock is defined as General Statistical Areas 001–018, 020, 022 and 024).

Two alternative sets of catch data are available, ‘estimated catches’ and ‘allocated landings’. Estimated catches are the catch data recorded by the fisher on an event-by-event basis. Estimated catches are limited to the top five or top eight species caught in an event. From 1 March 2014, most fishers in the SNA 1 QMA have been required to devote one of the estimated catch fields to recording of snapper beneath the minimum legal size, even if the catch was zero. Because these data, reported using the code SNX, are limited to SNA 1, they are not included in the extract. However, the SNX reporting regime will have impacted on reporting of other species caught in the area by reducing the number of fields available for estimated catches of other species.

Table 4.1: Number of fishing events and total allocated catch by fishing method for fishing events in trips that landed ELE 3, GUR 3, RCO 3, RSK 3, SNA 7, SPE 3, STA 3, TAR 1, TAR 2, TAR 3 or TAR 7. Data from all trips since 1989 are included, and allocated landings is the total landings of ELE, GUR, RCO, RSK, SNA, SPE, STA and TAR. Bold type indicates those methods where total landings exceeded 500 t.

Method	Number of events	Allocated landings (t)
BT	**4 238 630**	**658 240.799**
BLL	**400 230**	**33 613.028**
DS	**84 220**	**26 300.553**
SN	**263 604**	**16 725.604**
BPT	**45 165**	**12 354.076**
MW	**464 801**	**6 930.291**
PRB	**26 410**	**3 805.464**
CP	**18 792**	**611.498**
NA	2 847	373.866
DL	9 775	178.289
DI	255	175.096
HL	9 625	159.539
RLP	12 369	154.463
T	3 379	145.387
PSH	434	96.867
SLL	748	50.772
TL	1 726	45.801
D	1 205	41.410
PRM	3 190	27.402
PS	1 434	23.813
FP	1 077	23.258
BS	76	11.693
SJ	217	5.266
H	77	5.023
DPS	38	4.760
CRP	200	3.252
PL	215	1.579
RN	38	1.492
DN	40	1.312
FN	25	1.253
L	11	0.285
HG	1	0.245
POT	4	0.069
MPT	44	0.060
MH	5	0.056
EP	3	0.026
OCP	22	0.021
DPN	14	0.019
SCN	9	0.007

Allocated landings represent trip-by-trip landings data allocated to individual fishing events following the approach of Starr (2007). Unlike estimated catches, most landings comprise measured weights[2]. Groomed landing data from each trip are allocated to the fishing events on the trip by the following methods:

1. in proportion to estimated catches for the species, if any; otherwise
2. in proportion to number of effort units, if a single method trip; otherwise
3. equally across all events for the trip.

For all species considered, allocation method 1 was used to allocate the majority of landings (Figure 4.1, Table 4.2).

Table 4.2: Number of fishing events for which each allocation method was used to distribute landings of a species between fishing events.

	Allocation method		
Species	1	2	3
ELE	86 536	78 327	5 858
GUR	412 262	56 335	11 358
RCO	262 815	140 576	30 268
RSK	200 879	138 998	31 888
SNA	242 020	36 337	4 348
SPE	116 671	159 306	22 075
STA	153 477	176 772	33 354
TAR	250 953	102 515	24 623

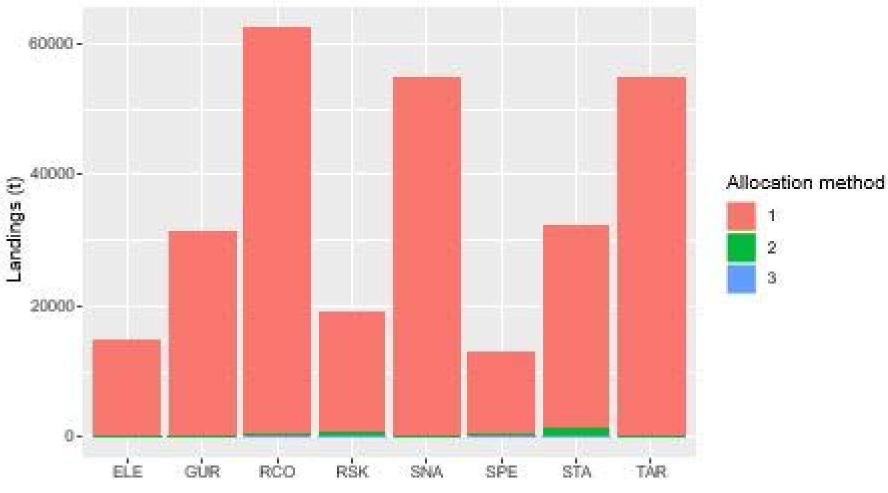


Figure 4.1: Methods used to allocate landings to events.

[2] Measurement usually takes the form of counting boxes of assumed average weight.

4.2 Dataset characteristics

The extracted dataset comprised 1 229 192 fishing events. Each event was flagged to indicate if it fell within the quota management areas for ELE 3, GUR 3, RCO 3, RSK 3, SNA 7, SPE 3 and STA 3, or the statistical areas that are used to define the east coast tarakihi stock.

The fishing methods included were reported on a variety of forms (Table 4.3) which has consequences both for the effort variables available and the number of species included in estimated catches. The different forms, and the associated effort variables, are documented in Ministry of Fisheries (2010).

Table 4.3: Number of fishing events by form type in the data extract.

	Reporting form used								
Method	CEL	ERS-	HLC	HTC	LCE	LTC	NCE	TCE	TCP
BLL	2 944	0	44	0	34 904	122 865	0	0	0
BPT	10	0	0	0	0	0	0	2 427	8
BT	1 525	15 159	0	764	0	0	0	463 714	265 708
CP	52 941	0	0	0	0	0	0	0	0
DS	27 815	0	0	0	0	0	0	0	0
MW	0	6 700	0	19	0	0	0	8 886	70 387
PRB	0	727	0	0	0	0	0	2 651	2 923
SN	77 929	0	0	0	0	0	68 142	0	0

Other than for sub-MLS snapper in SNA 1, only positive estimated catches are required to be reported. A small number (5671) of the 6 103 867 estimated catch records, have reported catch weights of zero. Of the 615 species codes that appear in the estimated or allocated catches, 506 can be associated with a known species or group description (see Appendix 2, Table A2.1)[3] while the remainder are not, it appears, real species codes (Appendix 2, Table A2.2). Amongst the latter are secondary product codes such as 'OFF' (mixed species offal). Unknown species codes were dropped from the dataset.

Different reporting requirements for some fish stocks that comprise groups of species create differences between the estimated and allocated catch data; for example, individual flatfish species codes appear in the estimated catch data but are aggregated as flatfish (FLA) in the allocated catches. The reported latitude and longitude places 10 864 fishing events on land. These events were flagged in the dataset.

Danish seine (DS) effort is reported using the CELR form (Table 4.3). Two effort variables are available, the number of shots in the event and the 'total net length'. The CELR seining template clarifies that this is 'Groundrope length only on Danish seine net'. However, the values recorded in this field span a large range of values, which probably indicates that some fishers include the length of the seine ropes, (Figure 4.2; note that the x-axis has been truncated: the maximum reported value is 80 000 m). Discussions with Danish seine fishers indicate that total (warp plus net) lengths in use in New Zealand will vary between 2000 m and 9000 m. Regulations impact on the maximum length of seine ropes that can be used in some areas, and larger mesh sizes have also been adopted in some areas.

[3] See McMillan et al. (2019) for a full list of species codes used in New Zealand.

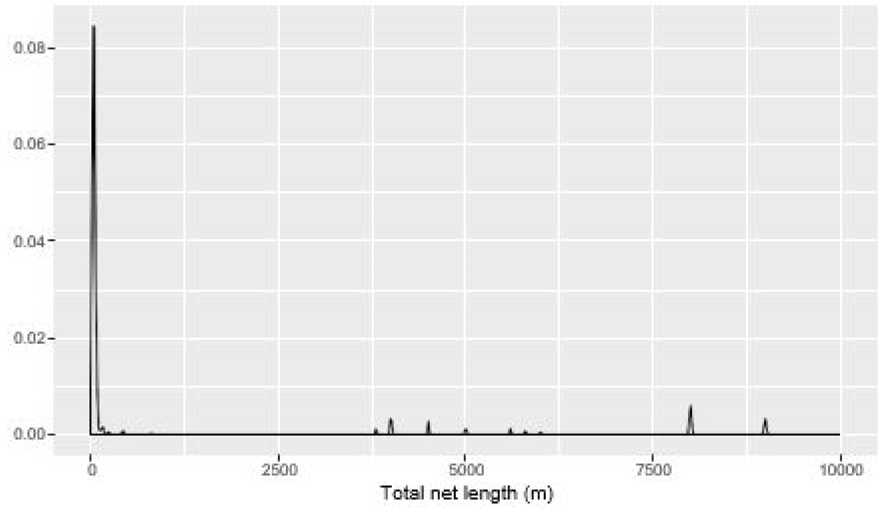


Figure 4.2: Total net length (m) reported for Danish seine fishing events.

5. LIKELIHOOD-BASED CLUSTERING OF COMMERCIAL FISHING DATA (FLEET CHARACTERISATION)

The aim of this strand of the project was to help identify homogenous fishing units in New Zealand waters. Such units are groups of fishing events with similar catch compositions, indicating a common fishing activity[4]. The knowledge of these groupings should help to improve estimates of stock distributions and catch estimates, by refining the definitions of fishery units expected to have a similar catchability (e.g., the inshore trawl fishery might be separated spatially, and/or seasonally, into more units than just “inshore trawl”; this project work was intended to justify such splits using an objective statistical method). Having more homogenous fisheries units is beneficial to methods such as eSAFE, where statistical estimation of efficiency (catchability) takes place.

The overall aim had two components. One was to determine groupings of commercial fishing events. The second was to develop a model describing the probability of catching a species in an event based on group membership and other available covariates. While this was successful, further development can be made in determining the optimum number of clusters and utilising additional fishing event records.

The work was carried out in two phases. The purpose of the first phase was to determine if the methods of finite mixture models were suitable for application to the given commercial fishing data set. That phase was successful and provided the foundation for the second phase of the project, with the aim of producing more actionable results (scaling-up the method to large data sets). The second phase is reported here.

5.1 Data

The data used were commercial fishing records containing information about fishing events, (see Section 4). A fishing event is “a specific temporal occurrence for a vessel or fisher...For example, one set or tow and all its effort data constitutes a fishing event (MPI).” Each row in the data set represents a fishing event; containing the amount of catch per species, the effort data, and details about the location and time of the event. The variables present in the data set are listed in Table 5.1.

[4] This definition differs from the French métier classification, which describes a fishery with regard to the fishing gear used, its main target species, and its fishing area and season (Mesnil & Shepherd, 1990), although it is similar to an operational UK definition (i.e., expected catch compositions for a given activity, including details of gear specification and use; where a catch composition is outside of that expected for a given fishery it might be an indication of mis-reporting).

Table 5.1: Variables in original data set

Variable	Description
Event key	Unique value that identifies the fishing event
Vessel key	Number that identifies the fishing vessel
Start datetime	Start date and time for an event
Form type	Type of form used to record the event
Start lat trunc	Decimalised latitude of the start of the event truncated to 1/10th of a degree
Start long trunc	Decimalised longitude of the start of the event truncated to 1/10th of a degree
Statistical area	Geographical areas within the exclusive economic zone (EEZ)
Primary method	Code for the fishing method used (see Table 5.2)
Pair trawl yn	Indicates whether event was a pair trawl; Y = yes, N = no
Target species	Code for the targeted fish species (see Appendix 2 for species code definitions)
Fishing duration	Length of time of fishing event (definition differs for different methods)
Total hook number	This and the following 7 variables differ with form type and method (see Ministry of Fisheries, 2010 for a comprehensive list of definitions)
Effort length	.
Effort speed	.
Effort width	.
Effort height	.
Effort num	The number of tows, nets, hauls, lines etc
Effort total num	.
Total net length	.
Catch (kg) (one column per species)	Catch (kg) for a species. Column headings are the three character species codes

Catch and effort data for each event is recorded on the relevant reporting forms by fishers. They record the estimated weights of the most abundant five to eight species caught, on an event by event basis. Effort data consists of information such as the length of time spent fishing, the mesh size of nets, and the number of hooks on a line. This raw data from varying forms is merged together into one standardised format by fisheries analysts. The final step in this procedure uses the landing weights and allocates the amount of fish caught in a fishing trip to each fishing event in a trip, (see Starr 2007; Langley 2014).

Three estimated catch and three allocated landings data sets were provided for this project. In the estimated datasets the catch weights are recorded on board the fishing vessel, whereas in the allocated data the weights are recorded at landing. Both types range in time from September 2007 to September 2018 and include the same 817 348 fishing events.

The estimated catch data sets include the best estimates of fishers at the time of the catch (on board the vessel) of the catch weight of the five to eight most abundant species in the event. The allocated landings data gives a more accurate representation of the species caught as it uses the actual catch weight at the time of landing rather than on-board estimates; allocated landings data were therefore used in this analysis.

Effort data includes all the variables that describe the method and gear used in the fishing event. General gear type is indicated by the primary method variable (Table 5.2) and the specific characteristics of that gear are contained in the columns: fishing duration to total net length (see Table 5.1). The form type used by fishers is determined by the size of the vessel and what fish they are catching and the methods they use (Table 5.2). This variable, however, contains little information not represented in primary method, and was therefore not used. The gear specific data was also not utilised in this analysis which restricted gear information to the primary method variable.

Table 5.2: Fishing methods.

Method Code	Description
BLL	Bottom longline
BPT	Bottom pair trawl
BT	Bottom trawl
CP	Cod potting
DS	Danish seining
MW	Midwater trawl
PRB	Precision bottom trawl
SN	Set net (including gill nets)

5.2 Data processing

A fisheries management year runs from 1 October to 30 September. A fisheries management year variable was created to assign an event to the correct management year, denoted as the year-starting – (rather than by the year-ending, which is often used). For example, events in the month of January 2015 were assigned to the 2014 fisheries management year. Unique row names were created for each event using the event key variable[5].

Not all species are caught in every fishing event causing many NAs (missing weight values) in the data. These were converted to zeros; i.e. if there were no landings recorded for a species it was given a catch weight of zero. Converting NA values to zero may not always be correct as there could have been a non-zero catch of a species where the value was not recorded. However, in this context a lack of information about a species in an event is most likely indicative of the species not being present.

The data sets were converted from the wide format (one event per row) to long format (one event and species combination per row). The data need to be in long format to be used by the clustering package (**clustglm,** see methods below). The data were too large to use the 'mat2df' function in the **clustglm** package as originally intended. Instead each data set was read into R (R Core Team, 2018), converted

[5] Row names start with an E and are followed by the ID number, left padded with leading zeros to a length of 8 digits.

and written out to file line by line (see Appendix 3 for code). In this process species with 0 catch were removed from each event. The resulting long data table had 11 variables: event id (originally the row label), month, fish.year, catchsum (total biomass caught for event), form type, start lat trunc, start lon trunc, primarymethod, target species, species code (originally a column label) and catch weight (response variable) and a combined total of just over 11 million rows. For this phase of the project, the events in the 2017 fisheries management year were extracted for analysis. This was comprised of 78 940 events which made up 552 407 rows.

The weight variable in the sample was converted into a binary variable. A traditional presence/absence indicator could not be used as the data only contained weights for the top 5 or 8 species caught. To make a binary variable, a percentage catch cut-off value was used so that events catching a small amount of a species when few species were caught were equivalent to events where fish representing the same proportion of catch would fail to see the species recorded. All catch that was less than 5% of the total catch per event was given the value 0 and all catch greater than or equal to 5% was assigned the value 1. There were 25 species included in the analysis (Table 5.3). The data were made balanced at this point by ensuring that there was a row for each combination of species and event. If the species had to be added to that event it was given a value of 0.

Table 5.3: List of 25 species included in analysis.

Code	Name
BAR	Barracouta
BNS	Bluenose
ELE	Elephant Fish
FLA	Flats
GSH	Ghost Shark
GUR	Gurnard
HOK	Hoki
HPB	Hapuku
JMA	Jack Mackerel
LIN	Ling
MOK	Moki
ORH	Orange Roughy
RCO	Red Cod
RSK	Rough Skate
SCH	School Shark
SCI	Scampi
SNA	Snapper
SPD	Spiny Dogfish
SPO	Rig
SQU	Arrow Squid
SSO	Smooth Oreo
STA	Giant Stargazer
SWA	Silver Warehou
TAR	Tarakihi
TRE	Trevally

5.3 Methods

The main analytical method applied in this research project is the fitting of finite mixture models using the Expectation Maximisation (EM) algorithm. This procedure performs clustering and model fitting to give estimates for group membership probabilities and model parameters. As this approach uses an underlying probability distribution it also means that model selection and evaluation can occur (Matechou et al. 2016). The package **clustglm** implementing the models of Pledger & Arnold (2018) was used to perform the cluster analysis. This does finite mixture clustering using the EM algorithm with generalised linear models (GLMs). This format means that data with Poisson, Binomial or Bernoulli (binary) distributions modelled with GLMs can be clustered easily.

5.3.1 Finite Mixture Models

In finite mixture models the data is assumed to come from G groups. The distributions of the observations in the various groups are in the same family (in this case the Bernoulli distribution) but have different values of their parameters. The proportion of the data in each group and the true number of groups are unknown. In a general case the overall combined probability density of all the groups is

$$f(x;\boldsymbol{\theta}) = \sum_{g=1}^{G} \pi_g f_g(x;\theta_g) \tag{5.1}$$

where π_g is the prior probability of an event being in group g, f_g is the probability density for x for the g^{th} group $\boldsymbol{\theta}$ is a vector of all the parameters including $\boldsymbol{\pi}$; a vector of group member probabilities. In this case $\boldsymbol{x}$ is the vector of binary presence/absence values for the 25 species in each event.

From this density the likelihood and log likelihood can be found. In order to estimate the parameters of the distributions and the probabilities the log likelihood

$$\ell(\boldsymbol{\theta}, \boldsymbol{\pi}; \boldsymbol{x}) = \sum_{i=1}^{n} \log \left\{ \sum_{g=1}^{G} \pi_g f_g(x_i;\theta_g) \right\} \tag{5.2}$$

where n is the number of events, must be maximised over $\boldsymbol{\theta}$ and $\boldsymbol{\pi}$.

The clusters here are groups of fishing events. The events are the rows of the data set so a row clustering model was used. It is assumed that rows belonging to the same cluster have the same distribution of responses. In the model (Marchal, 2008) there is a row group effect and each column (species) has its own species effect within each group. A basic row model is

$$f(E(X_{ij})) = \mu + a_g + b_{gj} \text{ for } I \in g \tag{5.3}$$

where $E(X_{ij})$ is the probability that species j is observed in event i, μ is the overall effect, a_g is the row group effect, b_j is the j^{th} column effect and I □ g indicates that row I is in group g. Here $f(\cdot)$ is the link function, which in the case of a Bernoulli distribution is the logit function. The model parameters satisfy the constraints:

$$\textstyle\sum_{g=1}^{G} a_g = 0 \text{ and } \sum_{j=1}^{p} b_j = 0.$$

5.3.2 EM Algorithm and Model Selection

The EM (expectation-maximisation) algorithm can be used for this maximisation problem because it is faster than direct maximisation of the log likelihood (eq. 5.2), (Dempster et al. 1977). In the EM algorithm the observed data are augmented by missing (unobserved) data. The missing data in this case is the group membership and is represented as the G×1 vector, z. This is incorporated into the log likelihood with z_{ig} as an indicator variable to give:

$$\ell(\theta, \pi; x, \boldsymbol{z}) = \sum_{i=1}^{n} \sum_{g=1}^{G} z_{ig} \log \left\{ \pi_g f_g(x_i; \theta_g) \right\} \tag{5.4}$$

z_{ig} takes the value 1 when event i is in group g and 0 otherwise.

The algorithm:

- Choose some initial estimated starting values for the parameters, $\widehat{\theta}_1, \ldots, \widehat{\theta}_G$ and $\widehat{\pi}_1, \ldots, \widehat{\pi}_G$
- E step: find the expected value of z_{ig}, $\widehat{z}_{ig}$, conditional on X, π, and θ.
- M step: use the current value of $\widehat{z}_{ig}$ to update the parameter estimates, $\widehat{\pi}_g$ and $\widehat{\theta}_g$ by maximising the complete data log likelihood (eq. 5.2).
- Repeat the E and M steps until parameter estimates have converged.

The group membership is taken from the estimated z matrix. In that matrix each row, i, is an event and the columns represent the G clusters. In each row the column with the highest value indicates the group that the event is most likely to belong to.

Although the true number of clusters and the coefficients of the model are unknown, models with different combinations can be fitted and compared. This was done using the model selection criteria AIC which was calculated for each fitted model; the model with the lowest value was considered best.

5.3.3 Application

This stage of the analysis focused on achieving practicable results on a small data set as a proof of concept. As such, the data under consideration was restricted to the 2017 fisheries management year. This allowed for simplification of the model through the removal of the year covariate which led to more efficient model fitting. In addition, the number of species under consideration was reduced to 25. This was based on the assumption that only 20–30 species were likely to be important in the definition of clusters. The selection of these 25 species was based upon catch weight proportion criteria. For each event it was determined which species made up 30% or more of the catch of that event by weight. The 25 species meeting the criteria for the highest number of events were then chosen for inclusion in the analysis.

Early sensitivity runs determined 5% of the catch weight of an event to be an appropriate cut-off value for determining species presence. As such, the 5% threshold was again used to establish which of the 25 selected species were considered to be present in a given event It was assumed that for group membership to be useful, there would need to be roughly 10–30 groups. Due to computational demand increasing markedly with an increase in the number of groups, this phase of the analysis focused on optimising the construction of 10 groups.

To increase computational efficiency and more effectively optimise the models, several modifications were made on the first stage methods. In order to identify the area of the parameter space with the highest likelihood, an initial stratified random sample of 230 events was taken, which ensured that every combination of month and gear which was present in the data was represented in the sample. A binomial generalised linear model of the form:

$$\text{logit}(P_{ij}) = Intercept + Month_i + Gear_i + Species_j \tag{5.5}$$

was fitted to this sample. Here P_{ij} is the probability that species j is caught in fishing event i. K-means clustering was then applied to the residuals of this model, utilising 10 000 random starting allocations (Jain, 2010). Each of these starting allocations were iteratively improved until a local minimum of within cluster variance was reached. Of these optimum allocations the one which resulted in the lowest overall within cluster variance was selected. This allocation was then converted to a group membership probability matrix. In this case all elements of the matrix were one or zero since k-means performs hard (non-probabilistic) clustering. This membership probability matrix was then utilised as a starting allocation for the EM algorithm clustering. While the k-means criteria for what constitutes the best allocation is not the same as that used by the likelihood-based method, it is enough to be usable in determining a starting point. This substitution allowed far more random allocations to be explored, in a much shorter time, compared with random starts in the EM algorithm. The purpose of conducting k-means on the residuals of the linear model, rather than the original data, is because this is what the likelihood-based method does. Making the allocation from k-means as similar as possible to what would be selected by the EM algorithm, reduces the distance that must be covered by the algorithm, thereby reducing computation time. It also reduces the chances that the EM algorithm will converge to a local (non-global) maximum of the log likelihood surface.

After candidate models were fitted to obtain the probability of species presences in events, the AIC of each was compared. The model with the lowest AIC was then fitted with additional data. A random sample of an additional 230 events was taken from the 2017 fisheries management year data. The final parameter estimates for group membership from the initial (K-means) fitting of the model were used to construct a group membership probability matrix for the expanded 460 event sample. This allocation was then refined again using the EM algorithm on the expanded data set. Finally, an additional 290 events were randomly selected from the 2017 fisheries management year. The process was then repeated for the further expanded sample of 750 events using the results of the second fitting (using EM algorithm only), to compute a starting allocation for the third.

5.4 Results

5.4.1 Model selection

While the model coefficients are numerous, making them difficult to interpret directly, the selected variables and clustering patterns are still enlightening. Several of the variables present in the data were briefly considered as potential covariates but ruled out for practical reasons. The target species of an event was not utilised as a covariate because the species is sometimes recorded on the form after the catch has been determined. In these instances, it is not a predictor of species presence but a response and for this reason cannot be used as a covariate. The form type used in an event was also not utilised because it was determined to contain very little information not already captured by the gear variable. Finally, the effects of a full spatial model incorporating latitude and longitude were determined to be too complex for this stage of the analysis. Once the methods have been further refined, then the location information captured in these variables may be considered for inclusion in the model.

Six models were considered. They were each of the form logit(P_{ij}) = *Intercept* + $Month_i$ + $Gear_i$ + $Species_j$ + $Group_i$ + *Interactions*, where P_{ij} is the probability of species *j* being present in event *i*. Since the interaction terms were the source of most of the parameters in the model, only models containing all main effects were considered. Further, because the primary interest was in group membership and the associated effects, only interactions involving *Group* were considered in the candidate models. Models that didn't contain an interaction between species and group resulted in only one or two clusters being constructed and therefore the model containing the two interactions between gear and group and between month and group was not fitted. As seen in Table 5.4 the model with the lowest AIC was that containing the species by group and gear type by group interactions.

Table 5.4: Interaction terms, in addition to the main effects of species, month, gear and group, included in each model, and the AIC and effective number of groups resulting from the model. These are results of the models being fitted to a stratified sample of 230 events. Choice of interaction terms leading to lowest AIC value is highlighted yellow.

Interactions	AIC	Number of Groups
Gear×Group	2 946	1
Month×Group	3 036	2
Species×Group	2 591	10
Species×Group, Gear×Group	2 495	10
Species×Group, Month×Group	2 675	10
Species×Group, Gear×Group, Month×Group	2 763	10

5.4.2 Primary Model and Resulting Clusters

The model selected based on AIC is of the form:

$$\text{logit}(P_{ij}) = Intercept + Month_i + Gear_i + Species_j + Group_i + Species_j \times Group_i + Gear_i \times Group_i \quad (6)$$

where P_{ij} represents the probability of a species being present in an event at greater than 5% of the catch weight of the event. All results discussed in this section follow from this model being fitted to 750 events. For an event to be assigned to a given cluster, the probability of membership in that cluster was higher than the probability of membership for other clusters.

The spatial distribution of events as assigned to clusters is given in Figure 5.1 and the patterns observed in each cluster are presented in Table 5.5. Further diagnostics of the resulting clusters are given in Figures 5.2 to 5.7.

Table 5.5: Summary of main results. It gives the group number, the number of events assigned to that group, the areas of New Zealand that showed a higher density of events from that group, gear types common for events in that group, target species common for events in that group (along with what species were most commonly present in the events assigned to that group), and the level of uncertainty (Low, Mild, Moderate, High) that exists in the group membership of events primarily assigned to that group.

Group	Events in Group	Spatial Grouping	Gear	Target/ Common Species	Uncertainty
1	30	None	BLL, SN	SCH	Mild
2	73	East coast South Island	BT, MW	BAR	Mild
3	62	None	BLL	LIN	Low
4	119	West coast South Island, Chatham Rise	BLL, MW	HOK	Low
5	100	Northern North Island	BLL, DS, PRB	SNA	Moderate
6	89	None	BT	TAR	Mild
7	50	None	BT	None	Low
8	144	South Island, Hawke's Bay	BT	FLA, GUR	Moderate
9	22	Northern North Island	PRB	SNA, TAR	Low
10	61	Northern North Island	BLL, BT, DS, PRB	SNA, GUR	Mild

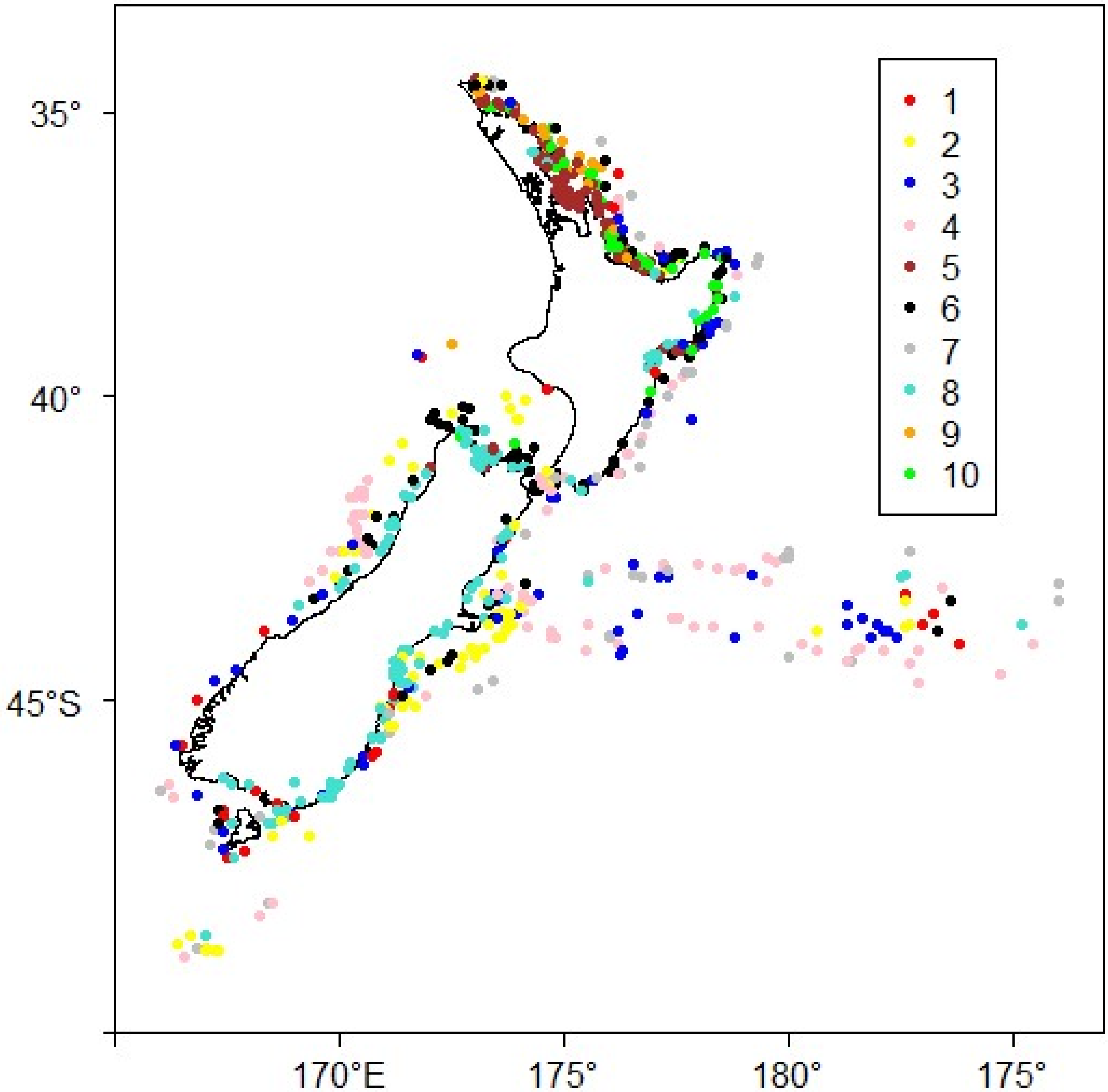


Figure 5.1: Location of all 750 fishing events included in the model, coloured according to which group they most likely belonged to.

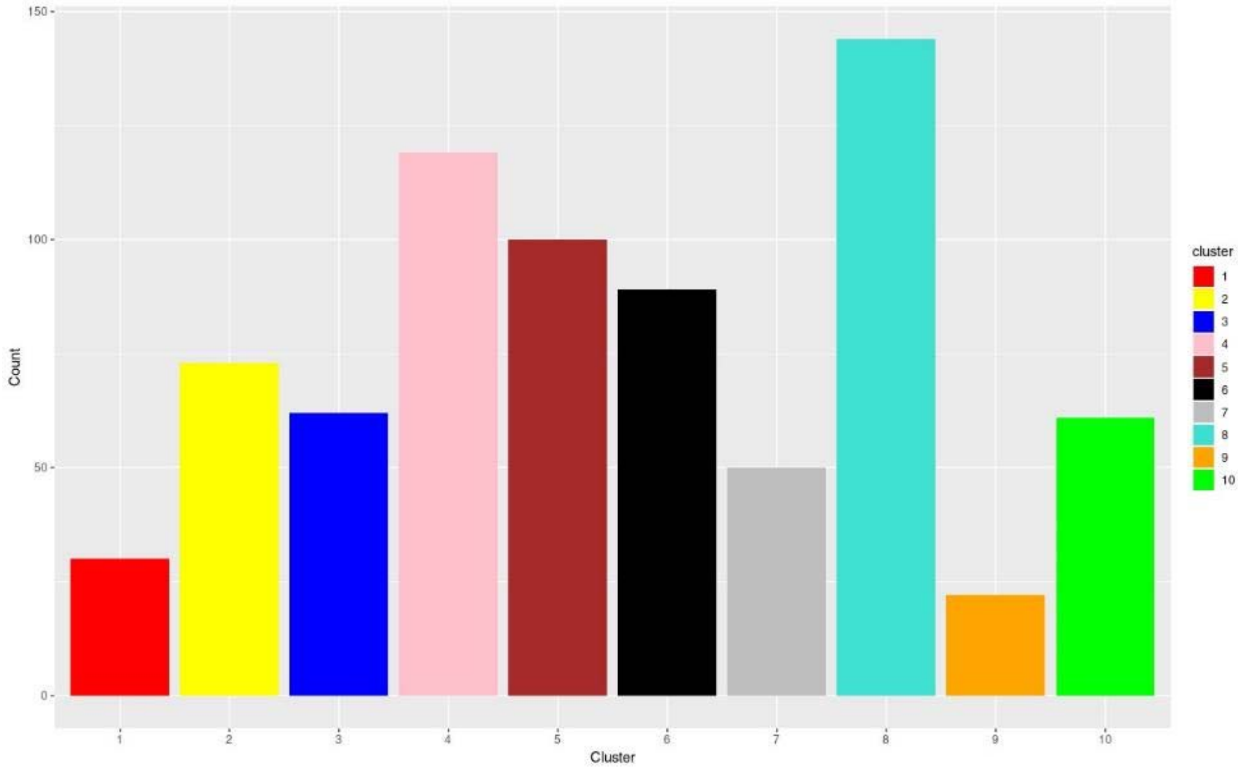


Figure 5.2: Number of events (out of 750 in total) assigned to each group based on their highest membership probability.

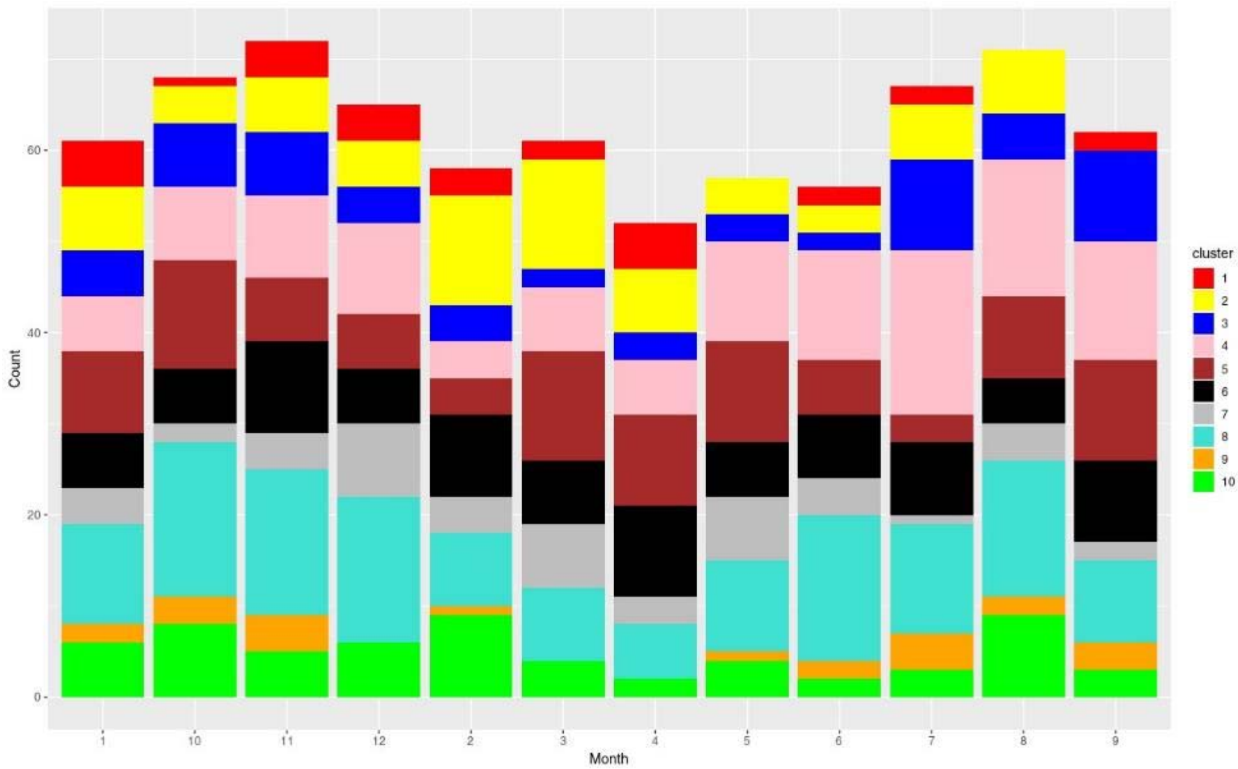


Figure 5.3: Relationship between cluster membership and the month of occurrence for the event.

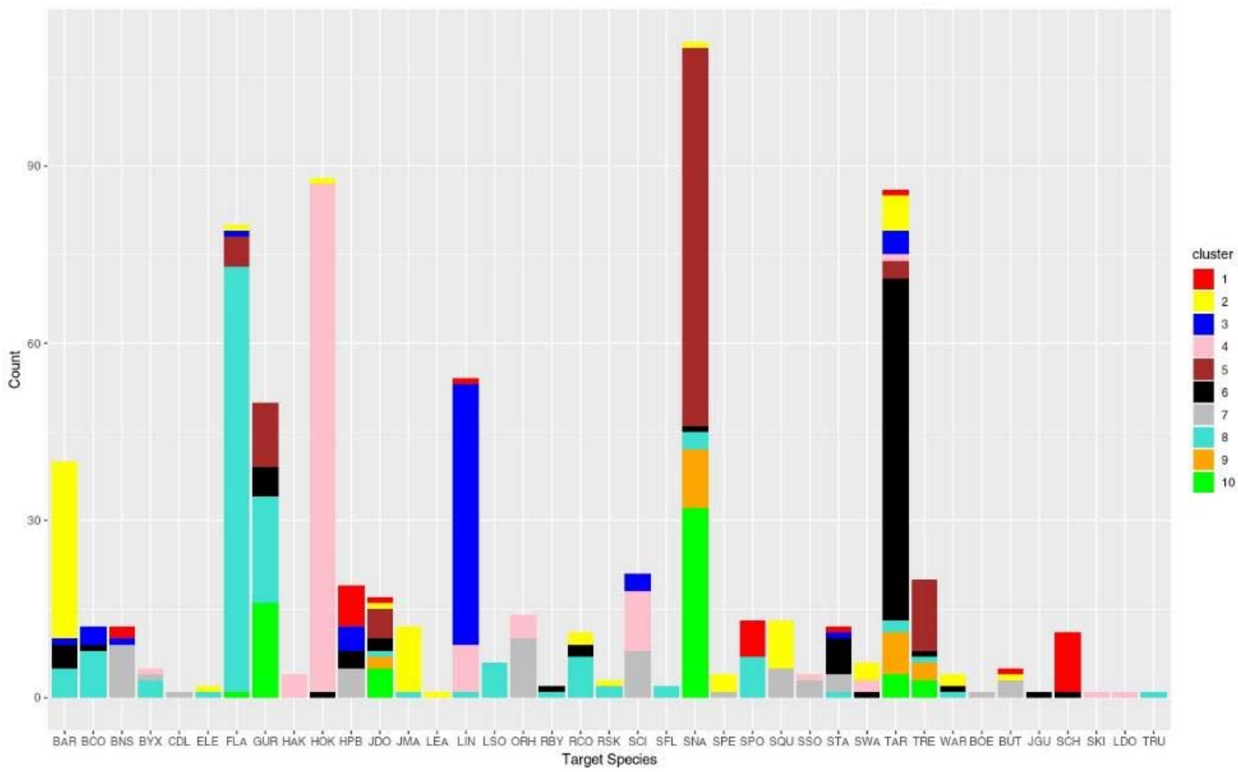


Figure 5.4: Relationship between cluster membership and the target species of the event.

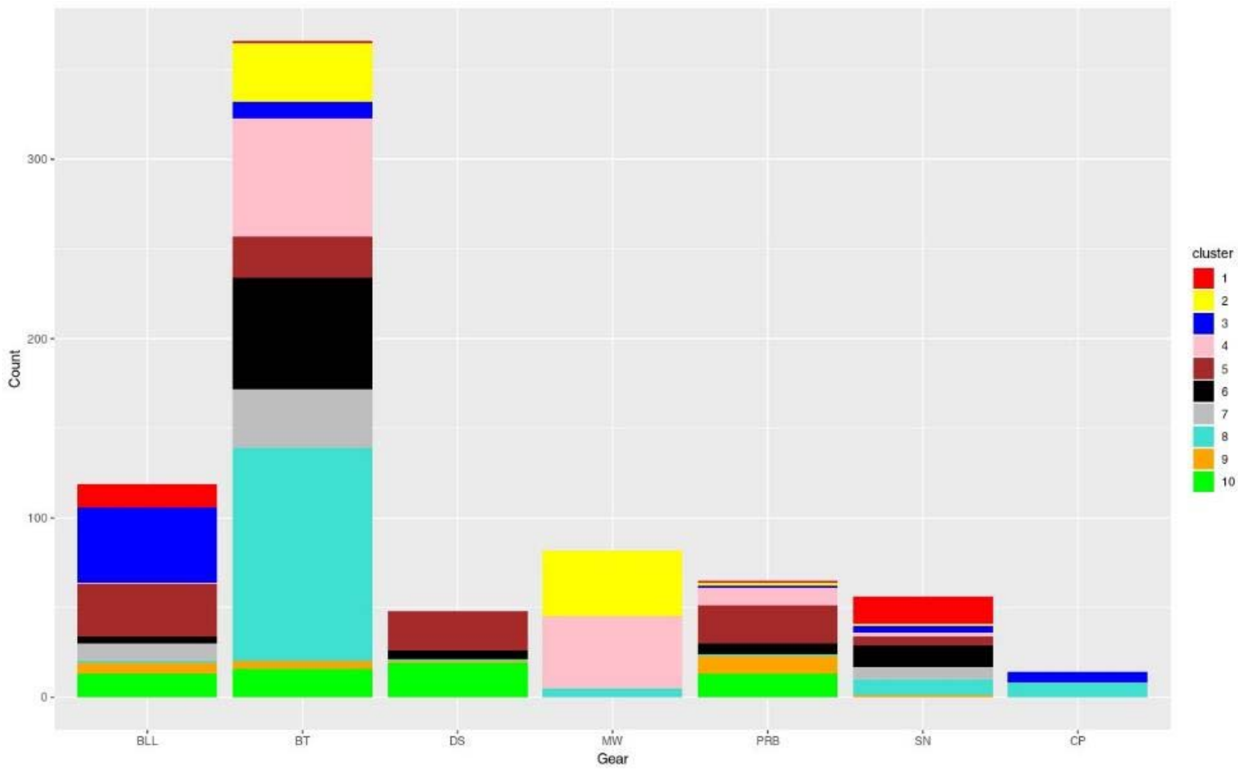


Figure 5.5: Relationship between cluster membership and the primary gear type utilised in the event.

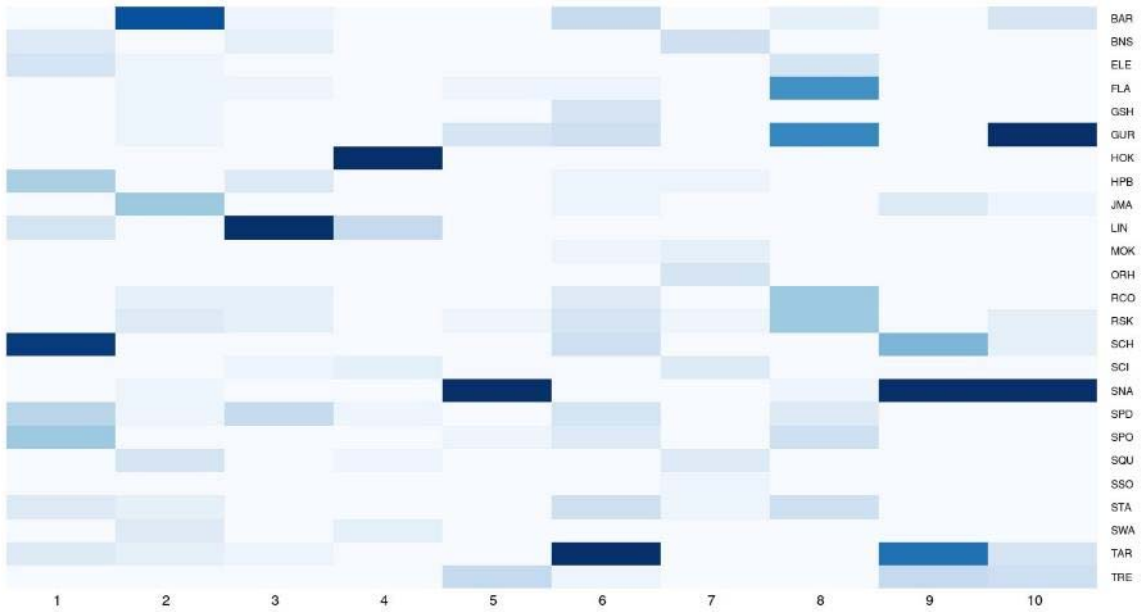


Figure 5.6: Proportion of events within each cluster that contained each species at 5% or more of the catch weight. Dark blue corresponds to 100% of events while white represents 0%.

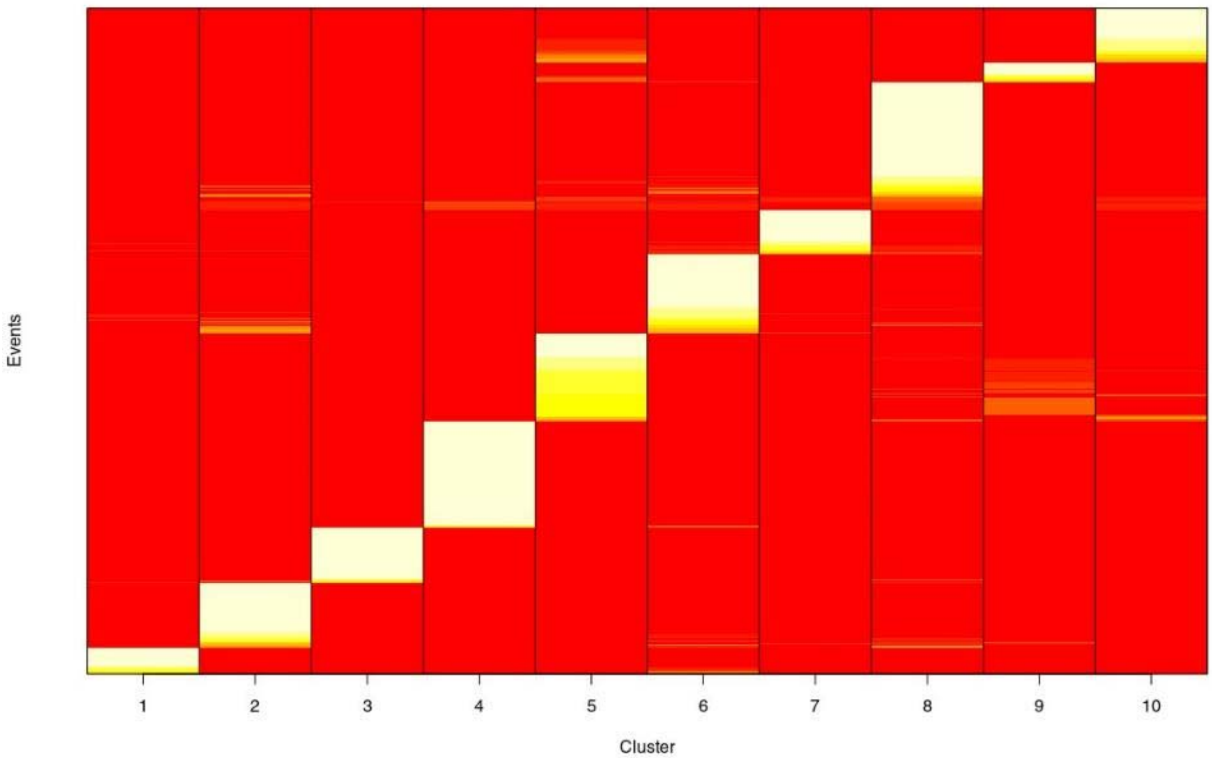


Figure 5.7: Visual representation of the group membership probabilities of each of the 750 events. White corresponds to high group membership probability, and red represents low (or zero) probability.

5.5 Discussion of clustering

Under likelihood-based clustering, events were not definitively assigned to a cluster but discussing them in terms of their probabilistic assignment allows for understanding of patterns. The spatial grouping shown in Figure 5.1 illustrate a relationship between location and group membership. Figures giving a breakdown of the spatial patterning by region are given in Appendix 3. The model selected based on AIC included the interaction between species and group as well as the interaction between gear and group. This indicates that the probability of encountering a given species in an event varies based on which group the event belongs to. Additionally, the inclusion of the gear by group interaction indicates that the effect that gear type has on the probability of encountering a given species in an event also varies based on which group the event belongs to. A probabilistic approach is advantageous because we can identify fisheries which are most variable and poorly defined, and for which catchability is likely to be most poorly defined also.

A relationship between target species and group membership can be seen from Figure 5.4 where many of the events with a given target species, such as hoki, flatfish, or ling, are assigned to the same group. Not too surprisingly, target species and species presence are strongly related, illustrated by the fact that species which were present in most events within each group (Figure 5.6) aligned with the target species that occurred most frequently in the events of that group (Figure 5.4).

The general lack of ambiguity present in Figure 5.7 suggests that there may be more than 10 groups present in the data set. From general knowledge of the fisheries this seems very plausible. If the model had been specified with too many groups, then it would be expected that events would be assigned to groups with less certainty. This is because as more groups are included, some of them will become more similar. In further analysis, exploration into the optimal number of groups present in this data set would improve the identification of fishing units.

A further indication that the number of groups is lower than optimal are the very broad geographic distributions of some of the groups in Figure 5.1. More generally, the necessity to convert the catch records to binary (presence/absence) data is expected to limit the ability to discriminate between groups. For this project considerable focus was placed on improving efficiency (speed) of the algorithm and incrementally scaling the application to a greater number of data records. That process of scaling will continue and if work on efficiency gains prove successful, it is proposed to use ordinal data in the clustering.

We note that this analytical method may also be useful for fisheries characterisation and other research work, where understanding the associations between fishing gear and multi-species catch, and how these are temporally and spatially variable, is of value.

6. SURFACES OF FISH DENSITY

6.1 Available survey data

All Fisheries New Zealand survey data from 1978 to 2016 was made available to the project (Roberts pers comm.). The two main research vessels are the *Kaharoa*, used for inshore surveys such as the East Coast South Island survey (ECSI) and *Tangaroa*, used mainly for offshore surveys such as the Chatham Rise survey (CHAT) and Sub-Antarctic survey (SUBA). A considerable number of other vessels have been used, especially in earlier years (see Appendix 4), but none were used for a significant number of years and to avoid problems of vessel effect on catchability only data from surveys conducted by the *Kaharoa* and *Tangaroa* were used.

In response to the idea of investigating seasonal shifts a 'summer' and 'winter' season was adopted based on the seasons used in the spatial risk assessment study of Hector's and Māui dolphins (Roberts et al. 2019). Both vessels have performed hauls in both seasons but in some areas only in the one season (Figure 6.1). As shown later, different specific survey series are particularly important for different stocks. Figures 6.2 and 6.3 give a breakdown of information by vessel, survey series, month, and trip code. From Figures 6.2 and 6.3 it can be seen that it was impossible to select seasonal changes based on month that kept all the data from a given survey series in one season. The selection made did, however, keep all recent ECSI survey data in winter and the ECSI survey can be considered the most important for this project.

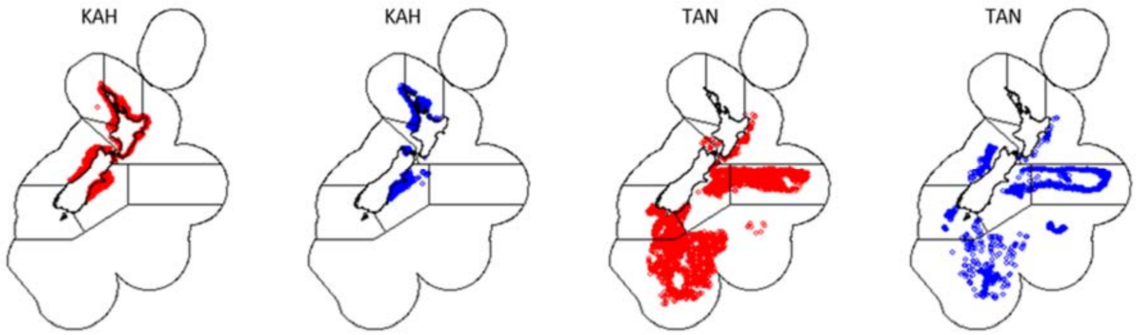


Figure 6.1: Spatial coverage of the two main research vessels, *Kaharoa* (KAH) and *Tangaroa* (TAN). Data includes all surveys where gear type was 'bottom trawl' or 'high opening bottom trawl' and gear performance was recorded as 'excellent' or 'satisfactory'. Symbols are plotted at the locations of haul mid points. Red indicates hauls performed between 1 November and 31 April, blue hauls performed between 1 May and 31 October. Polygons surrounding New Zealand are the fisheries management areas.

Data were restricted to gear methods 01 (Bottom trawl) and 03 (High opening bottom trawl) to remove any hauls associated with prawn/scampi trawls (code 05) or midwater trawling (code 06). The survey database categorises gear performance on tows as follows:

1. Excellent
2. Satisfactory, catch unlikely to be reduced by performance
3. Unsatisfactory, catch probably reduced by malfunction or damage
4. Unsatisfactory, catch reduced by malfunction or damage

Only tows with gear performance 1 or 2 were retained.

The dependent variable being used in the GAM fits is kg/km^2. The area is calculated from the trawl survey information. The survey design specifies trawls to be 3 n. miles long, but some recorded tow distances are much greater. A rule of thumb screening of only allowing area values of less than 0.8 km^2 was applied. Figure 6.4 shows that very little species abundance information is lost when this is done. Data was converted to the 'Mercator M41' projection for compatibility with available environmental covariate data (see Section 6.2).

Figures 6.5 to 6.11 show heat plots of the survey data for the species chosen for the project. The inclusion of FMA 4 seems unnecessary for elephant fish and the inclusion of FMAs 4 and 6 unnecessary for red gurnard. In contrast the figures for sea perch and giant stargazer suggest the stocks need to be assessed over both FMA 3 and FMA 4.

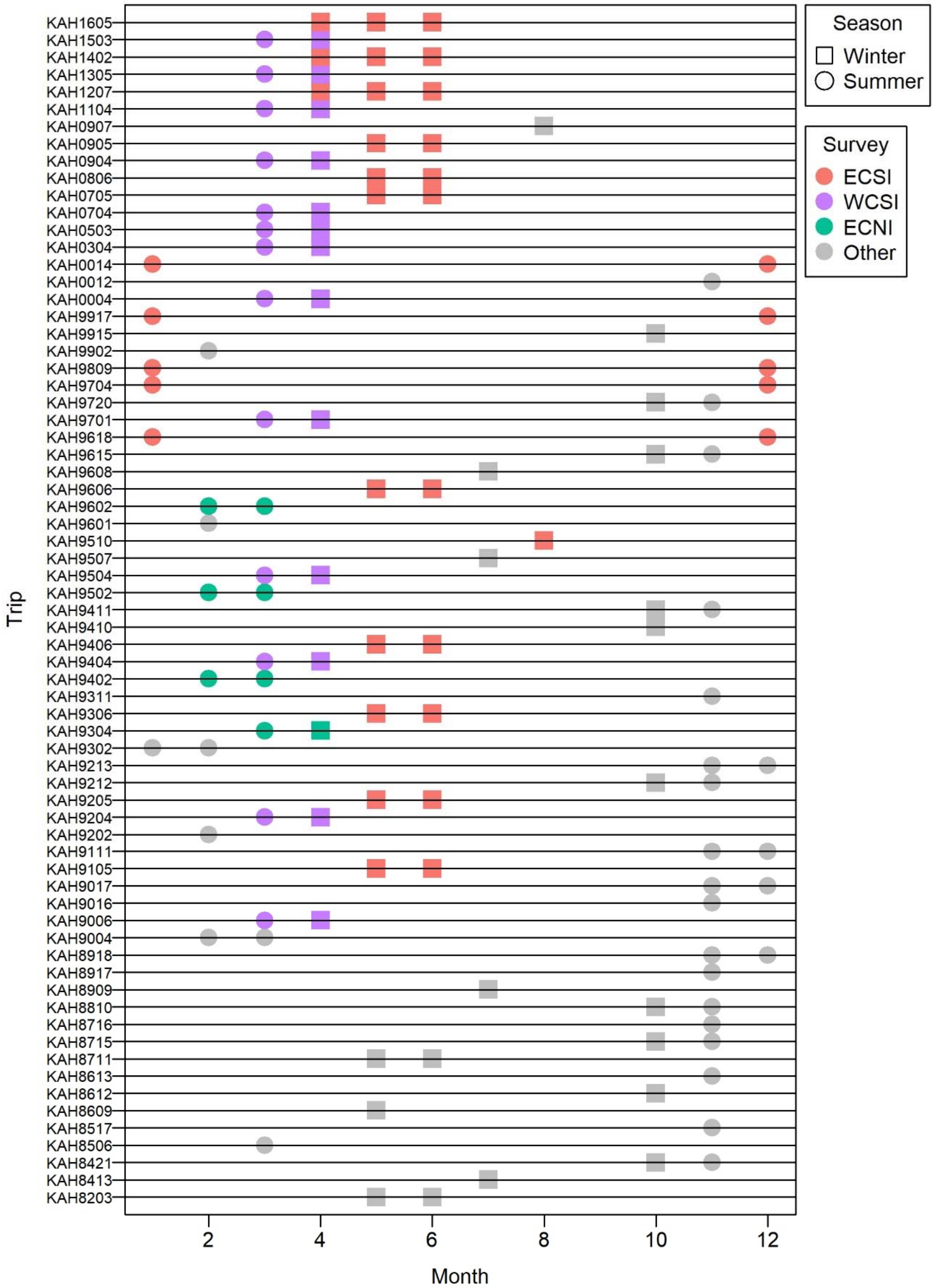


Figure 6.2: Available *Kaharoa* (KAH) survey data. Left hand axis gives survey code. 'Summer' and 'winter' hauls are indicated by symbol shape. Surveys significant to the stocks in this project are colour coded; ECSI: East Coast South Island; WCSI: West Coast South Island; ECNI: East Coast North Island; Other: other surveys.

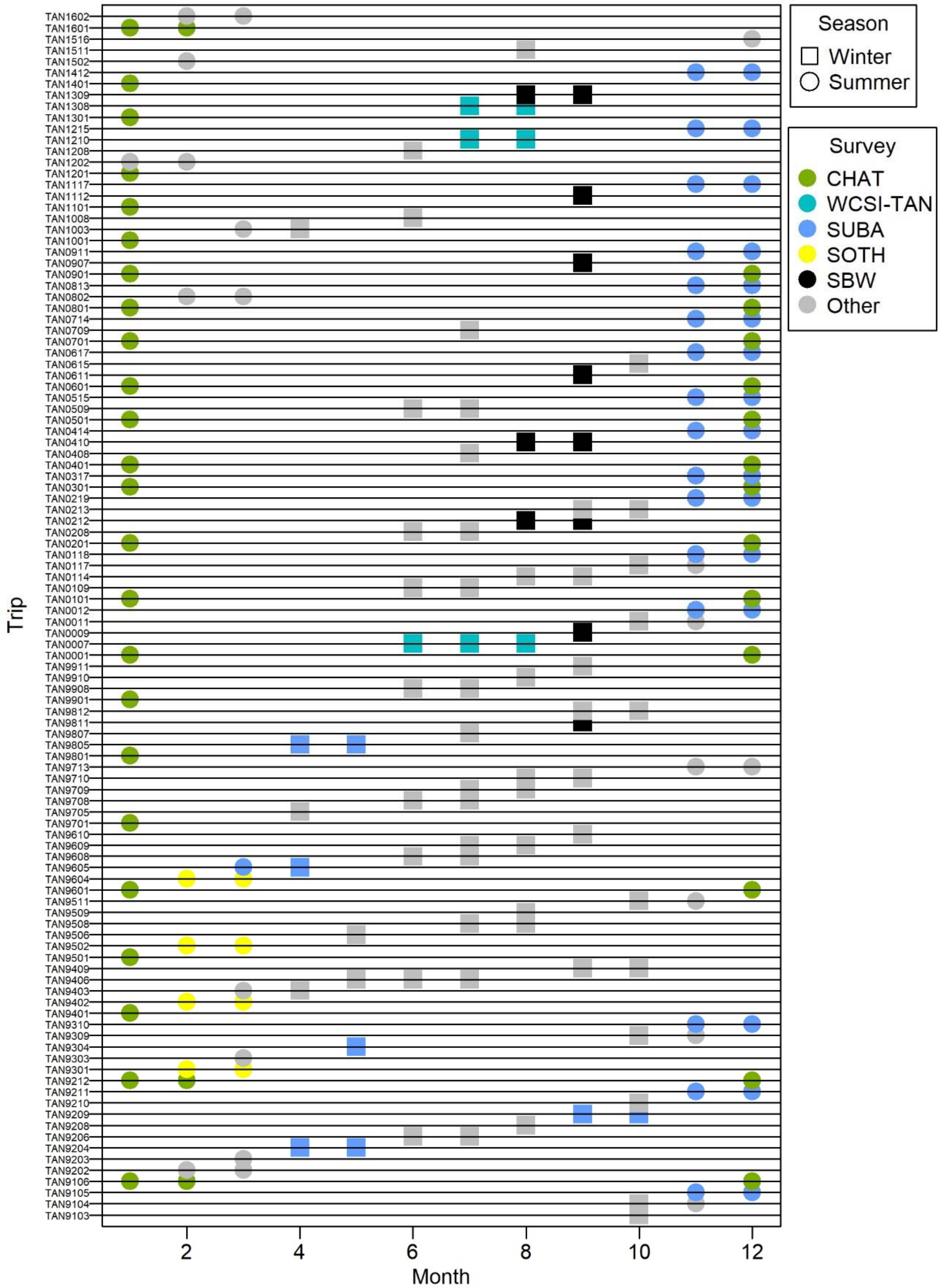


Figure 6.3: Available *Tangaroa* (TAN) survey data. Left hand axis gives survey code. 'Summer' and 'winter' hauls are indicated by symbol shape. Surveys significant to the stocks in this project are colour coded; CHAT: Chatham Rise; WCSI-TAN: Offshore West Coast South Island; SUBA: Sub-Antarctic; SOTH: Southland; SBW: Southern Blue Whiting; Other: other surveys.

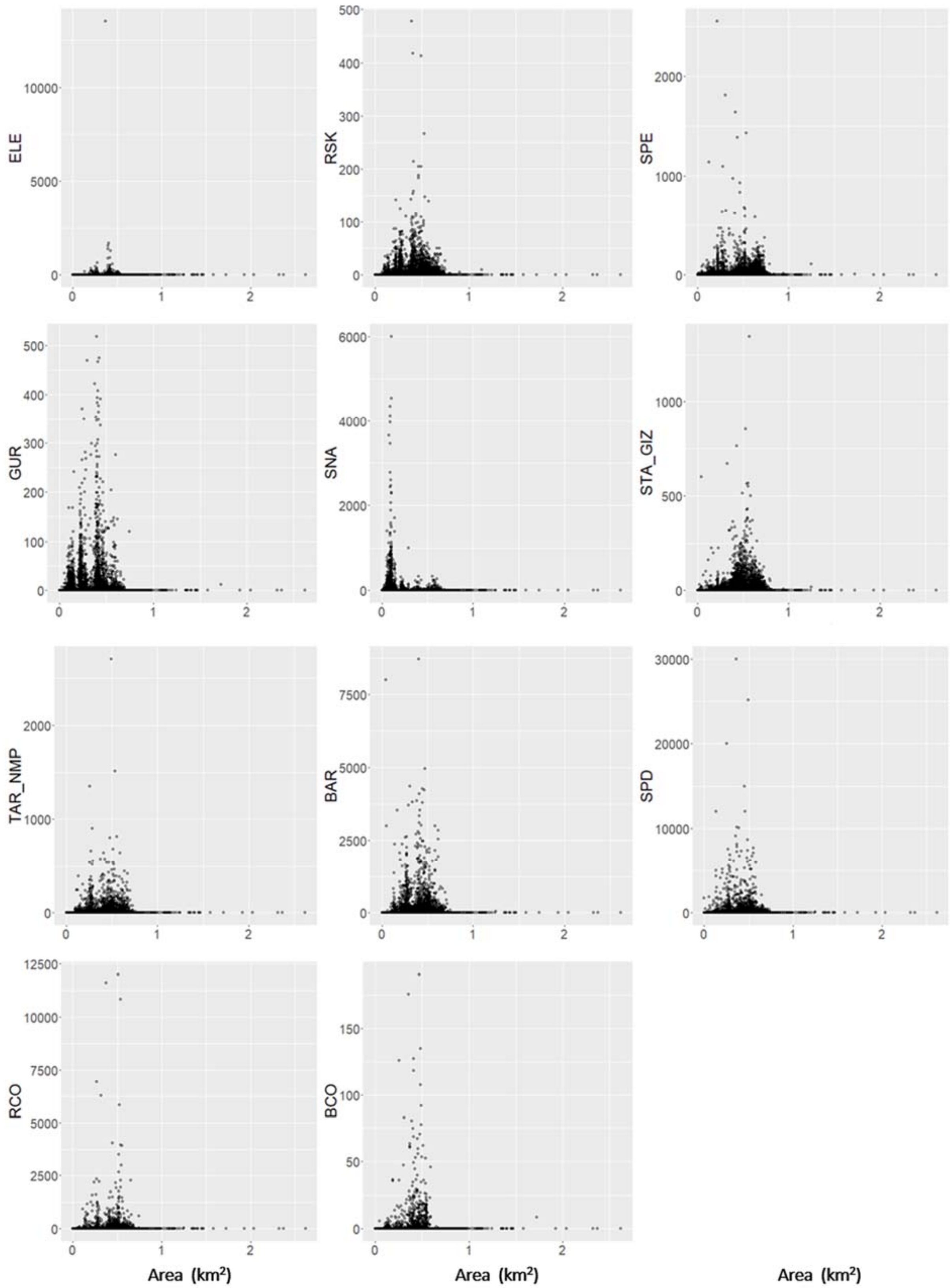


Figure 6.4. Species catch (kg) recorded against calculated area (km^2) for each tow. Data filtered to that from *Kaharoa* and *Tangaroa* vessels.

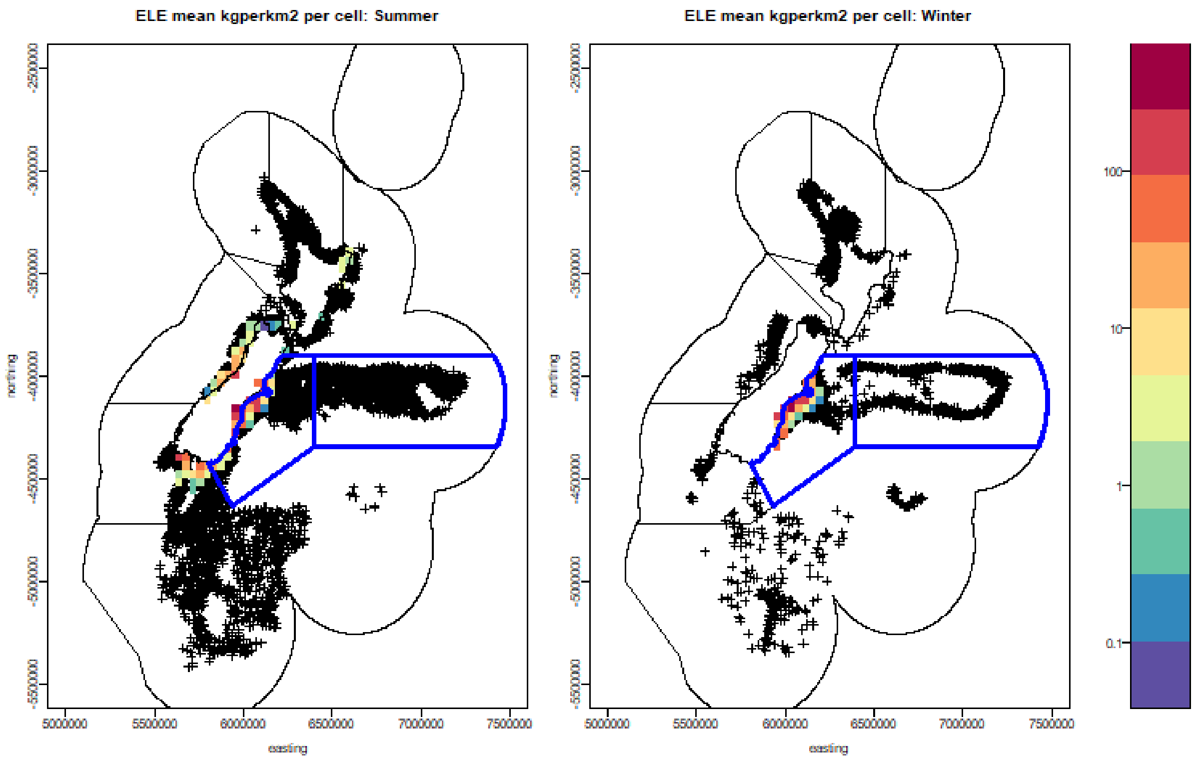


Figure 6.5. Elephant fish catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of elephant fish. FMAs highlighted blue are those associated with the stock chosen for the project.

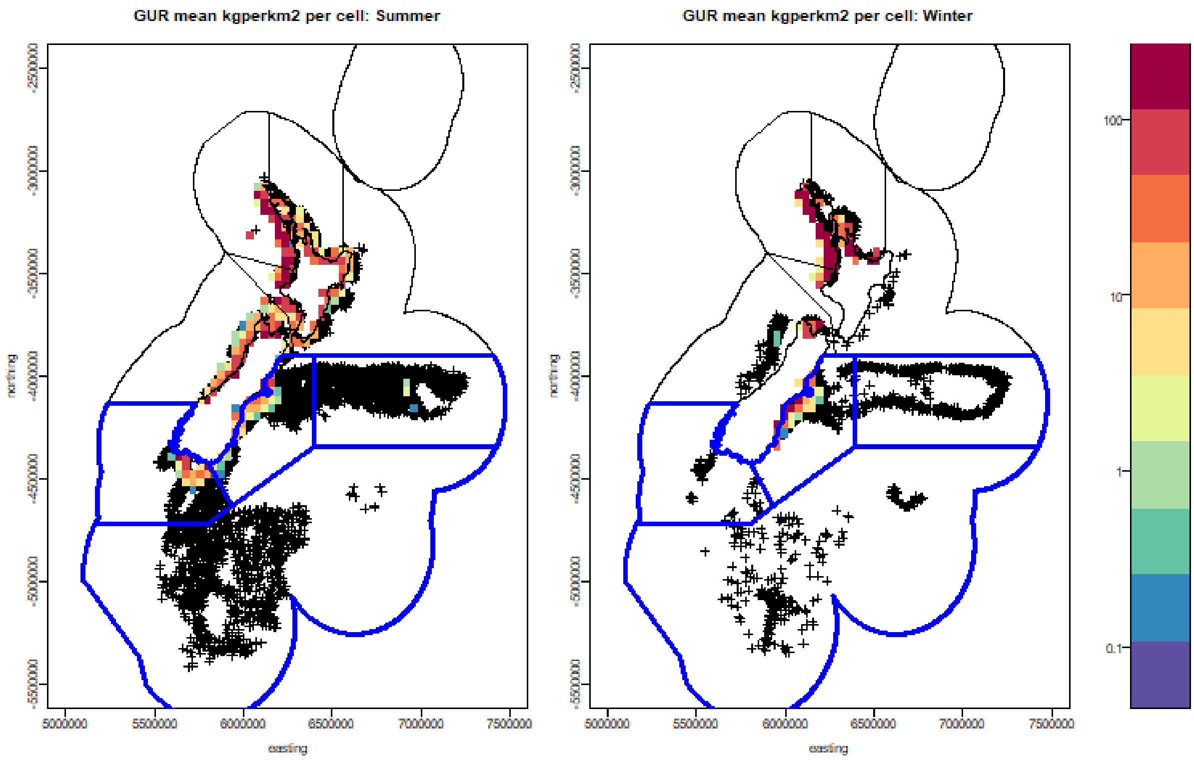


Figure 6.6. Red gurnard catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of red gurnard. FMAs highlighted blue are those associated with the stock chosen for the project.

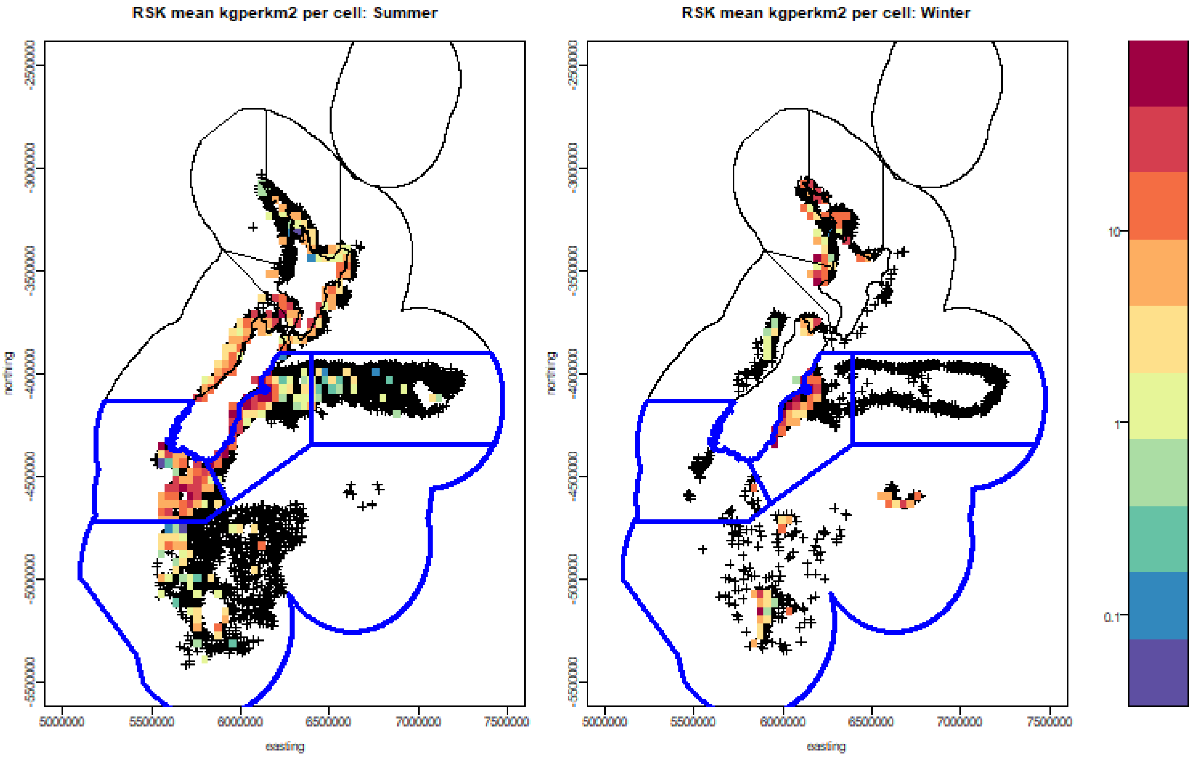


Figure 6.7. Rough skate catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of rough skate. FMAs highlighted blue are those associated with the stock chosen for the project.

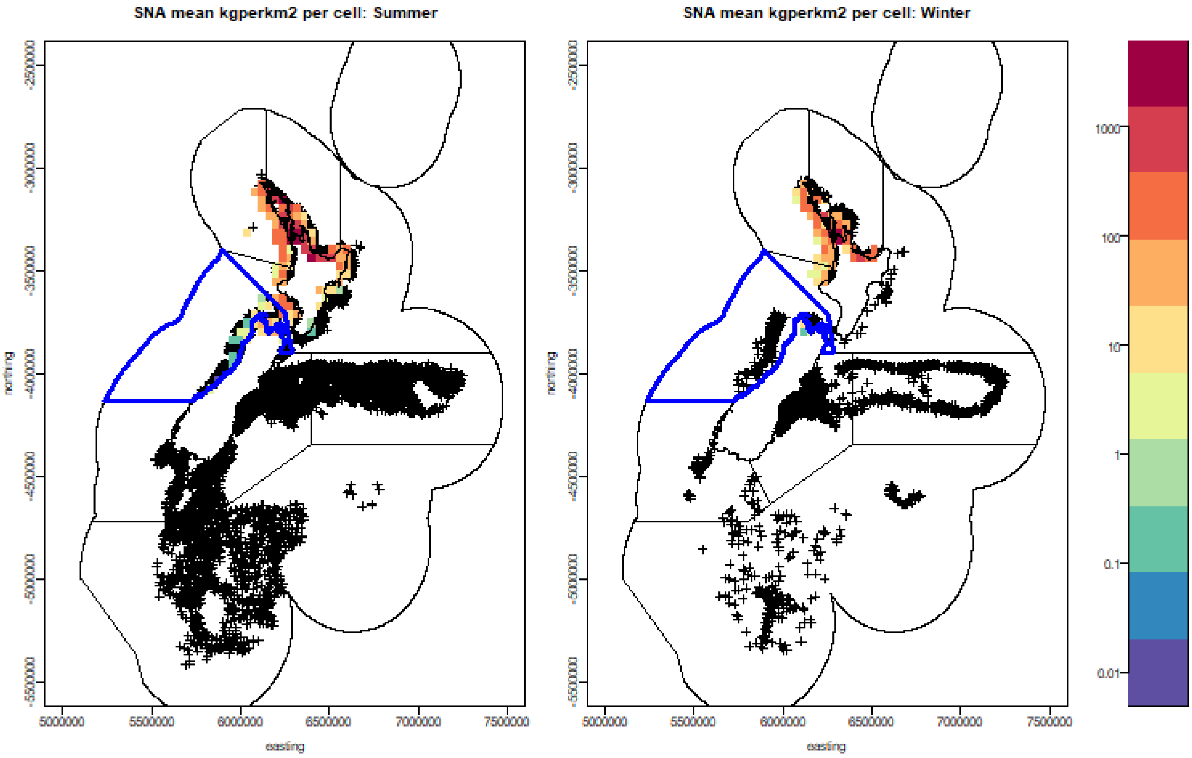


Figure 6.8. Snapper catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of snapper. FMAs highlighted blue are those associated with the stock chosen for the project.

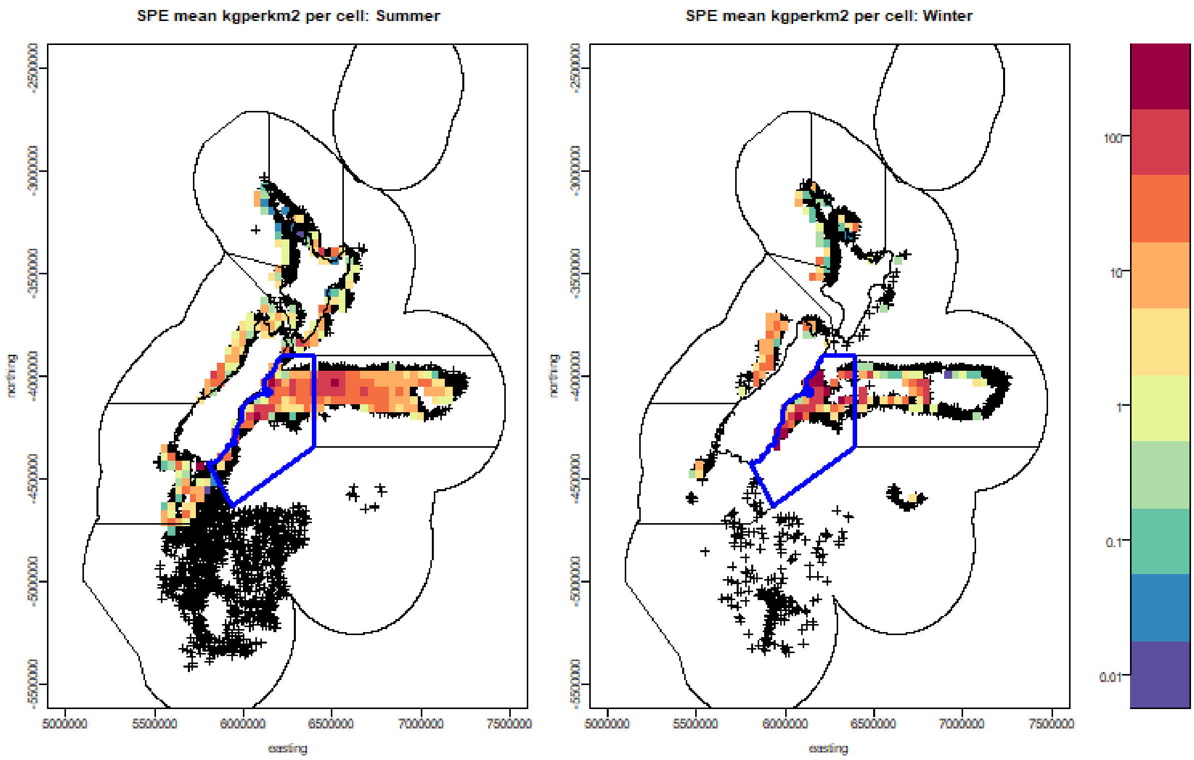


Figure 6.9. Sea perch catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of sea perch. FMAs highlighted blue are those associated with the stock chosen for the project.

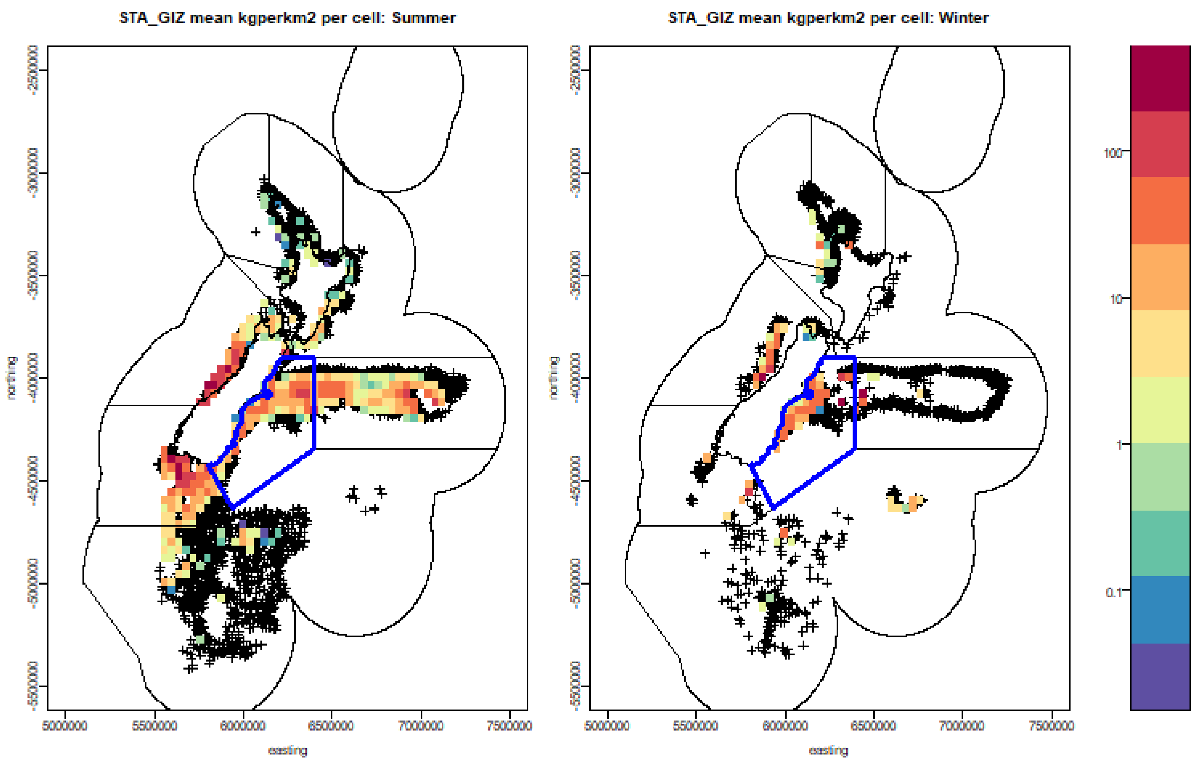


Figure 6.10. Giant stargazer catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of giant stargazer. FMAs highlighted blue are those associated with the stock chosen for the project.

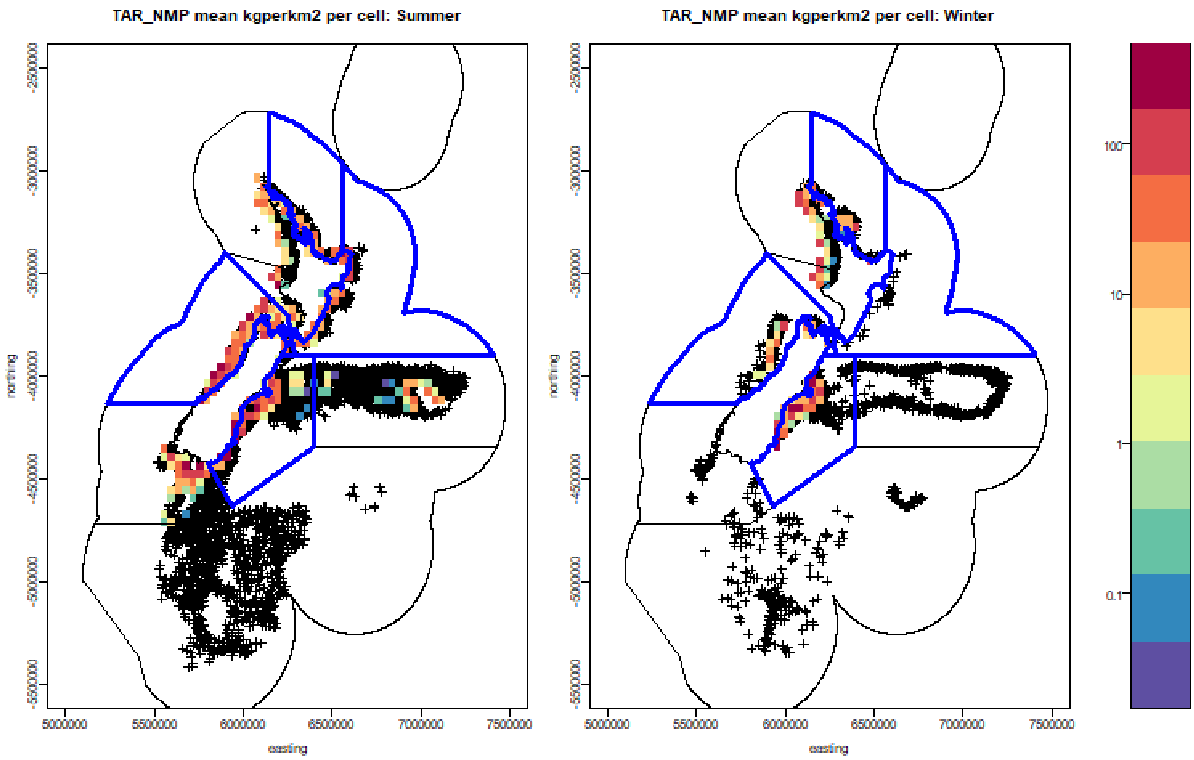


Figure 6.11. Tarakihi catch rates (kg/km^2) (mean over 0.5×0.5 degree cells) for aggregated survey data over summer period (left) and winter period (right). Crosses indicate tows with no catch of tarakihi. FMAs highlighted blue are those associated with the stock chosen for the project.

6.2 Available covariate data

Environmental data were adopted from that used on recent projects (Stephenson et al. 2018, Stephenson et al. in press).

Tables 6.1 and 6.2 show the covariates made available to the GAM model. The environmental data was supplied in two different projections. The data were means over 2002–2017 at 1×1 km spatial resolution. Some data was available as both annual means and means aggregated over the summer and winter periods defined, as highlighted in the tables. These were standardised to the single 'Mercator 41' projection using the 'sp' package in R (Bivand et al. 2013).

Table 6.1: Environmental covariates available for this project (table reproduced from Stephenson et al. 2018).

Abbreviation	Full name	Description	Original Resolution	Units	Source
Bathy	Bathymetry	Depth at the seafloor was interpolated from contours generated from various sources, including multi-beam and single-beam echo sounders, satellite gravimetric inversion, and others (Mitchell et al. 2012).	250 m	m	CANZ (2008)
Beddist	Benthic sediment disturbance	Combination of seabed orbital velocities (estimates the average mixing at the seafloor as a consequence of orbital wave action, calculated from a wave climatology derived hindcast (1979 to 1998) of swell-wave conditions in the New Zealand (NZ) region (Gorman et al. 2003)) and friction velocity for seabed types (based on grain size). Benthic sediment disturbance from wave action was assumed to be zero where depth ≥ 200 m.	1 km	unitless	NIWA, unpublished
BotNi	Bottom nitrate	Annual average water nitrate concentration at the seafloor (using NZ bathymetry layer) based on methods from Ridgway et al. (2002). Oceanographic data from CARS2009 (2009).	250 m	umol l^{-1}	NIWA, unpublished
BotOxy	Dissolved oxygen at depth	Annual average water dissolved oxygen concentration at the seafloor (using NZ bathymetry layer) based on methods from Ridgway et al. (2002). Oceanographic data from CARS2009 (2009).	250 m	ml l^{-1}	NIWA, unpublished
Disorgm	Coloured dissolved organic matter (CDOM)	Indicative of Coloured dissolved organic matter (CDOM) absorption at 440 nm. Based on SeaWiFS ocean colour remote sensing data; modified Case 2 atmospheric correction; modified Case 2 inherent optical property algorithm(Pinkerton et al. 2005).	4 km	Indicative of CDOM absorption at 440 nm $a_g(440)$ (m^{-1})	Pinkerton (2016)
Roughness	Roughness	Roughness of the seafloor calculated as the standard deviation of depths in a surrounding 3 × 3 km neighbourhood (Leathwick et al. 2012).	250 m	unitless	Leathwick et al. (2012) NIWA, unpublished data
SeasTDiff	Annual amplitude of sea floor temperature	Smoothed difference in seafloor temperature between the three warmest and coldest months. Providing a measure of temperature amplitude through the year.	250 m	°C km^{-1}	NIWA, unpublished data

Abbreviation	Full name	Description	Original Resolution	Units	Source
SstGrad	Sea surface temperature gradient	Smoothed magnitude of the spatial gradient of annual mean SST. This indicates locations in which frontal mixing of different water bodies is occurring (Leathwick et al., 2006). Derived from Sea-Viewing Wide-Field-of-view Sensor (SeaWIFS) satellite imagery (Pinkerton et al., 2005).	1 km	°C km^{-1}	Pinkerton et al. (2005)
TidalCurr	Tidal current speed	Maximum depth-averaged (NZ bathymetry) flows from tidal currents calculated from a tidal model for New Zealand waters (Walters et al. 2001)	250 m	m s^{-1}	NIWA, unpublished data
VGPM	Productivity Model	Provides estimates of surface water primary productivity based on the Vertically generalized productivity model of Behrenfeld & Falkowski (1997). Net primary productivity by phytoplankton (mean daily rate of water column carbon fixation) is estimated as a function of remotely sensed chlorophyll concentration, irradiance, and photosynthetic efficiency estimated from remotely sensed Sea-Viewing Wide-Field-of-view Sensor (SeaWIFS) satellite imagery (M. Pinkerton, NIWA, pers. Comm.)	9 km	mgC m^{-2} d^{-1}	NIWA, unpublished
Slope	Slope	Terrain metrics were calculated using a 5-cell window size (5 km) using the NIWA bathymetry layer in the Benthic Terrain Modeler in ArcGIS 10.3.1.1 (Wright et al. 2012)	1 km	Degrees	NIWA, unpublished
BPI	Bathymetric Position Index – Broad	Terrain metrics were calculated using a 5-cell window size (5 km) using the NIWA bathymetry layer in the Benthic Terrain Modeler in ArcGIS 10.3.1.1 (Wright et al. 2012)	1 km	Na	NIWA, unpublished
Mud	Percent mud	The percent mud layers for the region were developed from more than 30 000 raw sediment sample data compiled in dbseabed (Jenkins 1997), which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock, pers comm)	1 km	%	NIWA, unpublished
Gravel	Percent gravel	The percent gravel layers for the region were developed from more than 30 000 raw sediment sample data compiled in dbseabed (Jenkins 1997), which were then imported into ArcGIS and interpolated using Inverse Distance Weighting (Bostock, pers comm)	1 km	%	NIWA, unpublished

Table 6.2: Environmental covariates available for this project (data as used in Stephenson et al. in press).

Variable abbreviation	Variable name	Timescale	Unit	Description	Source
MLD	Mixed layer depth	Monthly	m	The depth that separates the homogenized mixed water above from the denser stratified water below.	Calculated from the CARS climatology, NIWA unpublished
SST	Sea surface temperature	Monthly	°C	MODIS-Aqua SST product, calculated as long-term (2002–2017) average values at 1000 m resolution.	NIWA unpublished; Based on processing described in Pinkerton et al. (2018)
Turb	Turbidity	Monthly	NTU	Optical backscatter as measured by turbidity sensor. Estimated using quasi-analytic inversion algorithm applied to MODIS-Aqua data. Result calculated based on long-term (2002–2017) average values of particulate backscatter bbp(555) at 500 m resolution, converted to normalised turbidity units (NTU) using in situ turbidity measurements in the New Zealand coastal zone.	NIWA unpublished; Based on processing described in Pinkerton et al. (2018)
ChlA	Chlorophyll-a concentration	Monthly	mg m^{-3}	A proxy for the amount of photosynthetic plankton, or phytoplankton, present in the ocean. Estimated using quasi-analytic inversion algorithm applied to MODIS-Aqua data. Result calculated based on long-term (2002–2017) average values of phytoplankton absorption aph(555) at 500 m spatial resolution.	NIWA unpublished; Based on processing described in Pinkerton et al. (2018)
Kpar	Diffuse downwelling attenuation	Monthly	m^{-1}	Attenuation of broadband irradiance (Photosynthetically Available Radiation, PAR) with depth. Estimated using quasi-analytic inversion algorithm applied to MODIS-Aqua data. Result calculated based on long-term (2002–2017) average values at 500 m spatial resolution.	NIWA unpublished; Based on processing described in Pinkerton et al. (2018)
VGPM	Productivity Model	Monthly	$mgCm^{-2}d^{-1}$	Provides estimates of surface water primary productivity based on the Vertically generalized productivity model of Behrenfeld & Falkowski (1997). Net primary productivity by phytoplankton (mean daily rate of water column carbon fixation) is estimated as a function of merged remotely sensed chlorophyll concentration, irradiance, and photosynthetic efficiency estimated from remotely sensed Sea-Viewing Wide-Field-of-view Sensor (SeaWIFS) and MODIS-Aqua satellite imagery (M. Pinkerton, NIWA, pers. Comm.)	NIWA unpublished; Oregon State University (www.science.oregonstate.edu/ ocean.productivity/)

6.3 Density surface fitting

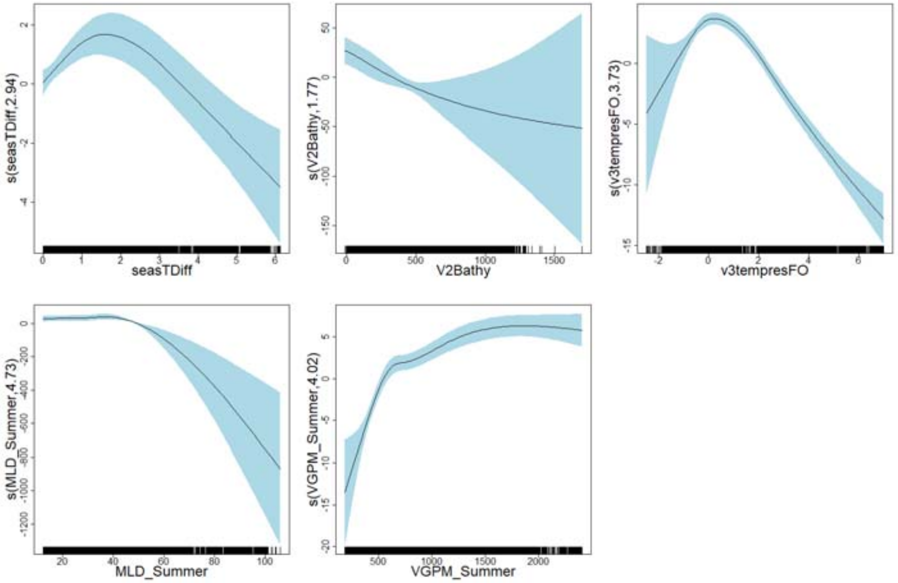
Species density surfaces were constructed using generalised additive models (GAMs) with the survey data as the response variable and the environmental covariate data as predictors. The modelling was performed within the R software environment (R Core Team 2018) and made use of the 'mgcv' package (Wood 2017). Selection of the final model for prediction (over FMAs) followed the same general procedure for each species and was essentially stepwise regression using backward elimination. That is:

1. A GAM smooth was performed using all available covariates.
2. The p-values of the smooth components of the GAM were inspected and non-significant covariates removed.
3. The process was repeated until removing any more covariates caused a large drop in the % deviance explained and/or the number of covariates had been reduced to two or three.

In performing the above, scope was left for manual intervention based on expert judgement. Surfaces were produced separately for summer and winter survey data, making use of summer and winter averages of covariate data where available, but the final covariates were either forced to be the same between summer and winter or with one additional covariate for a season if merited by the % deviance explained. Sometimes alternative routes to the final covariates were also explored. This was done when covariates expected to be influential were given non-significant p-values early in the stepwise regression. Through extensive simulation tests, Marra & Wood (2011) found that backward elimination compared favourably to other covariate selection methods but could eliminate influential covariates, especially if there was a low signal to noise ratio level and high covariate correlation. Often, after other potential covariates had been eliminated, the 'preferred' covariate was found to be significant. This is believed to be because of correlation between variables, although lack of time prevented a formal exploration of covariate correlation. Response to covariate plots of the final GAM fits for those species selected are given in Figure 6.12.

Before fitting the GAM, covariate grids at 10×10 km resolution were constructed using the 'aggregate' function of R package 'raster' (Rodriguez-Sanchez 2013). Covariate data was associated with survey density data (at the survey trawl location) using the 'over' function of R package 'sp'. This associates the value from the appropriate covariate grid square to the survey data point using a 'point-in-grid' algorithm. Predictions of species' densities, based on the covariates, were again made over a 10×10 km grid. For each species, surfaces covering all FMAs affected by the project (FMAs 1 to 7) were supplied to CSIRO for use in eSAFE (see Section 8). Surfaces restricted to the FMAs associated with the stock were also created and are shown in Appendix 5.

Elephant fish: Summer



Elephant fish: Winter

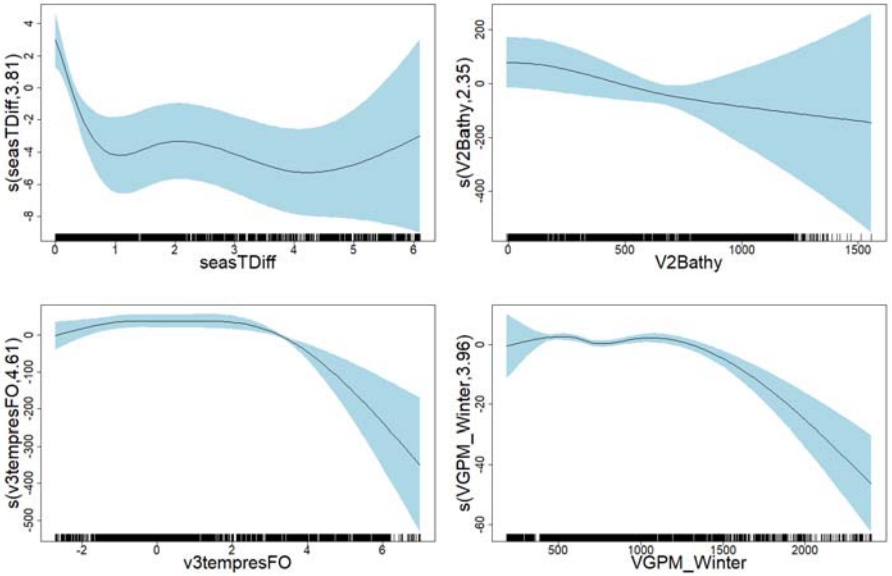
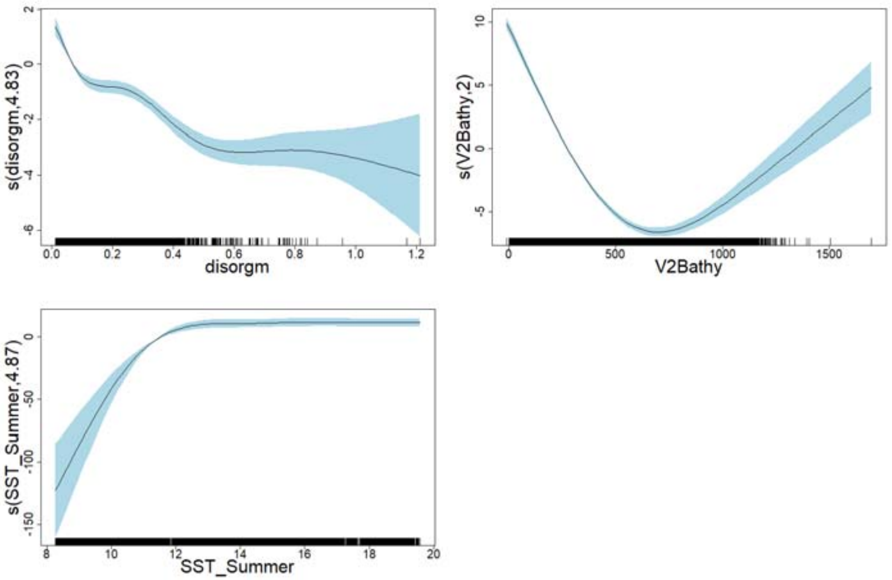


Figure 6.12. Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Gurnard: Summer



Gurnard: Winter

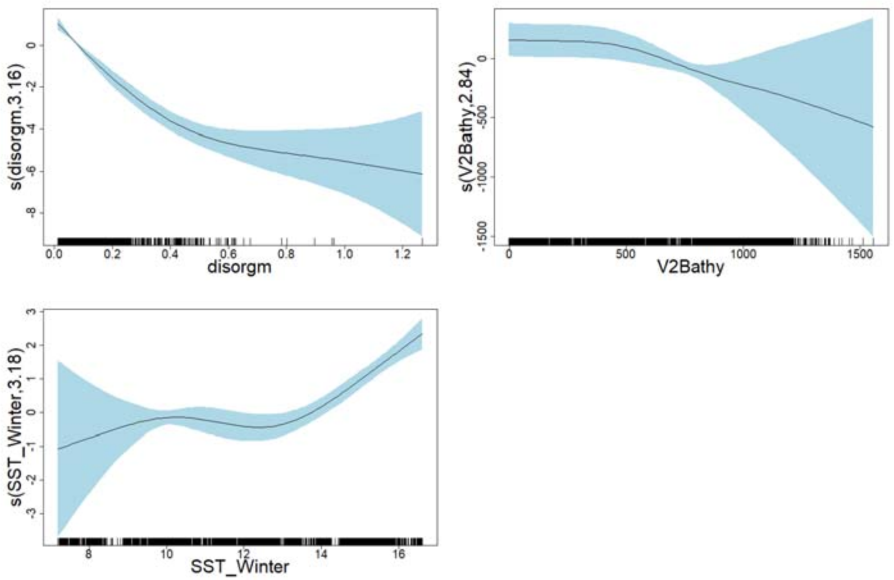


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Rough skate: Summer Rough skate: Winter

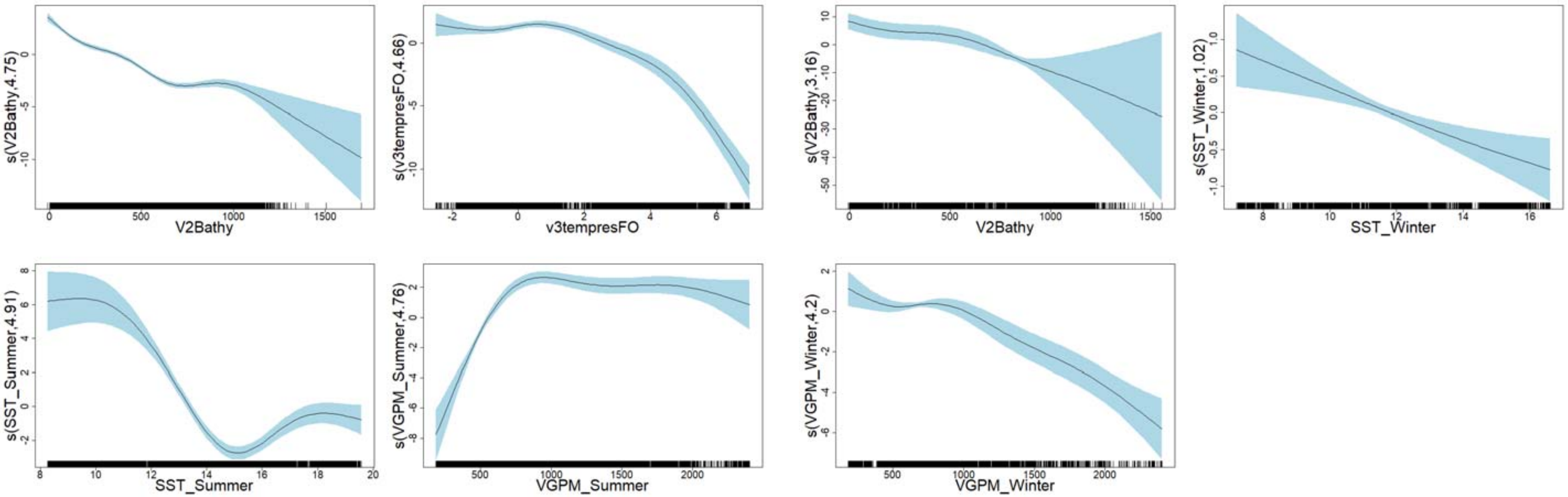


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Snapper: Summer

Snapper: Winter

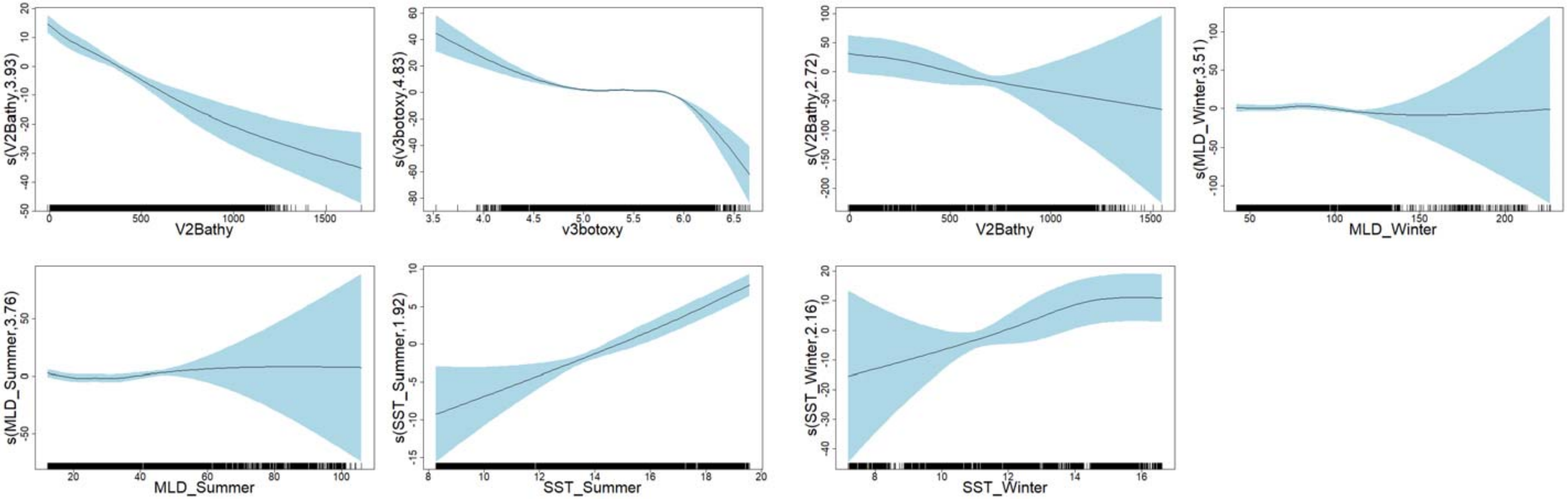
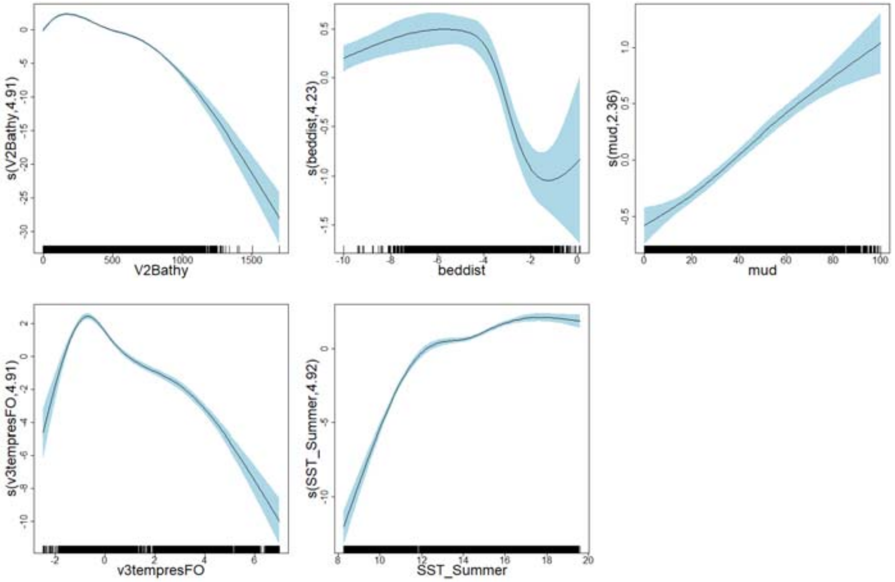


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Sea perch: Summer



Sea perch: Winter

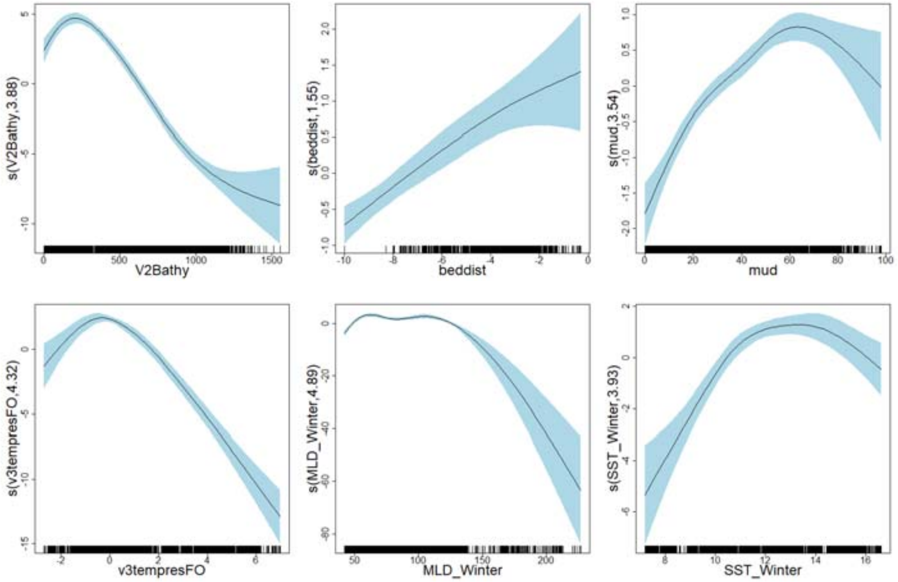
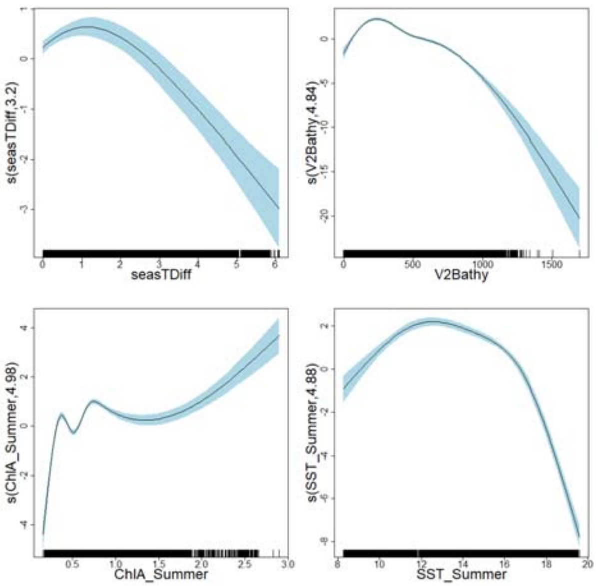


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Giant stargazer: Summer



Giant stargazer: Winter

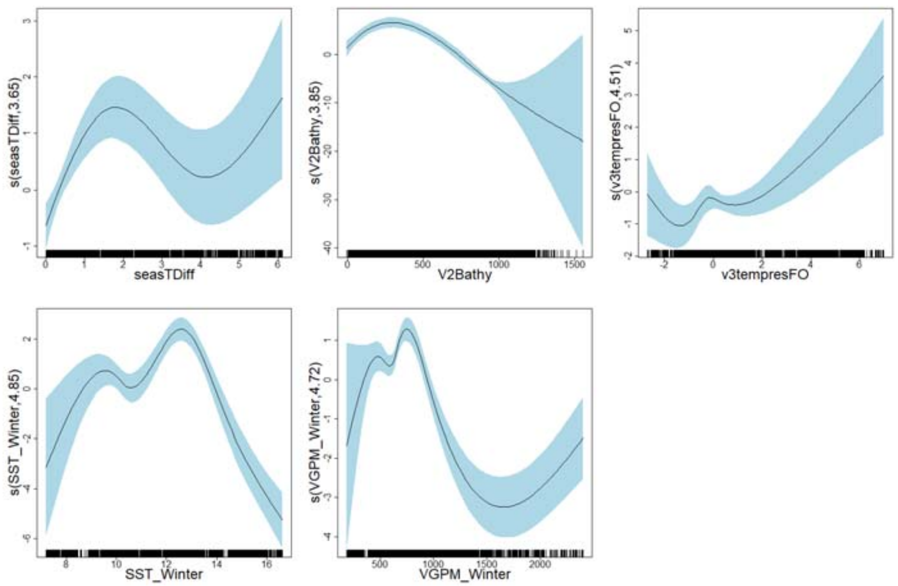
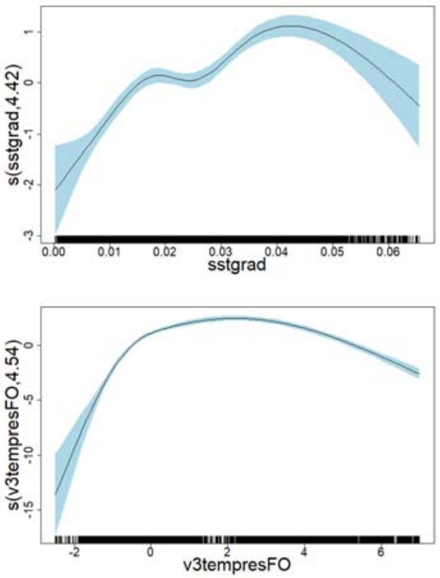


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km^2) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

Tarakihi: Summer



Tarakihi: Winter

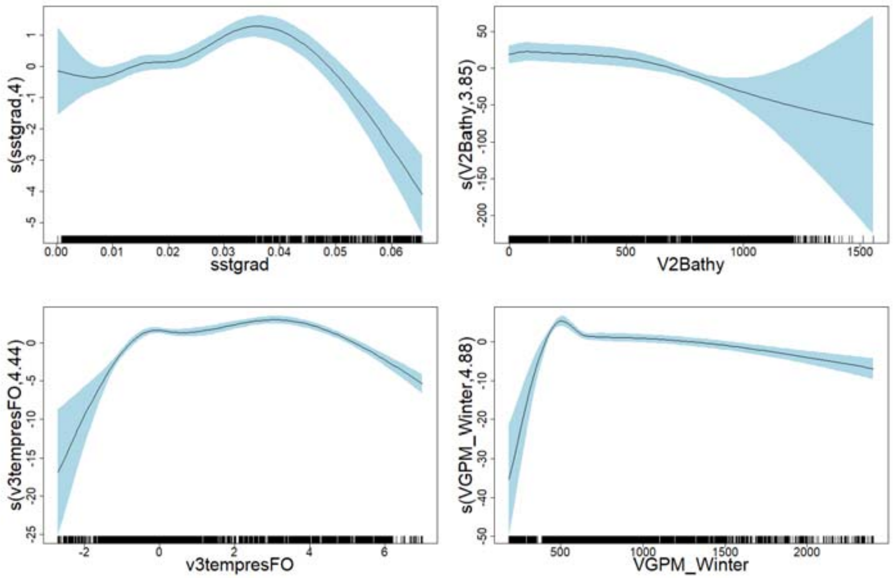


Figure 6.12 (cont). Smooth function estimates of the response variable (kg/km²) against each individual covariate. The numbers in brackets in the y-axis captions are the estimated degrees of freedom (edf) of the smooth curves. The 'rug plot' at the bottom of each graph shows the covariate values. The shaded regions represent 95% Bayesian 'confidence' intervals.

6.4 Biomass predictions within and outside survey areas

Biomass estimates made over large areas with no survey data and without outputs from an integrated assessment to compare against are impossible to verify. Biomass predictions were therefore compared to the relative biomass estimates from the surveys by integrating over the areas of those surveys. Figure 6.13 shows the outline of the surveys used for comparison (the Chatham Rise survey area includes 'deep-water' strata). It also shows the 'tarakihi statistical rectangles' used to compare to the tarakihi stock assessment (see Section 6.5).

A) B)

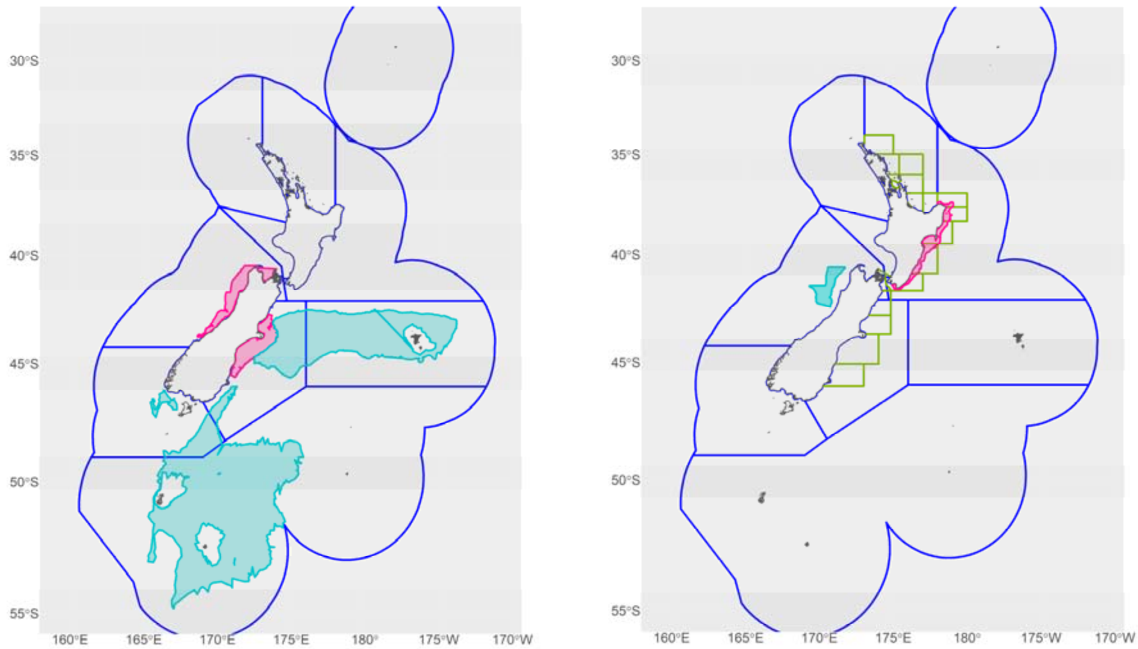


Figure 6.13. Surveys used for comparison to GAM density surface derived biomasses. Pink: surveys conducted by *Kaharoa*; blue: surveys conducted by *Tangaroa*. A) Pink: ECSI, WCSI; blue: Chatham Rise, Sub-Antarctic. B) Pink: ECNI; blue: WCSI-offshore; also 'tarakihi statistical rectangles', the statistical rectangles assumed in the tarakihi stock assessment to contain the east coast tarakihi stock and all fishing activity on it.

Survey biomass estimates are estimated according to the standard approach laid out in Francis (1989); i.e. the relative biomass estimates calculated from the survey data assume that areal availability, vertical availability and vulnerability all equal 1.0 making catchability equal to 1.0. The survey(s) with the greatest coverage for each stock are listed in Table 6.3.

For each of the species-survey combinations, Figure 6.14 shows a comparison of the (single) estimate of species biomass from the GAM density surface (as integrated over the area contained within the outer boundary of the survey) compared to the estimates of the relative biomass estimated and presented in the survey reports. The confidence intervals of the GAM result were formed by summing over ± 2×s.e. of the density estimates in each cell of the prediction grid.

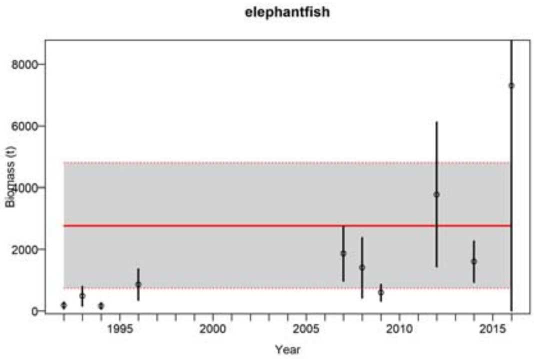
Table 6.3: Fisheries New Zealand research surveys holding catch information on project stocks.

Stock	Survey with catch information	Season
Elephant fish: ELE 3	ECSI	Winter
Red gurnard: GUR 3	ECSI	Winter
Rough skate: RSK 3	ECSI	Winter
	Chatham Rise	Summer
	Sub-Antarctic	Summer
Snapper: SNA 7	WCSI	Summer
Sea perch: SPE 3	ECSI	Winter
	Chatham Rise	Summer
Giant stargazer: STA-GIZ 3	ECSI	Winter
	Chatham Rise	Summer
Tarakihi: TAR-NMP 1,2,3,7	ECSI	Winter
	ECNI	Summer

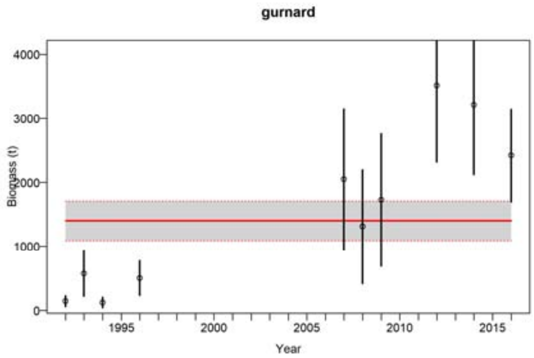
Except for tarakihi in the area of the ECNI survey and giant stargazer in the area of the ECSI the point estimate from the GAM passes through at least one confidence interval from the survey estimates or falls within the range of survey estimates. Results are most comparable when survey estimates have remained relatively constant over time. This would be expected as the GAM fit was made using all survey data and long-term averages of the covariates. The ability of GAMs fitted to a restricted number of surveys to track changes in biomass over time is discussed in Section 6.5.

The GUR 3 and RSK 3 stocks are designated as managed over FMAs 3, 4, 5 and 6. Figure 6.6 indicates that there is no need to consider red gurnard biomass outside of FMAs 3 and 5 and in winter there are only indications of fish in FMA 3. Figure 6.15 shows the percentage of biomass attributable to each survey area and to areas outside of survey areas when the GAM (winter) prediction is made over FMAs 3, 4, 5 and 6. Only a small proportion of the total biomass for red gurnard is predicted from the ECSI survey area with the majority attributed to the Sub-Antarctic survey area. Figure 6.16 shows the density surface for red gurnard. High densities of fish are predicted in a few ‘hot spots’ within the Sub-Antarctic area. This is likely to be because the covariates have values that, from the GAM fit, give a high value of the response variable (kg/km^2) rather than because any red gurnard have been found at these locations. It indicates the importance of restricting predictions using covariates to an area no larger than needed to encompass the stock.

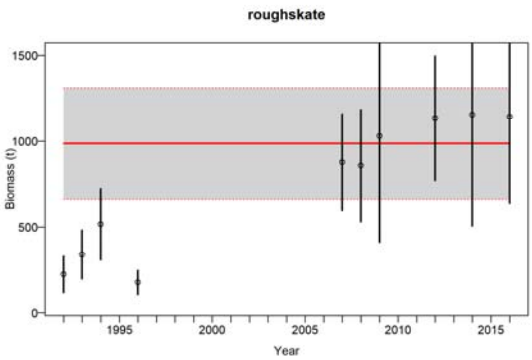
Elephant fish: ECSI winter



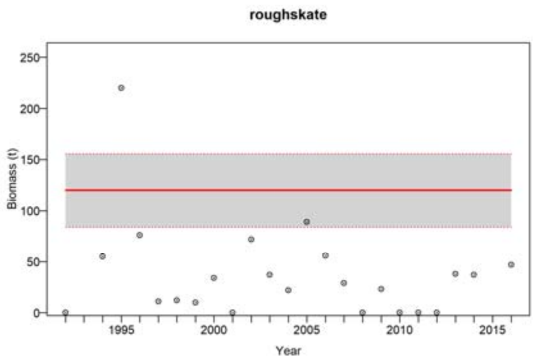
Gurnard: ECSI winter



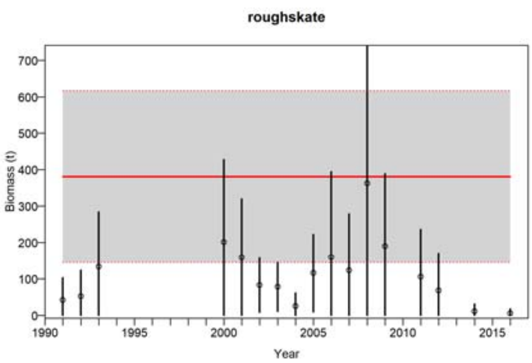
Rough skate: ECSI winter



Rough skate: Chatham Rise summer



Rough skate: Sub-antarctic summer



Snapper: WCSI summer

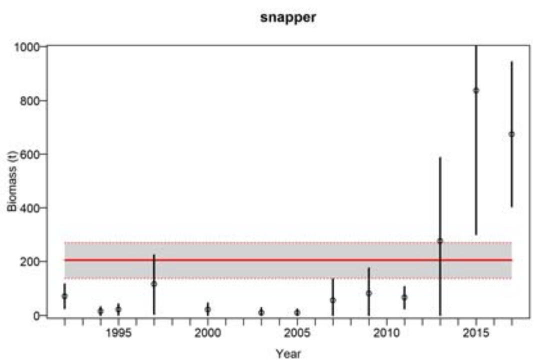
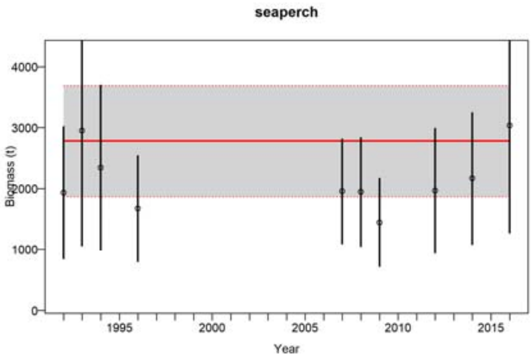
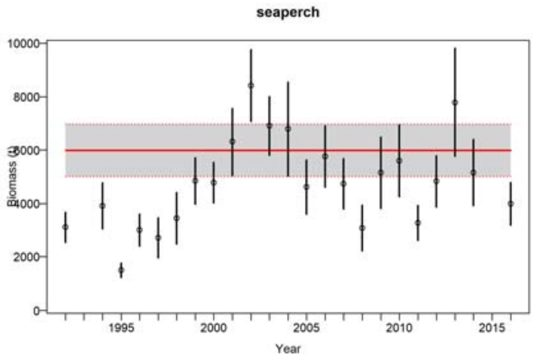


Figure 6.14. Survey relative biomass estimates (vertical lines ± 2×std. dev.) compared to single GAM prediction using all survey data from the appropriate season (horizontal line). Shaded area gives approximate confidence interval; lower value formed by summing over cells, values of density estimate – 2×s.e. from each prediction grid cell , upper value formed by summing over cells, values of density estimate + 2×s.e. from each prediction grid cell.

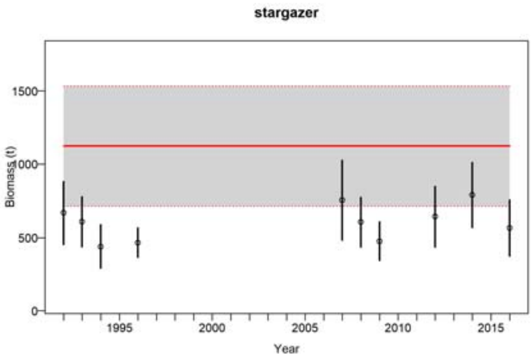
Sea perch: ECSI winter



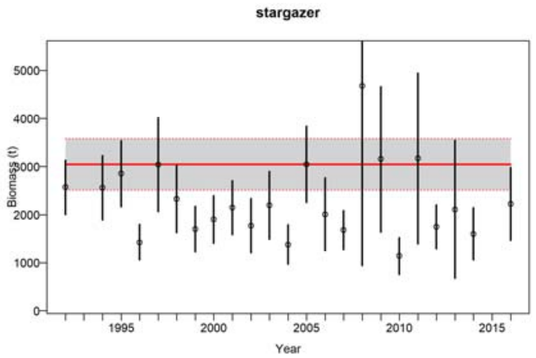
Sea perch: Chatham Rise summer



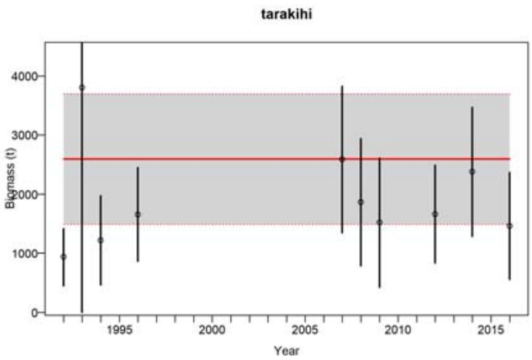
Giant stargazer: ECSI winter



Giant stargazer: Chatham Rise summer



Tarakihi: ECSI winter



Tarakihi: ECNI summer

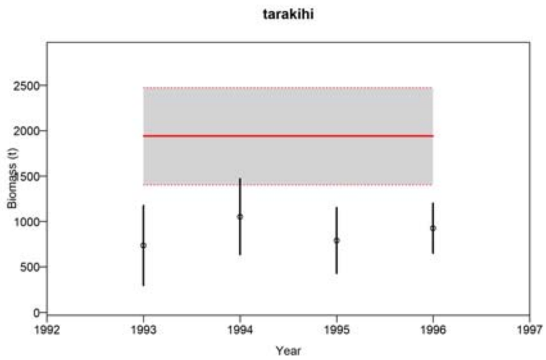


Figure 6.14 (cont). Survey relative biomass estimates (vertical lines ± 2×std. dev.) compared to single GAM prediction using all survey data from the appropriate season (horizontal line). Shaded area gives approximate confidence interval; lower value formed by summing over cells, values of density estimate – 2×s.e. from each prediction grid cell, upper value formed by summing over cells, values of density estimate + 2×s.e. from each prediction grid cell.

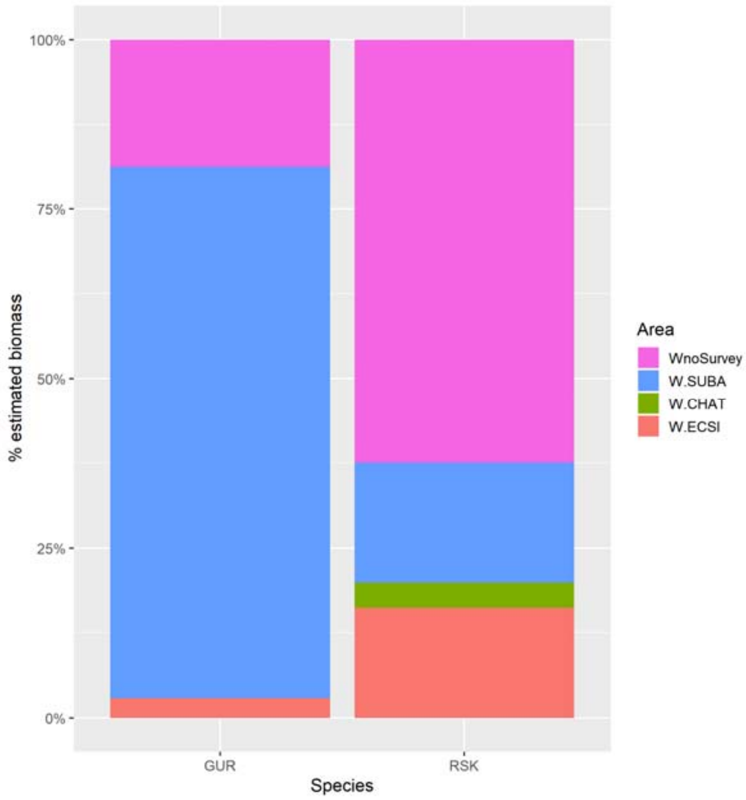


Figure 6.15. Percentages of biomass predicted to come from within the boundary of survey areas and from elsewhere over FMAs 3, 4, 5 and 6. Left: red gurnard. Right: rough skate.

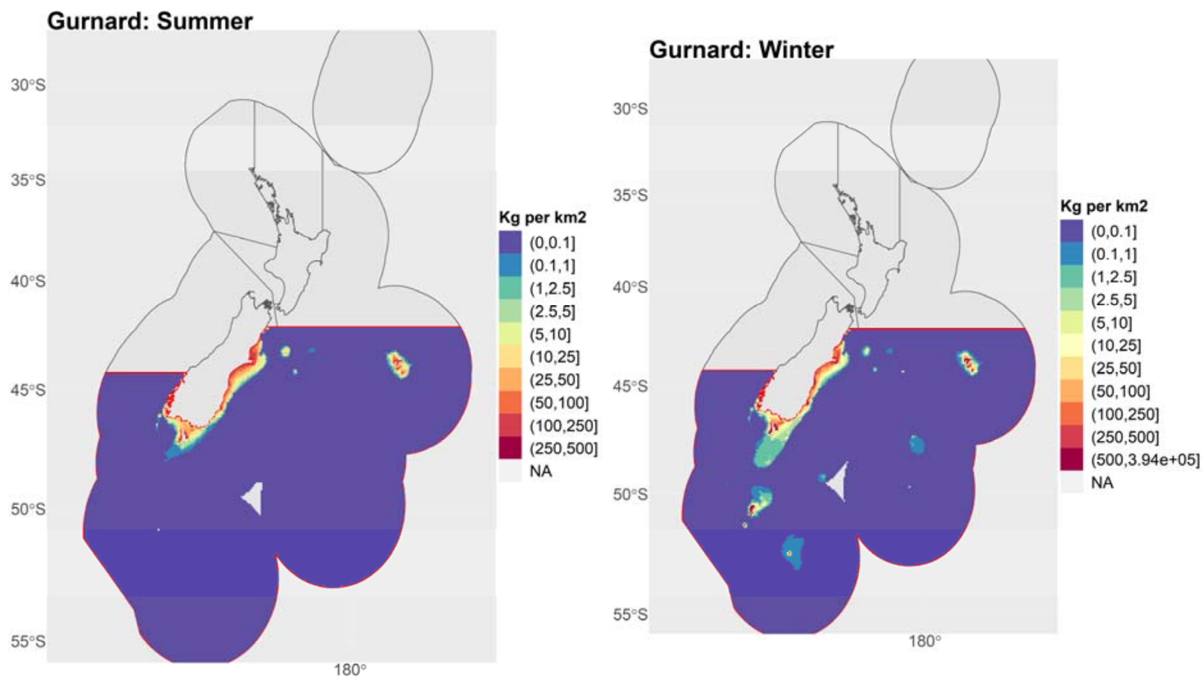
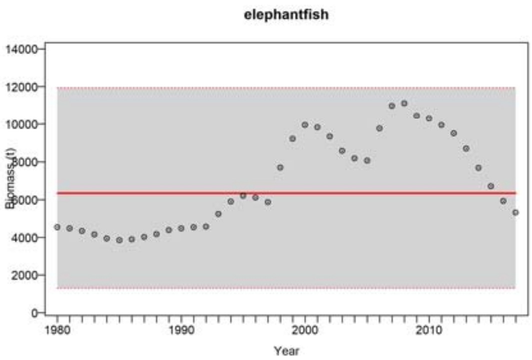


Figure 6.16. Density surfaces predicted for red gurnard over FMAs 3, 4, 5 and 6. Left: using survey data from the summer period. Right: using survey data from the winter period.

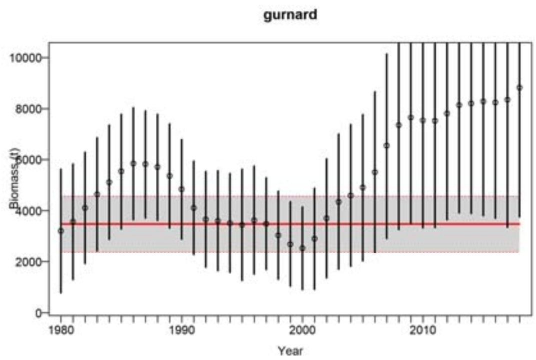
6.5 Biomass predictions in comparison to integrated assessments

Conventional integrated assessments were available for elephant fish (ELE 3), gurnard (GUR 3), snapper (SNA 7), and tarakihi east coast (TAR-NMP 1, 2, 3, 7) (see Section 3). Figure 6.17 shows the comparison between the results for total biomass from these assessments compared to the (single) biomass estimate from GAM fits using all survey data (for a given season). Biomasses from the GAM surfaces were obtained by integrating over FMA 3 (elephant fish and gurnard), FMA 7 (snapper) and the General Statistical Areas used in the tarakihi east coast assessment (see Figure 6.13). The management area for ELE 3 is FMAs 3 and 4 but the survey data indicates the stock to be contained within FMA 3. Similarly, the management area for gurnard covers FMAs 3, 4, 5 and 6 but survey data indicates the stock to be contained within FMA 3. A biomass estimate for gurnard formed over FMAs 3–6 (not shown) was over 10 times that for FMA 3 with an upper confidence level at nearly 130 000 tonnes.

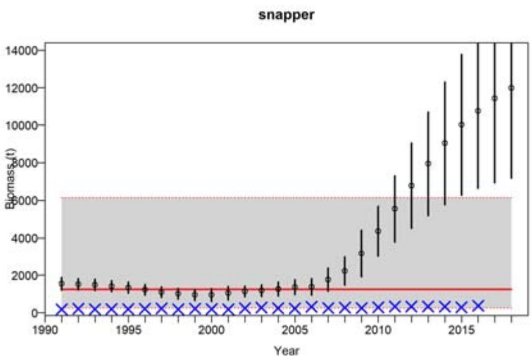
ELE 3



GUR 3



SNA 7



TAR-NMP 1,2,3,7

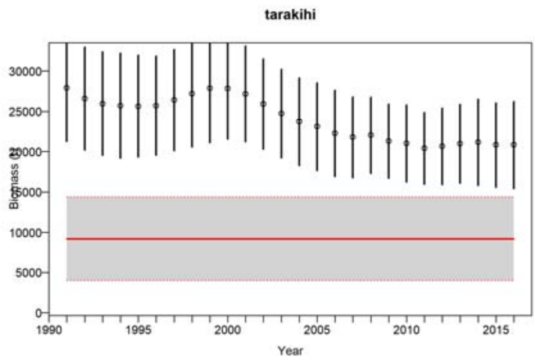
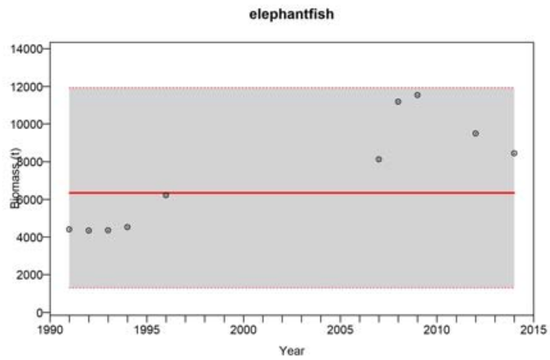


Figure 6.17. Estimates of total biomass from integrated assessments (vertical lines ± 2×std. dev.) compared to single GAM prediction using all survey data from the appropriate season (horizontal line). Shaded area gives approximate confidence interval; lower value formed by summing values of density estimate – 2×s.e., upper value formed by summing values of density estimate + 2×s.e. The snapper figure also shows estimated catches of snapper from FMA 7 (blue crosses).

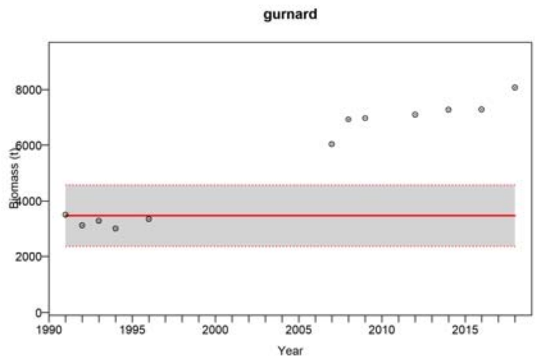
The results for gurnard and snapper show a good match between the integrated GAM surface and a proportion of the assessment series, but as already shown in comparisons against survey relative biomass estimates, the GAM results represent an averaging over years and as such it is not possible to reproduce the temporal dynamics of the biomass. This is most noticeable in the snapper assessment.

The result for elephant fish sits in the mid region of stock assessment biomasses but confidence intervals are wide. The result for tarakihi would indicate a consistent underestimate from the GAM compared to the assessment. It is known, however, that the ECSI survey catches predominantly young tarakihi (ages 1 and 2) and it is assumed that older fish migrate further north (but still within the tarakihi east coast assessment area) (Langley 2018b). If the GAM biomass estimate is compared to the integrated assessment estimate of the biomass vulnerable to the ECSI survey a very close match is obtained, (Figure 6.18). Estimates of vulnerable biomass from the integrated assessment are at two distinct levels for gurnard. The result from the GAM fit matches the estimates for the early surveys when it might have been expected to sit somewhere between the 1990s and post 2000 values, as appears the case for elephant fish. The WCSI survey was not used in the SNA 7 integrated assessment.

Elephant fish: ECSI winter



Gurnard: ECSI winter



Tarakihi: ECSI winter

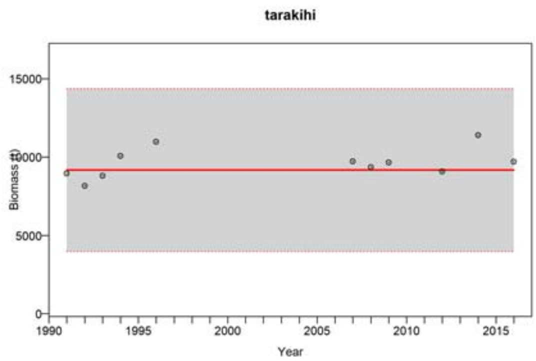


Figure 6.18. Estimates of biomass vulnerable to the ECSI winter survey from an integrated assessment compared to single GAM prediction using all survey data from the appropriate season (horizontal line). Shaded area gives approximate confidence interval; lower value formed by summing values of density estimate – 2×s.e., upper value formed by summing values of density estimate + 2×s.e.

To attempt to reproduce the temporal dynamics of the different stocks, GAM fits were made to a succession of short sequences of survey data. An attempt to perform GAM fits on individual surveys to estimate SNA 7 biomass showed poor stability in results with years of very high or very low estimated biomass (see Figure A5.8 in Appendix 5). It was therefore decided to fit to three surveys at a time. Given the well-defined and limited geographic range of the ELE 3, GUR 3 and SNA 7 stocks, survey data was restricted to the ECSI winter survey for ELE 3 and GUR 3 and the WCSI survey for SNA 7.

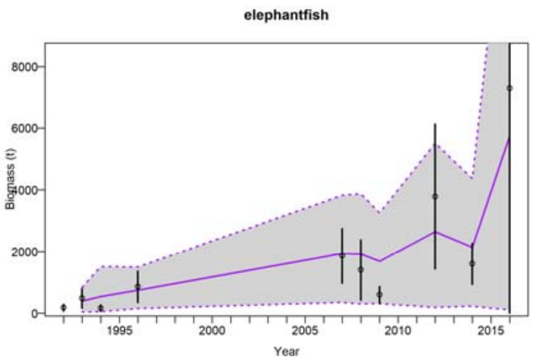
The trip codes of the surveys used in each fit are given in Table 6.4. For tarakihi any data available within a window of years that included three ECSI winter surveys was used.

Table 6.4: Sequences of Fisheries New Zealand research surveys used to make a 'time-series' of GAM fits.

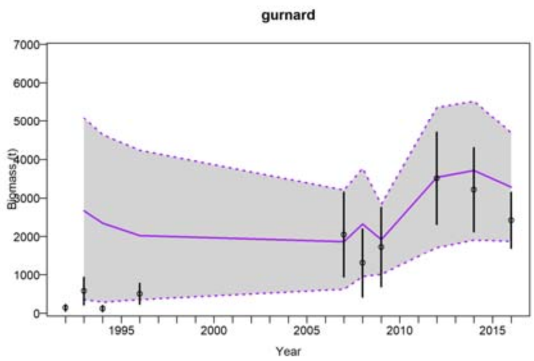
Stock	Sequence of surveys used for GAM fits (trip codes)
ELE 3 and GUR 3	"kah9105.kah9205.kah9306"; "kah9205.kah9306.kah9406"; "kah9306.kah9406.kah9606"; "kah9406.kah9606.kah0705"; "kah9606.kah0705.kah0806"; "kah0705.kah0806.kah0905"; "kah0806.kah0905.kah1207"; "kah0905.kah1207.kah1402"; "kah1207.kah1402.kah1605"
SNA 7	"kah9006.kah9204.kah9404"; "kah9204.kah9404.kah9504"; "kah9404.kah9504.kah9701"; "kah9504.kah9701.kah0004"; "kah9701.kah0004.kah0304"; "kah0004.kah0304.kah0503"; "kah0304.kah0503.kah0704"; "kah0503.kah0704.kah0904"; "kah0704.kah0904.kah1104"; "kah0904.kah1104.kah1305"; "kah1104.kah1305.kah1503"
TAR-NMP 1,2,3,7	"1991.1992.1993"; "1992.1993.1994"; "1993.1994.1995"; "1994.1995.1996"; "1995.1996.2007"; "1996.2007.2008"; "2007.2008.2009"; "2008.2009.2012"; "2009.2012.2014"; "2012.2014.2016"

Figures 6.19 and 6.20 show the result of applying this 'moving window' approach. Figure 6.19 shows that the predictions over the survey area reflect the relative biomass estimates of the surveys for all species, although confidence intervals are sometimes wide in the case of snapper. The left-hand frames of Figure 6.20 contrast the total biomasses estimated from the fully quantitative assessments and integrations over GAM surfaces. The right-hand frame shows the ratio between the point estimates. If the absolute values were different but the ratio effectively static, the difference between results could be considered as the catchability multiple needed to convert the GAM derived value to an absolute biomass.

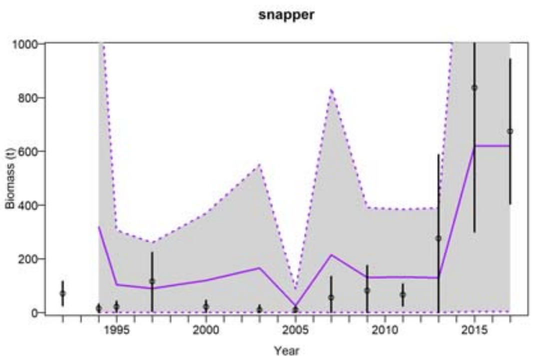
Elephant fish: ECSI winter



Gurnard: ECSI winter



Snapper: WCSI summer



Tarakihi: ECSI winter

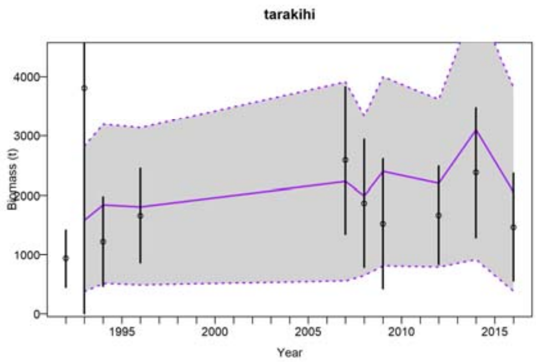
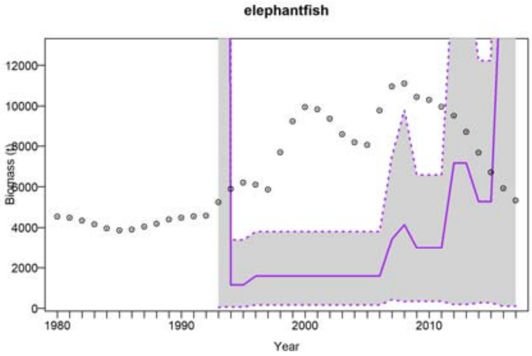
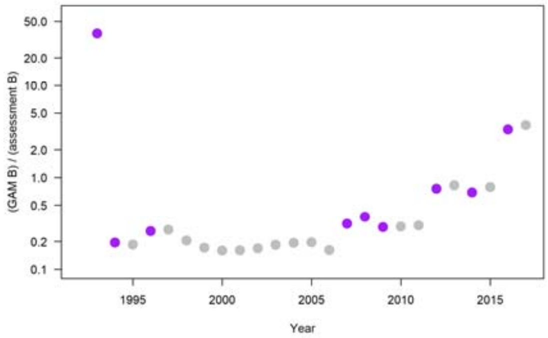


Figure 6.19. Survey relative biomass estimates (vertical lines ± 2×std. dev.) compared to estimates of biomass, over an area bounded by the outer survey perimeter, from GAMs fitted to density data from surveys listed in Table 6.4.

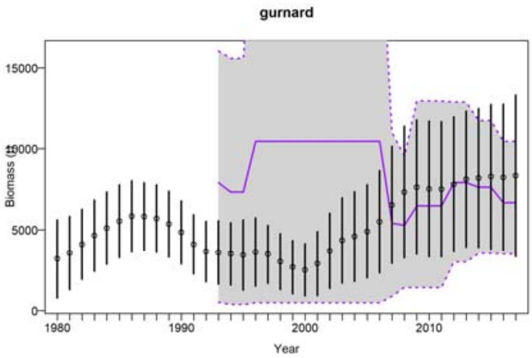
ELE 3: Biomasses



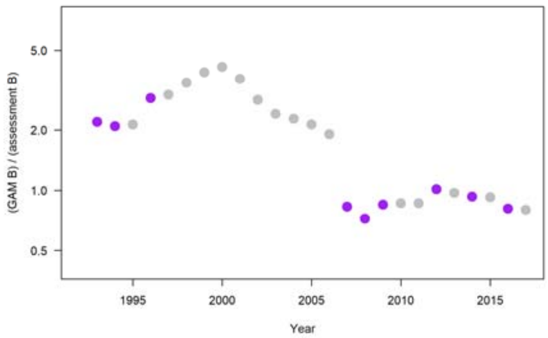
ELE 3: ratio of biomasses



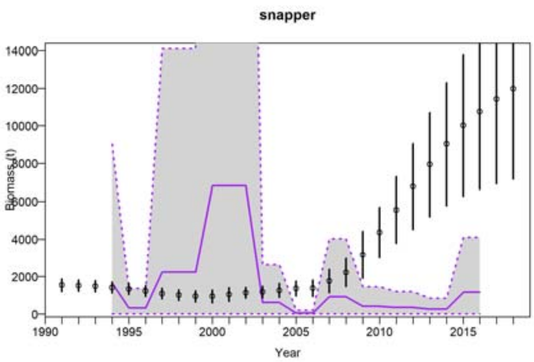
GUR 3: Biomasses



GUR 3: ratio of biomasses



SNA 7: Biomasses



SNA 7: ratio of biomasses

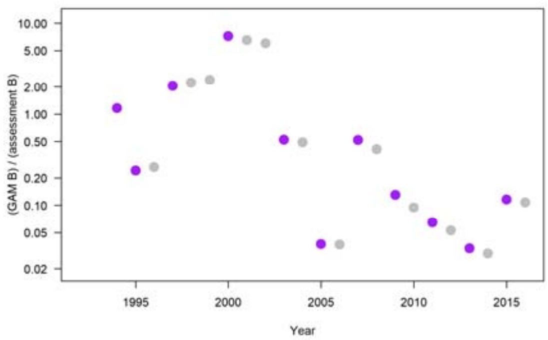
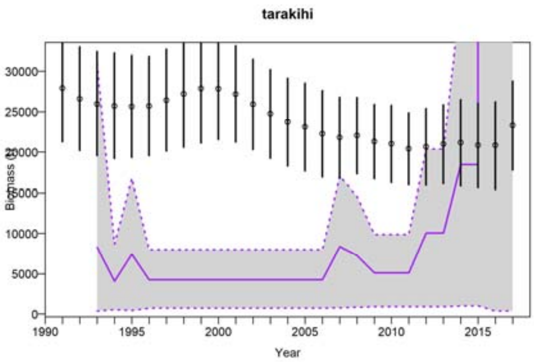


Figure 6.20. Left hand panels: Total stock biomass estimates from integrated stock assessment (black circles with ± 2×std dev.). Purple line (solid): Biomass estimates after GAM fitted to density data from surveys listed in Table 6.4, (line is horizontal across years where no new survey data is available). Shaded region: approximate confidence interval; lower value formed by summing values of density estimate – 2×s.e., upper value formed by summing values of density estimate + 2×s.e. Right hand panels: Ratio between GAM derived biomass estimates and integrated assessment estimates. Purple points relate to third year of three survey years, grey points use same GAM result as previous year.

TAR-NMP 1,2,3,7: Biomasses



TAR-NMP 1,2,3,7: ratio of biomasses

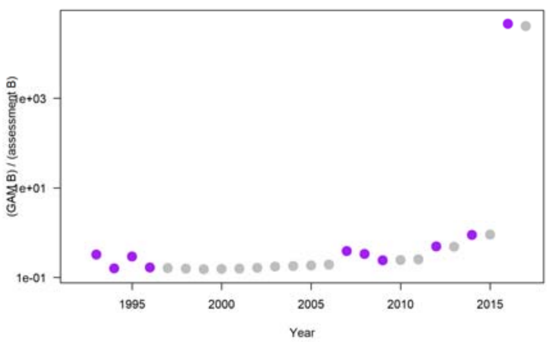


Figure 6.20 (cont). Left hand panels: Total stock biomass estimates from integrated stock assessment (black circles with ± 2×std dev.). Purple line (solid): Biomass estimates after GAM fitted to density data from surveys listed in Table 6.4, (line is horizontal across years where no new survey data is available). Shaded region: approximate confidence interval; lower value formed by summing values of density estimate – 2×s.e., upper value formed by summing values of density estimate + 2×s.e. Right hand panels: Ratio between GAM derived biomass estimates and integrated assessment estimates. Purple points relate to third year of three survey years, grey points use same GAM result as previous year.

For snapper the sequence of GAM surfaces fails to yield biomass estimates that reflect the assessment time sequence. Estimates from the late 1990s are much larger than the stock as assessed from the integrated assessment. The recent large increase in biomass estimated from the assessment is also absent. For tarakihi, the ratio between GAM derived biomass and integrated assessment biomass is relatively consistent until inclusion of the final ECSI survey data. The possible cause is shown in Figure 6.21. To the left are figures of individual haul catch weights, reproduced from Beentjes et al. (2016). The right-hand panels show the density surfaces over the area of the tarakihi assessment using these survey data. In 2016 an unusually large haul of tarakihi was taken from the southern end of the survey area in relatively deep water. The fit to the covariates caused a prediction of high biomass in that area and throughout most of the north island region. A similar explanation appears plausible for elephant fish although the effect is less extreme as the prediction is only over FMA 3 (Figure 6.22). These results indicate high sensitivity to survey variability from this approach to the GAM fitting.

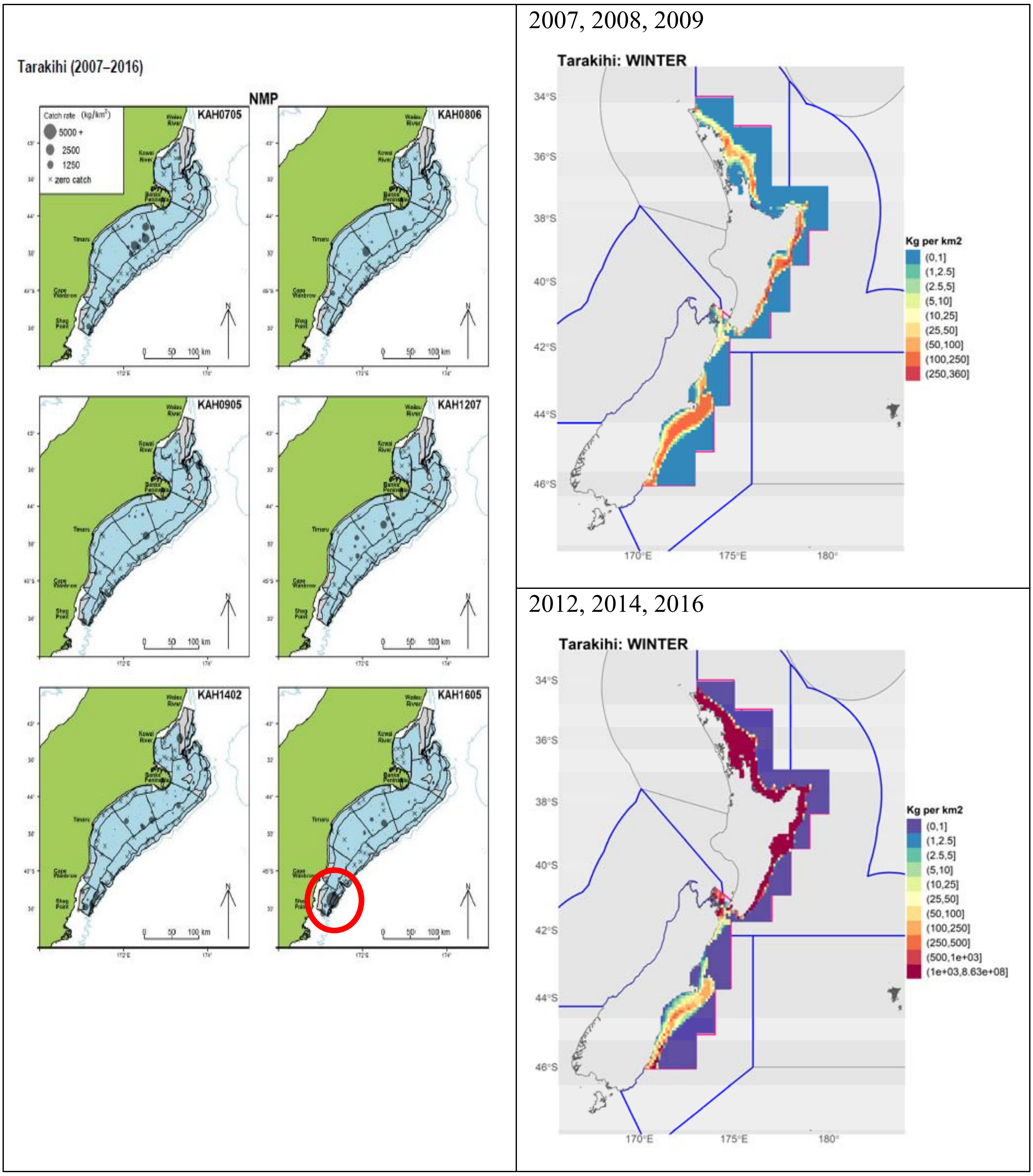


Figure 6.21. Left-hand panel: research survey catch weight per haul, reproduced from Beentjes et al. (2016). Right-hand panel: Surfaces of tarakihi density using GAM fits to data from 2007, 2008 and 2009 (top) and 2012, 2014 and 2016 (bottom).

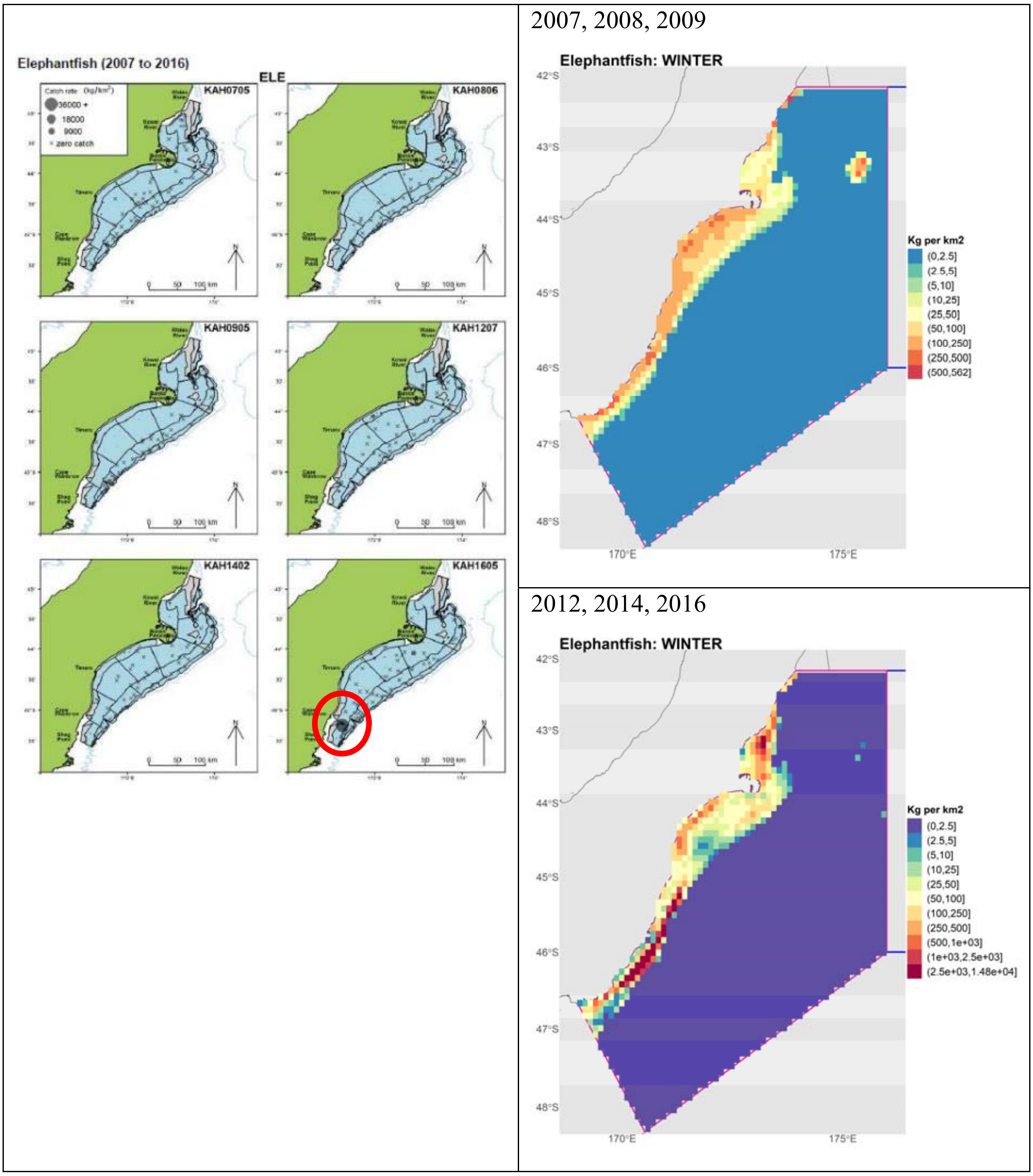


Figure 6.22. Left-hand panel: research survey catch weight per haul, reproduced from Beentjes et al. (2016). Right-hand panel: Surfaces of elephant fish density using GAM fits to data from 2007, 2008 and 2009 (top) and 2012, 2014 and 2016 (bottom).

For snapper, as an alternative to fitting three-year blocks of survey data, the GAM fit using all available survey data (as shown in Figure 6.17) was scaled according to the relative biomass results from the WCSI survey. The result is shown in Figure 6.23.

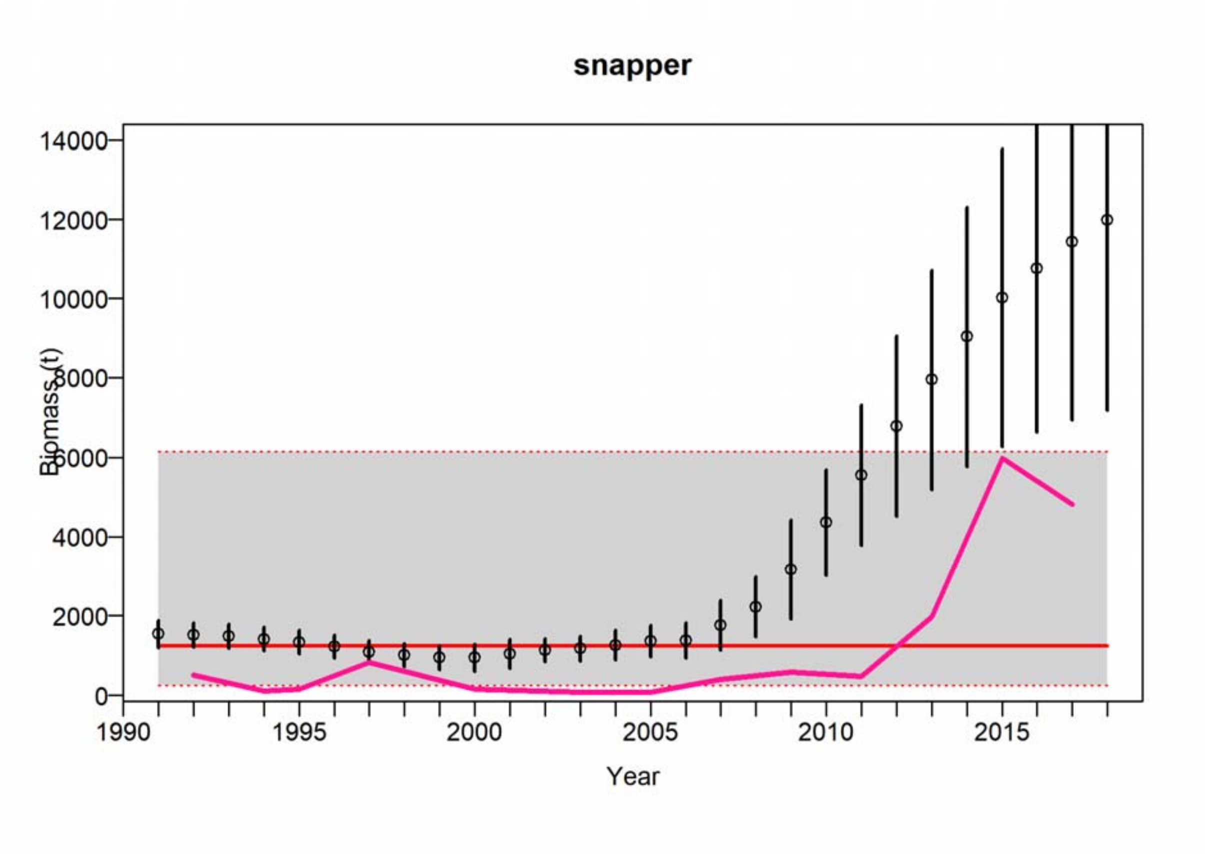


Figure 6.23. Total stock biomass estimates from integrated stock assessment (black circles with ± 2×std dev.). Red line: GAM prediction using all survey data from the appropriate season. Pink line: GAM prediction using all survey data from the appropriate season scaled according to mean standardised WCSI survey values.

7. ESTIMATING GEAR EFFICIENCY FROM CATCH DATA

This section describes a newly developed cross-sampling method used within the eSAFE method (see Section 8) to estimate Q the gear efficiency (catchability within gear-affected area, a combination of encounterability q^h and selectivity q^λ for different gear types.

7.1 Statistical model structure

The previous model developed by Zhou et al. (2014) estimated the catch efficiency using count data with appropriate, discrete probability distributional assumptions. In this project the method for estimating gear efficiency has been modified by using alternative statistical distributions that can account for the semi-continuous nature of the catch data.

Efficiency Q, was defined in terms of the expected catches per shot i, in grid strata j and for gear type k:

$$E[C_{ijk}] = Q_k.(a_i.D_j)^{\eta_k} \tag{7.1}$$

where a_i is the gear affected area and D_{ij} is the fish density in stratum j available for shot i. The power term was included to allow better fits to the catch data and represents a non-linear catch process whereby the magnitude of the catch per biomass unit will depend on the absolute biomass value. Efficiency was estimated within a hierarchical framework, starting with the density, for which the average density per stratum was assumed to follow a Gamma distribution, parameterised on the log-scale to assist with model convergence:

$$\log(D_j) \sim logGamma(\alpha, \beta)$$

This represents an implicit assumption that the density is distributed uniformly within the grid. We treat the probability of a positive catch per strata and gear type θ_{jk} as being representative of the stochastic nature of sampling across a uniform density surface. Using a standard normal prior distribution, the probability of a positive catch was:

$$\text{logit}(\theta_{jk}) \sim Normal(0, 1)$$

$$I(C_{ijk} > 0) \sim Bernoulli(\theta_{jk})$$

The positive catches themselves were modelled using a log-Normal distribution that is conditional on both D_j and θ_{jk}:

$$\mu_{ijk} = \log(Q_k) + \eta_k.\log(a_i.D_j) - \log(\theta_{jk}) - \sigma_k^2/2 \tag{7.2}$$

$$C_{ijk} | \, C_{ijk} > 0 \sim logNormal(\mu_{ijk}, \sigma_k^2)$$

which has an expected value:

$$E[C_{ijk}] = \theta_{jk}.\exp(\mu_{ijk} + \sigma_k^2/2) = Q_k.(a_i.D_j)^{\eta_k} \tag{7.3}$$

and therefore allows us to estimate the parameters of our catch equation (Equation 7.1). We note that the efficiency term Q is only present in the log-normal model component. The model in its current form is therefore unable to estimate the catch efficiency in the absence of any positive catches. When there is no positive catch recorded for a fishing method, the efficiency follows the Beta prior bounded between (0, 1):

$$\log(Q_k) \sim logBeta(1, 10)$$

A notable feature of this model is that the probability of capture θ_{jk} will inform estimation of the efficiency: for a given μ_{ijk}, lower θ_{jk} will bias the estimation of Q down, whereas with a higher θ_{jk}, Q will be biased high. Having estimation of Q informed by both the magnitude and probability of a catch is desirable given that it represents an average efficiency across zero and non-zero catches.

7.2 Applications to simulated and actual data

The model was tested on simulated data using two fishing groups as well as data for snapper and red gurnard.

The simulated data placed densities in 100 grid cells (strata) according to the gamma distribution. The probability of a non-zero tow, yield given a non-zero tow and mean catch weight were all simulated according to the above described model. The MCMC prediction was run for two chains using 10 000 iterations with a burn-in length of 5000 and with every 10th sample kept. Good agreement was obtained between observed and predicted values for probability of positive tow, catch rate and density within strata, Figure 7.1.

Strata were established for the red gurnard and snapper data according to where catch data was present (Figure 7.2). For each species four variants of the model were tested. In version 1 the η_k term was removed from equation (7.2); version 2 was as described by equation (7.2); version 3, as well as having the strata mean density modelled according to a gamma distribution also attempted to model variation about that mean according to

$$D_{ij} \sim LN\left(\log\left(D_j\right), \tau\right)$$

Version 4 modelled the gear efficiency as a fishing event specific parameter Q_{ik} given by

$$Q_{ik} \sim BetaBinomial(Q_k, \tau)$$

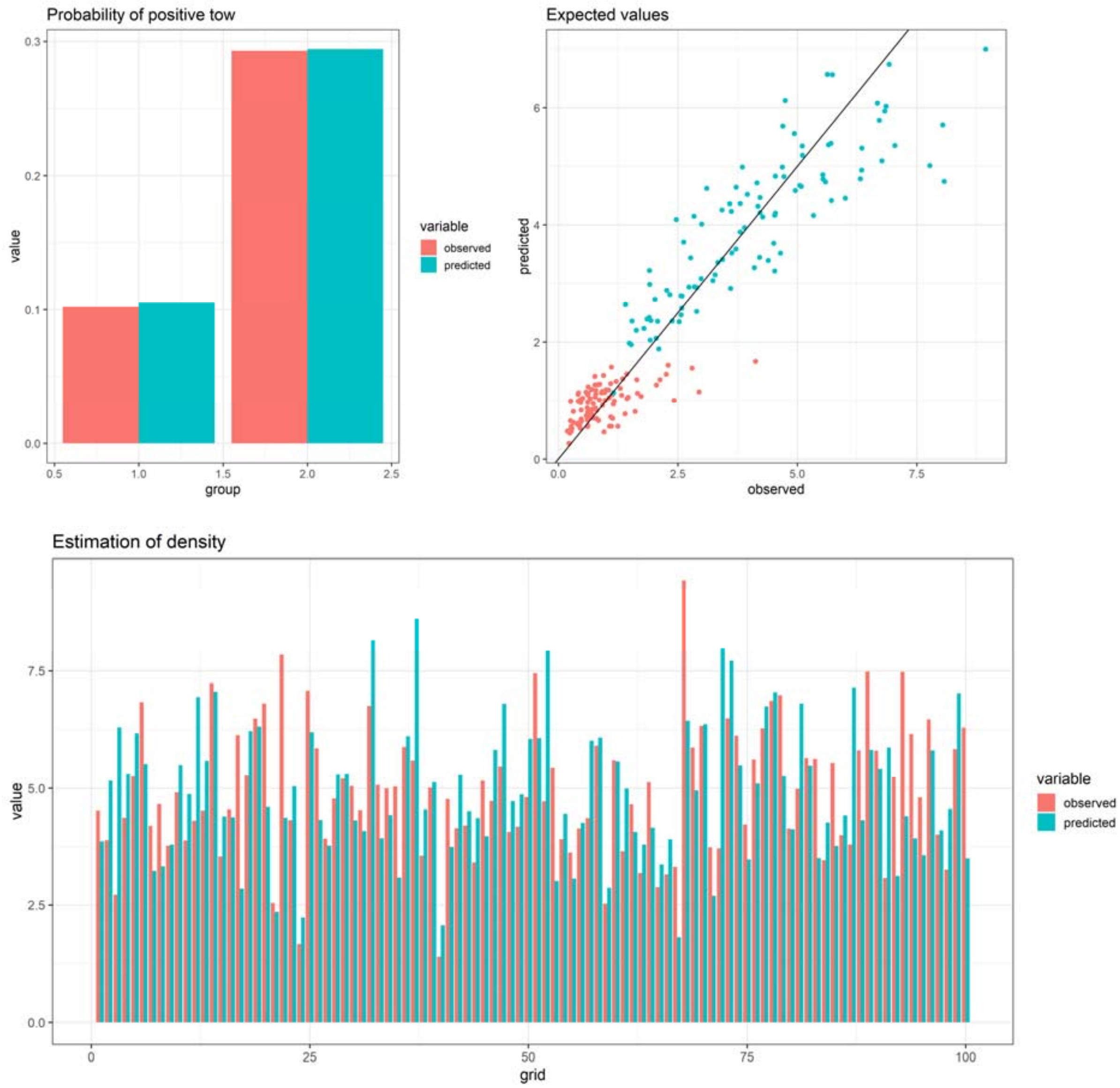


Figure 7.1. Results of a simulation exercise where the data supplied to the prediction model results from the same model structure. The two groups in the upper frames relate to two different fishing groups (for example different gear types).

Expected against observed mean catch rates for the four model variants are given in Figures 7.3 and 7.4. There is a tendency for the models to predict higher than observed catch rates when catch rates are low and lower than observed when catch rates are high. This flattening of the catch rate contrast was most noticeable from model variants 1 and 3. Overall model variant 2, as described in the statistical description section was considered to perform best. Figures 7.5 and 7.6 show the comparison of absolute catch per fishing event between modelled data and observations for the model variant 2. An over-prediction at low absolute catch values is clear for some gear types but the correspondence between predicted and observed values tends to improve at higher values of absolute catch.

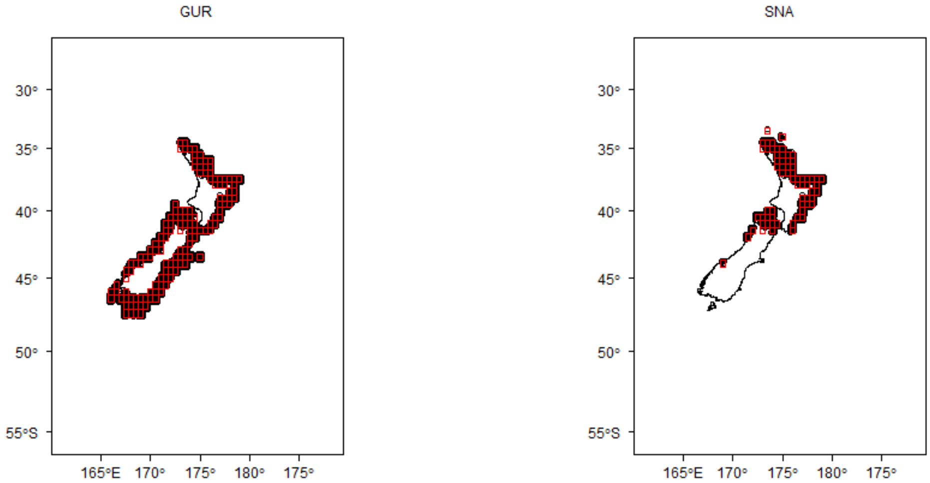


Figure 7.2. Catch-effort grids established for red gurnard (GUR) and snapper (SNA).

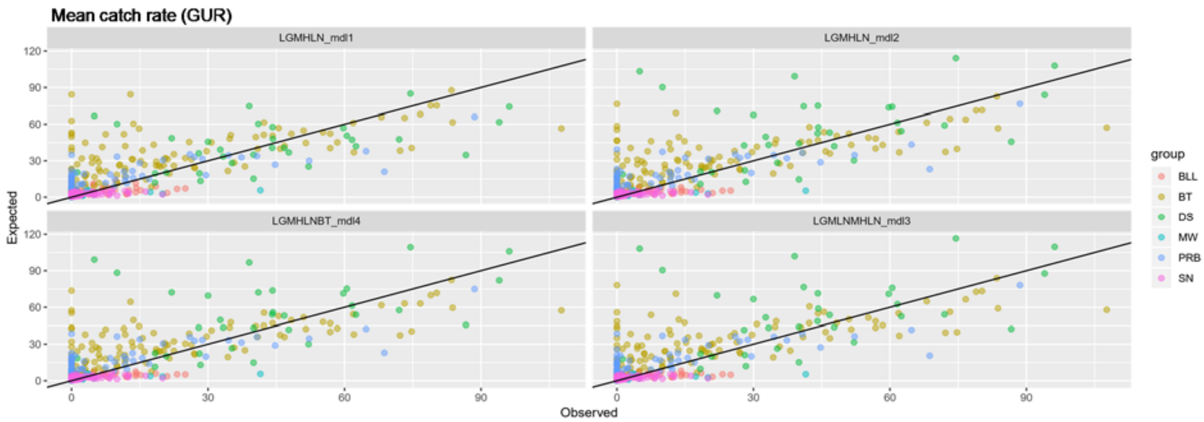


Figure 7.3. Predicted versus observed mean catch rate for red gurnard (GUR). Gear codes are BLL: bottom long line; BT: bottom trawl; DS: demersal seine; MW: mid-water trawls; PRB: precision bottom trawl; SN: seine net.

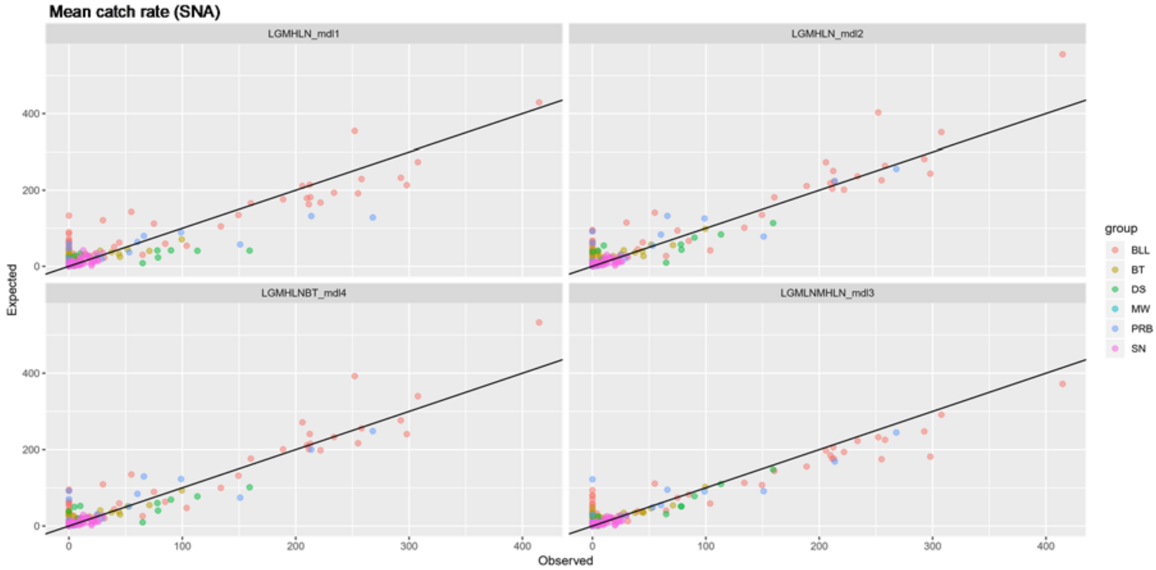


Figure 7.4. Predicted versus observed mean catch rate for snapper (SNA). Gear codes are BLL: bottom long line; BT: bottom trawl; DS: demersal seine; MW: mid-water trawls; PRB: precision bottom trawl; SN: seine net.

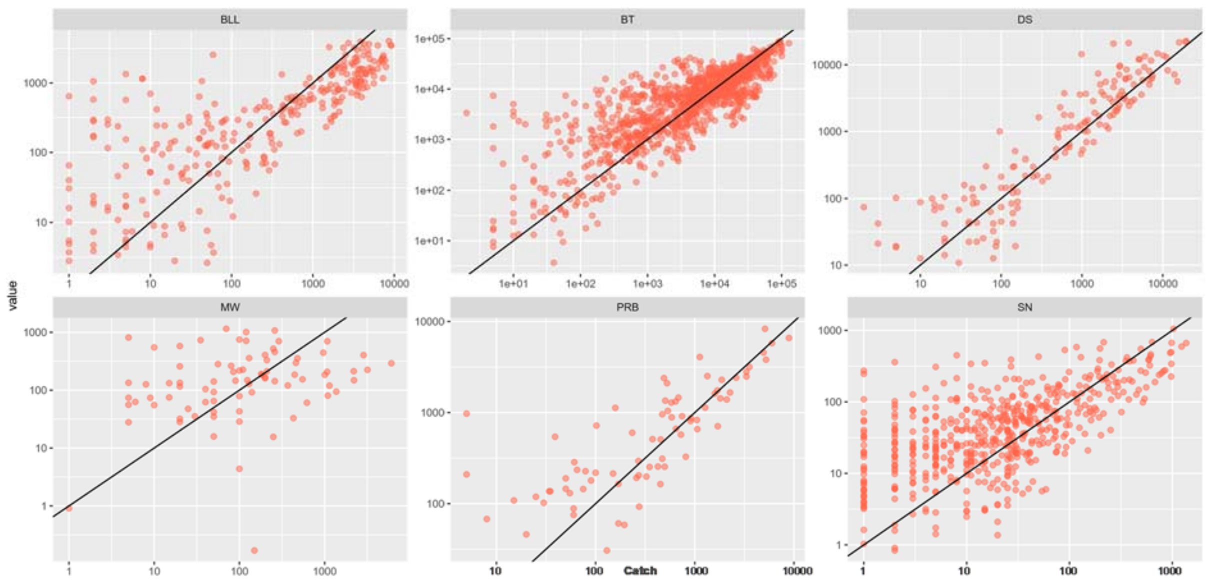


Figure 7.5. Predicted versus observed absolute catch for red gurnard. Gear codes are BLL: bottom long line; BT: bottom trawl; DS: demersal seine; MW: mid-water trawls; PRB: precision bottom trawl; SN: seine net.

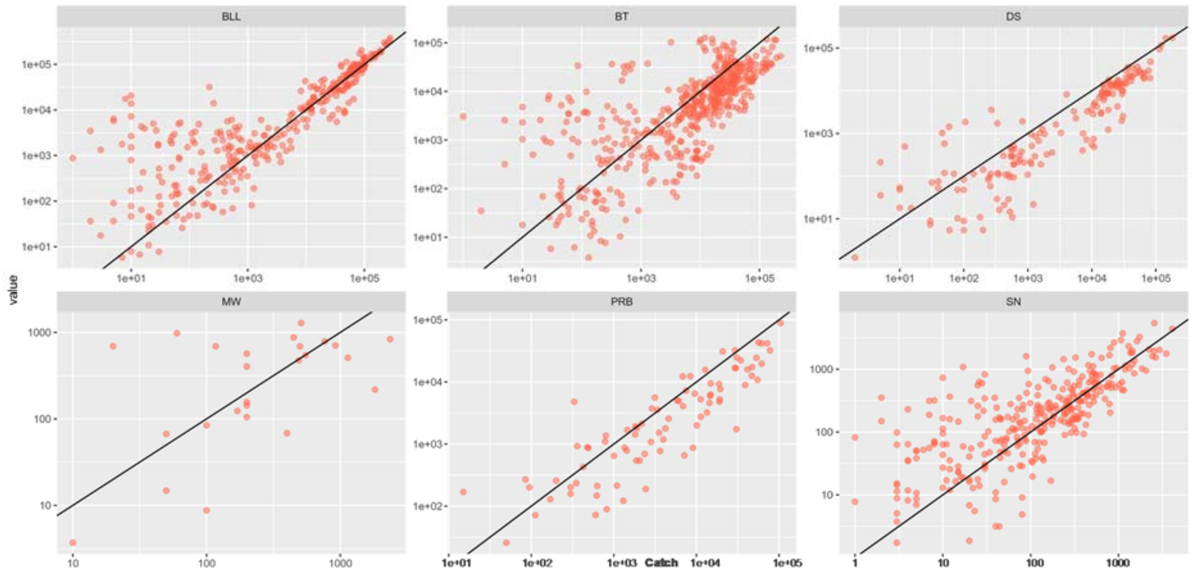


Figure 7.6. Predicted versus observed absolute catch for snapper. Gear codes are BLL: bottom long line; BT: bottom trawl; DS: demersal seine; MW: mid-water trawls; PRB: precision bottom trawl; SN: seine net.

7.3 Current limitations and future enhancements

The work to date demonstrates the successful application of the N-mixture modelling approach to semi-continuous fisheries data. There is, however, scope for further development, testing, and enhancements. Fish density is currently assumed to be uniform within strata and over time, i.e. to be constant across fishing events within a stratum. It is potentially possible to relax this assumption and account for variance in density between fishing events. Over longer time scales, this could be achieved by inclusion of a temporal component into the estimation of the density surface. This would add substantial complexity and would need to be fully simulation tested.

Inclusion of survey catch data could also help to bring greater stability to the model estimates and is certainly worth investigating. Lastly, because this method generates a density surface through use of commercial catch data, it is potentially possible to extract exploitation rates directly from the model.

8. eSAFE

The eSAFE method was applied to more stocks than those chosen for focus in the initial workshop (see Section 2). In this section all stocks to which eSAFE was applied are incorporated in tables. Figures for stocks not included in the project at the first workshop are contained in Appendix 6.

The rationale for this project is to provide scientific stock size and status advice for fish stocks where data are insufficient to employ traditional stock assessment methods and spatially explicit risk assessment is considered promising. The Sustainability Assessment for Fishing Effect (SAFE) is a spatially explicit risk assessment approach. SAFE was originally developed for risk assessment of bycatch species (Zhou & Griffiths, 2008; Zhou et al., 2011, 2019). It is based on spatial overlap between fishing effort and species distribution, fine-tuned by relative fish density, gear efficiency, escapement rate, and discard survival rate (for species returned to the sea). There are two major versions of SAFE: the base method (bSAFE) and an enhanced method (eSAFE) (AFMA, 2017; Zhou et al., 2019). bSAFE is a data-poor method that only requires fishing effort, species distribution range, and some life-history parameters. In contrast, the enhanced eSAFE requires more information, including some detailed shot-by-shot catch data for estimating gear efficiency and fish density over their distribution range. Reviewing low-information stocks in New Zealand indicated that the more advanced version, eSAFE, can be implemented for these stocks. Hence, this report focuses on this method and its application to inshore finfish stocks.

8.1 The basic concept of SAFE

New Zealand's low information stocks generally have total landings statistics but lack abundance (biomass) estimates so it is difficult to derive their fishing mortality rates. However, fishing effort data (for target species in the same fishery) are generally available. The SAFE approach derives a fishing mortality rate for each species based on the area of overlap between the species distribution and fishing effort (Zhou et al. 2011). Assuming that all fish are retained, or, if there are discards, all discarded fish are dead, fishing mortality for gear type k can be estimated as:

$$\boldsymbol{F_k} = \frac{\sum_i \boldsymbol{a_i d_i}}{\sum_j \boldsymbol{A_j d_j}} \boldsymbol{Q_k} \qquad \textbf{(8.1)}$$

where a_i is the effective gear-affected area for gear set (hereafter, shot) i, d_i is fish density at location i that is within the species distribution range, Q_k is gear efficiency (catchability within gear-affected area, a combination of encounterability q^h and selectivity q^{λ} for gear type k, and A_j is area in polygon or grid cell j with an assumed homogeneous fish density. In the bSAFE method, d is assumed constant across the whole distribution range so d_j and d_i can be removed from the equation. Also, in bSAFE, q^h and q^{λ} are species- and gear-specific but not estimated. Instead, one of three values is assumed (0.33, 0.67, or 1.0), except for trawl where q^{λ} uses one of three values (0.30, 0.47, or 1.0).

For the eSAFE method, heterogeneous density across space and gear efficiency are estimated from sporadic shot-by-shot catch records in fisheries logbooks or scientific surveys. We describe the procedures to estimate these two parameters in the following sections.

8.2 Estimating gear efficiency from catch data

Fishing gears typically catch only a fraction of the fish that reside within the gear-affected area (e.g., swept area for trawl) in each gear deployment. Gear efficiency is affected by various factors but is generally species- and gear-specific. Zhou et al. (2014) developed a cross-sampling method to model multiple fishing gear efficiencies and abundance for aggregated populations using fisheries or survey data. They divided a fisheries management area into multiple cells with relatively homogeneous catch-per-unit-effort (CPUE). The method involves a mixture of statistical models (Royle, 2004): a negative binomial model describing an aggregated fish distribution pattern between cells, a Poisson model describing distribution within a cell, and a binomial model describing each catch process. For gears that have a low efficiency for a species, the method combines fisheries or survey data that use more than one gear type but catch the same population in some of the cells at approximately the same time, to estimate gear efficiency (Q). Note that Q is gear- and species- specific, but is assumed to be constant over time and space. The distribution and catch processes are modelled in a Bayesian hierarchical framework.

Since our focus in estimating gear efficiency is on average gear efficiency (per gear) for multiple gear types, the cross-sampling method typically uses only a subset of the data. Strata were selected that contained multiple samples from at least one gear type, and which were assumed *a priori* (based on the density modelling below) to contain a non-zero biomass density (Figure 8.1). Fishing event data per strata and gear type were trimmed for outlying catch rate values and sampled randomly to provide a subset of the data for estimation of the efficiency. Although the cross-sampling method produces estimates of gear efficiency and abundance, the latter is not considered reliable because only a subset of data are used.

The size of gear-affected area a, for each gear setting is a variable that needs to be defined for each gear type. We calculated a for each gear type as in Table 8.1 based on the following rationale (Zhou et al. 2019). For actively moving gears such as trawl, a is the swept area for each shot. For gears that use bait to attract fish, it is difficult to define the gear-affected area, as it will depend on the distance over which a fish may be attracted and then be caught. For these gears, gear-affected area depends on various factors, including bait, current, and the type of fish (Lokkeborg et al. 1989). Field estimates are rare, but one study on sablefish showed that within the first hour, the maximum length of the active space is 925 m (Lokkeborg et al. 1995). Sablefish were caught within 3 hours of soak time from about 800 m (Sigler, 2000). In another field study using baited gillnets, cod were attracted from distances up to 400 m (Kallayil et al. 2003). In a baited video experiment, bait soaked for 1 hour had an effective range of attraction of about 480 m for fish of 200–300 mm length (Cappo et al. 2004). Elasmobranchs are sensitive to chemical signals via taste, common chemical sense, and olfaction. They can detect chemical sources greater than 2000 m away (Jordan et al. 2013). Based on these studies, for baited gears we assumed that the gear-affected distance was w = 1 km from the gear (Table 8.1). 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 a is calculated in the same way in estimating Q and in estimating density or biomass (see below).

Table 8.1. Gear-affected area for various gear types used in New Zealand commercial fisheries.

Gear	Formula	Value and note
Bottom Longline (BLL)	$a = wL$	w = 1 km is bait attraction distance and L is the length of the line
Bottom Trawl (BT)	$a = dhs$	d is fishing duration, h is the net wing width when the trawl is towed under the water, s is tow speed
Cod Pot (CP)	$a = n\pi/4\ w \approx 0.8n$ km^2	N is total number of pot lifts, w = 1 km is attraction distance
Danish Seine (DS)	$a = \pi(L/2\pi)^2$	L is the groundrope length of the seine (total_net_length)
Midwater trawl (MW)	$a = dhs$	d is fishing duration, h is the net wing width when the trawl is towed under the water, s is tow speed
Precision Seafood Harvesting Trawl (PRB)	$a = dhs$	d is fishing duration, h is the net wing width when the trawl is towed under the water, s is tow speed
Set Net (SN)	$a = wL$	w = 1 km is net affected distance and L is the length of the net (total_net_length)

This original cross-sampling method was applied to estimate Q for two species only as a comparison with a newly modified method described in detail in Section 7. One reason for using the cross-sampling method is because records of zero catch or NA in fisheries logbooks may not be true zeros but rather a reflection of catch unrecorded because the species was not in the top 5 or 8 species by catch weight. For this purpose, we excluded all zero catches. Furthermore, catch per shot data often exhibits large variability even for the same gear type within the same grid-time stratum (e.g. variance to mean ratio greater than 100). The large variance makes it difficult to accurately estimate gear efficiency and fish density. Hence, for this exercise, we excluded grid-time strata with extremely variable catches.

8.3 Estimating relative density, biomass, catch and fishing mortality

Summer and Winter relative density surfaces were provided for nine species. With the relative density distribution and species-specific gear efficiency Q_k for each gear type, we can calculate relative catch:

$$\boldsymbol{C_{ijk}^{rel} = Q_k a_{ij} d_j^{rel}} \qquad \textbf{(8.2)}$$

where C_{ijk}^{rel} is relative catch in grid j shot i, a_{ij} is gear-affected area in grid j for shot i, d_j^{rel} is mean relative density from the GAM based on survey catch data in (10×10 km) grid j.

We derived gear-affected area using equations in Table 8.1 for various gear types. Some fishing events recorded unrealistic values or did not have complete information such as fishing duration, tow speed, and net width. For these records, we used the gear-specific median values from all events that had complete information.

The relative biomass in each grid-cell can be calculated from survey density and cell size as:

$$\boldsymbol{B_j^{rel} = A_j d_j^{rel}} \tag{8.3}$$

where A_j is the total area size in grid j. Because the same relative density is used to estimate catch and available biomass, fishing mortality can be directly calculated as

$$\boldsymbol{F = \frac{\sum_{ijk} C_{ijk}^{rel}}{\sum_j B_j^{rel}} = \frac{\sum_{ijk} Q_k a_{ij} d_j^{rel}}{\sum_j A_j d_j^{rel}}} \tag{8.4}$$

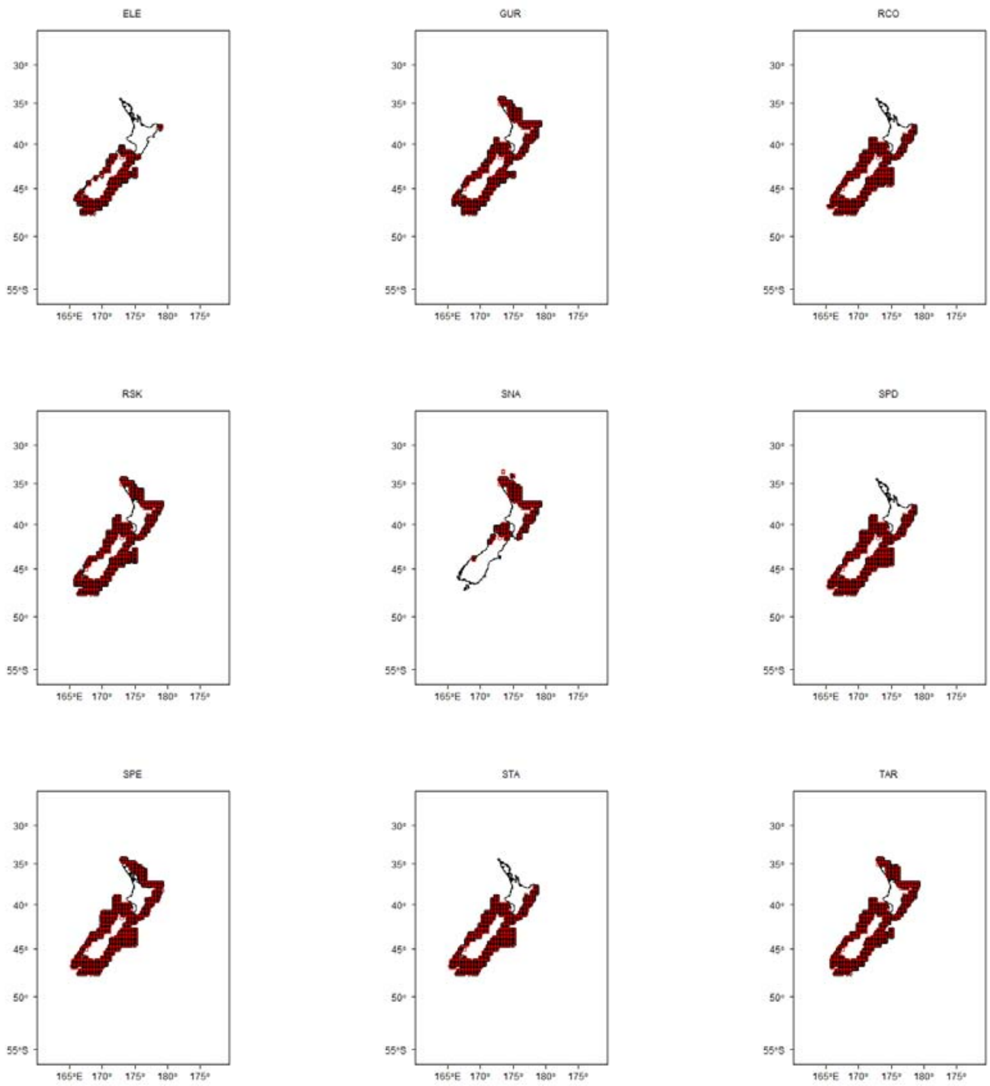


Figure 8.1. Grids (red squares) for estimation of catch efficiencies for each species. Fishing events are also shown (black circles).

8.4 Deriving biological reference points and comparing with estimated fishing mortality rate

Sustainability reference points (e.g., F_{msy}) were derived from simple life history parameters, such as the natural mortality rate, M (Zhou et al. 2012):

F_{msy} **= 0.41*M* (SD = 0.09) for chondrichthyans**

F_{msy} **= 0.87*M* (SD = 0.05) for teleosts** **(8.5)**

If M is not available for some species, it can be obtained from other life-history parameters if some of these parameters are available, for example using estimators developed for teleosts by Then et al. (2015), Charnov et al. (2013), and Jensen (1996), and for elasmobranchs by Frisk et al. (2001) and Hisano et al. (2011). Using these and other empirical relationships it is possible to estimate F_{msy} based on M for most data-poor species.

Finally, risk was determined as for previous applications of SAFE by comparing the estimated cumulative fishing mortality rate with the F_{msy} based reference points: low risk when $F < F_{msy}$, medium risk when $F \geq F_{msy}$, and high risk when $F \geq F_{lim} = 1.5\ F_{msy}$, ($F_{lim}$ is the limit fishing mortality rate) (Zhou et al. 2011).

8.5 New Zealand fisheries data and survey data

Two types of fisheries catch data were available: estimated catches and allocated landings, (see Section 4). The landings by trip data (assuming no error in their reporting) are larger than the estimated catch on the same trip because fishers only record the catch of the 5 or 8 most abundant species in each tow. Other species are recorded as “0” or “NA” in the raw data even though they may or may not appear in the catch. Hence, the allocated landings are considered more accurate than the estimated catches, but because the landings come from a trip and are often evenly allocated to each tow in that trip, these allocated landings can be biased.

For estimating gear efficiency Q, using estimated catches that do not include 0 or NA will overestimate Q, while including 0 and assuming NA is zero is likely to underestimate Q. Similarly, using estimated catches may lead to some bias in the density estimation since they do not equate to the total landings.

The scientific survey data used is described in Section 6. Estimating biomass from survey data has two major concerns: i) the dates of survey and commercial fishing may differ; ii) gears used in surveys are not commercial fishing gear so their efficiency and type of fish (e.g. size) may differ.

Considering these factors, we opted to use estimated catches for estimating gear efficiency and use survey data to produce relative density of species. Together with fishing effort, it is possible to derive ‘relative catch’ for each shot. Annual fishing mortality rate for each sub-stock can be estimated by dividing the sum of the relative catch in each FMA region by the ‘relative biomass’ derived from survey data in the same region.

8.6 Results

8.6.1 Gear efficiency

Using the estimated catch from fisheries logbooks, we estimated gear-efficiency for all gear types for nine species: elephant fish (ELE), gurnard (GUR), red cod (RCO), rough skate (RSK), sea perch (SPE), snapper (SNA), spiny dogfish (SPD), stargazer (STA), and tarakihi (TAR) (Table 8.2). These species were selected on the basis that they had a relative density surface available (estimated from survey data). Positive density grids of 0.5 degree squared were selected for the estimation of Q by species and gear type (Figure 8.1). Six major gear types were included: bottom longline (BLL), bottom trawl (BT), crab pot (CP), Danish seine (DS), midwater trawl (MW), precision seafood harvesting modular trawl system bottom trawl (PRB) and set net (SN). For all species the model was able to predict positive catches and the probability of a positive catch. The estimated mean Q ranged from 0.02 for SPE captured by set net (SN), to 0.83 for GUR captured by bottom trawl (BT) (Table 8.2). The average annual efficiency across all species is 0.33. Note that in Table 8.2, when there is no catch for a specific gear type, (i.e., catch per unit area is zero), the estimated Q is essentially the prior with a mean of 0.09 and standard deviation of 0.08.

Using the estimated Q values from Table 8.2, estimated fish density from the same model, and gear-affected area, the estimated catch for each gear setting (shot) can be derived. There is a good linear relationship between this estimated catch and the observed catch from logbooks for most species and gear types (Figures 8.2 to 8.8). Q can vary significantly between gear types for the same species and between species (Figures 8.9 to 8.15). Uncertainty can also be very large for some gear types. Results for species outside of the seven selected at the initial workshop are given in Appendix 6.

The original cross-sampling method was tested for two species, ELE and RSK. Zero and NA records were excluded, as we assumed that they are not necessarily true zeros. The estimated Qs from this method are smaller than the modified method (Table 8.3). Using the estimated Q and fish density from the original cross-sampling model, as well as gear affected area, we again calculated estimated catch for each shot by each gear type. The model appears to produce unbiased estimates, but with moderate uncertainty (Figures A6.5 and A6.6, Appendix 6).

8.6.2 Relative biomass, relative catch and fishing mortality

Using the GAM predicted density surfaces we derived relative biomass for each stock in both summer and winter seasons (Table 8.4). Clearly, relative biomass varies among species, stocks, and seasons. For example, in FMA 3, spiny dogfish is most abundant both in summer and winter, followed by sea perch and red cod. As this relative biomass is derived from catch, the order of absolute abundance may differ from the relative one because of differences in gear efficiency.

Fishing mortalities from 2016 to 2018 were estimated for selected stocks and 2018 estimates are presented in Table 8.5. Again, relative fishing mortality varies among species, stocks, and seasons. For example, TAR 1 has the highest F using either the summer ($F_{2018} = 0.62$) or winter survey ($F_{2018} = 0.73$). STA 3 has the lowest F_{2018} (= 0.12) when biomass is estimated from the winter survey, while snapper has the lowest F_{2018} (= 0.15) when biomass is from the summer survey. It is important to point out that these estimates may be highly inaccurate due to a range of issues considered in the discussion section.

Comparing with the F_{msy} reference point derived from life-history parameters, the estimated fishing mortality in 2018 is greater than the mean F_{msy} for 19, and greater than F_{lim} for 15, out of the 24 stock-season combinations (Table 8.5). F_{lim} is similar to the F_{msy} upper confidence interval (uci). When compared to uci F_{msy}, F_{2018} is higher in 13 out of the 24 combinations.

In contrast to the results from Table 8.5, if fishing mortality is based on gear efficiency estimated by the cross-sampling method used for elephant fish and rough skate (Table 8.3), F_{2018} is lower than mean F_{msy} for both species (stocks ELE 3, RSK 3, and RSK 7). It is likely that excluding zeros and limiting spatial-temporal strata to those with less volatile catch rates have contributed considerably to the difference between the two modelling approaches.

Table 8.2: Estimated gear efficiency for nine species captured by six gear types. Values for a simulated prior are also shown for comparative purposes. Catch per unit area is the average CPUE for that species and gear type from fisheries data.

Species	Group	Mean and SD	Median and 95% CI	Catch per unit area
ELE	BLL	0.11 (0.09)	0.09 (0.01, 0.33)	0.11
ELE	BT	0.6 (0.09)	0.61 (0.43, 0.77)	11.64
ELE	CP	0.1 (0.09)	0.07 (0, 0.33)	0
ELE	DS	0.09 (0.08)	0.07 (0, 0.3)	0
ELE	MW	0.09 (0.08)	0.07 (0, 0.32)	0
ELE	PRB	0.09 (0.09)	0.07 (0, 0.32)	0
ELE	SN	0.22 (0.08)	0.21 (0.09, 0.41)	17.01
GUR	BLL	0.16 (0.06)	0.15 (0.07, 0.31)	0.65
GUR	BT	0.83 (0.05)	0.84 (0.73, 0.92)	24.23
GUR	CP	0.09 (0.08)	0.07 (0, 0.27)	0
GUR	DS	0.44 (0.11)	0.44 (0.24, 0.66)	35.82
GUR	MW	0.28 (0.1)	0.27 (0.11, 0.49)	1.78
GUR	PRB	0.15 (0.06)	0.14 (0.06, 0.3)	7
GUR	SN	0.07 (0.03)	0.07 (0.03, 0.14)	1.3
RCO	BLL	0.17 (0.07)	0.16 (0.06, 0.34)	0.82
RCO	BT	0.75 (0.07)	0.76 (0.61, 0.88)	30.55
RCO	CP	0.33 (0.1)	0.33 (0.16, 0.53)	20.07
RCO	DS	0.14 (0.09)	0.12 (0.01, 0.37)	0.42
RCO	MW	0.1 (0.06)	0.08 (0.02, 0.25)	1.84
RCO	PRB	0.12 (0.09)	0.1 (0.01, 0.35)	0.32
RCO	SN	0.17 (0.07)	0.16 (0.07, 0.34)	0.52
RSK	BLL	0.26 (0.07)	0.25 (0.15, 0.41)	0.35
RSK	BT	0.79 (0.05)	0.8 (0.68, 0.89)	9.52
RSK	CP	0.09 (0.08)	0.07 (0, 0.3)	0
RSK	DS	0.11 (0.09)	0.09 (0.01, 0.32)	0.36
RSK	MW	0.19 (0.09)	0.17 (0.05, 0.41)	0.39
RSK	PRB	0.5 (0.1)	0.5 (0.31, 0.7)	2.24
RSK	SN	0.09 (0.03)	0.08 (0.04, 0.16)	0.7
SNA	BLL	0.47 (0.1)	0.46 (0.3, 0.68)	26.97
SNA	BT	0.76 (0.06)	0.76 (0.62, 0.87)	54.96
SNA	CP	0.09 (0.08)	0.07 (0, 0.32)	0
SNA	DS	0.4 (0.11)	0.4 (0.2, 0.62)	167.61
SNA	MW	0.13 (0.08)	0.11 (0.02, 0.34)	0.62
SNA	PRB	0.53 (0.1)	0.53 (0.32, 0.72)	108.41
SNA	SN	0.49 (0.08)	0.48 (0.33, 0.65)	6.99
SPD	BLL	0.46 (0.1)	0.46 (0.27, 0.67)	4.14
SPD	BT	0.54 (0.09)	0.54 (0.38, 0.71)	9.73
SPD	CP	0.09 (0.08)	0.07 (0, 0.3)	0
SPD	DS	0.15 (0.1)	0.14 (0.02, 0.4)	0.9
SPD	MW	0.45 (0.1)	0.44 (0.28, 0.66)	4.99
SPD	PRB	0.3 (0.11)	0.29 (0.13, 0.56)	17.86
SPD	SN	0.51 (0.1)	0.5 (0.32, 0.71)	7.34

Table 8.2 (cont). Estimated gear efficiency for nine species captured by six gear types. Values for a simulated prior are also shown for comparative purposes. Catch per unit area is the average CPUE for that species and gear type from fisheries data.

Species	Group	Mean and SD	Median and 95% CI	Catch per unit area
SPE	BLL	0.52 (0.08)	0.52 (0.38, 0.68)	0.95
SPE	BT	0.36 (0.08)	0.36 (0.22, 0.54)	2.64
SPE	CP	0.47 (0.09)	0.47 (0.29, 0.65)	27.88
SPE	DS	0.11 (0.08)	0.09 (0.01, 0.3)	0.03
SPE	MW	0.07 (0.04)	0.06 (0.02, 0.15)	0.16
SPE	PRB	0.55 (0.1)	0.55 (0.37, 0.74)	3.95
SPE	SN	0.02 (0.01)	0.02 (0.01, 0.05)	0.03
STA	BLL	0.03 (0.03)	0.02 (0, 0.12)	0
STA	BT	0.77 (0.06)	0.77 (0.63, 0.88)	25.42
STA	CP	0.09 (0.08)	0.06 (0, 0.3)	0
STA	DS	0.09 (0.09)	0.07 (0, 0.33)	0
STA	MW	0.1 (0.08)	0.08 (0.01, 0.33)	0.06
STA	PRB	0.14 (0.08)	0.12 (0.03, 0.32)	0.48
STA	SN	0.33 (0.07)	0.33 (0.21, 0.5)	1.85
TAR	BLL	0.18 (0.06)	0.16 (0.08, 0.32)	0.93
TAR	BT	0.78 (0.06)	0.78 (0.65, 0.89)	45.78
TAR	CP	0.09 (0.08)	0.07 (0, 0.31)	0
TAR	DS	0.37 (0.11)	0.37 (0.19, 0.59)	9.4
TAR	MW	0.18 (0.1)	0.16 (0.03, 0.44)	1.79
TAR	PRB	0.06 (0.03)	0.06 (0.02, 0.14)	36.92
TAR	SN	0.24 (0.08)	0.23 (0.11, 0.45)	2.41
Prior		0.09 (0.08)	0.07 (0, 0.31)	

Table 8.3: Estimated gear efficiency for elephant fish and rough skate for six gear types using the cross-sample method. Zero catches are excluded.

Species	Gear	Mean	sd	p2.5	Median	p97.5
ELE	BLL	0.03	0.01	0.02	**0.03**	0.05
ELE	BT	0.15	0.00	0.14	**0.15**	0.16
ELE	MW	0.03	0.02	0.01	**0.03**	0.07
ELE	SN	0.10	0.00	0.09	**0.10**	0.10
RSK	BLL	0.02	0.00	0.02	**0.02**	0.02
RSK	BT	0.10	0.00	0.10	**0.10**	0.11
RSK	DS	0.14	0.01	0.12	**0.14**	0.15
RSK	MW	0.25	0.01	0.23	**0.25**	0.27
RSK	PRB	0.13	0.01	0.11	**0.13**	0.14
RSK	SN	0.02	0.00	0.02	**0.02**	0.02

Table 8.4: Relative biomass derived from GAM predicted density surface based on survey data. For each stock S is summer survey and W is winter survey. Area in km^2 and relative biomass in tonnes.

ID	Stock	FMA	Area	Biomass
1	elephantfishS	3	234 000	2 763
2	elephantfishW	3	234 000	6 476
3	gurnardS	3	234 000	1 289
4	gurnardW	3	234 000	3 547
5	redcodS	3	234 000	19 178
6	redcodW	3	234 000	11 437
7	roughskateS	3	234 000	6 932
7	roughskateS	7	342 300	762
8	roughskateW	3	234 000	1 651
8	roughskateW	7	342 300	357
9	seaperchS	3	234 000	3 774
10	seaperchW	3	234 000	27 941
11	snapperS	7	342 300	1 269
12	snapperW	7	342 300	31
13	spinydogS	3	234 000	87 966
14	spinydogW	3	234 000	63 615
15	giant stargazerS	3	234 000	3 567
16	giant stargazerW	3	234 000	4 027
17	tarakihiS	3	234 000	3 414
17	tarakihiS	1	203 600	1 683
17	tarakihiS	2	430 100	2 633
18	tarakihiW	3	234 000	16 858
18	tarakihiW	1	203 600	2 414
18	tarakihiW	2	430 100	3 182

Table 8.5: Estimated relative biomass, relative catch and fishing mortality rate in 2018 based on density surface using summer (S) and winter (W) surveys. Reference point F_{msy}, its lower and upper 90% confidence intervals, and F_{lim} are also listed.

Stock	Season	Year	Rel.biom	Rel.catch	F	F_{msy}	lci.F_{msy}	uci.F_{msy}	F_{lim}
ELE 3	S	2018	2 763	126	0.05	0.12	0.07	0.17	0.17
ELE 3	W	2018	6 476	340	0.05	0.12	0.07	0.17	0.17
GUR 3	S	2018	1 289	74	0.06	0.12	0.07	0.17	0.17
GUR 3	W	2018	3 547	158	0.04	0.12	0.07	0.17	0.17
RCO 3	S	2018	19 178	1 230	0.06	0.37	0.12	0.62	0.56
RCO 3	W	2018	11 437	630	0.06	0.37	0.12	0.62	0.56
RSK 3	S	2018	6 932	325	0.05	0.37	0.12	0.62	0.56
RSK 7	S	2018	762	70	0.09	0.37	0.12	0.62	0.56
RSK 3	W	2018	1 651	103	0.06	0.37	0.12	0.62	0.56
RSK 7	W	2018	357	28	0.08	0.37	0.12	0.62	0.56
SPE 3	S	2018	3 774	237	0.06	0.14	0.04	0.08	0.21
SPE 3	W	2018	27 941	1 392	0.05	0.14	0.04	0.08	0.21
SNA 7	S	2018	1 269	50	0.04	0.15	0.03	0.27	0.22
SNA 7	W	2018	31	4	0.12	0.15	0.03	0.27	0.22
SPD 3	S	2018	87 966	7 395	0.08	0.12	0.04	0.08	0.18
SPD 3	W	2018	63 615	6 713	0.11	0.12	0.04	0.08	0.18
STA 3	S	2018	3 567	323	0.09	0.06	0.04	0.08	0.08
STA 3	W	2018	4 027	122	0.03	0.06	0.04	0.08	0.08
TAR 1	S	2018	1 683	293	0.17	0.22	0.13	0.30	0.32
TAR 2	S	2018	2 633	262	0.10	0.22	0.13	0.30	0.32
TAR 3	S	2018	3 414	228	0.07	0.22	0.13	0.30	0.32
TAR 1	W	2018	2 414	493	0.20	0.22	0.13	0.30	0.32
TAR 2	W	2018	3 182	360	0.11	0.22	0.13	0.30	0.32
TAR 3	W	2018	16 858	871	0.05	0.22	0.13	0.30	0.32

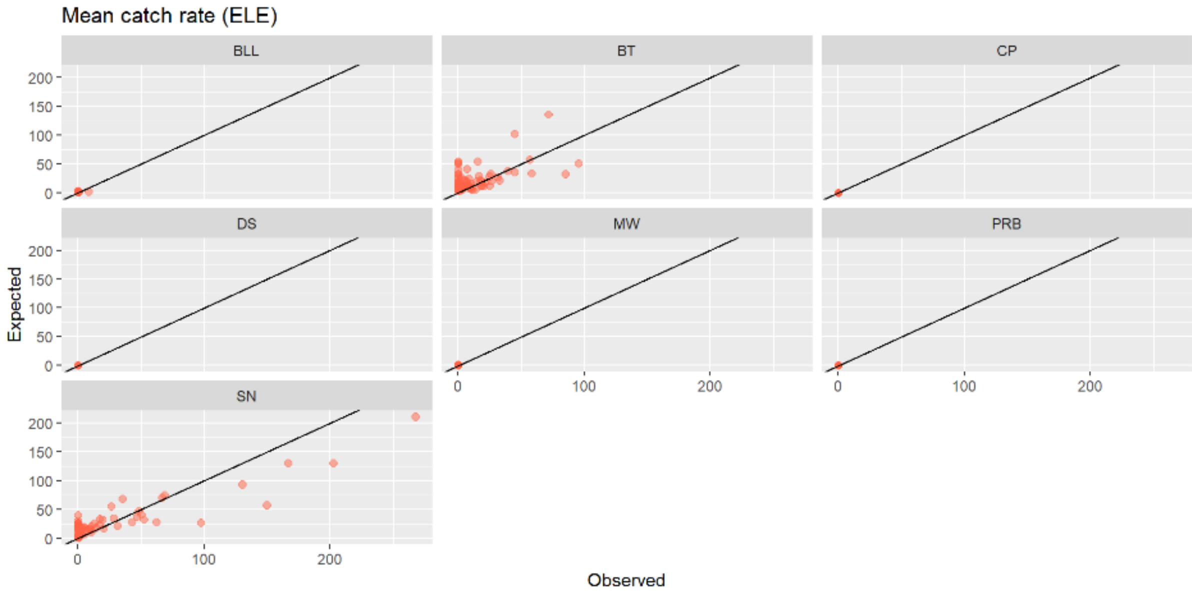


Figure 8.2. Comparison of observed and estimated catch values per density strata for each gear type capturing ELE (elephant fish).

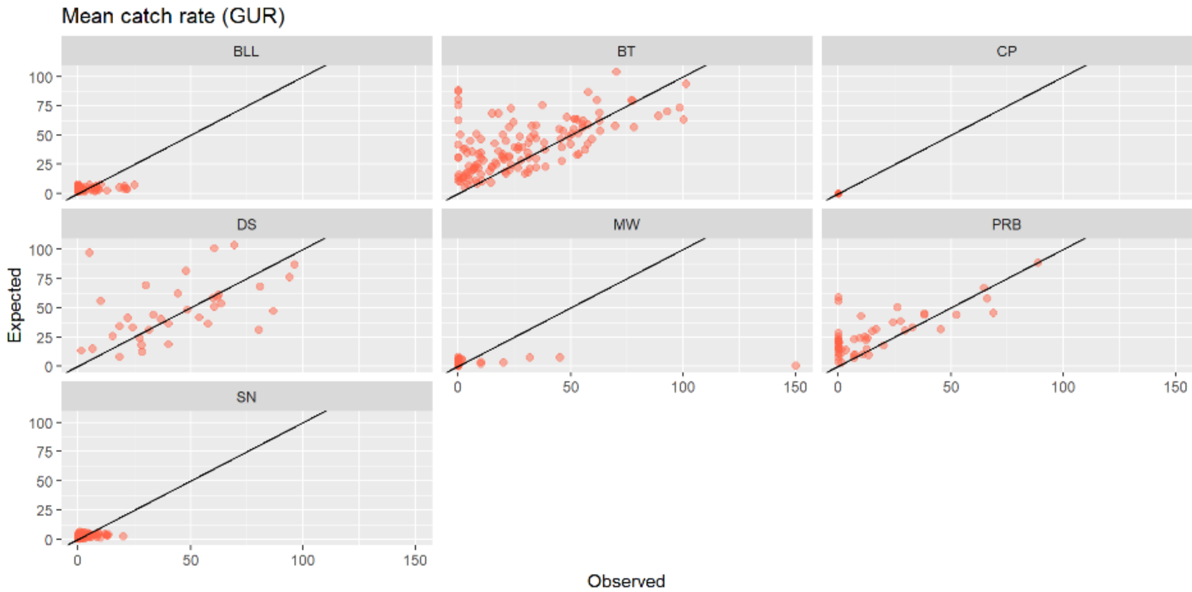


Figure 8.3. Comparison of observed and estimated catch values per density strata for each gear type capturing GUR (red gurnard).

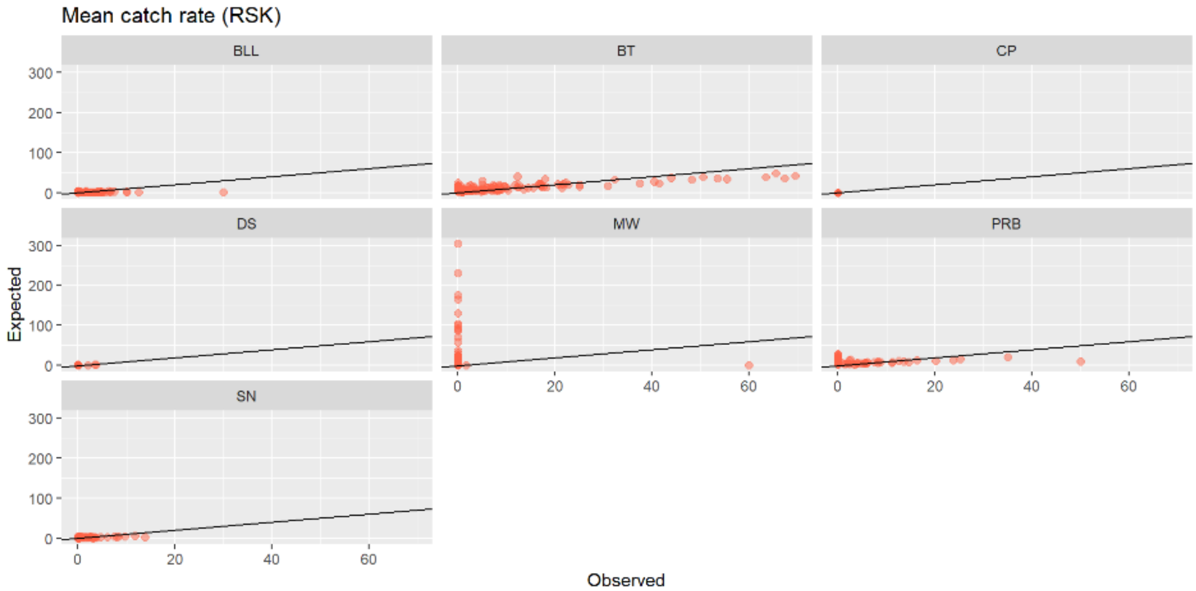


Figure 8.4. Comparison of observed and estimated catch values per density strata for each gear type capturing RSK (rough skate).

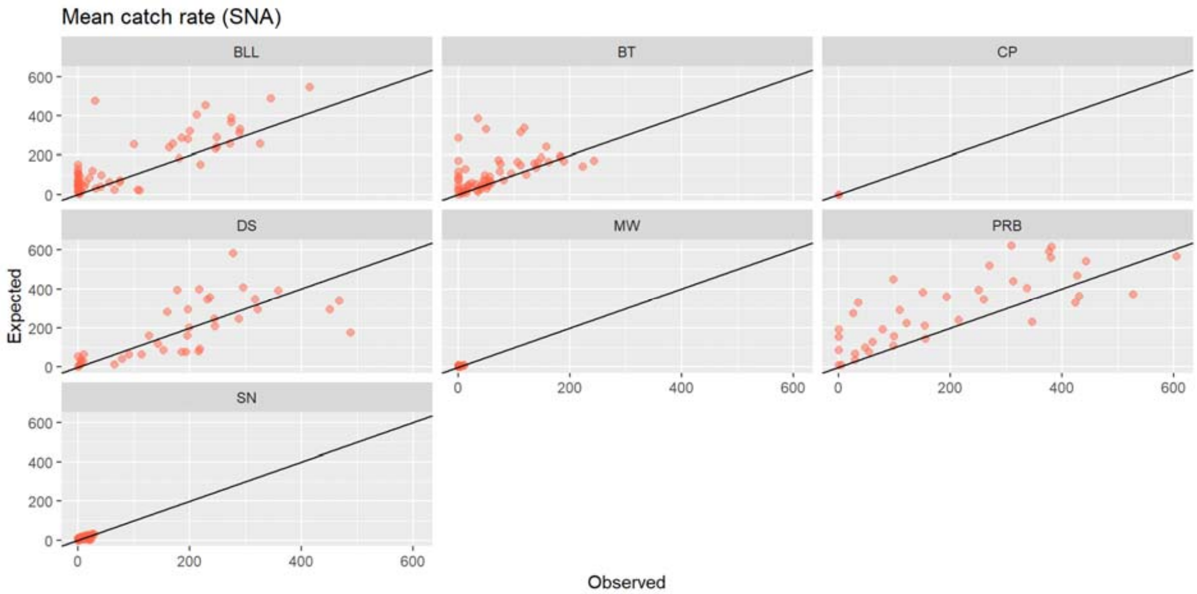


Figure 8.5. Comparison of observed and estimated catch values per density strata for each gear type capturing SNA (snapper).

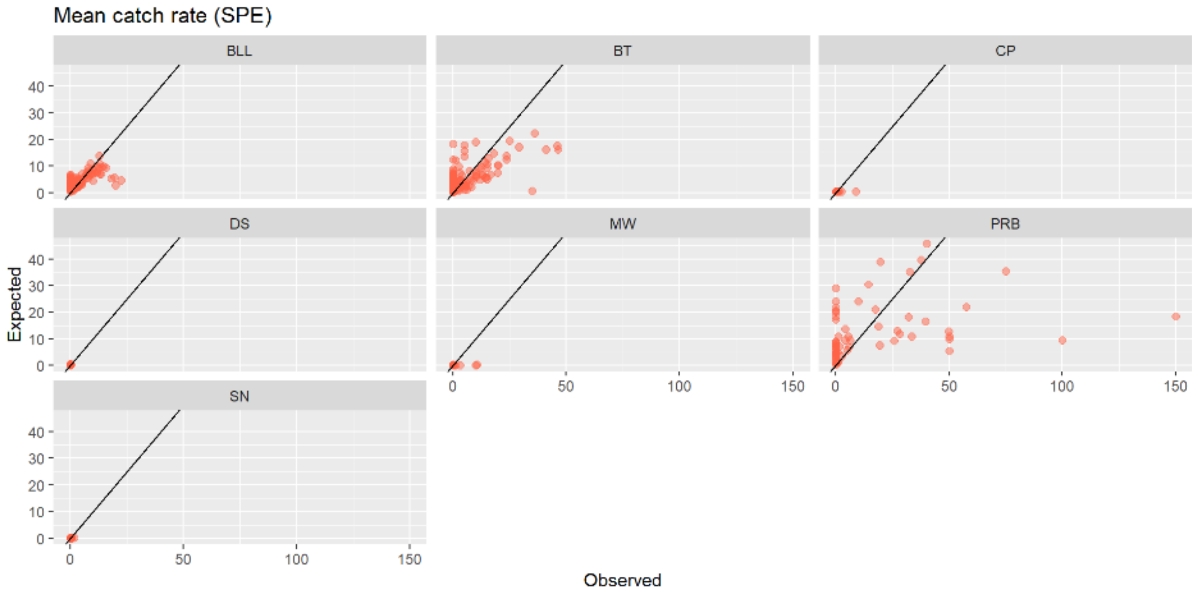


Figure 8.6. Comparison of observed and estimated catch values per density strata for each gear type capturing SPE (sea perch).

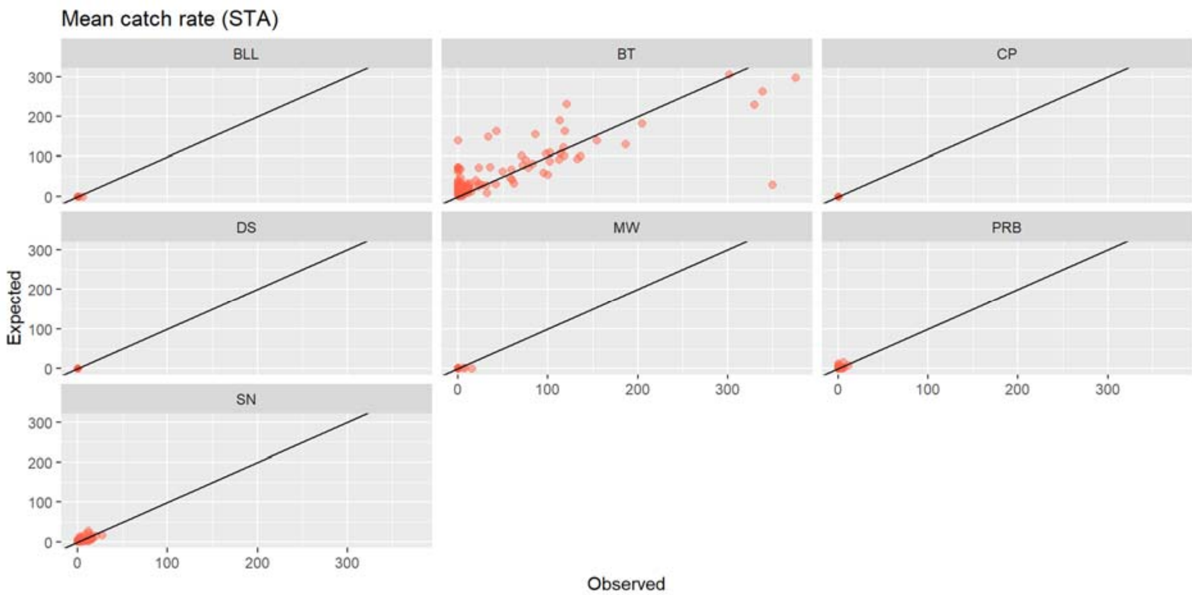


Figure 8.7. Comparison of observed and estimated catch values per density strata for each gear type capturing STA (giant stargazer).

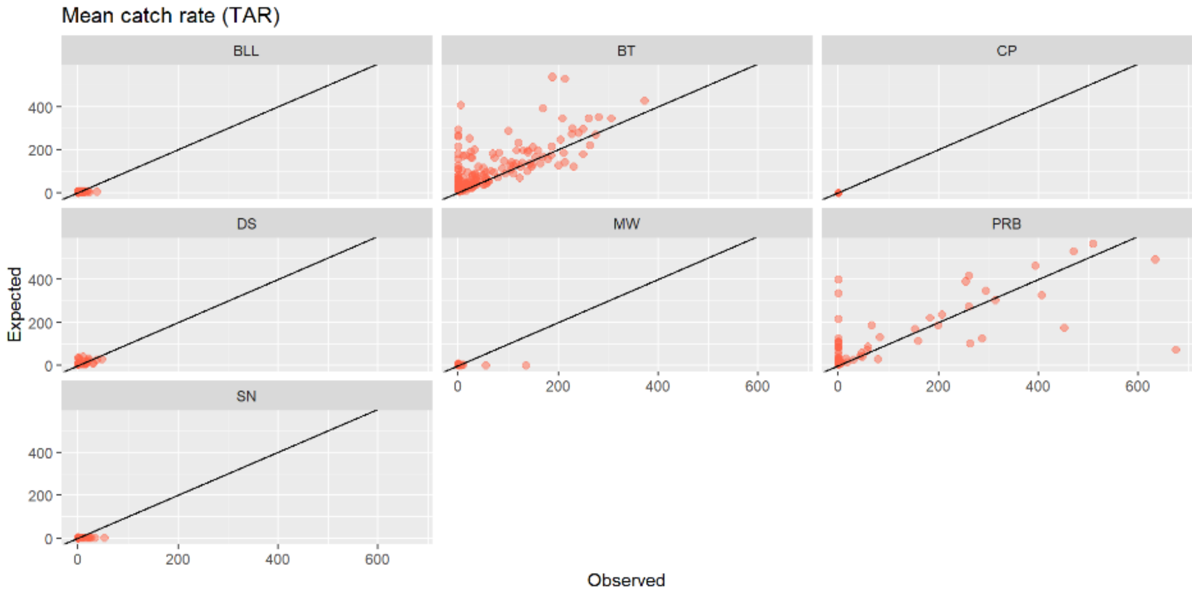


Figure 8.8. Comparison of observed and estimated catch values per density strata for each gear type capturing TAR (tarakihi).

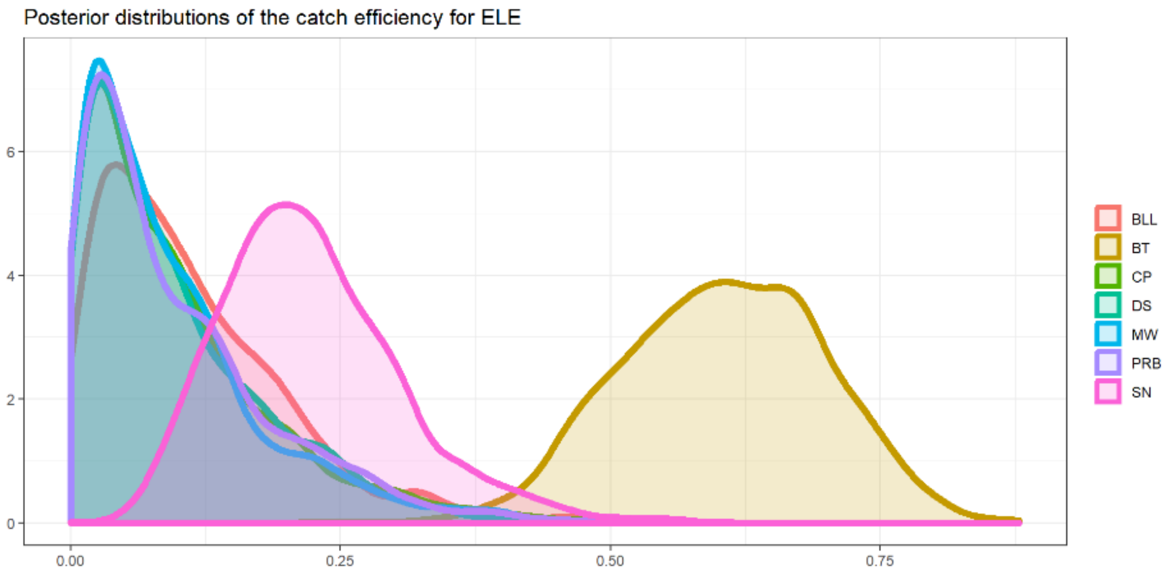


Figure 8.9. Posterior distributions of the gear efficiency for ELE (elephant fish) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

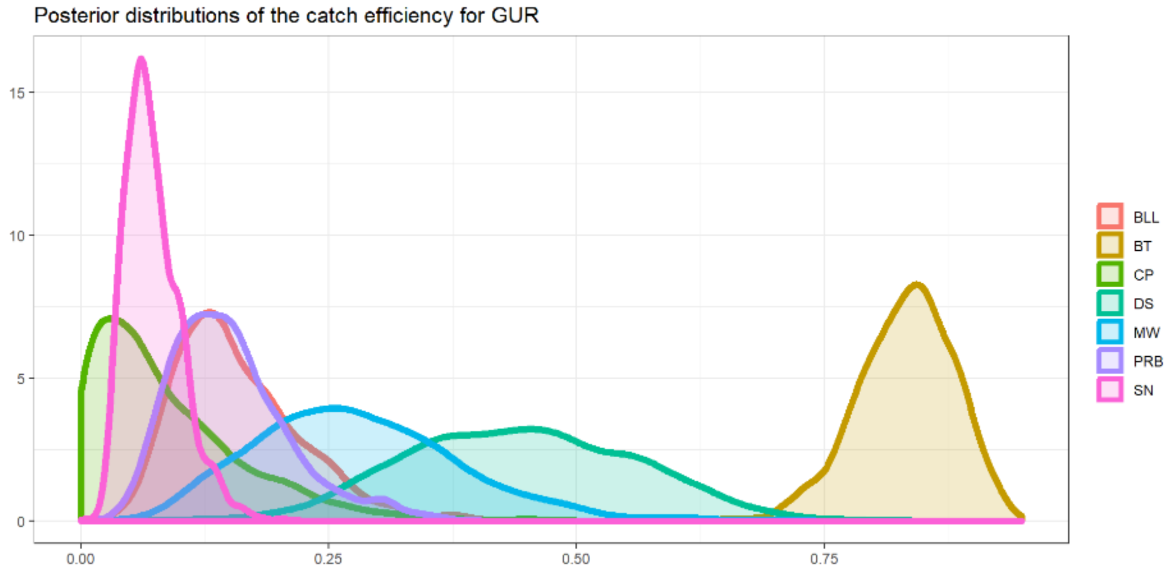


Figure 8.10. Posterior distributions of the gear efficiency for GUR (red gurnard) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

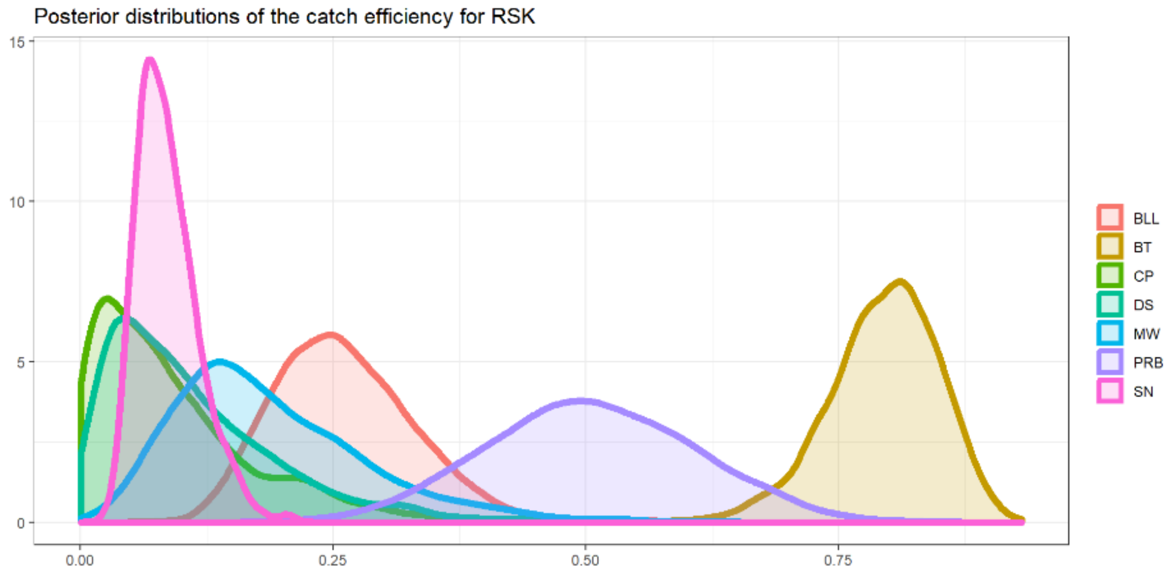


Figure 8.11. Posterior distributions of the gear efficiency for RSK (rough skate) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

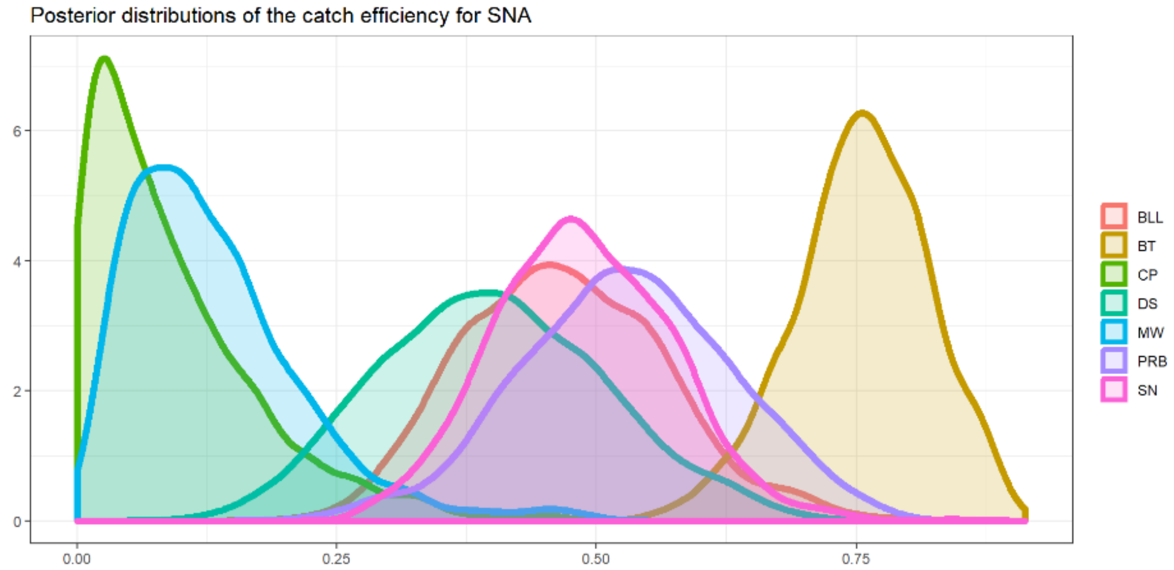


Figure 8.12. Posterior distributions of the gear efficiency for SNA (snapper) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

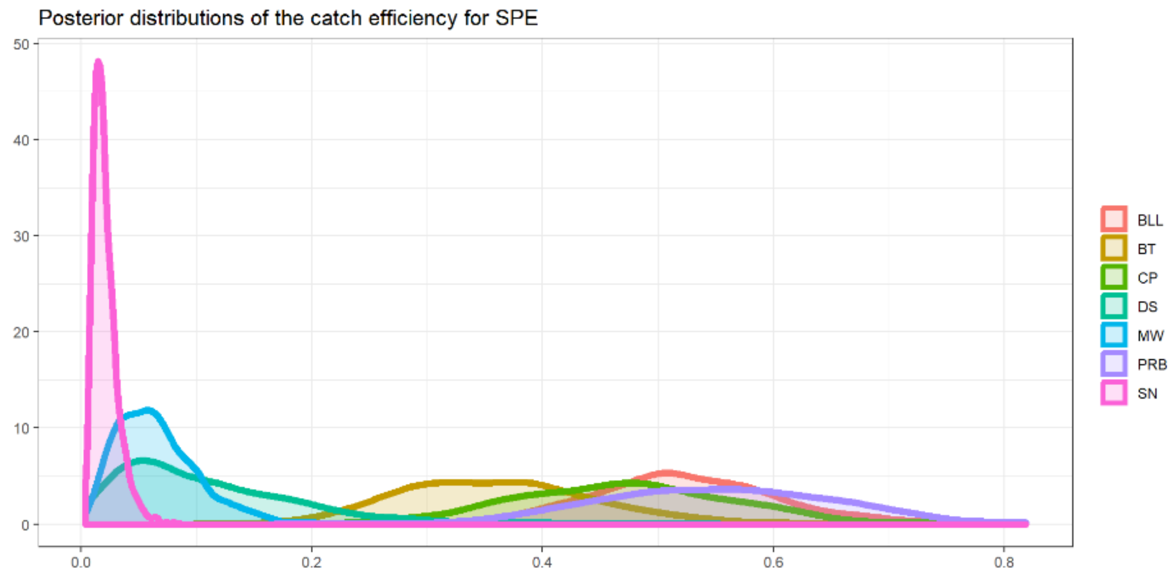


Figure 8.13. Posterior distributions of the gear efficiency for SPE (sea perch) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

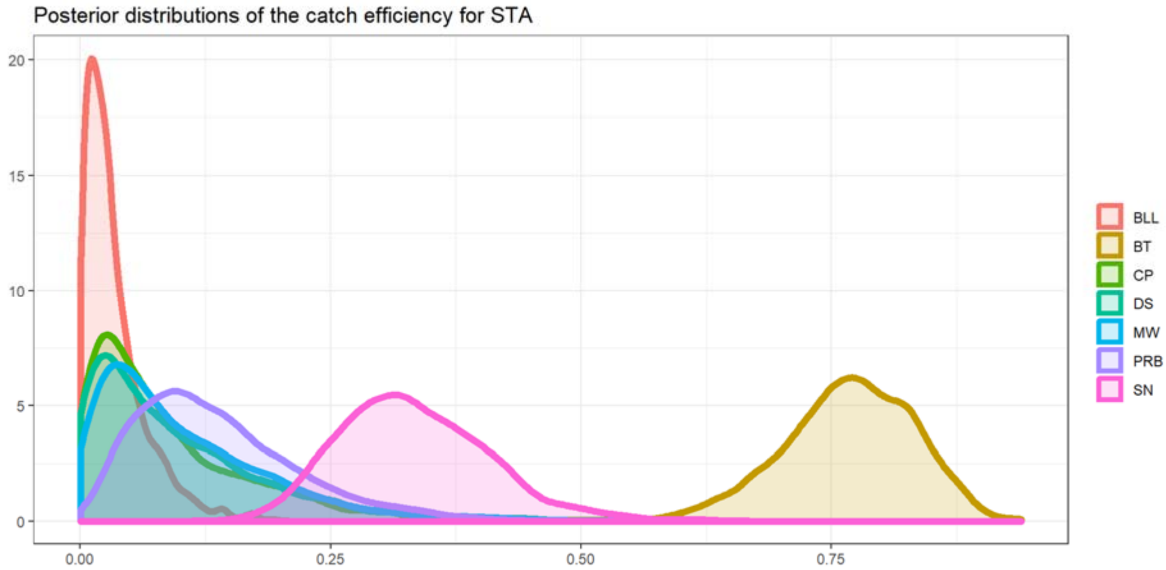


Figure 8.14. Posterior distributions of the gear efficiency for STA (giant stargazer) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

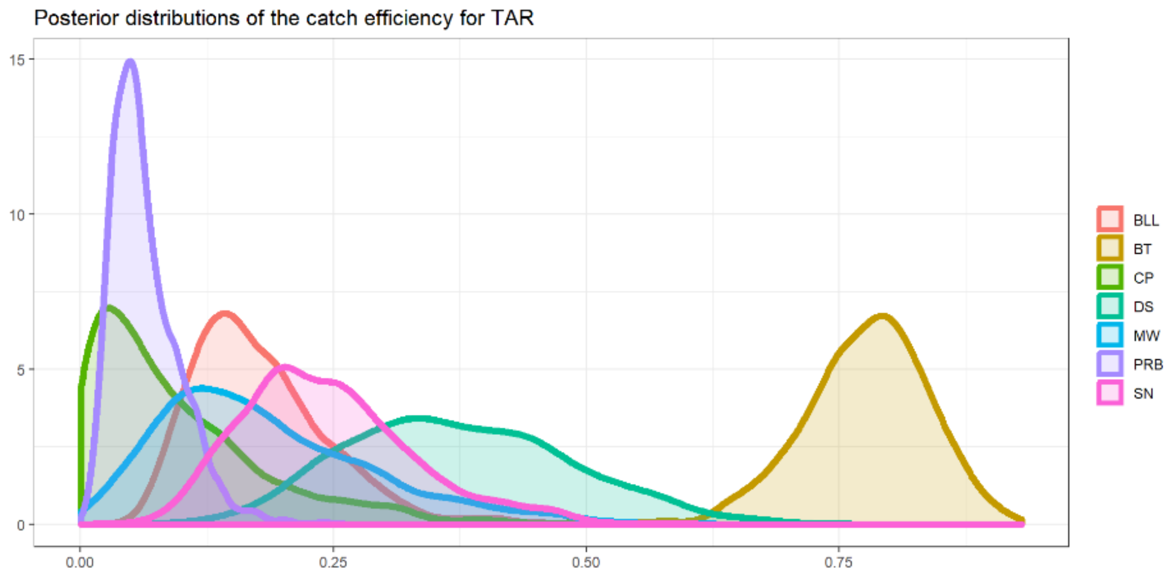


Figure 8.15. Posterior distributions of the gear efficiency for TAR (tarakihi) captured by each gear type. The prior in all cases was a normal distribution with a mean of 0.09 and standard deviation of 0.08.

8.7 Discussion of eSAFE

It is not recommended that the results from the current eSAFE model (Table 8.5) are used for management purposes because of the following caveats.

Survey data were used to map fish density distributions. Because the timing and spatial coverage differ between surveys and much of the commercial fishing, it is more appropriate to model density using both survey and fisheries catch data together. Furthermore, year must be included in the model because fishing mortality is assessed on an annual basis and a species abundance fluctuation over time should be captured in the fishing mortality estimation. The current assessment assumes that biomass remains unchanged over the whole survey history which, depending on species, will be a considerable source of error when estimating final year fishing mortalities. Difficulties in moving from a single (long term average) estimate of species density surface to surfaces specific to short time periods were demonstrated in Section 6.

A problem for the estimation of gear efficiency is the non-reporting of catch given that only the 5 to 8 species with the highest catch are recorded in the logbooks for each shot. Although allocated catches match the landings for each fishing trip, the amount of catch allocated back to fishing events will not be the same as actual catch for that event. One way to circumvent this data concern is to select fishing trips where estimated catches and allocated catches are identical for the studied species, i.e., the studied species is always in the top 5 to 8 species in these trips. To accommodate records of zero catch identified as true zeros, a zero-inflated N-mixture model should be developed. Until then the method should be limited to more abundant species; the current work does not model the probability of absence at the fish distribution stage.

Large variability in catch within spatial-temporal strata renders the model ineffective in estimating gear efficiency and fish density. Since a great volume of logbook data are available, if the main goal is to estimate gear efficiency but not to estimate total abundance simultaneously, it would be justifiable to choose a subset of high-quality strata where catch variability is reasonable low. Sensitivity tests should be able to suggest the suitable level of variability.

The modified N-mixture model developed in this report (Section 7) appears to be able to produce sensible estimates. It would be ideal to validate the model through simulation testing and comparison with the original cross-sampling method.

Fishing gears used in scientific surveys differ from those used in commercial fisheries. In this report we used relative density to derive relative biomass based on survey data. We believe that the cross-sampling method can be applied to survey data to estimate survey gear efficiency. If successful this would allow estimation of absolute density and absolute biomass. The latter could then be used together with fisheries catch to directly derive fishing mortality.

9. OCOM

The catch only method was applied to more stocks than those chosen for focus in the initial workshop (see Section 2). In this section all stocks to which the catch only method was applied are incorporated in this section Figures for stocks not included in the project at the first workshop, as well as detailed results tables, are contained in Appendix 7.

Spatially explicit approaches are the focus of the LSP project but during the first project workshop on 17–18 December 2018, it was recommended that additional data-limited approaches, such as catch-only methods, should be considered. Two recently developed catch-only methods appeared to be particularly promising: the optimised catch-only method (OCOM) (Zhou et al. 2018) and the improved Catch-MSY method (Martell & Froese 2013) called CMSY (Froese et al. 2016). Amongst the selected low information stocks, limited CPUE information exists. To enhance the analysis, we have modified the OCOM to incorporate these sporadic CPUE data.

9.1 Catch data and life-history parameters

Data was compiled from three sources: (1) historical catch data for 1931 to 1982 from Francis & Paul 2013[6]; (2) post-1982 data as published in the Fisheries New Zealand plenary reports (Fisheries New Zealand 2018); (3) complete time series of data for five stocks (ELE 3, GUR 3, SNA 7, STA 3, and eastern coast TAR) as used in data intensive stock assessments for these stocks. The earliest catch record starts from 1931 for six stocks, and the last year is either 2016, 2017, or 2018 for all stocks (Table 9.1). The number of years with available data ranges from 39 for spiny dogfish to 88 for red gurnard and snapper. Catch consists of official landings (tonnes) and recreational catch, but the latter is either very small or not available in many years. Compared to the total official landings of 847 677 t for all stocks in all years, the total recreational catch is only 4385.3 t (i.e. 0.52%). The annual catch for elephant fish includes a discarded component, which is assumed to be a constant 20% of recorded catch (A. Langley, pers comm.).

Amongst the 12 stocks, incomplete CPUE data are available for five stocks that have been assessed by traditional data-rich models (Table 9.1). These are standardised CPUE, and the number of years available ranges from 18 to 28.

[6] The same data are incorporated in Fisheries New Zealand plenary reports.

Table 9.1: Summary of catch and CPUE data for 12 stocks. Annual catch (tonnes) is the combined official landings and recreational catch.

Common name	Stock	Years of catch	First year	Last year	Mean catch	N year of CPUE
Barracouta	BAR 1	75	1942	2016	6 224	0
Barracouta	BAR 4	45	1972	2016	1 579	0
Elephant fish	ELE 3	82	1937	2018	809	26
Red Gurnard	GUR 3	88	1931	2018	767	25
Red Cod	RCO 3	86	1931	2016	3 203	0
Rough skate	RSK 3	79	1938	2016	437	0
Rough skate	RSK 7	60	1958	2016	52	0
Snapper	SNA 7	88	1931	2018	546	28
Spiny dogfish	SPD 3	39	1978	2016	2 031	0
Sea perch	SPE 3	73	1944	2016	271	0
Giant stargazer	STA 3	64	1955	2018	459	18
Tarakihi	TAR	87	1931	2017	4 374	28

The catch-only methods require basic life-history parameters to infer stock productivity. For OCOM, natural mortality *M* is the primary parameter, which is often derived from other life-history information such as von-Bertalanffy growth parameters κ and L_{inf}, maximum age t_{max}, and age at maturation t_{mat} (two methods also require water temperature *T*). Sources for life history parameter values and water temperature are given in Appendix 7. A total of nine methods were used to calculate *M*:

1. From literature
2. $M = \exp[-0.0152 - 0.279 * \ln(L_{inf}) + 0.654 * \ln(k) + 0.4634 * \ln(T)]$ (Pauly, 1980)
3. $M = 10\text{^}(0.566 - 0.718 * \ln(L_{inf}) + (0.02 * \mathrm{T})$ (www.Fishbase.org)
4. $M = 1.65/t_{mat}$ (Jensen, 1996)
5. $M = exp(1.44 - 0.982 * ln(t_{max}))$ (Hoenig 1983, all data)
6. $M = exp(1.46 - 1.01 * ln(t_{max}))$ (Hoenig 1983, fish data)
7. $M = -ln(0.01)/t_{max})$ (Quinn & Deriso, 1999)
8. $M = at_{max}^{b} = 4.899\ t_{max}^{-0.916}$ (Then et al. 2015)
9. $M = ak^{b}L_{inf}^{c} = 4.118\ k^{0.73}L_{inf}^{-0.33}$ (Then et al. 2015)

Table 9.2: Estimated natural mortality M from nine alternative methods.

Stock	M1	M2	M3	M4	M5	M6	M7	M8	M9	Mean	SD
BAR	0.30	0.43	0.20	0.60	0.30	0.28	0.31	0.22	0.46	0.34	0.13
ELE	0.23	0.33	0.24	0.43	0.22	0.21	0.23	0.32	0.35	0.28	0.07
RCO 3	0.76	0.55	0.24	0.70	NA	NA	NA	NA	0.55	0.56	0.20
RCO 7	NA	0.61	0.24	0.81	NA	NA	NA	NA	0.61	0.57	0.24
GUR 3	0.32	0.59	0.24	0.68	0.30	0.28	0.31	0.41	0.63	0.42	0.17
GUR 7	0.31	0.59	0.24	0.68	0.30	0.28	0.31	0.41	0.63	0.42	0.17
GUR	NA	0.59	0.24	0.68	0.30	0.28	0.31	0.41	0.63	0.43	0.18
RSK 3	0.30	0.19	0.18	0.21	0.49	0.47	0.51	0.66	0.19	0.35	0.18
SNA 1	0.08	0.22	0.24	0.16	0.08	0.08	0.09	0.13	0.20	0.14	0.07
SNA 2	0.08	0.15	0.24	0.10	0.08	0.08	0.09	0.13	0.13	0.12	0.05
SNA 7	0.08	0.24	0.24	0.20	0.08	0.08	0.09	0.13	0.22	0.15	0.07
SNA 8	0.05	0.29	0.24	0.26	0.08	0.08	0.09	0.13	0.27	0.17	0.10
SNA	0.08	0.21	0.23	0.16	0.08	0.08	0.09	0.13	0.19	0.14	0.06
SPE	NA	0.19	0.11	0.20	0.12	0.11	0.13	0.18	0.26	0.16	0.05
SPD	0.20	0.12	0.12	0.15	0.11	0.11	0.12	0.15	0.15	0.14	0.03
STA 3	NA	0.29	0.22	0.27	0.20	0.19	0.21	0.29	0.28	0.24	0.04
STA 5	0.20	0.30	0.11	0.29	0.20	0.19	0.21	0.29	0.30	0.23	0.06
STA 7	0.21	NA	0.00	0.22	0.20	0.19	0.21	0.29	0.23	0.19	0.08
STA	NA	0.29	0.19	0.32	0.20	0.19	0.21	0.29	0.31	0.25	0.06
TAR 3	0.12	0.35	0.21	0.33	0.11	0.10	0.11	0.16	0.37	0.21	0.11
TAR 4	0.12	0.34	0.21	0.31	0.11	0.10	0.11	0.16	0.35	0.20	0.11
TAR 7	0.12	0.39	0.21	0.39	0.11	0.10	0.11	0.16	0.42	0.22	0.14
TAR	0.12	0.37	0.24	0.32	0.11	0.10	0.11	0.16	0.36	0.21	0.11

Life history parameters for males and females are provided separately for some stocks. *M* may be stock-specific or species-specific depending on available information. To arrive at a single value of *M*, the average *M* over both sexes, if data exist, and across the nine methods was used for each stock. Not all the 12 stocks have sufficient information to produce the nine estimates listed in Table 9.2. For example, only four methods can be applied to RCO 7. Deviation exists among the nine methods to a greater or lesser extent depending on stock. The average cv[*M*] over all stocks is 41%.

9.2 Catch-only methods

Two catch-only methods, OCOM and CMSY, were considered. Both methods use the Graham-Schaefer surplus production model, as it is very simple and has been widely used:

$$B_{y+1} = B_y + rB_y\left(1 - \frac{B_y}{K}\right) - C_y \qquad (9.1)$$

where B_y is the biomass at the start of time step *y*, *r* is the intrinsic growth rate, *K* is the carrying capacity (equal to the unfished or initial biomass B_0 for a surplus production model), and C_y is the (known) catch during time-step *y*. This model has two unknown parameters, *r* and *K*.

CMSY attempts to construct priors for these two parameters. It defines a possible range for *r* based on stock productivity, called 'resilience', and defines a range for *K* based on maximum catch and constructed *r* values. Stock saturation $S_{last} = B_{last}/K$ at the end of the catch time series (i.e. 2016–2017) is required to infer depletion. CMSY defines the range for S_{last} based on the ratio C_{last}/C_{max}. With these three pieces of information, a large number of biomass trajectories are produced by Monte Carlo simulation and trajectories that satisfy the predefined constraints set by the three priors (range of r, range of K and range of S_{last}) are retained for inferring model outputs.

In contrast, OCOM uses two priors on r and S; i.e. there is no prior on K. The prior distribution for population growth rate r is deduced from natural mortality M, which in turn can be estimated from other life-history parameters as described in the previous section. The prior distribution for the saturation parameter S_{last} is derived from the catch trend over the history of a fishery. With these two priors, K in equation (9.1) can be solved by using an optimisation algorithm.

Note that these priors ("soft data" in the sense of Bentley 2014) are essentially just the range or distribution of possible values and are slightly different from priors as defined in Bayesian models.

Both OCOM and CMSY may have some unique advantages so it can be beneficial to integrate certain features from both approaches. A straightforward option is to combine the priors from both methods. Hence, we used both natural mortality M and resilience to derive a prior for r with equal weight and used catch trend and $C_{\text{last}}/C_{\max}$ to derive a prior for S_{last}.

OCOM derives the prior population growth rate r based on a surplus production model in which $r = 2\,F_{MSY}$. F_{MSY} in turn was based on the following relationships with the instantaneous natural mortality rate M after Zhou et al. (2012): $F_{MSY} = 0.87M$ for teleosts; $F_{MSY} = 0.41M$ for chondrichthyans. Measurement error in M was estimated to be $\sigma_M^2 = 0.23$ and the process error in the $F_{MSY} \sim M$ relationship $\sigma_e^2 = 0.0012$. To avoid potentially negative values being sampled, a lognormal distribution was used for r, i.e.: $r \sim \text{lognormal}(\mu_r, \sigma_r^2)$, where $\mu_r = \log(2F_{MSY})$ and $\sigma_r^2 = \sigma_M^2 + \sigma_e^2$. Measurement error and variability resulting from alternative life-history invariant equations can be large. This uncertainty can lead to unrealistic r values. For example, using $\sigma_r^2 = 0.23$ can yield $r >> 1$ for some stocks. To avoid this dilemma, values of $r > 2$ were excluded, (note that r can be greater than 1 for highly productive species). In CMSY, the broad range of the r prior is predefined by the 'resilience' parameter which was obtained from fishbase.org (Table 9.3).

Table 9.3: CMSY rule for defining r range.

Resilience	r (lower limit)	r (upper limit)
High	0.6	1.5
Medium	0.2	0.8
Low	0.05	0.5
Very low	0.015	0.1

The prior for stock saturation level at the end of the time series (i.e. 2016–2018) is set differently between the two methods. OCOM uses the following distributions:

$$\begin{aligned} &S_{last} \sim sNorm(\text{mean} = S_{BRT,last} - 0.072,\ \text{SD} = 0.189,\ \text{skewness} = 0.763),\ \text{when } S_{BRT,last} \leq 0.5 \\ &S_{last} \sim sNorm(\text{mean} = S_{BRT,last} + 0.179,\ \text{SD} = 0.223,\ \text{skewness} = 0.904),\ \text{when } S_{BRT,last} > 0.5, \end{aligned} \tag{9.2}$$

where $sNorm$ is a skewed normal distribution and S_{BRTe} is the predicted value of S from a boosted regression tree (BRT) model as described in Zhou et al. (2017). Equation (9.2) accounts for bias in the BRT estimates by adjusting the prediction of the mean, as described by Zhou et al. (2017). The samples from the S prior are constrained within the range of [0, 1].

CMSY defines three broad saturation ranges (Table 9.4) and assumes a uniform distribution between the upper and lower limits of S. The range may not cover the estimate from the BRT model (Table 9.5). Agreements between the two approaches were found in 10 out of the 12 stocks.

Table 9.4: CMSY rule for saturation.

$C_{\text{last}}/C_{\text{max}}$	S (lower limit)	S (upper limit)
> 0.7	0.50	0.9
< 0.3	0.01	0.4
≥0.3, ≤0.7	0.20	0.6

The two priors on r and S from OCOM and CMSY may complement each other as one method may not always perform better for every species. A third approach is therefore to combine the two methods. To do so an equal number of random samples for both r and S are taken from OCOM and CMSY. The combined samples formed the prior distribution of the two parameters, r and S. The three approaches are referred to as Methods 1 to 3 in the results section:

- Method 1: use OCOM priors, i.e., r from life-history correlation and S from boosted regression tree modelling of the catch history of data-rich species;
- Method 2: use CMSY priors, i.e., r from resilience parameter and S from predefined rule based on C_{last}/C_{max};
- Method 3: integrate r and S priors from OCOM and CMSY with equal weight.

Implementation of the surplus production model (equation 9.1) uses the OCOM approach because of its higher efficiency (compared to CMSY) and the lack of need for a K prior. Specifically, model implementation involves:

(i) drawing a large number (n = 10 000 is used in this study) of values for r and S from their priors;
(ii) deriving K (from equation 1) by solving $B_{\text{last}}/K = S$ using an optimisation algorithm (function "optimize" in R), and
(iii) computing any output quantities of interest such as reference points F_{MSY}, B_0, and the time series of B_y and F_y.

The OCOM method has been coded in the R package 'datalimited2' by C. Free (https://github.com/cfree14/datalimited2). Some of the code from that package was adopted for the use in this study.

Table 9.5: Stock saturation prior from BRT and CMSY for the 12 stocks. The mean column shows the mean of S_{BRT} and the average of the lower and upper limits of *S*.

		CMSY		
Stock	S_{BRT}	*S* (lower)	*S* (upper)	Mean
BAR 1	0.23	0.2	0.6	0.32
BAR 4	0.73	0.01	0.4	0.47
ELE 3	0.27	0.2	0.6	0.33
GUR 3	0.56	0.5	0.9	0.63
RCO 3	0.47	0.2	0.6	0.44
RSK 3	0.41	0.5	0.9	0.55
RSK 7	0.59	0.5	0.9	0.64
SNA 7	0.30	0.01	0.4	0.25
SPD 3	0.59	0.2	0.6	0.49
SPE 3	0.54	0.2	0.6	0.47
STA 3	0.58	0.2	0.6	0.49
TAR	0.31	0.2	0.6	0.36

9.3 Incorporating CPUE data into OCOM

For the stocks ELE 3, GUR 3, SNA 7, STA 3, and TAR, CPUE data exist, ranging from 18 to 28 years in length. If two or more years of CPUE data are available, it is possible to include them in the OCOM. Since $cpue_y = qB_y$, assuming that the catchability coefficient q is constant over years y, the mean squared error between the scaled CPUE and scaled biomass B is:

$$MSE_{cpue} = \frac{1}{n}\left(\frac{cpue_y}{\overline{cpue}} - \frac{B_y}{\bar{B}}\right)^2 \tag{9.2}$$

where n is the number of years with CPUE data, $\overline{cpue}$ is the mean CPUE over those available years, and $\bar{B}$ is the mean biomass over the same period.

There are three alternative optimisation options:

(iv) minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$. This is the original OCOM method;

(ii) minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight;

(v) minimising MSE_{cpue} only.

With the prior on r and S, the optimisation function enables the model to find a corresponding K for each random r and *S combination*. Note minimising MSE_{cpue} alone (option (iii)) does not require an S prior, which gives the possibility to independently estimate depletion status.

To see the difference between the three optimisation options, we used relative deviation. For example, between options (ii) and (i):

$$RE = \frac{\theta_2 - \theta_1}{\theta_1} \tag{9.3}$$

where θ_i is the K value from method i.

9.4 Results

The optimised catch-only method estimates several key parameters, including K, r, MSY, B_{msy}, F_{msy}, B_{last}, F_{last}, S_{last}, $B_{\text{last}}/B_{\text{msy}}$, and F_{last}/F_{msy} (Table 9.6). As the prior of the productivity parameter r is based on life-history parameters, the estimated r and F_{msy} may differ for different stocks of the same species (e.g., BAR 1 and BAR 4, RSK 3 and RSK 7) because their life-history parameters may not be identical (Table 9.2). Catch history may also affect the final values of the estimated r and F_{msy}. In addition to common reference points, the catch-only method also produces time series of B_y, F_y, and the status of fishing mortality and biomass relative to their corresponding reference points such as B_y/B_{msy} and F_y/F_{msy} (Table 9.6, Figures 9.1 to 9.7 and A7.1 to A7.5).

Methods 1 to 3 for forming r and S priors were applied to the 12 inshore stocks. However, we focus on the integrated Method 3 so the detailed results from this method are presented in Table 9.6 and Figures 9.1 to 9.7 and A7.1 to A7.5. For each of the 10 primary parameters (i.e., K, r, MSY, B_{msy}, F_{msy}, B_{last}, F_{last}, S_{last}, $B_{\text{last}}/B_{\text{msy}}$, and F_{last}/F_{msy}), five quantiles are provided: 0.05, 0.25, 0.50, 0.75, and 0.95 in Appendix 7 (Tables A7.1 to A7.3).

In the figures, information is illustrated in six panels. Panel 1 shows the time series of catch used by the model and compares catch history with estimated MSY. Panel 2 shows r-K pairs estimated by the model and used to calculate other parameters. Panels 3 and 4 are time series of B_y and F_y. Combining the B_y and F_y series with corresponding reference points leads to a graph known as a Kobe plot (often used to plot the status of a fishery over time). The last panel lists three key reference points (MSY, B_{msy}, and F_{msy}) and three quantities describing stock status (S_{last}, F_{last} and F_{last}/F_{msy}).

Comparing Methods 1 and 2 reveals that Method 1 consistently yields a lower K but a higher r than Method 2 (Figure 9.8). Other parameters lack a clear pattern between the two methods. Among the six key parameters, MSY is more similar between the two methods than other parameters.

For the five stocks that have limited CPUE data, optimisation option (ii) which minimises both the saturation prior and MSE_{cpue} together can be applied. Including CPUE has some impact on most stocks and parameters (Table 9.6), but it has little effect on K, r, and MSY (Figure 9.9). The effect on SNA 7 is substantial, particularly for S, B/B_{msy}, and F/F_{msy}. The estimated biomass in 2018 increases by 87% compared to the model without using CPUE. This increase in biomass leads to a reduced F2018 (-46%) and improved B_{2018}/B_{msy} (72%). These large changes apparently result from a big jump (6.7 fold) of CPUE from an average of 0.45 between 1989 and 2010 to an average of 3.02 between 2011 and 2016 (Figure 9.10).

Optimisation option (iii) which relies on MSE_{cpue} alone could be applied to SNA 7, STA 3, and TAR but did not work on ELE 3 and GUR 3 (results for K were unrealistically high). Not using a prior on S and relying on MSE_{cpue} alone, the model produced significantly different estimates from options (i) and (ii) for most parameters (Table 9.6). This may be due to an extremely variable CPUE pattern (for SNA 7, Figure 9.11), or a lack of contrast in CPUE series (for STA 3 and TAR; Figures 9.12 to 9.15).

Table 9.6. Estimated key parameters from OCOM for 12 stocks. There are three methods for obtaining r and S priors. Only results from method 3 are listed (priors taken from OCOM and CMSY with equal weight). Minimisation methods are (i) optimisation through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$; (ii) optimisation using both CPUE and saturation prior S (i.e. minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight) ; (iii) optimisation on CPUE only (minimising MSE_{cpue} only). Dev 2 to 1, Dev.3 to 1 and Dev. 3 to 2 are the relative deviation between minimisation options (ii) and (i), options (iii) and (i) and options (iii) and (ii) respectively. Values are for 50% quantile. Detailed results tables for each minimisation method showing 5%, 25% 50%, 75% and 95% quantiles can be found in Appendix A7.

Stock	*r* and *S* priors method	Minimisation method	*K*	*r*	*MSY*	S_{last}	B_{msy}	F_{msy}	B_{last}	F_{last}	B_{last}/B_{msy}	F_{last}/F_{msy}
BAR 1	3	(i)	92 432	0.46	10 560	0.36	46 216	0.23	37 320	0.26	0.71	1.33
BAR 1	3	(ii)	--	--	--	--	--	--	--	--	--	--
BAR 1	3	(iii)	--	--	--	--	--	--	--	--	--	--
BAR 4	3	(i)	20 040	0.46	2 279	0.60	10 020	0.23	8 014	0.33	1.20	0.96
BAR 4	3	(ii)	--	--	--	--	--	--	--	--	--	--
BAR 4	3	(iii)	--	--	--	--	--	--	--	--	--	--
ELE 3	3	(i)	17 030	0.21	892	0.32	8 515	0.10	5 449	0.20	0.65	1.96
ELE 3	3	(ii)	16 901	0.21	887	0.36	8 451	0.10	5 813	0.19	0.72	1.77
ELE 3	3	(iii)	--	--	--	--	--	--	--	--	--	--
ELE 3	3	Dev 2 to 1	0.00	0.00	-0.01	0.12	0.00	0.00	0.09	-0.08	0.12	-0.12
GUR 3	3	(i)	13 685	0.49	1 558	0.71	6 843	0.24	9 054	0.17	1.42	0.71
GUR 3	3	(ii)	15 213	0.49	1 725	0.75	7 606	0.24	10 749	0.15	1.50	0.61
GUR 3	3	(iii)	--	--	--	--	--	--	--	--	--	--
GUR 3	3	Dev 2 to 1	0.11	0.01	0.11	0.06	0.11	0.01	0.17	-0.15	0.06	-0.15
RCO 3	3	(i)	54 429	0.53	7 247	0.50	27 215	0.27	27 631	0.16	1.01	0.67
RCO 3	3	(ii)	--	--	--	--	--	--	--	--	--	--
RCO 3	3	(iii)	--	--	--	--	--	--	--	--	--	--

Table 9.6 (cont). Estimated key parameters from OCOM for 12 stocks. There are three methods for obtaining r and S priors. Only results from method 3 are listed (priors taken from OCOM and CMSY with equal weight). Minimisation methods are (i) optimisation through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$; (ii) optimisation using both CPUE and saturation prior S (i.e. minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight) ; (iii) optimisation on CPUE only (minimising MSE_{cpue} only). Dev 2 to 1, Dev.3 to 1 and Dev. 3 to 2 are the relative deviation between minimisation options (ii) and (i), options (iii) and (i) and options (iii) and (ii) respectively. Values are for 50% quantile. Detailed results tables for each minimisation method showing 5%, 25% 50%, 75% and 95% quantiles can be found in Appendix A7.

Stock	r and S priors method	Minimisation method	K	r	MSY	S_{last}	B_{msy}	F_{msy}	B_{last}	F_{last}	B_{last}/B_{msy}	F_{last}/F_{msy}
RSK 3	3	(i)	21 660	0.24	1 214	0.55	10 830	0.12	11 160	0.14	1.10	1.19
RSK 3	3	(ii)	--	--	--	--	--	--	--	--	--	--
RSK 3	3	(iii)	--	--	--	--	--	--	--	--	--	--
RSK 7	3	(i)	2 912	0.31	195	0.71	1 456	0.15	1 952	0.08	1.43	0.61
RSK 7	3	(ii)	--	--	--	--	--	--	--	--	--	--
RSK 7	3	(iii)	--	--	--	--	--	--	--	--	--	--
SNA 7	3	(i)	16 587	0.20	820	0.26	8 293	0.10	3 999	0.10	0.51	1.02
SNA 7	3	(ii)	16 513	0.20	823	0.43	8 257	0.10	7 171	0.05	0.86	0.53
SNA 7	3	(iii)	22 698	0.12	665	0.48	11 349	0.06	10 755	0.04	0.95	0.60
SNA 7	3	Dev 2 to 1	0.02	-0.03	-0.01	0.72	0.02	-0.03	0.87	-0.46	0.72	-0.48
SNA 7	3	Dev 3 to 1	0.40	-0.43	-0.20	0.90	0.40	-0.43	1.80	-0.64	0.90	-0.41
SNA 7	3	Dev 3 to 2	0.37	-0.41	-0.19	0.10	0.37	-0.41	0.50	-0.33	0.10	0.14
SPD 3	3	(i)	87 958	0.08	1 693	0.52	43 979	0.04	43 011	0.04	1.04	1.10
SPD 3	3	(ii)	--	--	--	--	--	--	--	--	--	--
SPD 3	3	(iii)	--	--	--	--	--	--	--	--	--	--
SPE 3	3	(i)	11 109	0.21	579	0.52	5 554	0.11	5 107	0.12	1.04	1.06
SPE 3	3	(ii)	--	--	--	--	--	--	--	--	--	--
SPE 3	3	(iii)	--	--	--	--	--	--	--	--	--	--

Table 9.6 (cont). Estimated key parameters from OCOM for 12 stocks. There are 3 methods for obtaining r and S priors. Only results from method 3 are listed (priors taken from OCOM and CMSY with equal weight). Minimisation methods are (i) optimisation through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$; (ii) optimisation using both CPUE and saturation prior S (i.e. minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight) ; (iii) optimisation on CPUE only (minimising MSE_{cpue} only). Dev 2 to 1, Dev.3 to 1 and Dev. 3 to 2 are the relative deviation between minimisation options (ii) and (i), options (iii) and (i) and options (iii) and (ii) respectively. Values are for 50% quantile. Detailed results tables for each minimisation method showing 5%, 25% 50%, 75% and 95% quantiles can be found in Appendix A7.

Stock	r and S priors method	Minimisation method	K	r	MSY	S_{last}	B_{msy}	F_{msy}	B_{last}	F_{last}	B_{last}/B_{msy}	F_{last}/F_{msy}
STA 3	3	(i)	8 083	0.40	766	0.54	4 041	0.20	3 843	0.19	1.08	0.93
STA 3	3	(ii)	8 294	0.41	776	0.64	4 147	0.20	4 538	0.16	1.29	0.77
STA 3	3	(iii)	14 358	0.51	1 815	0.92	7 179	0.25	13 138	0.06	1.83	0.22
STA 3	3	Dev 2 to 1	0.02	0.01	0.01	0.20	0.02	0.01	0.16	-0.14	0.20	-0.18
STA 3	3	Dev 3 to 1	0.77	0.25	1.37	0.70	0.77	0.25	2.36	-0.70	0.70	-0.76
STA 3	3	Dev 3 to 2	0.73	0.24	1.34	0.42	0.73	0.24	1.89	-0.65	0.42	-0.71
TAR	3	(i)	77 739	0.24	4 698	0.36	38 870	0.12	24 851	0.18	0.71	1.42
TAR	3	(ii)	77 594	0.24	4 700	0.43	38 797	0.12	33 318	0.14	0.86	1.23
TAR	3	(iii)	197 675	0.15	6 980	0.80	98 837	0.07	102 221	0.04	1.60	0.41
TAR	3	Dev 2 to 1	-0.02	0.03	0.00	0.19	-0.02	0.03	0.32	-0.24	0.19	-0.12
TAR	3	Dev 3 to 1	1.50	-0.37	0.49	1.21	1.50	-0.37	3.06	-0.75	1.21	-0.71
TAR	3	Dev 3 to 2	1.55	-0.39	0.48	0.85	1.55	-0.39	2.07	-0.67	0.85	-0.67

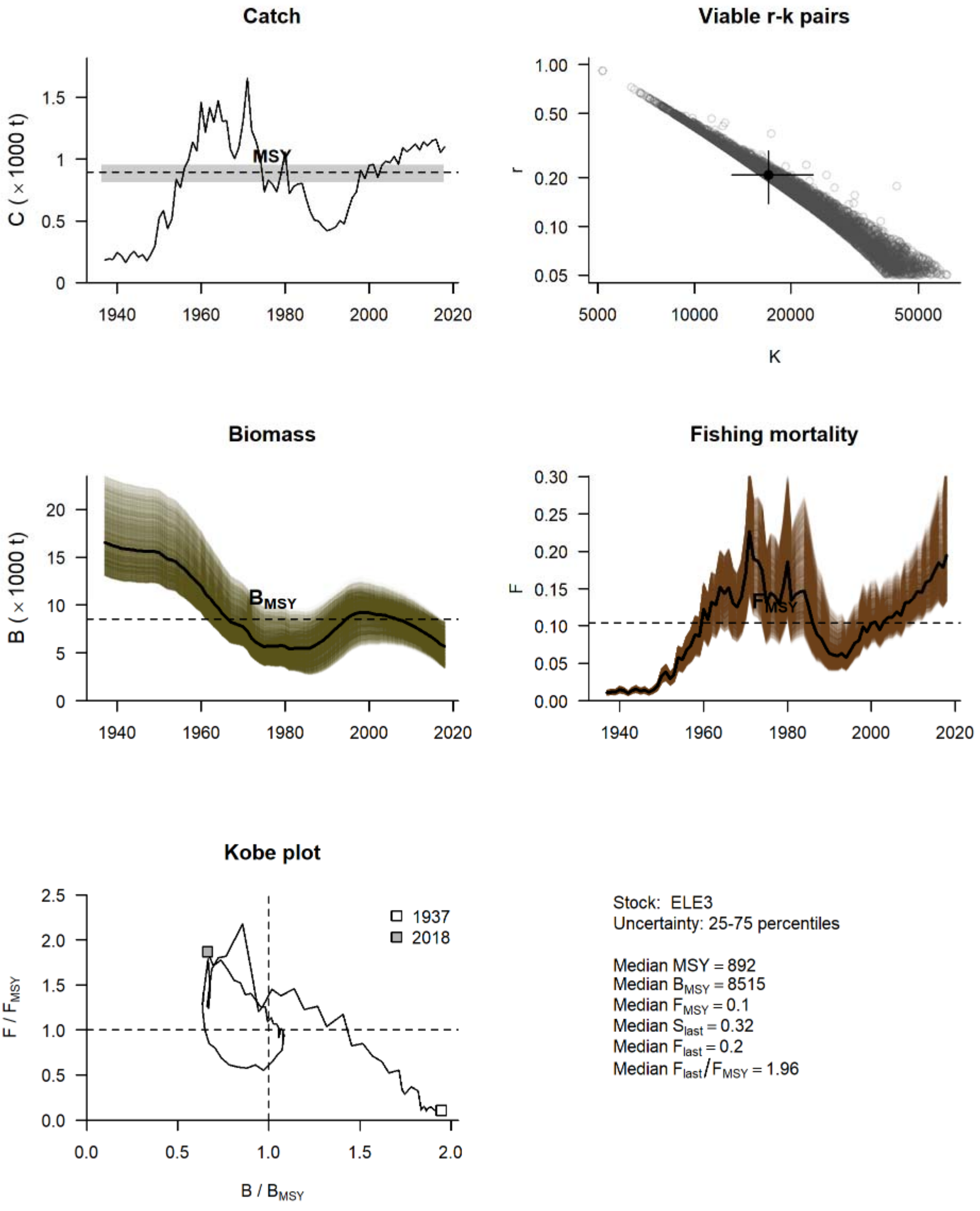


Figure 9.1. Result from the integrated catch-only method for ELE 3 (elephant fish). Results using r and S priors taken from OCOM and CMSY with equal weight.

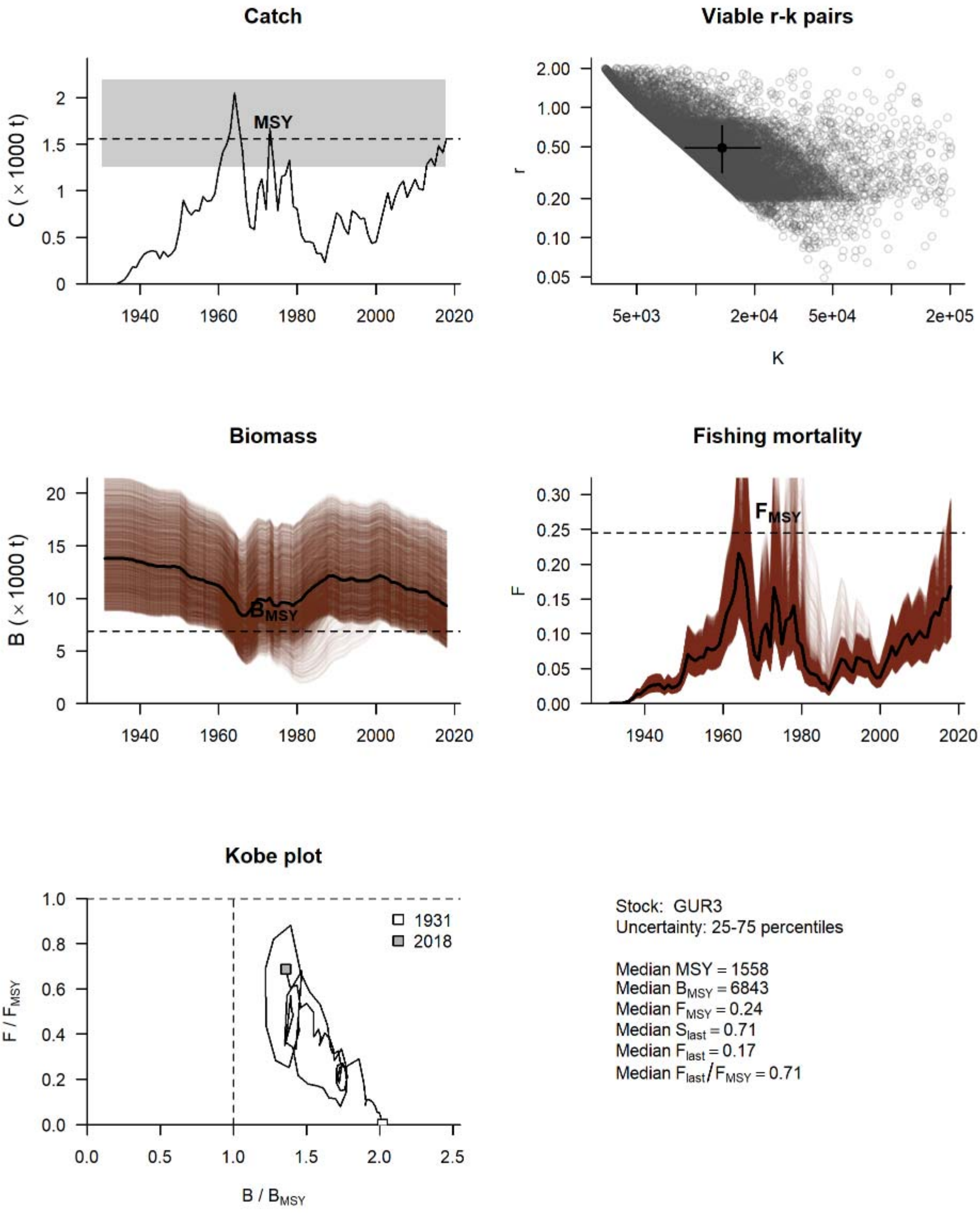


Figure 9.2. Result from the integrated catch-only method for GUR 3 (red gurnard). Results using r and S priors taken from OCOM and CMSY with equal weight.

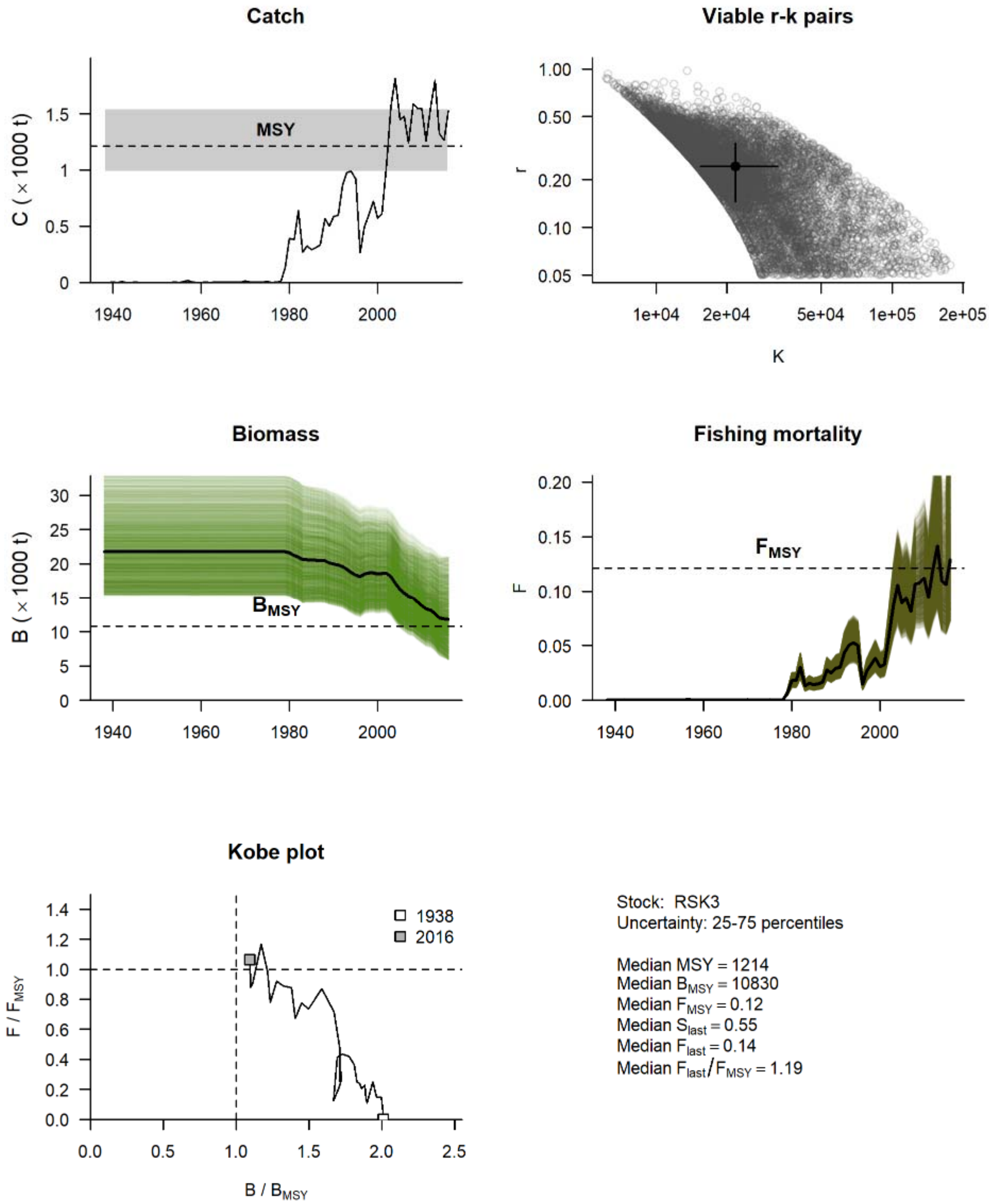


Figure 9.3. Result from the integrated catch-only method for RSK 3 (rough skate). Results using r and S priors taken from OCOM and CMSY with equal weight.

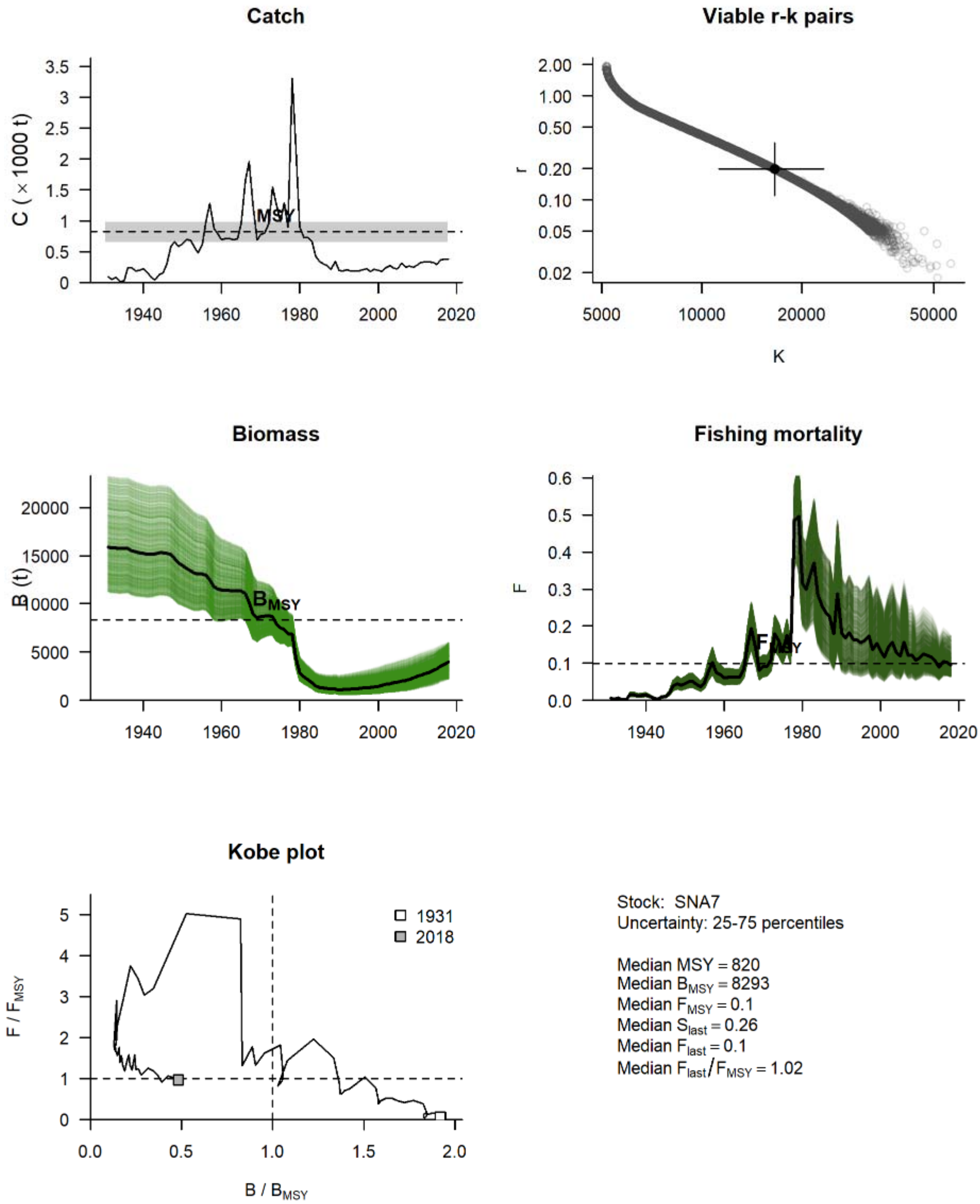


Figure 9.4. Result from the integrated catch-only method for SNA 7 (snapper). Results using r and S priors taken from OCOM and CMSY with equal weight.

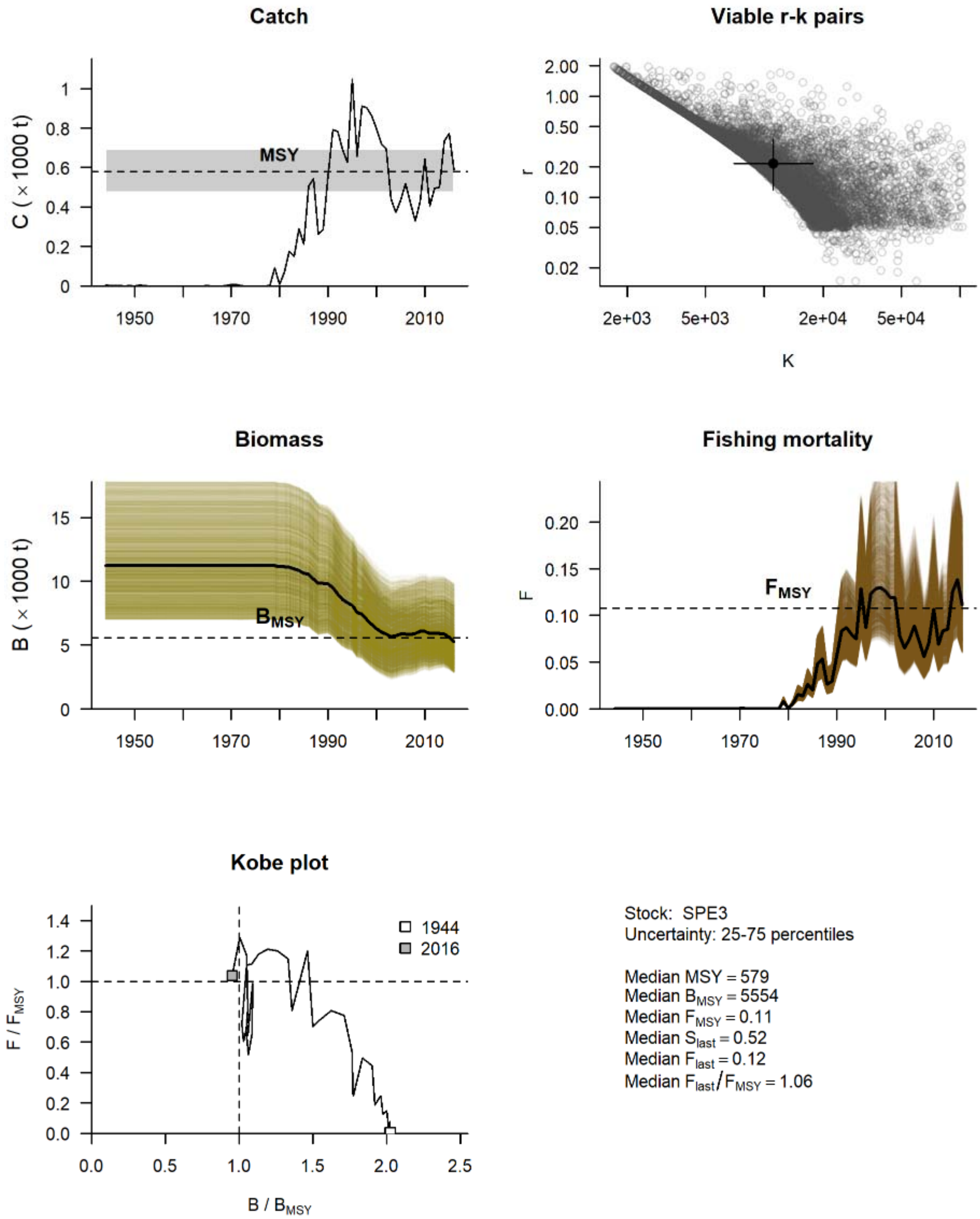


Figure 9.5. Result from the integrated catch-only method for SPE 3 (sea perch). Results using r and S priors taken from OCOM and CMSY with equal weight.

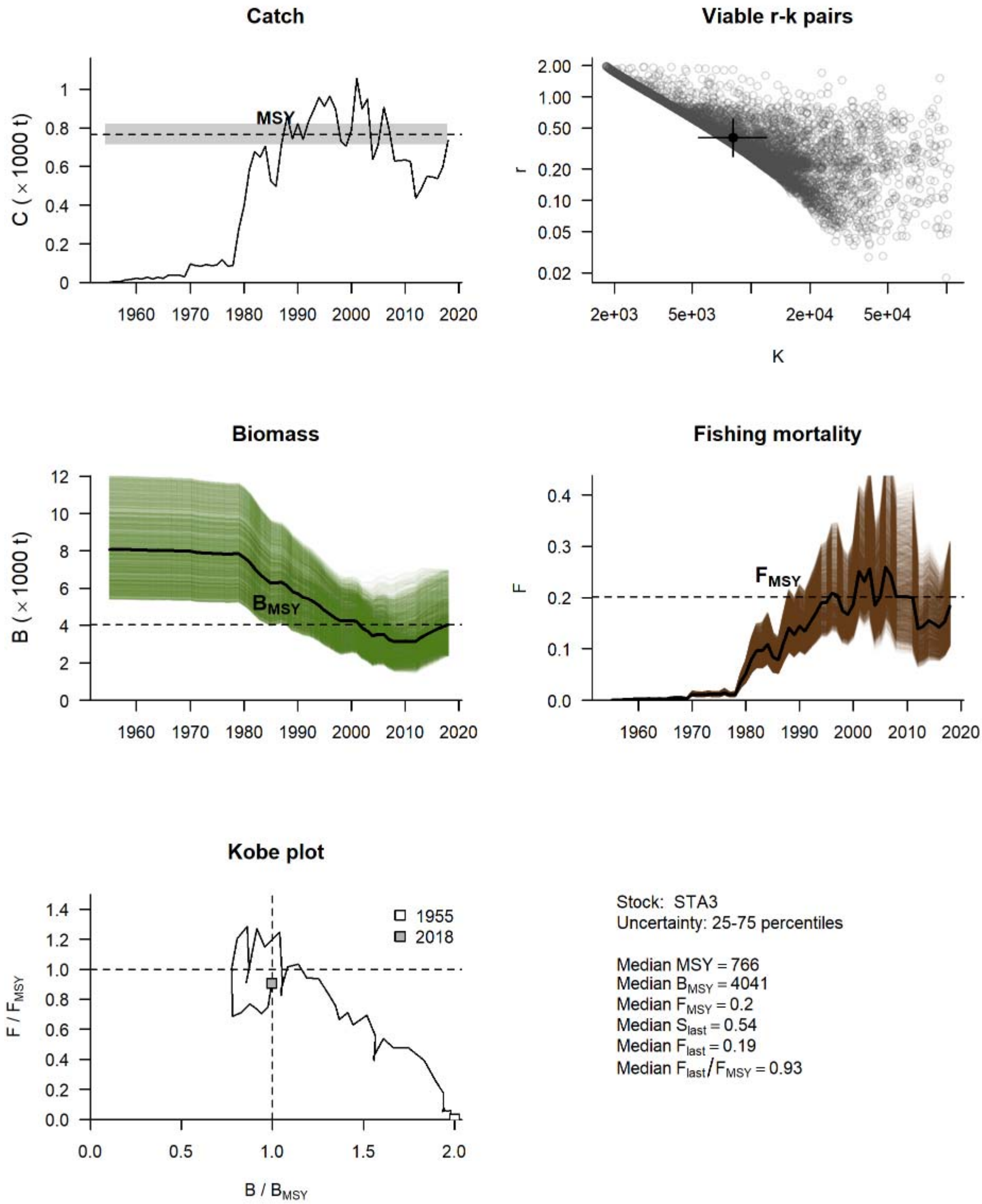


Figure 9.6. Result from the integrated catch-only method for STA 3 (giant stargazer). Results using r and S priors taken from OCOM and CMSY with equal weight.

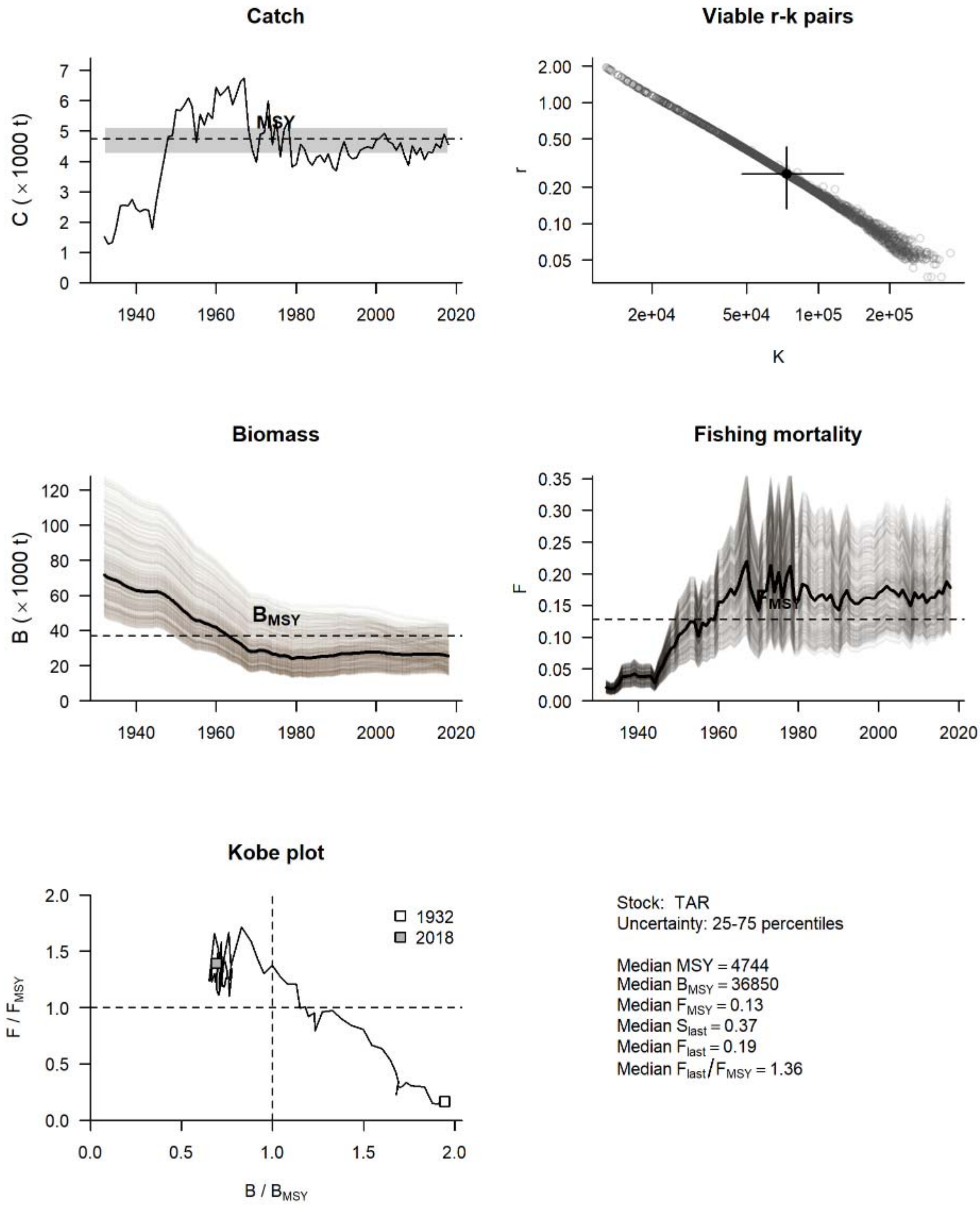


Figure 9.7. Result from the integrated catch-only method for TAR (tarakihi). Results using r and S priors taken from OCOM and CMSY with equal weight.

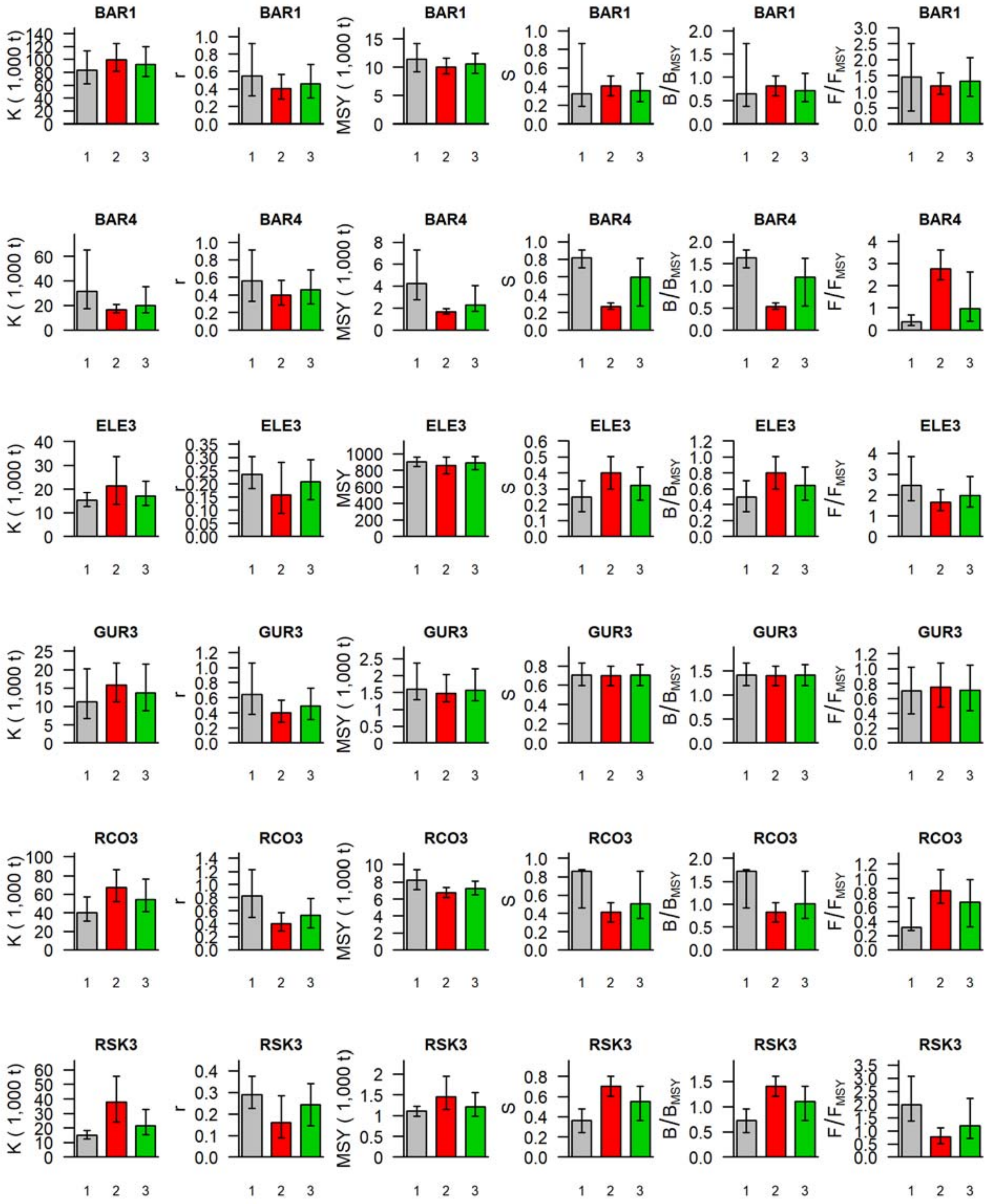


Figure 9.8. Comparison of two catch-based methods. Prior r and S in Method 1 is based on OCOM and in Method 2 is based on CMSY rules. Method 3 combines Methods 1 and 2. The error bars are 25–75 percentiles.

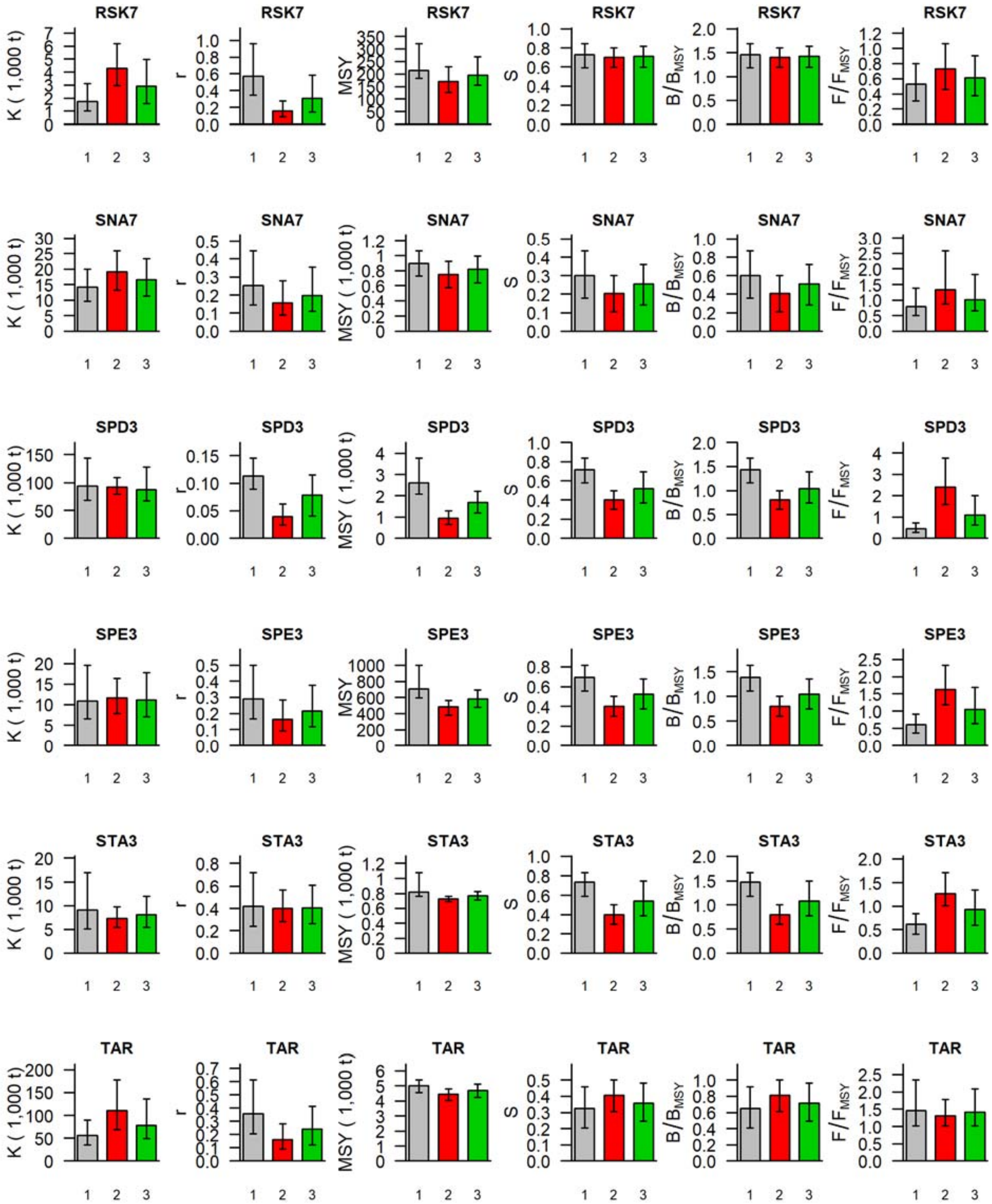


Figure 9.8 (cont). Comparison of two catch-based methods. Prior r and S in Method 1 is based on OCOM and in Method 2 is based on CMSY rules. Method 3 combines Methods 1 and 2. The error bars are 25–75 percentiles.

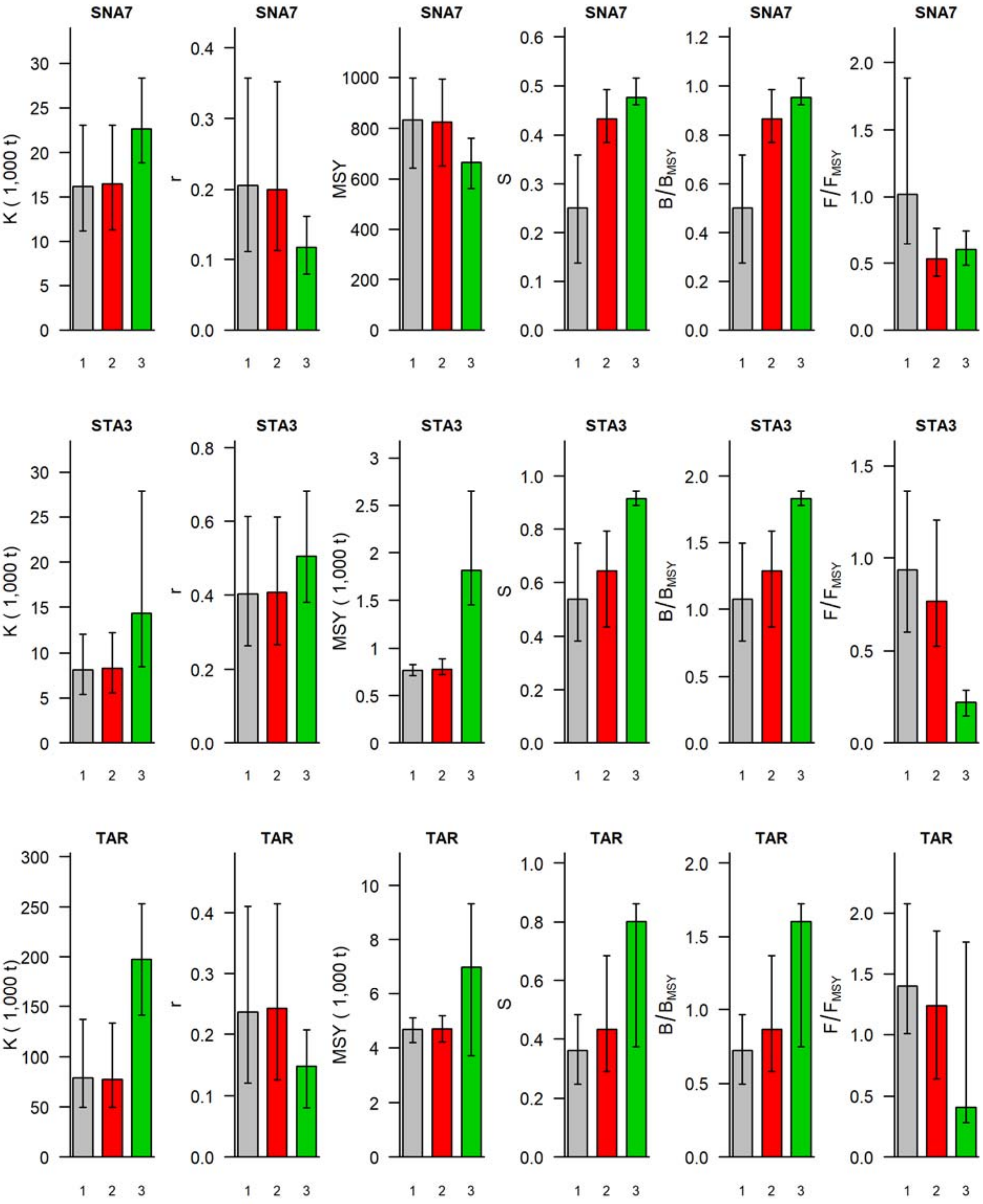


Figure 9.9. The effect of including CPUE data on integrated catch-only method (Method 3) for three stocks (SNA 7: snapper in FMA 7; STA 3: giant stargazer in FMA 3; TAR: east coast tarakihi). Optimisation: 1 = minimising on stock saturation, *S* only, i.e., not using CPUE (grey), 2 = minimising both on *S* and CPUE with equal weight (red), and 3 = minimising CPUE only (green). The error bars are 25–75 percentiles.

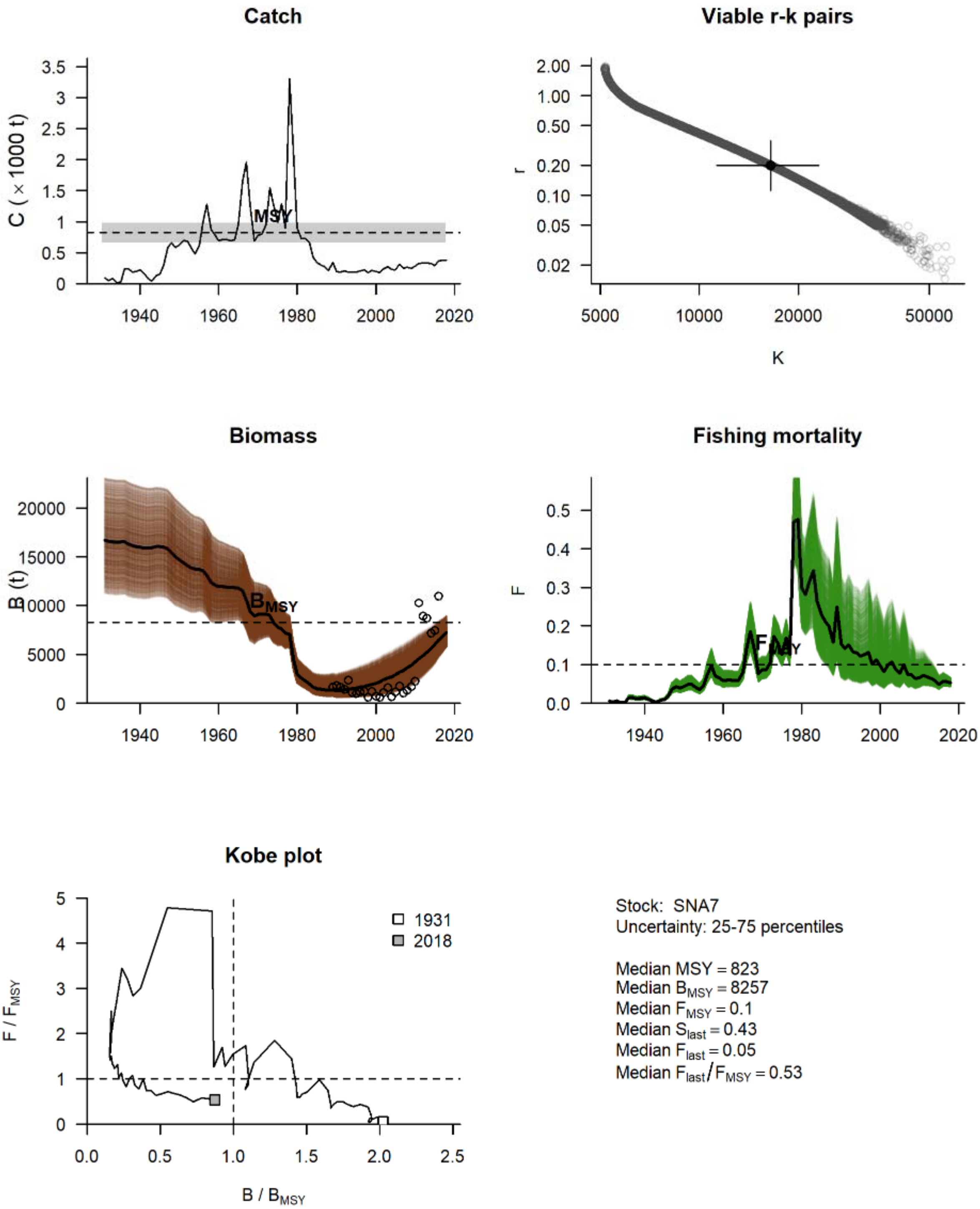


Figure 9.10. SNA 7 stock (snapper in FMA 7). Optimisation option 2: minimising both saturation prior S and CPUE using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

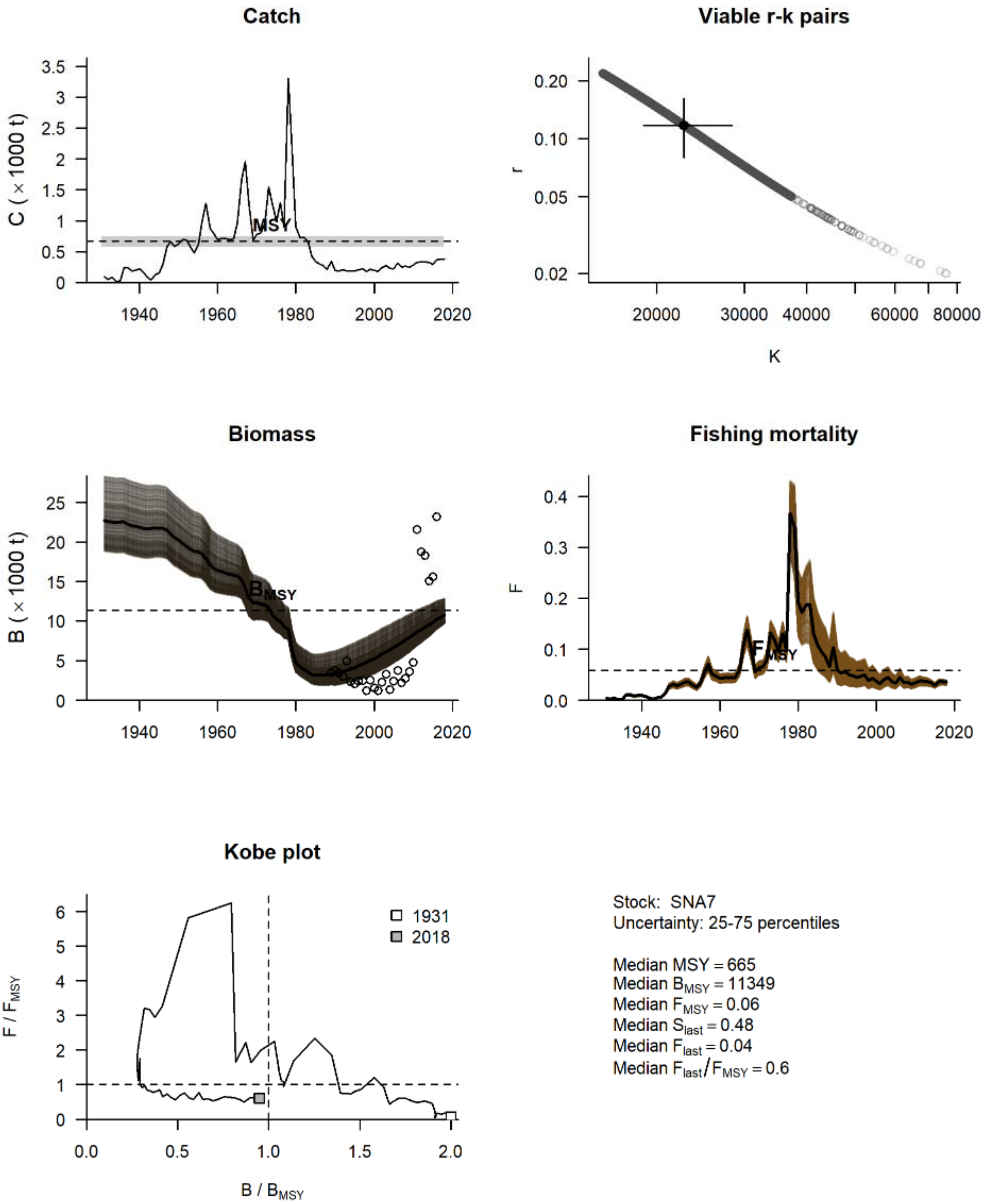


Figure 9.11. SNA 7 stock (snapper in FMA 7). Optimisation option 3: minimising CPUE only using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

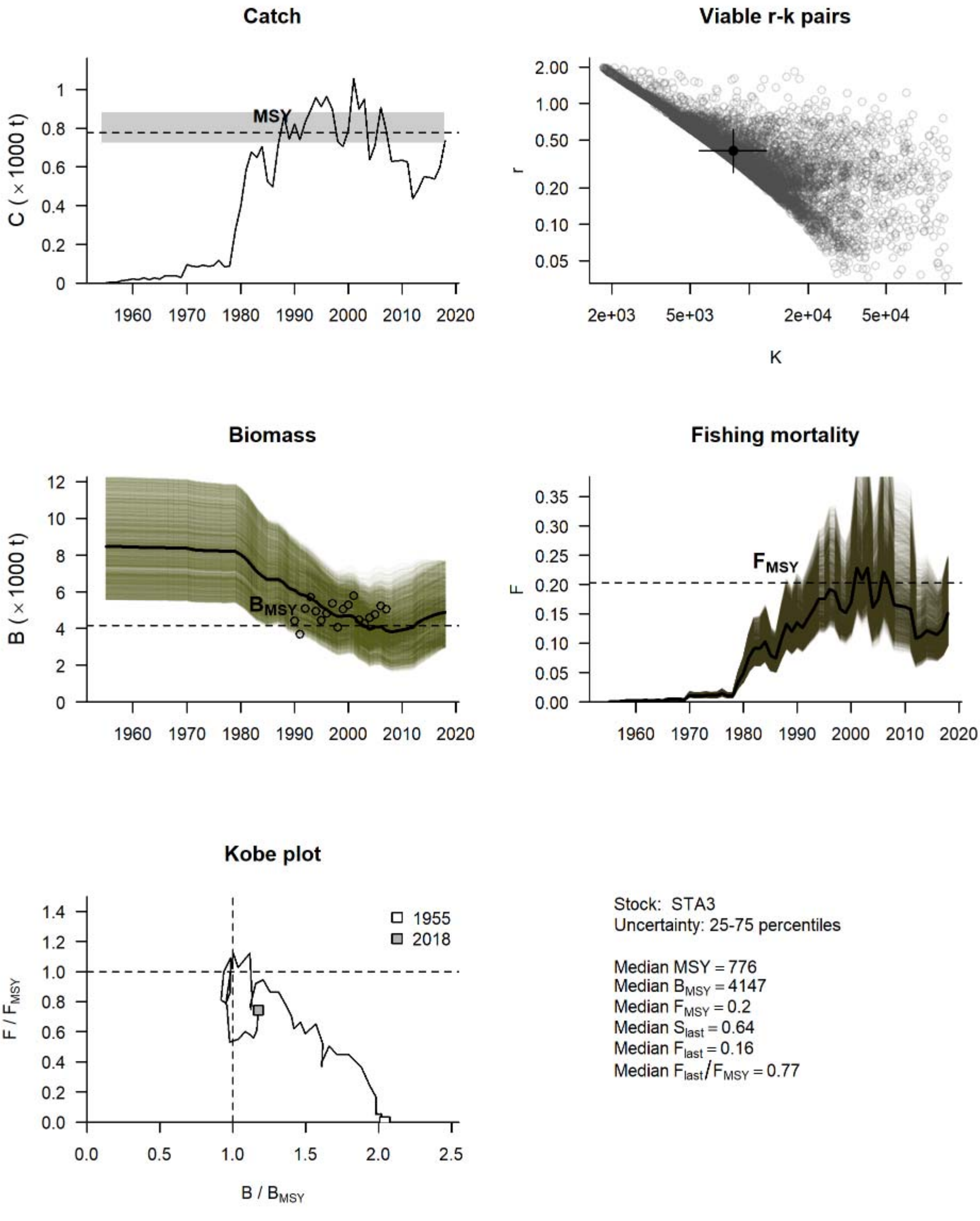


Figure 9.12. STA 3 stock (giant stargazer in FMA 3). Optimisation option 2: minimising both saturation prior S and CPUE using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

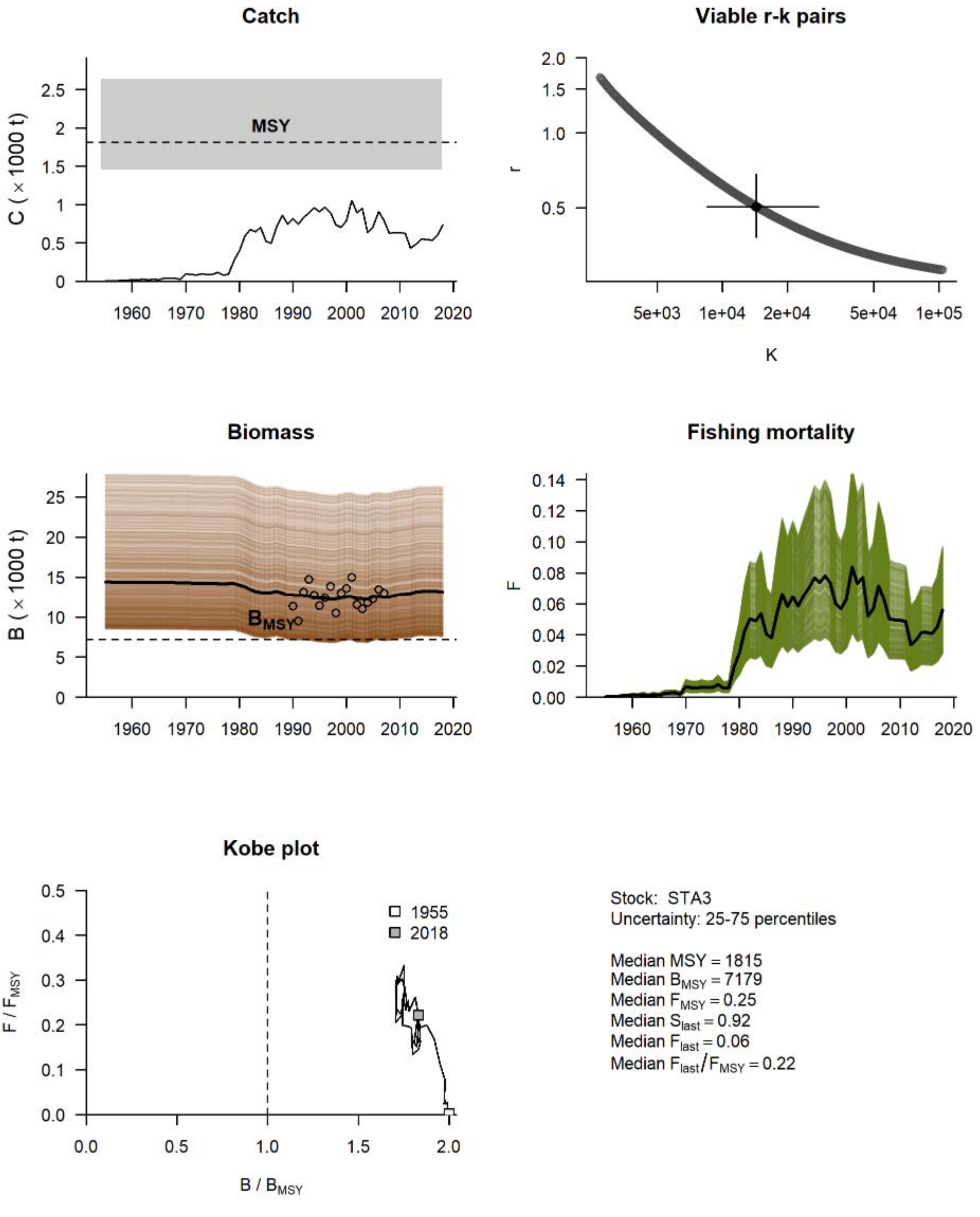


Figure 9.13. STA 3 stock (giant stargazer in FMA 3). Optimisation option 3: minimising CPUE only using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

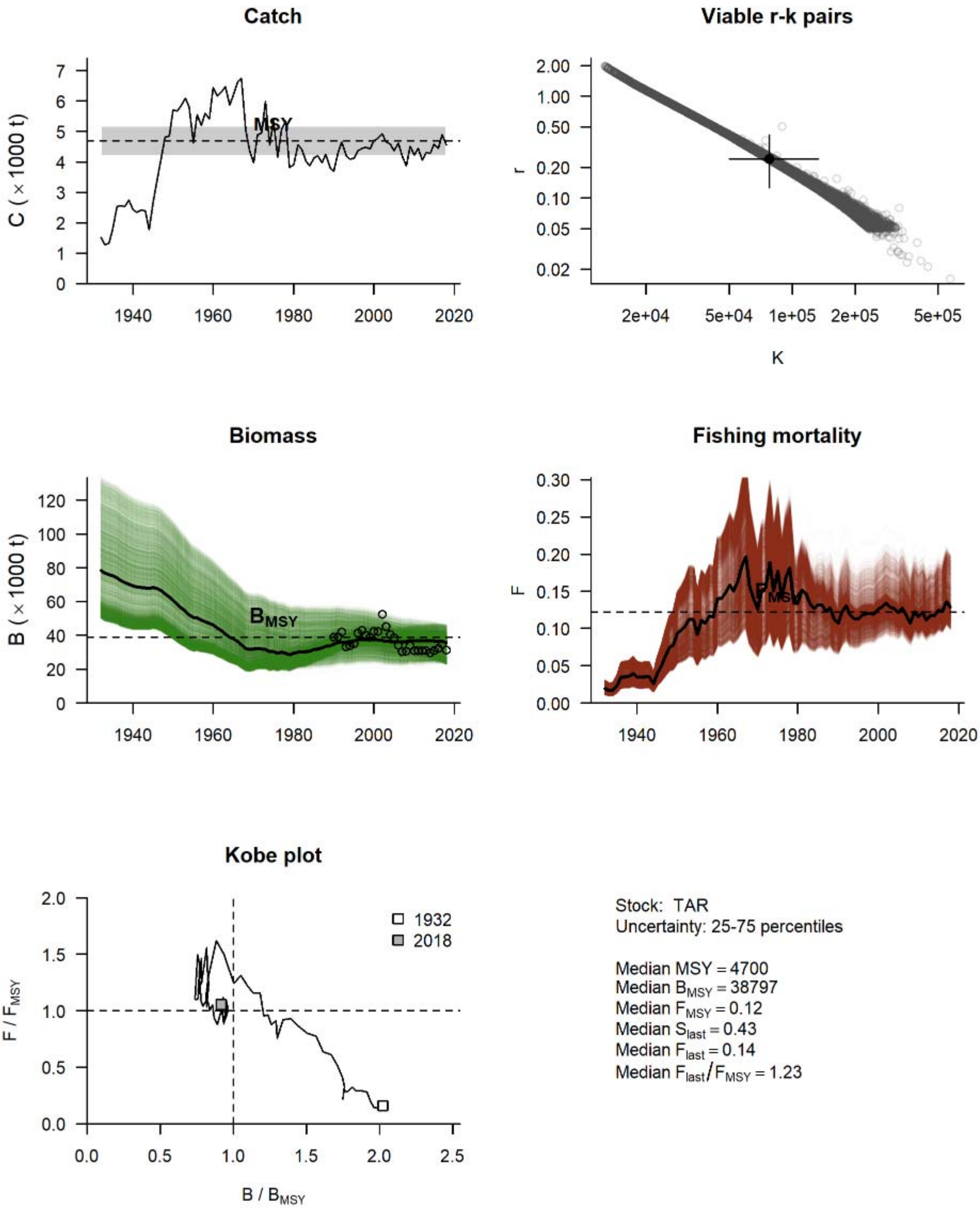


Figure 9.14. TAR stock (east coast tarakihi). Optimisation option 2: minimising both saturation prior S and CPUE using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

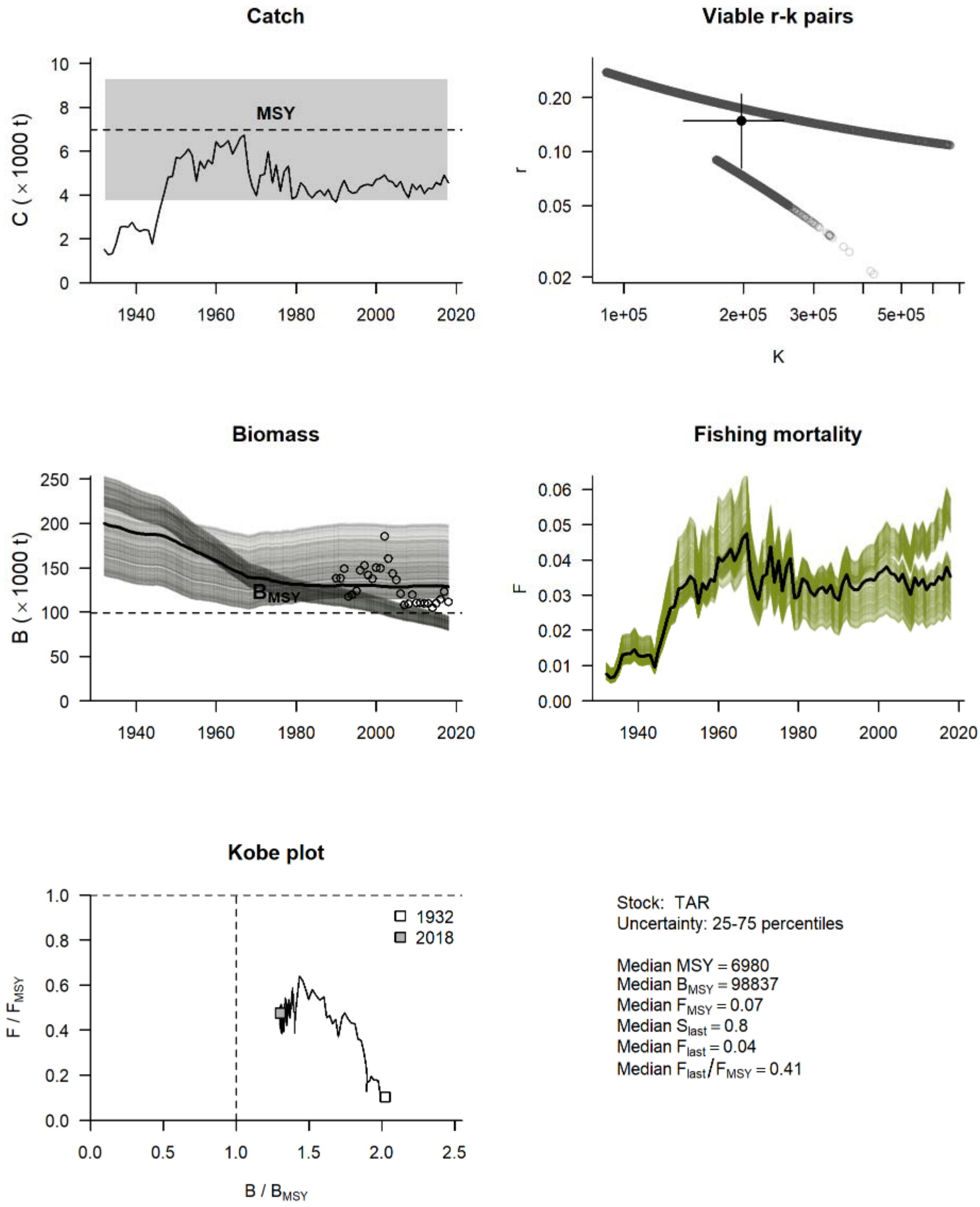


Figure 9.15. TAR stock (east coast tarakihi). Optimisation option 3: minimising CPUE only using integrated catch-only method (i.e. 'Method 3': r and S priors taken from OCOM and CMSY with equal weight). Circles in biomass plot represent mean standardised CPUE data scaled by the mean biomass over years with CPUE data.

9.5 Discussion of OCOM and OCOM with CPUE

The level of biomass relative to the unfished state is perhaps the most difficult quantity to determine. We used two approaches to construct a prior distribution for saturation S. The stock classification approach using C_{last}/C_{max} tends to be less optimistic than the approach using various trends based on the entire catch history. Combining the two approaches has led to high uncertainty around the final depletion level for some stocks (e.g., BAR 4 and RSK 3) because the median S_{BRT} is not within the range of CMSY's rule-based stock classification approach. A positive outcome is that other information (i.e., catch history and r prior) can ease the impact of the S prior to some degree such that the resulting S_{last} can be higher or lower than the mode of the prior.

Among the quantities listed in Table 9.6, the estimated *MSY* is more stable than other parameters. This is because the two parameters (K and r) used to calculate *MSY* are negatively correlated (panel 2 in Figures 9.1 to 9.7). Even if K and r are biased, their joined value will be less biased than either individual estimate.

Incorporating CPUE data does affect the catch-only method. Since the optimisation process aims to simultaneously minimise two functions, the difference between estimated and prior saturation and the difference between scaled CPUE and scaled biomass, the effect of CPUE does not fully determine the outcome as would be the case when fitting a biomass dynamics model to CPUE data. However, when a prior on S is not used, biomass trajectories are fully determined by the CPUE pattern and r prior. Lack of contrast in the CPUE time series, or a very strong trend, can lead to poor model estimation.

10. COMPARISONS OF RESULTS FOR BIOMASS AND EXPLOITATION BETWEEN FULLY INTEGRATED ASSESSMENTS AND GAM FITS, ESAFE AND OCOM

In Section 6 the results for overall biomass were compared between the GAM derived density surfaces and the fully integrated stock assessments described in Section 3. In this section, comparisons are made between integrated assessments, GAM derived density surfaces, eSAFE, and OCOM. Gear efficiency was estimated within eSAFE for commercial gears, but the biomass of stocks is still considered a relative value. Outside of eSAFE it is not yet possible to scale the density surfaces to produce absolute biomass and derive exploitation rates. The OCOM model estimates a total biomass (all age and size classes) and biomasses from this method can be compared to total biomass estimates from the integrated assessments.

Within the New Zealand management regime, the status of stocks are described in terms of % B_0 with target, soft limit and hard limit reference points typically of 40% B_0, 20% B_0 and 10% B_0 respectively. The overfishing threshold is the F corresponding to the target %B_0. Stock status in relation to the target is expressed as the probability of B being at or above the target. Stock status in relation to overfishing is expressed as the probability of F being at or above the overfishing threshold (Table 10.1).

The eSAFE and OCOM methods derive F_{MSY} from F_{MSY} = 0.87M for teleosts, and F_{MSY} = 0.41M for chondrichthyans and used a model averaging approach to derive a value for natural mortality M using up to 9 equations relating M to other life history traits. For the OCOM model, because the Graham-Schaefer surplus production model is used, maximum sustainable yield is taken as $MSY = rK/4$ and $B_{MSY} = K/2$ where r is intrinsic growth rate and K carrying capacity of the species respectively.

In summary, total biomass estimates from the integrated assessments can be compared to those from OCOM and the relative biomass estimates from the integrated GAM surfaces, (as also used by eSAFE) (Table 10.2). The probability of F being at or above the overfishing threshold can be compared to F/F_{MSY} for eSAFE and OCOM. The probability of being above target % B_0 can be compared to the B_{last}/B_{MSY} values of OCOM (Table 10.3).

Table 10.1. Symbols and colour coding used for Stock synthesis derived stock status.

		>99%	>90%	>60%	40–60%	<40%	<10%	<1%
Stock status	Evidence for stock being at or above target levels	++++	+++	++	+	--	---	----
Overfishing	Evidence for stock being overfished	----	---	--	-	++	+++	++++

Table 10.2. Comparison of biomass estimates. 'GAM (3 survey)' columns give results for fit using the three most recent surveys in the FMA of interest. The year associated with GAM density surface results is the year of the final survey. Grey shaded cells show results where little or no survey data was available from the FMA-season combination of interest.

Common name	Stock	Year	Stock Synthesis	OCOM	GAM area	GAM (all years) B: Summer	GAM (all years) B: Winter	GAM (3 survey) B: Summer	GAM (3 survey) B: Winter
Elephant fish	ELE 3	2016	5 926	6 150	FMA 3	2 863	6 333	--	19 688
Elephant fish	ELE 3	2018	4 813	5 449	FMA 3	--	--	--	--
Red Gurnard	GUR 3	2016	8 233	9 800	FMA 3	1 325	3 473	--	6 663
Red Gurnard	GUR 3	2018	8 818	9 054	FMA 3	--	--	--	--
Snapper	SNA 7	2015	10 023	2 575	FMA 7	1 240	29	1 164	--
Snapper	SNA 7	2018	11 990	3 999	FMA 7	--	--	--	--
Giant stargazer	STA 3	2016	25 431	3 760	FMA 3	2 437	4 377	--	--
					FMA 3&4	5 533	14 473	--	--
Giant stargazer	STA 3	2018	26 858	3 843	FMA 3	--	--	--	--
Tarakihi	TAR[1]	2016	20 838	27 000	TAR Stat areas[1]	7 757	9 175	4 748	9.59E+08
Tarakihi	TAR	2017	23 285	24 851	TAR Stat areas	--	--	--	--

1: Tarakihi biomass is considered that from General Statistical Areas 002, 003, 004, 005, 006, 007, 008, 009, 010, 011, 012, 013, 014, 015, 016, 017, 018, 020, 022, and 024.

Table 10.3. Comparison of results between stock synthesis-derived stock status, eSAFE and OCOM. For symbols and colours under B status and F status refer to Table 10.1. Grey shaded cells show results where little or no survey data was available from the FMA-season combination of interest. eSAFE(S) and eSAFE(W) refer to eSAFE method using density surface formed using summer survey data and winter survey data respectively.

Common name	Stock	Assess year	B status	F status	B_{last}/B_{msy} OCOM	F_{last}/F_{msy} OCOM	Last year OCOM	F/F_{msy} eSAFE (S)	F/F_{msy} eSAFE (W)	Last year eSAFE
Barracouta	BAR 1	2016	+++	++	0.71	1.33	2016	--	--	--
Barracouta	BAR 4	UA			1.20	0.96	2016	--	--	--
Elephant fish	ELE 3	2016	+	-	0.65	1.96	2018	0.42	0.42	2018
Red Gurnard	GUR 3	2015	++	-	1.42	0.71	2018	0.5	0.33	2018
Red Cod	RCO 3	UA			1.01	0.67	2016	0.16	0.16	2018
Rough skate	RSK 3	UA			1.10	1.19	2016	0.14	0.16	2018
Rough skate	RSK 7	UA			1.43	0.61	2016	0.24	0.22	2018
Snapper	SNA 7	2015	---	++	0.51	1.02	2018	0.27	0.8	2018
Spiny dogfish	SPD 3	UA			1.04	1.10	2016	0.67	0.92	2018
Sea perch	SPE 3	UA			1.04	1.06	2016	0.43	0.36	2018
Stargazer	STA 3	2017	+	++	1.08	0.93	2018	1.5	0.5	2018
Tarakihi	TAR	2018	----	----	0.71	1.42	2017	0.77 (TAR 1) 0.45 (TAR 2) 0.32 (TAR 3)	0.91 (TAR 1) 0.5 (TAR 2) 0.23 (TAR 3)	2018

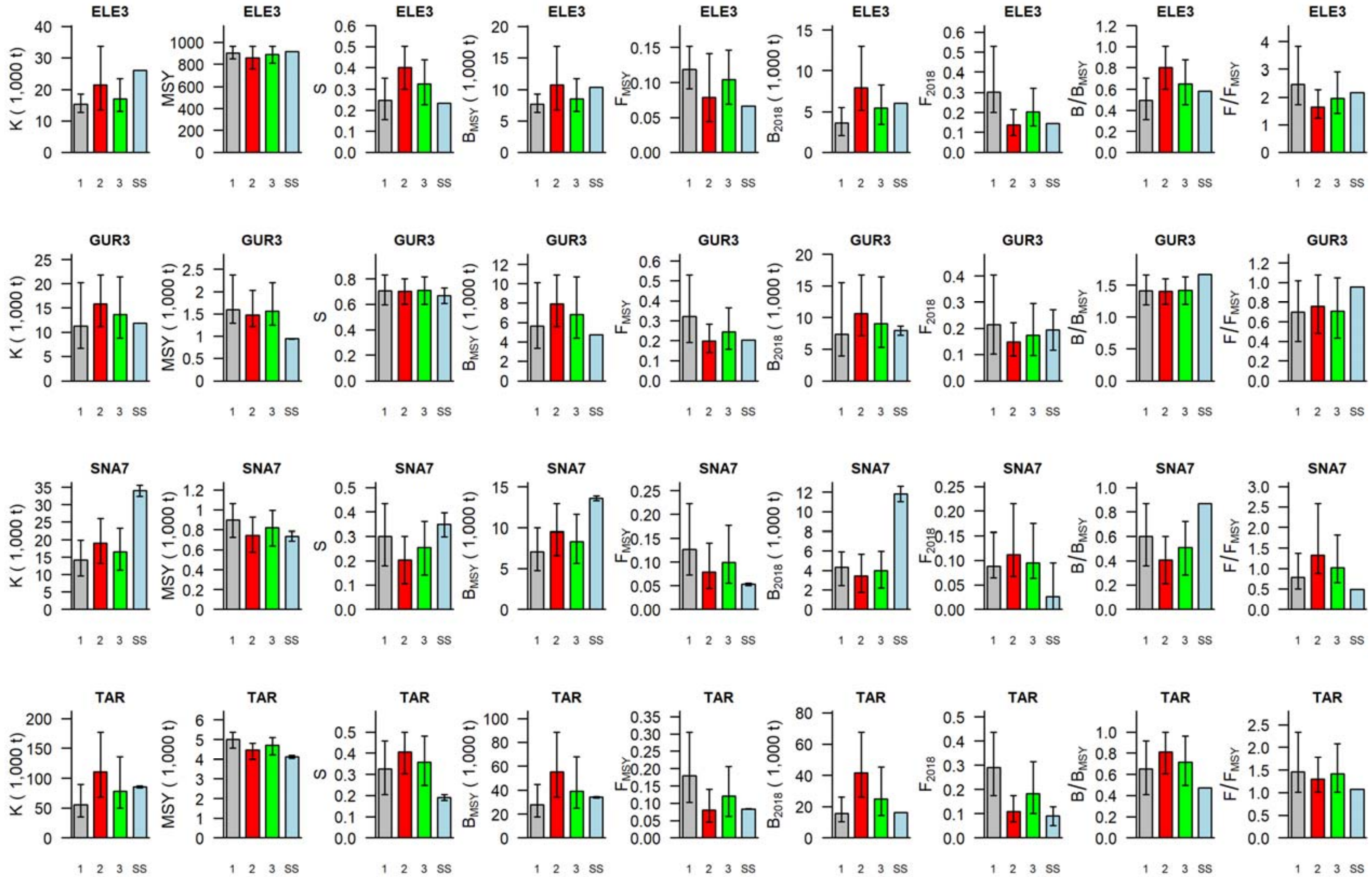


Figure 10.1. Comparison between catch-only method and Stock Synthesis (SS) output for four stocks. The numbers 1-3 refer to approach to optimisation: 1 = minimising on stock saturation, S only, i.e., not using CPUE (grey), 2 = minimising both on S and CPUE with equal weight (red), and 3 = minimising CPUE only (green). The error bars are 25–75 percentiles.

From Table 10.2 it is clear that relative biomass estimates are considerably lower in an area if survey data is lacking or completely absent for that area-season combination. In some instances, this appears to adversely affect eSAFE results in that F/F_{msy} results are inconsistent with those from the alternative season and the *F* stock status from the existing assessment (Table 10.3). Final year biomasses are similar between the integrated assessment results and OCOM results for ELE 3, GUR 3 and TAR, but the biomass estimates for SNA 7 and STA 3 are much smaller from OCOM (Table 10.2).

The eSAFE method is not consistent with the F status result from the integrated assessment. As explained in Section 6, the GAM surface for tarakihi (using all years of survey data) matches the estimate of biomass vulnerable to the ECSI survey from the integrated assessment but is formed primarily using survey data from a survey that tends to only sample younger fish. However, the gear efficiency estimated by eSAFE leads to a low F/F_{MSY} ratio (Table 10.3, Figure 10.1). The F/F_{MSY} ratios from the three versions of OCOM considered are reasonably close to the integrated assessment result for tarakihi. Confidence intervals from the OCOM results also overlap the integrated assessment result for elephant fish and gurnard. The biggest difference in F/F_{MSY} result is for snapper (Figure 10.1).

The integrated assessment biomasses for SNA 7 and STA 3 are considerably higher than from OCOM. The value for giant stargazer from the integrated assessment is for FMAs 3 and 4 (see Section 3). Integrating the GAM density surface over FMAs 3 and 4 produces a result closer to the integrated assessment result but only notably so for the fit to winter survey data. This is despite the fact that the Chatham Rise survey data are from the summer.

As demonstrated in Section 6, GAM fits based on data from three consecutive surveys did not give robust results. Biomass estimates for ELE 3 and TAR were inflated from the fit to the most recent three surveys. Estimates from other combinations of surveys more closely matched the integrated assessment results (see Figures 6.21 and 6.22).

11. DISCUSSION

A large part of the research completed this year was concerned with bringing researchers together, discussing alternative methods and ideas, and then collating and grooming the data sets required. A variety of low information assessment methods were attempted, and the results were generally not consistent. However, in all estimation methods there are areas where estimates can be improved, either through refined use of the available data sets, or through improvements to the statistical methodology. Some of the key issues arising in the research are discussed here.

11.1 Density surfaces

Density surfaces were predicted over a 10×10 km grid. This was partly out of concern that a finer grid would cause data handling issues for the eSAFE method. In hindsight this was probably unnecessary and in future a prediction grid at the full resolution of the covariate data can be employed.

The results using long time series of survey data provided biomass estimates that fell into the range of the relative biomass estimates of surveys from the same area for all species except giant stargazer in the ECSI area and tarakihi compared to ECNI surveys. For those stocks that could be compared to an integrated stock assessment (elephant fish, red gurnard, snapper and tarakihi) biomass estimates matched the estimates of vulnerable biomass over a suitably defined area. However, using all survey data together with long term averages of environmental covariates would always produce some form of smoothed average. Using a long series of survey data to produce a GAM density surface before scaling by mean-standardised survey values (Figure 6.23) showed to some extent that it was possible for the model to reflect a strong change in species abundance but the approach has drawbacks. It requires relatively long survey series and, as seen in Figure 6.23, large increases or decreases in abundance may cause estimates from relatively stable periods to be decreased/increased away from what are sensible values.

Reducing the number of survey years input to the model demonstrated results that tracked survey relative biomass or assessment vulnerable biomass to a limited extent but at the expense of a lack of robustness in results. Mannocci et al. (2017) summarise how the suitability of climatological covariates depends on the inter-annual variability of those covariates. The inter-annual variability of all available covariates is outside the scope of this project but given that annual covariate data are available and that the ultimate aim of the project are reliable density surfaces from a short series of surveys (easing data handling issues associated with separate data sets for each year), an obvious next step is to fit to annual covariate data. Separate years can be accounted for through an interaction term making use of a tensor product to allow for different natural spatial and temporal scales (Wood 2017).

The idea to include annual data with a temporal interaction term is further supported by evidence of year effects from the inshore surveys. The ECSI summer time series was discontinued after the fifth in the time series because of extreme fluctuations in catchability between surveys (Beentjes et al. 2016). Relative biomass estimates of some species also show signs of synchronised year effects suggesting a common annually varying environmental driver (Hurst pers. comm.) The ECNI survey was abandoned because of high variability in relative abundance estimates. One reason postulated was slight shifts in fish distribution between trawlable and hard ground making changes in fish availability (Stevenson & Hanchet 1999).

For the ECSI survey the vessel and gear have remained constant but sampling strata have changed. There was a minor variation from 1994 but more significantly the addition of shallow strata (10–30 m depth) which became a regular inclusion in the survey starting in 2012, (Beentjes et al. 2016). The integrated GAM surfaces for red gurnard in FMA 3 seem to better reflect the integrated assessment result from the point at which the shallow strata are included (Figure 6.20).

The GAM fitting package mgcv includes as outputs standard errors for each density prediction. Biomass confidence intervals were constructed by summing over all values of fitted value plus 2×s.e. and value minus 2×s.e. (or zero to avoid negative numbers). Although quick to produce, these confidence intervals may not reflect the true confidence interval around the estimated overall biomass. A better indication of the overall uncertainty can be obtained through block cross-validation, (Roberts et al. 2017). For relating catch to biomass within each prediction grid cell, however, the variance estimated from mgcv might be reasonable. Through simulation studies, Wood (2017) found the coverage and accuracy of the variance to be reasonable for the overall fit, even when estimates of variance in individual covariate influence did not reflect the true variance so well.

The management area for giant stargazer is FMA 3. Analysis of trawl length frequency distributions from the ECSI and Chatham Rise trawl surveys in preparation for the fully analytic stock assessment led to the conclusion "The comparative length compositions from the two trawl surveys may indicate that the ECSI trawl survey area (essentially STA 3) encompasses a nursery area for a stock whose total distribution extends over a wider area including the Chatham Rise.", (Section 3). The plots of survey data (Section 6) also indicate a stock that extends from FMA 3 over the Chatham Rise. To make use of density surfaces scaled by a survey catchability it seems necessary to assess the stock over FMAs 3 and 4 and include the areas surveyed by the ECSI and Chatham Rise surveys. The problem then arises that these surveys are conducted at different times of year. The assumption that fish do not migrate seasonally must hold for the LSP method to be valid for such stocks as well as an assumption that the relationship between fish density and covariates remains consistent. The ECSI and Chatham Rise surveys are also conducted by different vessels. It may be possible to establish the general behaviour of different species in front of trawls to establish a coefficient for vulnerability to the trawl gear (see below) but overall catchability may still be influenced by a vessel effect.

At the start of the project it was felt necessary to form density surfaces over the nominal management areas for the stocks. The data for giant stargazer (and sea perch) indicate management areas that do not encompass the stock. In the case of red gurnard, the nominal management area seems clearly too large. Prediction to areas not containing response data can cause problems. The covariates used may indicate suitable conditions for a species in a remote area, but the species may simply have never colonised the area. Another problem is predicting to areas where the covariate values fall outside of those used in the fit. This would be a minor issue if density surfaces could be produced with well-defined limits (in the covariate space) to positive densities. With GLMs and GAMs this can be difficult to achieve (Elith & Graham 2009) and manual intervention based on expert knowledge might be needed to define limiting values for covariates (as was done for depth with respect to gurnard in this study) or outer stock area limits in physical space.

In summary, for future work any method creating the density surfaces needs to make use of annual and seasonally explicit covariate data and to take the interaction between year and spatial effects into account, as well as incorporating vessel as a random effect. User defined outer stock area limits may also be necessary.

11.2 Moving from relative density surfaces to estimates of absolute abundance

Section 6 described the estimation of relative density surfaces. Here we briefly describe how to derive absolute abundance estimates together with an estimate of uncertainty.

For each species and cell is an estimate of density (an expectation and variance) from which we can simulate a density

$$d_{si} \sim \phi_1(\mu_{si}, \sigma_{si})$$

where ϕ_1 is a distribution (in Section 6 this was a negative binomial distribution[7]), and μ_{si} and σ_{si} are the parameters of this distribution. Using the area of each cell (a_i) the biomass vulnerable to capture in each cell (v_{si}) can be calculated as

$$v_{si} = d_{si} a_i$$

Given a prior distribution for catchability for each species, we can simulate

$$q_s \sim \phi_2(\eta_s, \omega_s)$$

where ϕ_2 is a distribution (usually a lognormal distribution), and η_s and ω_s are the parameters of the distribution. Now the biomass for each species and cell can be derived from vulnerable biomass by applying the catchability coefficient

$$b_{si} = v_{si}/q_s$$

Integrating over cells provides the total biomass for each species

$$B_s = \int_{i=1}^{n} b_{si}$$

This integration can be done for any user defined area (e.g. a statistical area or FMA). Remembering that B_s is a distribution, one can calculate any statistic (e.g. mean, median, quantiles) of the biomass for each species.

11.3 Catchability

In the above section a distribution for the catchability coefficient q_s is required *a priori*. The statistical model of Section 7 improves on the previous method for estimation of gear efficiency, *Q*, used by the eSAFE method. If using absolute fish densities, the method gives catchabilities (assuming the fish density is constant over each spatial stratum used). Currently only relative fish densities are available so the *Q* values are not necessarily catchabilities. This does not prevent calculation of exploitation rates from eSAFE because the method only needs to compare a relative catch to a relative biomass (see equation 7.4 of Section 7).

Francis (1989) defined three components of survey catchability

i. Vulnerability (v): Of the fish in the volume swept, the average proportion (by weight) that are caught.
ii. Vertical availability (u_v): Of the fish in the survey area at the time of the survey, the proportion (by weight) that are available to the net; i.e. those whose distance from the bottom is less than the headline height. Vertical availability is then the proportion of fish above the area swept that are in the volume swept.
iii. Areal availability (u_a): Of the fish in the population area, the proportion (by weight) that is in the survey area at the time of the survey.

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[7] The negative binomial distribution is a discrete distribution, but the response variable is continuous (the density in kg per km^2). For future iterations continuous distributions that can model excessive zeroes or alternative modeling frameworks should be considered (e.g., the Tweedie distribution, zero-inflated or hurdle models).

The gear efficiency estimated in eSAFE is effectively a combination of the vulnerability and vertical availability components but can only be considered a true catchability if calculated using absolute fish densities. By relating survey catch rates (and therefore fish densities) to environmental covariates that can be measured both inside and outside the survey area, the creation of density surfaces (through GAM smooths in this project), if successful, can be thought of as rendering areal availability equal to 1 but can only give estimates of absolute density if estimates of vulnerability and vertical availability can be applied as coefficients to the catch rate data.

Direct observations have shown the behaviour of demersal fish in front of the trawl mouth to be species and size specific (Larsen et al. 2018). Direct observations of New Zealand commercial species in New Zealand waters have been conducted for deep water species on the Chatham Rise (Ian Doonan pers. comm.) but not of the inshore species considered in this project. Piasente et al. (2004) used cameras on demersal trawl gear as used by Australia's South East Trawl Fishery. One species observed was tarakihi[8] where a summary of their behaviour stated:

> "Individuals were motionless or swimming slowly in the trawl path located on or within 2 m of the seafloor. The behaviour [of tarakihi] at the mouth of the trawl did not appear to change until immediately before contact with the ground gear. Individuals then reacted with haphazard, horizontal burst swims. These manoeuvres generally continued until the trawl overran the fish. No [tarakihi] exited upwards and over the headline of the trawl."

No tarakihi were observed to escape through meshes having entered the trawl (unlike other species). The headline height of the New Zealand inshore trawl survey gear is 4–5 m on average. Assuming that tarakihi behave in the same way in New Zealand as in Australian waters this would make both vulnerability and vertical availability of tarakihi to the survey equal to 1. This in turn implies the catchability to be multiplied to the GAM fitted density surface for tarakihi of 1. This result corroborates the very close match between the GAM estimated biomass (using all years of survey data) and the stock assessment estimate of biomass vulnerable to the ECSI survey (see Figure 6.18, Section 6).

The example of tarakihi, however, also exposes the problem for this technique if surveys only sample a proportion of the stock size and age range. The GAM estimated biomass is some way below the stock assessment estimate of total biomass. It can be speculated that older, bigger fish may demonstrate a different relationship to the covariates used to predict the species' density surface.

Another species observed of relevance to this study was sea perch (*Helicolenus spp*.). Again, in the trawl mouth sea perch responded with randomly directed, horizontal burst swims. For this species small individuals were observed to pass through the meshes in the bottom panels of the wing ends (28% of observations) but none to escape under the footrope or by swimming out of the path of the gear. Wing end mesh was 102 mm compared to 150 mm for the ECSI survey (Beentjes et al. 2013) and 300 mm for the Chatham Rise survey (Hurst & Bagley 1994). The implication is of a vulnerability value no higher than 0.7. There are no conventional assessments of sea perch available for comparison.

A third species observed by Piasente et al. (2004) and found in New Zealand waters was ling (*Genypterus blacodes*). Ling was not included in the current study because it is considered a deep-water species. Good (low CV) survey data is available for ling from both the Chatham Rise (FMA 4) and Sub-Antarctic regions (FMA 6) and accepted stock assessments exist. While not forgetting the overall aim to provide assessment for inshore stocks it would seem beneficial while developing, and validating, the methodologies to include stocks such as ling.

The work of Piasente et al. (2004) are the only known direct observations of species found in New Zealand inshore fisheries. Advances in camera technology mean it is feasible to mount cameras on the

[8] The paper actually refers to 'Jackass morwong' rather than tarakihi as this is the common name for *Nemadactylus macropterus* in Australia.

trawl survey gear with negligible impact on the normal operation of the survey. Larsen et al. (2018) were able to operate GoPro cameras without lights to depths of 75 m. This suggests the possibility of mounting cameras during the ECSI survey which has strata of 10–30 m because of the high abundance of elephant fish and gurnard at these depths. Without new fieldwork, assumptions linking species with similar morphology is probably necessary, for example for giant stargazer the results of Reid et al (2007) could be used, who estimated the gear efficiency of trawl survey gear on anglerfish (*Lophius* spp.) in the west of Scotland.

11.4 Reference points

The aim of the LSP approach – spatially explicit estimation of current absolute biomass not reliant on a long time series of data – and the limited data characteristics of the stocks imply that targets and limits will be exploitation rate (fishing mortality rate) based. The catch only (OCOM) and eSAFE methods derive F_{MSY} from $F_{MSY} = 0.87M$ for teleosts, and $F_{MSY} = 0.41M$ for chondrichthyans and use a model averaging approach to derive a value for natural mortality M using up to 9 equations relating M to other life history traits. For OCOM, because the Graham-Schaefer surplus production model is used, maximum sustainable yield is taken as $MSY = rK/4$ and $B_{MSY} = K/2$ where r is intrinsic growth rate and K the carrying capacity of the species respectively.

The estimates of M as used for eSAFE and OCOM, combined with maturity ogive, growth parameters, length-weight relationships and gear selectivity allow calculation of a deterministic yield per recruit (*YPR*) and spawner per recruit (*SPR*). It is then possible to define an exploitation rate matching a target %spawner per recruit, $F_{\%SPR}$. The calculation can be performed using the CASAL package (Bull et al. 2012). If it is not possible to estimate commercial gear selectivity from commercial data, it could be determined for the survey gear. This would represent a conservative estimate of $F_{\%SPR}$ as the survey trawl will have a smaller L_{50} than commercial gear. The target $F_{\%SPR}$ values come from the operational guidelines for New Zealand's harvest strategy standard (Ministry of Fisheries, 2011) based on a stock's productivity level. The productivity levels are based on the same life history parameters used by eSAFE. The estimation of life history traits in themselves are a source of uncertainty and the confidence that can be placed in species life history parameters may be variable between species (see comments on those for elephant fish, Section 3). Any reference point thresholds need to be considered carefully and agreed with Fisheries New Zealand before stock advice from any low information species method could be applied.

11.5 Catch only methods

The optimised catch-only method (OCOM), is a simple solution for low-information stocks but comes with two major caveats.

First, the method assumes that catch time series are accurate. Proportional over- or under-estimation of the total annual catch (e.g., due to discards or recreational catch) will proportionally over- or underestimate carrying capacity K, annual biomass B_y and *MSY*, although this has little impact on their relative measures (i.e., B_y/K and C_y/MSY). However, an inconsistent pattern of bias (e.g., overestimation of catch in some years but underestimation in other years) will lead to error in both absolute (i.e., K, MSY, B_y) and relative estimates (i.e., B_y/K, C_y/MSY). Furthermore, the method requires that the catch time series be available as early as the beginning of the fisheries. Missing early years (e.g., very high catches in the early years) can result in unreliable estimates.

Second, the relationship between life-history parameters (or resilience parameters) and stock productivity were derived in a meta-analysis from a large number of species. Using such relationships as a prior for productivity may not be accurate for a particular stock. Applying multiple estimators, such as the average over nine M estimators and using both the $F_{msy} \sim M$ relationship and resilience, is expected to reduce potential bias. For some stocks considered in this project the estimates of M varied widely. One possible adjustment going forwards is to use expert judgement to limit the range of M values accepted. Generally, the prior for the productivity parameter is of less concern than the prior for depletion level.

For this project, incorporating CPUE data into OCOM has been attempted for the first time. Since the optimisation process aims to simultaneously minimise two functions, the difference between estimated and prior saturation and the difference between scaled CPUE and scaled biomass, the effect of CPUE does not fully determine the outcome as would be the case when fitting a biomass dynamics model to CPUE data. However, when a prior S is not used, biomass trajectories are fully determined by the CPUE pattern and *r* prior. Lack of contrast in the CPUE time series, or a very strong trend, can lead to poor model estimation.

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APPENDIX 1: INTEGRATED ASSESSMENT DATA TABLES

Table A1.1. Annual catch included in the eastern tarakihi stock assessment and estimated trawl survey (winter 10–400 m) vulnerable biomass (t), total biomass (t), spawning biomass (SSB, all mature fish t) and fishing mortality relative to the reference level of fishing mortality ($F_{SB40\%}$) from the MPD of the stock assessment model.

Year	Catch	Survey Bio	Total Bio	SSB	F/Fref
Virgin				86 146	
1975	4 910	15 572	35 033	21 609	1.85
1976	5 367	15 069	34 456	22 020	1.45
1977	4 157	15 368	35 009	21 864	1.74
1978	5 056	15 084	34 526	21 243	1.86
1979	5 334	14 436	33 631	21 583	1.37
1980	3 814	14 933	34 301	22 326	1.37
1981	3 912	15 591	34 932	22 500	1.57
1982	4 562	15 706	34 863	22 613	1.52
1983	4 411	15 731	34 679	22 920	1.39
1984	4 020	15 879	34 543	23 507	1.35
1985	3 875	16 189	34 189	23 575	1.45
1986	4 126	15 834	33 190	22 846	1.52
1987	4 202	14 676	31 958	21 535	1.50
1988	3 974	13 313	31 118	19 647	1.65
1989	4 255	11 742	30 209	18 333	1.52
1990	3 820	10 909	29 650	17 820	1.50
1991	3 692	11 144	29 098	17 644	1.78
1992	4 315	11 572	27 988	16 934	2.02
1993	4 665	11 302	26 860	15 942	1.90
1994	4 223	10 470	26 448	14 657	1.87
1995	4 104	10 033	26 359	14 463	1.89
1996	4 122	10 641	26 544	14 934	1.99
1997	4 367	11 605	27 025	15 477	2.01
1998	4 456	12 068	28 101	15 547	1.92
1999	4 481	12 360	29 075	16 015	1.84
2000	4 435	13 377	29 739	18 053	1.90
2001	4 696	15 330	29 520	19 546	1.95
2002	4 779	16 529	28 648	20 152	2.06
2003	4 918	15 529	27 248	18 448	2.06
2004	4 656	13 578	26 048	16 307	2.13
2005	4 596	11 283	25 095	14 467	2.10
2006	4 358	9 774	24 536	13 096	2.27
2007	4 622	9 021	23 662	12 936	2.14
2008	4 195	9 435	23 283	13 452	2.02
2009	3 872	10 263	23 518	13 153	2.30
2010	4 514	10 047	22 735	12 405	2.25
2011	4 228	9 731	22 432	12 715	2.39
2012	4 456	10 062	21 836	12 047	2.26
2013	4 062	10 034	22 160	12 343	2.37
2014	4 313	9 416	22 547	11 092	2.29
2015	4 283	9 532	22 831	11 727	2.42
2016	4 582	9 995	22 714	12 662	2.37
2017	4 445	11 410	22 757	13 037	2.60
2018	4 709	11 278	22 292	12 575	2.48

Table A1.2. Annual catch included in the SNA 7 stock assessment and estimated trawl survey vulnerable biomass (t), total biomass (t), spawning biomass (SSB, all mature female fish t) and fishing mortality relative to the reference level of fishing mortality ($F_{SB40\%}$) from the MPD of the stock assessment model.

Year	Catch	Survey Bio	Total Bio	SSB	F/Fref
1931	93	33 869	34 782	16 999	0.05
1932	53	33 775	34 687	16 952	0.03
1933	88	33 720	34 631	16 925	0.05
1934	18	33 627	34 538	16 879	0.01
1935	22	33 603	34 514	16 868	0.01
1936	243	33 575	34 485	16 854	0.13
1937	236	33 325	34 235	16 730	0.13
1938	189	33 086	33 995	16 612	0.11
1939	200	32 897	33 807	16 518	0.11
1940	219	32 703	33 612	16 422	0.12
1941	164	32 496	33 405	16 320	0.09
1942	88	32 350	33 260	16 247	0.05
1943	45	32 287	33 197	16 216	0.03
1944	125	32 273	33 182	16 208	0.07
1945	152	32 183	33 092	16 163	0.09
1946	288	32 071	32 980	16 108	0.17
1947	580	31 828	32 736	15 987	0.34
1948	663	31 300	32 207	15 725	0.39
1949	582	30 702	31 607	15 429	0.35
1950	627	30 198	31 088	15 179	0.39
1951	699	29 667	30 525	14 916	0.44
1952	686	29 081	29 858	14 625	0.44
1953	579	28 521	29 162	14 287	0.38
1954	479	27 998	28 529	13 981	0.32
1955	615	27 432	27 955	13 692	0.42
1956	996	26 664	27 216	13 318	0.70
1957	1 276	25 475	26 087	12 766	0.93
1958	875	24 040	24 683	12 083	0.68
1959	790	23 078	23 706	11 592	0.64
1960	698	22 214	22 932	11 150	0.58
1961	710	21 431	22 308	10 776	0.61
1962	709	20 680	21 905	10 449	0.62
1963	696	20 079	21 625	10 510	0.62
1964	705	20 078	21 428	10 425	0.63
1965	954	20 516	21 195	10 335	0.86
1966	1 648	20 194	20 656	10 055	1.53
1967	1 958	18 916	19 325	9 443	1.94
1968	1 268	17 212	17 575	8 604	1.38
1969	684	16 185	16 507	8 044	0.80
1970	778	15 585	15 990	7 739	0.93
1971	797	14 775	15 468	7 359	0.99
1972	952	13 946	15 017	7 249	1.22
1973	1 544	13 362	14 456	7 026	2.06
1974	1 267	12 642	13 289	6 434	1.84
1975	983	11 917	12 387	5 959	1.53
1976	1 286	11 225	11 788	5 674	2.10
1977	896	10 259	10 858	5 284	1.59
1978	3 305	9 862	10 278	4 997	6.18
1979	2 162	6 957	7 183	3 472	5.80
1980	903	4 962	5 187	2 510	3.35
1981	733	4 229	4 442	2 148	3.18
1982	731	3 681	3 846	1 859	3.66
1983	672	3 086	3 227	1 562	4.01
1984	425	2 527	2 648	1 281	3.09

Year	Catch	Survey Bio	Total Bio	SSB	F/Fref
1985	340	2 205	2 324	1 112	2.84
1986	298	1 943	2 084	978	2.77
1987	271	1 706	1 935	873	2.74
1988	210	1 515	1 840	854	2.24
1989	342	1 508	1 843	841	3.65
1990	196	1 446	1 706	798	2.25
1991	184	1 498	1 715	800	2.11
1992	205	1 567	1 718	818	2.34
1993	187	1 562	1 670	798	2.19
1994	191	1 547	1 613	769	2.31
1995	187	1 458	1 532	729	2.38
1996	205	1 350	1 435	680	2.77
1997	226	1 214	1 322	617	3.34
1998	182	1 048	1 192	557	3.00
1999	216	953	1 155	499	3.81
2000	196	822	1 111	447	3.55
2001	180	723	1 187	447	3.09
2002	238	753	1 333	599	3.66
2003	272	974	1 414	627	3.89
2004	234	1 200	1 466	628	3.24
2005	225	1 225	1 556	692	2.95
2006	315	1 304	1 662	712	3.82
2007	247	1 298	1 950	721	2.93
2008	266	1 341	2 335	816	2.40
2009	247	1 507	3 213	856	1.61
2010	283	1 819	4 414	1 952	1.34
2011	327	3 386	5 653	2 533	1.18
2012	331	6 006	6 925	3 064	0.96
2013	334	7 257	8 121	3 794	0.82
2014	323	8 429	9 238	4 332	0.69
2015	291	9 741	10 229	4 856	0.56
2016	369	10 664	11 102	5 302	0.65

Table A1.3. Annual catch included in the ELE 3 stock assessment and estimated trawl survey (winter 10–400 m) vulnerable biomass (t) and total biomass (t), and spawning biomass (SSB, all mature female fish t) from the MPD of the stock assessment model.

Year	Catch	Survey Bio	Total Bio	SSB
1937	99	23 226	27 583	10 997
1938	229	23 000	27 328	10 905
1939	243	22 762	27 073	10 804
1940	238	22 545	26 845	10 699
1941	304	22 284	26 565	10 568
1942	275	22 073	26 345	10 457
1943	204	21 957	26 232	10 381
1944	274	21 798	26 059	10 286
1945	314	21 614	25 859	10 189
1946	256	21 502	25 746	10 124
1947	285	21 380	25 616	10 052
1948	220	21 336	25 575	10 017
1949	284	21 243	25 471	9 961
1950	370	21 072	25 280	9 879
1951	653	20 630	24 780	9 686
1952	731	20 117	24 222	9 463
1953	550	19 810	23 914	9 306
1954	643	19 459	23 538	9 110
1955	1 049	18 744	22 737	8 768
1956	964	18 137	22 089	8 478
1957	1 166	17 385	21 268	8 105
1958	1 240	16 611	20 429	7 717
1959	1 425	15 715	19 448	7 268
1960	1 333	14 969	18 649	6 876
1961	1 827	13 809	17 349	6 301
1962	1 518	13 002	16 484	5 881
1963	1 772	12 025	15 393	5 368
1964	1 623	11 249	14 538	4 952
1965	1 844	10 315	13 475	4 470
1966	1 634	9 622	12 696	4 102
1967	1 638	8 968	11 943	3 750
1968	1 350	8 622	11 547	3 537
1969	1 257	8 392	11 271	3 383
1970	1 370	8 059	10 862	3 213
1971	1 641	7 448	10 126	2 950
1972	2 067	6 398	8 867	2 515
1973	1 543	5 836	8 204	2 250
1974	1 436	5 389	7 643	2 009
1975	1 273	5 089	7 245	1 851
1976	919	5 115	7 246	1 835
1977	1 034	5 014	7 097	1 790
1978	999	4 921	6 976	1 764
1979	918	4 896	6 944	1 753
1980	1 097	4 691	6 687	1 672
1981	1 320	4 250	6 136	1 504
1982	901	4 196	6 060	1 467
1983	971	4 072	5 883	1 401
1984	998	3 900	5 651	1 339
1985	1 006	3 695	5 384	1 264
1986	860	3 615	5 272	1 229
1987	718	3 665	5 321	1 240
1988	633	3 794	5 476	1 287
1989	624	3 934	5 654	1 345
1990	563	4 142	5 712	1 428
1991	528	4 360	5 814	1 528

Year	Catch	Survey Bio	Total Bio	SSB
1992	543	4 358	5 835	1 630
1993	563	4 343	6 695	1 723
1994	626	4 445	7 395	1 670
1995	594	5 436	7 915	1 665
1996	725	6 127	7 972	1 647
1997	860	6 073	7 674	2 112
1998	918	5 648	10 093	2 310
1999	1 138	5 571	11 708	2 160
2000	1 053	8 367	12 746	1 931
2001	1 188	10 234	12 641	1 811
2002	1 195	10 179	11 919	3 394
2003	1 065	9 368	11 145	4 134
2004	1 188	8 286	10 741	4 115
2005	1 230	7 424	10 505	3 644
2006	1 215	7 314	12 620	3 102
2007	1 279	7 833	13 880	2 664
2008	1 200	10 393	14 302	2 683
2009	1 365	11 529	13 501	2 811
2010	1 329	10 764	13 346	4 197
2011	1 362	9 527	12 960	4 584
2012	1 404	9 313	12 406	4 215
2013	1 343	9 185	11 582	3 586
2014	1 425	8 529	10 369	3 570
2015	1 388	7 518	9 299	3 422

Table A1.4. Annual catch included in the GUR 3 stock assessment and estimated trawl survey (winter 10–400 m) vulnerable biomass (t), total biomass (t) and spawning biomass (SSB, all mature female fish t) from the MPD of the preliminary model initialised in 1980.

Year	Catch	Survey Bio	Total Bio	SSB
Virgin				
1980	1 296	3 135	3 203	1 403
1981	805	3 500	3 562	1 648
1982	526	4 041	4 105	2 025
1983	454	4 575	4 640	2 367
1984	454	5 045	5 112	2 673
1985	439	5 471	5 534	2 954
1986	326	5 801	5 840	3 270
1987	326	5 776	5 816	3 418
1988	231	5 659	5 702	3 362
1989	425	5 318	5 359	3 150
1990	581	4 811	4 841	2 864
1991	763	4 072	4 104	2 453
1992	727	3 591	3 657	2 014
1993	593	3 568	3 601	1 876
1994	532	3 475	3 515	1 988
1995	782	3 354	3 444	1 704
1996	754	3 598	3 626	1 727
1997	696	3 468	3 489	1 994
1998	705	3 006	3 034	1 739
1999	525	2 669	2 694	1 507
2000	435	2 479	2 526	1 372
2001	452	2 796	2 902	1 270
2002	626	3 621	3 699	1 518
2003	789	4 278	4 348	2 080
2004	977	4 524	4 592	2 294
2005	798	4 817	4 904	2 478
2006	939	5 352	5 498	2 548
2007	1 053	6 411	6 532	2 929
2008	1 104	7 255	7 329	3 703
2009	926	7 565	7 632	4 212
2010	1 033	7 421	7 523	4 121
2011	1 120	7 399	7 506	3 928
2012	1 022	7 698	7 805	4 079
2013	1 007	8 033	8 130	4 324
2014	1 285	8 081	8 200	4 350
2015	1 345	8 178	8 278	4 331
2016	1 265	8 141	8 233	4 477
2017	1 483	8 160	8 340	4 244
2018	1 407	8 744	8 818	4 395

APPENDIX 2: COMMERCIAL FISHERIES DATA: ESTIMATED CATCH AND ALLOCATED LANDINGS; KNOWN AND UNKNOWN SPECIES CODES

Table A2.1: Estimated catch and allocated landings (kg) for recognised species codes from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
FLA	104 981	575 968	Flatfish
GUR	423 297	479 955	Gurnard
RCO	271 167	433 658	Red cod
LIN	274 906	422 021	Ling
TAR	258 666	378 091	Tarakihi
SCH	169 755	375 129	School shark
RSK	210 142	371 765	Rough skate
STA	159 908	363 602	Giant stargazer
HPB	96 289	348 777	Hapuku and bass
SQU	102 480	322 907	Arrow squid
SPD	204 803	298 257	Spiny dogfish
SPE	120 747	298 051	Sea perch
SPO	175 369	291 409	Rig
SNA	251 149	282 705	Snapper
HOK	211 931	274215	Hoki
BAR	191 071	273 196	Barracouta
OCT	19 473	243 436	Octopus
RAT	142 608	238 953	Rattails
SSK	59 763	237 836	Smooth skate
GSH	72 835	224 674	Ghost shark
JDO	146 311	218 463	John dory
BCO	87 534	214 419	Blue cod
CON	36 028	202 902	Conger eel
JMA	70 270	198 533	Jack mackerel
SKI	44 424	192 901	Gemfish
BNS	45 873	183 974	Bluenose
CAR	74 843	182 604	Carpet shark
JAV	108 285	177 783	Javelinfish
KAH	74 575	174 717	Kahawai
RBM	10 419	173 383	Ray's bream
ELE	89 803	170 721	Elephant fish
FRO	28 015	152 209	Frostfish
HAK	68 938	151 788	Hake
TRE	96 903	151 749	Trevally
SWA	62 636	148 909	Silver warehou
LEA	79 755	148 410	Leatherjacket
WAR	52 044	148 243	Common warehou
SSI	5 076	145 917	Silverside
SCI	48 915	144 065	Scampi
LDO	13 512	141 978	Lookdown dory
TOA	570	138 760	Toadfish
MOK	68 841	137 003	Blue moki
ERA	13 110	136 617	Electric ray
FHD	6 168	133 614	Deepsea flathead

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
RUD	560	129 485	Rudderfish
BYX	21 043	127 619	Alfonsino and long-finned beryx
RIB	40 391	126 532	Ribaldo
WSQ	5 188	124 979	Warty squid
LCH	2 382	116 016	Long-nosed chimaera
KIN	42 451	113 765	Kingfish
GSP	27 720	108 541	Pale ghost shark
RHY	5 212	101 835	Common roughy
WWA	19 157	97 515	White warehou
OSD	38 659	94 000	Sharks and dogfish not otherwise specified*
SDO	4 216	93 878	Silver dory
SFI	8 088	92 226	Starfish
POP	32 790	88 247	Porcupine fish
BSH	28 196	87 044	Seal shark
POR	21 316	86 087	Porae
BEL	3 233	85 654	Bellowsfish
SPZ	21 591	85 361	Spotted stargazer
CDL	3 656	84 972	Cardinal fish
SND	16 339	75 157	Shovelnose dogfish
PIG	2 936	73 314	Pigfish
RBT	5 255	70 828	Redbait
RBY	6 943	70 525	Rubyfish
JGU	13 168	67 079	Japanese gurnard
MDO	8 338	66 580	Mirror dory
BSQ	2 134	62 376	Broad squid
SBW	10 990	62 114	Southern blue whiting
BRZ	3 810	61 711	Brown stargazer
ORH	26 878	61 362	Orange roughy
POS	1 725	59 320	Porbeagle shark
SOR	5 640	56 966	Spiky oreo
SSO	25 432	56 343	Smooth oreo
HAG	12 132	55 256	Hagfish
PDG	35	54 956	Prickly dogfish
DWE	708	54 066	Deepwater eel (unspecified)
CRB	7 662	53 581	Crab (unspecified)
TRU	14 131	52 072	Trumpeter
SBK	27	50 519	Spineback
GON	512	50 049	Sandfish
EMA	4 990	49 530	Blue mackerel
ETL	293	48 749	Lucifer dogfish
BBE	1 429	48 302	Banded bellowsfish
KIC	149	46 873	King crab
CDO	9 398	45 829	Capro dory
RSN	10 493	44 179	Red snapper

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
EGR	11 969	44 067	Eagle ray
THR	2 901	43 910	Thresher shark
SRH	2 461	41 983	Silver roughy
ETB	3 262	41 237	Baxter's lantern dogfish
SCG	241	40 477	Scaly gurnard
OPE	1 190	39 003	Orange perch
SLK	7 404	38 801	Slickhead
DEA	135	38 555	Dealfish
BOE	18 189	38 044	Black oreo
SBO	3 427	37 463	Southern boarfish
CSQ	1 435	37 344	Leafscale gulper shark
STU	809	36 811	Slender tuna
SBR	94	36 668	Southern bastard cod
GSC	5 997	36 509	Giant spider crab
NSD	6 630	36 006	Northern spiny dogfish
BOA	2 259	35 717	Sowfish
SEV	2 699	34 928	Broadnose sevengill shark
MOD	5 030	34 534	Morids
BEE	4 186	34 456	Basketwork eel
DSK	41	30 773	Deepwater spiny skate
VSQ	112	30 532	Violet squid
OSK	293	30 125	Skate, Other
MAK	1 437	29 382	Mako shark
YCO	153	28 219	Yellow cod
ANT	239	27 932	Anemones
HAP	23 237	27 450	Hapuku
YBO	103	27 277	Yellow boarfish
HJO	3 451	27 085	Johnson's cod
BEN	588	25 463	Scabbardfish
DWD	7 257	25 343	Deepwater dogfish (unspecified)
HCO	18 375	24 233	Hairy conger
BRC	5 194	23 993	Northern bastard cod
SCO	9 312	23 431	Swollenhead conger
SSH	286	22 699	Slender smooth-hound
EPL	46	22 679	Cardinal fish, bigeye
DWO	10	22 559	Deepwater octopus
SUN	193	22 348	Sunfish
BWS	1 820	22 060	Blue shark
CHG	554	21 908	Purple chimaera
UNI	77	21 897	Unidentified fish
OPA	270	21 141	Opalfish
CYP	239	20 346	Longnose velvet dogfish
BRA	4 357	20 292	Short-tailed black ray
BER	15	20 066	Electric ray
TSQ	68	19 971	Todarodes filippovae
WRA	2 283	19 714	Whiptail ray
ALB	374	18 893	Albacore tuna

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
HEX	285	18 756	Sixgill shark
SQX	51	18 519	Squid (Unspecified)
NCB	5 994	18 117	Smooth red swimming crab
PRK	593	18 076	Prawn killer
QSC	1 125	17 054	Queen scallop
LAN	66	16 600	Lanternfish
URO	85	15 629	Sea urchin other (other than Kina)
JFI	719	15 628	Jellyfish (unspecified)
BSP	40	15 521	Big-scale pomfret
CBE	137	14 335	Crested bellowsfish
HHS	3 560	14 019	Hammerhead shark
PSK	213	13 899	Longnosed deepsea skate
STN	182	13 760	Southern bluefin tuna
LFB	261	13 674	Long-finned boarfish
PMA	3 081	13 097	Pink maomao
OFH	1 049	13 086	Oilfish
SWO	569	12 781	Swordfish
GMU	13 715	12 385	Grey mullet
RRC	8 191	12 244	Red scorpion fish
BCD	1 872	12 006	Black cod
PLS	726	11 657	Plunket's shark
CRA	981	11 594	Spiny red rock lobster
BCA	6	11 313	Barracudina
CUC	32	11 146	Cucumber fish
OPI	32	10 917	Umbrella octopus
GSQ	37	10 850	Giant squid
PAR	11 110	10 311	Parore
CHP	46	9 647	Chimaera, purple
SPI	92	9 207	Spider crabs (unspecified)
SCC	1 258	8 972	Sea cucumber
PHO	8	8 944	Lighthouse fish
PAD	4 524	8 704	Paddle crab
CYO	49	8 641	Smooth skin dogfish
TOP	12	8 471	Pale toadfish
BAS	8 478	8 369	Bass
WSE	3 443	8 262	Wrasses
AGR	21	8 230	Ribbonfish
API	0	8 159	Alert pigfish
VOL	1 005	8 003	Volute
SCD	41	7 964	Smallscaled cod
SAL	183	7 825	Salps
PAH	236	7 358	Opah
PRA	168	7 268	Prawn (unspecified)
RAY	267	7 259	Rays
EEL	83	7 242	Eels, marine (unspecified)
STR	678	7 086	Stingray (unspecified)
RPE	3 805	7 074	Red perch

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
APR	4	7 017	Cat shark
PIL	731	6 925	Pilchard
EPR	28	6 735	Cardinal fish, robust
LSK	5	6 629	Long-tailed skate
HTH	21	6 603	Sea cucumber (other than<a0>Stichopus mollis)
TAM	1	6 570	Tam O'Shanter urchins
EUC	2	6 461	Eucla cod
MOO	224	6 423	Moonfish
BUT	7 257	6 376	Butterfish
BSL	1 104	6 239	Black slickhead
BWH	1 386	5 946	Bronze whaler shark
MCA	8	5 815	Ridge scaled rattail
WHE	410	5 811	Whelks
DCS	3	5 609	Dawson's cat shark
WOE	94	5 347	Warty oreo
YEM	5 150	5 336	Yellow-eyed mullet
HEP	6	5 271	Sharpnose sevengill shark
WHX	150	5 085	Unicorn rattail
RAG	10	4 740	Ragfish
PIP	1 447	4 688	Pipefish
MIQ	30	4 514	Warty squid
FMA	2	4 512	Fusitriton magellanicus
BPE	461	4 338	Butterfly perch
CHI	635	4 334	Chimaera spp.
CYL	11	4 330	Portuguese dogfish
GPF	0	4 248	Girdled wrasse
HYP	2	4 245	Pointynose blue ghost shark
BMA	837	4 225	Blue maomao
SNI	211	4 132	Snipefish
CMO	525	4 112	Copper moki
SFN	16	4 088	Spinyfin
OSE	2 510	3 702	Snake eel
RSQ	20	3 655	Ommastrephes bartrami
RDO	65	3 563	Rosy dory
RCH	14	3 522	Widenosed chimaera
COD	24	3 462	Cod (unspecified)
RMU	146	3 161	Red mullet
SAM	318	3 142	Quinnat salmon
PLZ	2	3 048	Scaly stargazer
SDR	316	3 043	Spiny Seadragon
SMC	88	2 971	Small-headed cod
CHX	0	2 938	Pink frogmouth
OAR	15	2 925	Oarfish
TOD	5	2 844	Dark toadfish
SPF	433	2 832	Scarlet wrasse
GTR	2 954	2 743	Marblefish
TOR	26	2 559	Pacific bluefin tuna

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
LHO	0	2 466	Omega prawn
SKJ	97	2 465	Skipjack tuna
VCO	610	2 414	Violet cod
GRC	249	2 364	Grenadier cod
CSH	5	2 330	Cat shark
TRS	39	2 289	Cape scorpionfish
CUB	3	2 056	Cubeheads
POT	354	1 907	Parrotfish
MOR	180	1 882	Moray eel
PAL	0	1 858	Barracudinas
ANC	11	1 832	Anchovy
LCA	4	1 788	Unicornfish
PTO	356	1 717	Patagonian toothfish
HSI	664	1 633	Jack-knife prawn
PAG	1	1 575	Pagurid
ONG	4	1 550	Sponges
SLL	3	1 546	Slipper lobsters
MOB	61	1 537	Blunthead bristlemouth
RPI	29	1 533	Red Pigfish
SSM	7	1 532	Smallscaled brown slickhead
PHC	3	1 441	Packhorse rock lobster
DSP	11	1 425	Deepsea pigfish
CHC	63	1 343	Red crab
LEG	54	1 341	Giant lepidion
MSG	730	1 297	Green-lipped mussel
DIS	3	1 283	Discfish
YFN	13	1 278	Yellowfin tuna
GAR	530	1 250	Garfish
ROC	164	1 227	Rock cod
KOH	221	1 211	Koheru
CHA	1	1 158	Viper fish
NOT	151	1 147	Antarctic rock cods
BPF	529	1 144	Banded wrasse
NCA	110	1 128	Hairy red swimming crab
RBP	38	1 038	Red banded perch
SYN	2	998	Cutthroat eels (not basketwork eels)
SNE	1	983	Snubnosed eel
RMO	615	971	Red moki
SEO	44	949	Seaweed
FRS	3	946	Frill shark
SEE	11	897	Silver conger
ACS	1	895	Smooth deepsea anemones
SLG	2	873	Sea slug
SDE	3	848	Seadevil
KWH	98	834	Knobbed whelk
MNI	0	833	Krill, squat lobsters
HYD	75	822	Hydrolagus spp.

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
BSK	26	803	Basking shark
MST	1	775	Scaleless black dragonfishes
FOX	28	774	Fox fish
STY	317	740	Spotty
PSP	0	740	Scissortail
FAN	1	734	Fanfish
KBL	6	712	Bull kelp
PUF	284	705	Pufferfish
SBI	1	690	Bigscaled brown slickhead
TUB	503	657	Tasmanian ruffe
SCM	1	648	Roughskin dogfish
PSY	1	622	Blobfish
LAT	10	620	Lancetfish
KEL	484	549	Kelpfish
SPL	8	543	Scopelosaurus sp.
MUS	4	529	Mussels (unspecified)
GVO	0	527	Golden volute
STG	117	524	Stargazer (Unspecified)
GUL	31	512	Gulper eel
TET	0	509	Squaretail
SPP	50	502	Splendid perch
BCR	4	498	Blue cusk eel
BIG	2	493	Bigeye tuna
SPR	91	475	Sprats
BAC	1	464	Codheaded rattail
TRA	52	464	Roughies
SUR	81	449	Kina
SCA	80	420	Scallop
COT	1	409	Bonyskull toadfish
MUR	9	394	Moray cod
FHG	2	386	Taieri flathead galaxias
BAT	15	383	Slickheads
CAM	0	372	Sabre prawn
WLP	0	366	Wavy line perch
SHO	26	364	Seahorse
NTU	3	355	Northern bluefin tuna
DAP	30	355	Antlered crab
FLY	15	342	Flying fish
EGA	28	341	Euciroa galatheae
GRA	8	341	Gracilaria weed
BAF	0	335	Black anglerfish
BTU	1	327	Butterfly tuna
LEP	15	324	Escolar
WHR	15	322	White rattail
CPD	93	322	Centrolophidae
SEL	23	319	Ocean blue-eye
SNS	31	318	Sunset shells

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
PED	0	286	Scarlet prawn
ECO	40	286	Prickly shark
EPD	0	271	Cardinal fish, white
SAU	14	268	Saury
FTU	1	266	Frigate tuna
SOP	8	261	Pacific sleeper shark
HCR	235	255	Tunnelling mud crab
SPT	1	254	Purple-heart urchin
SPK	2	246	Spikefish
ASH	11	245	Circular saw shell
SIW	0	244	Siphon whelk
FOR	31	243	Forsterygion spp.
PAU	3	227	Blackpaua & yellowfoot paua
CAC	184	225	Cancer crab
TIN	0	224	Tinselfish
BRE	4	219	Codlet
OSP	18	214	Pacific oyster spat
CAN	3	208	Brown brotula
LYC	0	202	Lyconus sp.
VIT	1	202	Deep-sea spider crab
OYS	7	198	Oysters, dredge (except Foveaux Strait)
OYU	25	195	Oysters, dredge (Foveaux Strait)
SSC	13	191	Giant masking crab
TAS	3	186	Rough pomfret
SHR	3	183	Sea hare
COM	16	176	Cosmopolitan Rattail
WPS	0	174	White pointer shark
HOR	8	172	Horse mussel
PRO	1	171	Protomyctophum spp.
WIN	2	169	Wingfish
WHI	30	168	Whitebait
SLO	74	160	Spanish lobster
TEL	11	159	Telescope fish
SUM	0	158	Pelagic butterfish
DOF	4	154	Dolphinfish
LMI	0	149	Masking crabs
GMA	10	147	Inanga
AER	0	145	Aeneator recens
TUA	0	145	Tuatua
CAT	6	139	Brown bullhead catfish
KBB	4	139	Bladder kelp
BMO	24	136	Borostomias mononema
BAN	0	135	Borostomias antarcticus
ABR	1	124	Shortsnouted lancetfish
YSG	0	124	Yellow spotted gurnard
SRP	0	121	Silver carp
MRQ	1	114	Warty squid

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
CNG	0	108	Canterbury galaxias
GSE	6	104	Snake mackerel
ATO	0	101	Antarctic toothfish
EMO	2	101	Blackbelly lantern shark
ETM	0	100	Etmopterus spp.
PER	6	99	Persparsia kopua
CBO	1	98	Bollons rattail
AFO	0	97	Royal red prawn
COL	7	97	Olivers rattail
SHE	9	93	Sherwood's dogfish
LCO	1	89	Dwarf swimming crab
LIM	39	86	Limpets
HTR	0	85	Trojan star
SLR	0	81	Slender roughy
MRL	0	79	Moray cods
STM	2	78	Striped marlin
SSP	8	74	Scallop spat
MAO	2	68	Maomao (unspecified)
LUC	2	67	Luciosudis normani
WAT	3	65	Watercress
WAH	27	64	Wahoo
FLU	0	63	Perch
COU	4	62	Coral (Unidentified)
KAN	5	61	Krefftichthys anderssoni
BDA	1	60	Barracuda
SAE	0	60	Triangle shell
BLO	8	59	Feeler fish
ESQ	2	55	Enoploteuthis squid
RSC	17	55	Red scorpion fish
ART	1	54	Brine shrimp
MMI	6	54	Large trough shell
DSS	0	53	Deepsea smelt
CTU	3	53	Cook's turban shell
MSL	0	53	Sladen's star
PDS	0	53	False frostfish
SSF	59	52	Shortbill spearfish
CST	0	51	Manefish
PCS	0	48	McMillan's cat shark
TOH	0	46	Toheroa
MAR	9	44	Marlin
CFA	0	42	Banded rattail
MOY	4	42	Yellow moray eel
SAI	0	41	Sailfish
PIF	0	40	Pilot fish
CMA	1	38	Mahia rattail
OXO	0	38	Ox-eye oreo
NSP	2	37	Northern splendid perch

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
ICX	0	36	Icefishes
CTN	0	36	Calliostoma turnerarum
KPZ	0	36	Koura, southern
GRP	35	35	Grass carp
PGR	0	31	Plunderfish
ARN	0	31	Paper nautilus
CAX	0	31	White brotula
BLU	3	31	Bluefish
SOS	1	30	Sockeye salmon
BET	2	29	Bigeye thresher
SKO	1	29	Shortjawed kokopu
PZL	17	28	Deepwater clam
KAI	3	23	Kali indica
LAM	8	23	Lamprey
CGR	1	21	Convict groper
SQI	17	21	Squirrelfish
COC	5	20	Cockle
ODO	0	20	Smalltooth sandtiger shark (deepwater nurse shark)
CEN	0	19	Deepsea sharks
ELG	0	19	Eldon's galaxias
ESZ	1	18	Estuary stargazer
SNR	1	17	Rough shovelnose dogfish
POY	0	17	Pacific oyster
ETP	0	17	Smooth lanternshark
LES	31	15	Lessonia
PDO	0	15	Southern tuatua
DSU	1	15	Silky dosinia
MUN	0	15	Munida gregaria
SAZ	0	14	Sand stargazer
WGR	0	14	Macrourus whitsoni
BEA	0	14	Eaton's skate
SRR	0	14	Amblyraja georgiana
LFE	2	13	Long-finned freshwater eel
BRG	13	13	Armless stars
BSU	0	13	Benthosema suborbitale
PAV	0	12	Virgin paua
DRU	4	12	Silver drummer
PPI	3	12	Pipi
MUU	0	12	Mullet (unspecified)
MDI	3	11	Trough shell
DAN	1	7	Ringed dosinia
RFB	1	7	Redfin bully
EBP	0	6	Eyebrow seaperch
EMP	0	6	Emperor
ECK	1	5	Ecklonia
SWE	3	5	Sweep
FUR	2	5	New Zealand fur seal

Table A2.1 (cont): Known species codes in the estimated catch and allocated landings (kg) from fishing events included in the data extract for this project.

Code	Estimated	Allocated	Description
FIS	0	4	Fish (code used in feeding studies)
GCO	2	4	Common bully
CAU	2	3	Goldfish
OPH	4	3	Brittle stars, basket stars
STK	5	2	Stokells smelt
BEM	2	2	Blue marlin
REC	2	2	Red rock crab
KOI	1	1	Koi carp
TRI	1	1	Tripod fish
TRC	2	1	Triangle crab
DRE	1	1	Regan's lanternfish
TIS	1	1	Tiger shark
KOA	1	1	Koaro
STB	2	1	Striped boarfish
AMP	1	0	Deepwater octopus
YBF	53 226	0	Yellowbelly flounder
OTT	2	0	Otter clam
WIT	9 895	0	Witch
BFI	2	0	Bathophilus filifer
BFL	4 394	0	Black flounder
BRI	42 706	0	Brill
MAN	16	0	Finless flounder
MAL	1	0	Loosejaws
TUR	34 708	0	Turbot
MAC	15	0	Mackerels
LSO	83 529	0	Lemon sole
SBG	1	0	Spotted black grouper
LJG	1	0	Upland longjaw galaxias
BYA	1	0	Frilled venus shell
LEO	3	0	Leopard seal
LAE	2	0	Laemonema spp.
SDF	3	0	Spotted flounder
SWC	1	0	Swimming crabs
SEA	2	0	Seals and sealions
CWE	1	0	Freshwater mussel
SFE	17	0	Short-finned freshwater eel
DAS	3	0	Pelagic stingray
DFI	1	0	Dune Lakes galaxias
SFL	104 371	0	Sand flounder
GFL	10 173	0	Greenback flounder
SLS	1	0	Slender sole
ESO	101 514	0	NZ sole

Table A2.2: Estimated catch and allocated landings (kg) using unknown species codes, from fishing events included in the data extract for this project.

	Number of records	
Code	Estimated	Allocated
OFF	0	110 028
UNX	12	6 636
GAS	0	916
NULL	0	527
PSQ	0	380
TDQ	0	267
TEW	0	261
PZE	0	260
LLC	0	250
BTS	0	241
GOR	0	215
NOC	0	192
DIR	0	181
PPA	0	165
BNO	0	160
EPO	0	146
BPD	0	144
CBA	0	142
LAO	0	114
NAT	0	114
GLO	0	114
HMT	0	114
AMA	0	114
OMM	0	114
BYD	16	111
DGT	0	108
GSA	4	106
ECN	0	104
DPO	0	101
CJA	0	93
BFE	0	85
EGC	0	71
LLT	0	69
DCO	0	67
ROK	4	66
CHQ	3	63
ECH	0	60
SMK	0	59
EPT	0	58
OST	0	57
SGT	2	55
CAL	0	51
WOD	0	50
GMC	0	49
MOL	0	46
SHF	0	45

Table A2.2 (cont): Estimated catch and allocated landings (kg) using unknown species codes, from fishing events included in the data extract for this project.

Code	Number of records	
	Estimated	Allocated
CRU	0	45
AME	0	45
SPA	6	41
BTA	0	40
DHO	5	39
PLY	0	34
HIM	0	33
GPA	0	31
NEM	0	31
BIV	0	30
OEO	2	29
GLB	6	28
EZE	0	25
BYS	2	24
CAP	17	21
GLM	0	20
SRB	0	18
HIA	0	17
EBI	13	13
KTA	0	10
GOB	0	8
SKA	0	8
INV	0	6
FRA	0	5
CPL	0	4
ASR	0	4
OIL	6	4
DIL	0	3
ERE	0	3
PAP	0	2
ANS	0	2
CFE	0	2
BTH	0	2
EEU	1	1
GRE	0	1
REM	0	1
BRW	1	1
PCH	0	1
SOL	828	0
OEL	1	0
OBE	1	0
NIL	1	0
MSQ	1	0
RSF	1	0
RSH	1	0
RSO	1	0
MCH	1	0
RUB	2	0
Unknown	2 652	0
BRL	4	0

Table A2.2 (cont): Estimated catch and allocated landings (kg) using unknown species codes, from fishing events included in the data extract for this project.

Code	Number of records	
	Estimated	Allocated
TTA	1	0
CAA	1	0
LEE	2	0
HYB	2	0
COR	1	0
CRD	1	0
GUD	1	0
GST	1	0
SHA	1	0
SPS	1	0
FOL	1	0
FLO	6 693	0
ERO	1	0

APPENDIX 3: LIKELIHOOD-BASED CLUSTERING: ADDITIONAL FIGURES AND R-SCRIPT

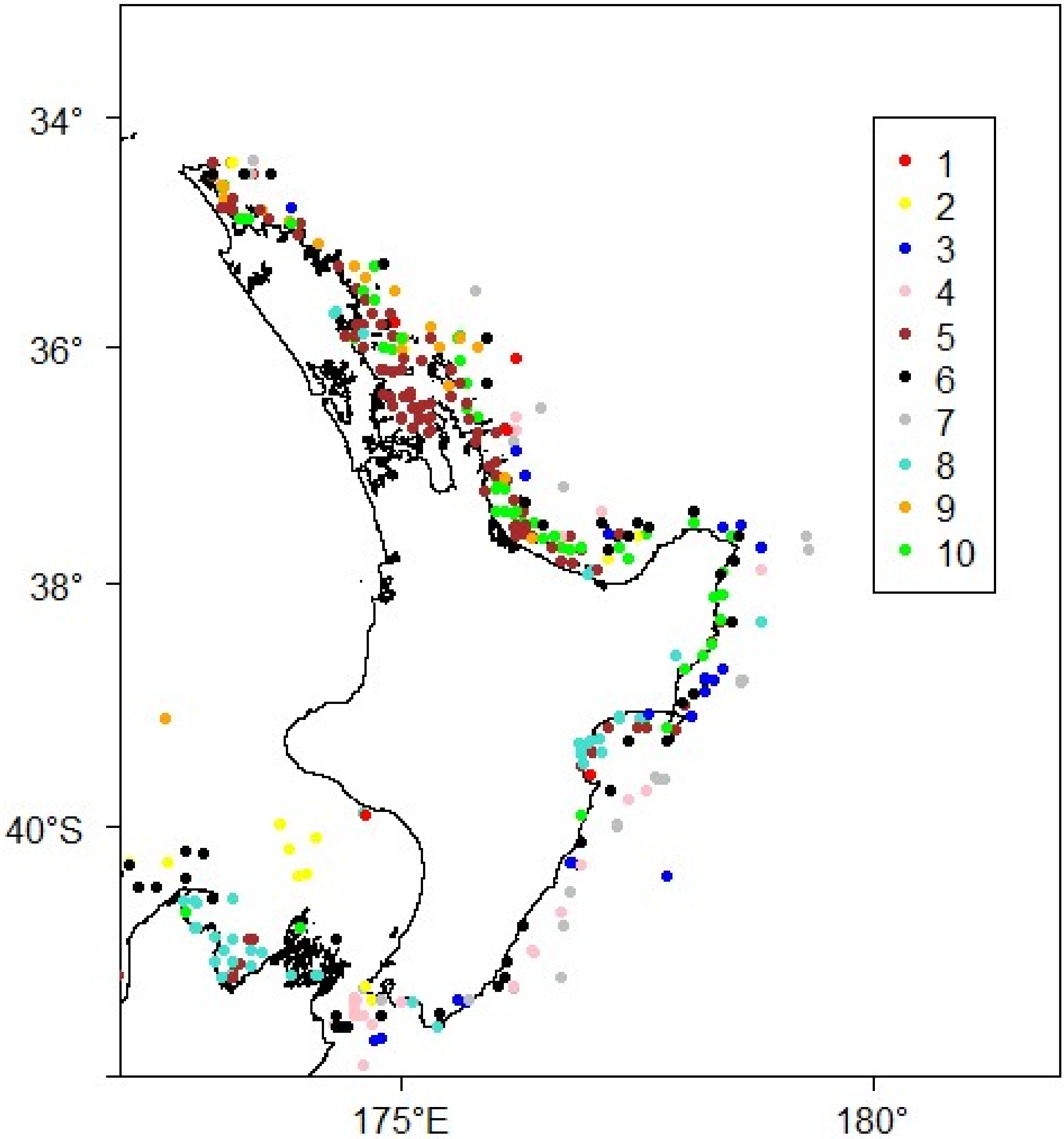

Figure A3.1: Location of fishing events around the North Island, coloured according to which group they most likely belonged to.

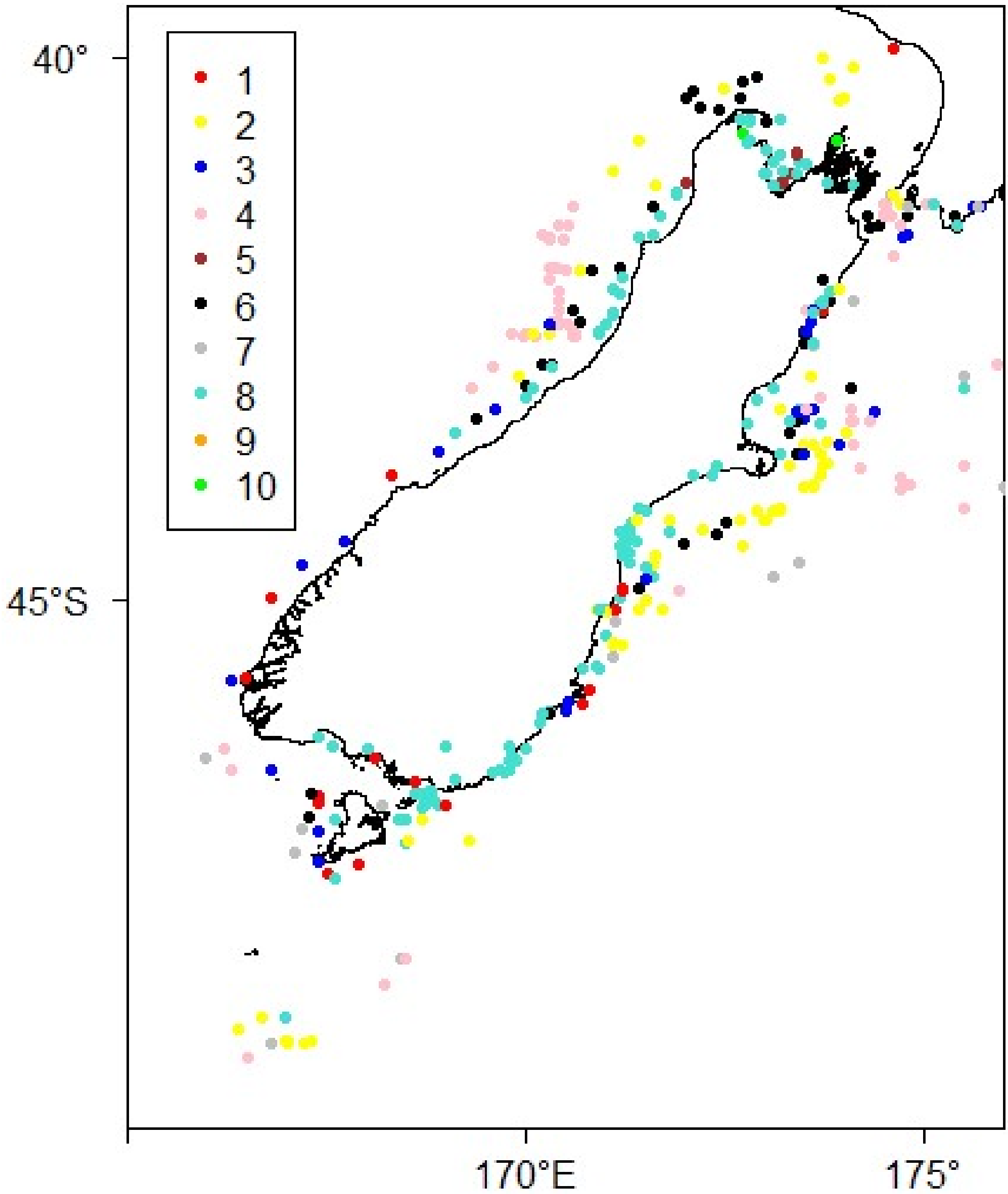

Figure A3.2: Location of fishing events around the South Island, coloured according to which group they most likely belonged to.

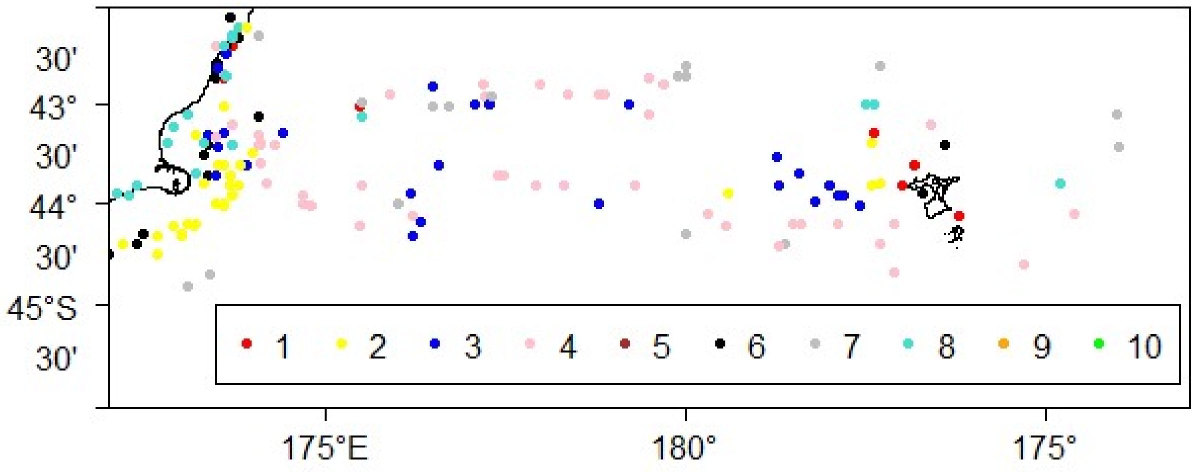

Figure A3.3: Location of fishing events on the Chatham Rise, coloured according to which group they most likely belonged to.

Code used in data processing

The following function was written and used for the conversion of wide to long format.

```
widetolong <- function(inputFile, species, outputFile){ con <- file(description = inputFile, open
= "r") #open connection to file

# read in 1 line at a time
while (length(oneLine <- readLines(con, n = 1, warn = FALSE)) > 0) {
    sink(file = outputFile, type = "output", append = TRUE)
    #make line a vector
    vec <- strsplit(oneLine,split = ",")[[1]]
    # save species weights as object
    spec_vec <- vec[24:length(vec)]
    # get index of species weights higher than 0
    idx <- spec_vec!=0 # make the event id vec[1] <- sprintf("E%08s",
    vec[1])
    # save id and covariate values
    stem <- paste(vec[c(1,5,6,7,8,9,10,12,14)],collapse = ",")
    # put each species with its stem on a new line
    cat(paste(paste(stem,species[idx],spec_vec[idx],sep=","),"\n",sep="")) sink()
    }
close(con) # close connection to the file
}
```

Code used to extract the 2017 fishing year subset from the converted long data.

```
cat out_data_15to17.csv | # take the long file
sed s/"\""/""/g | # removes the "" marks from the characters
sed s/" "/""/g | # removes whitespace around values
awk -F',' '{if($3=="2017"){print $0 > "2017long.csv" ;} }' # takes #fisheries year (3rd column)
values 2017 and prints the whole row
#in a file called snapper.csv. To append more lines to the snapper
#file use a >> instead of >.
```

Code used to extract the 25 species of interest from the 2017 fishing year subset.

```
cat 2017long.csv | # take the long file
sed s/"\""/""/g | # removes the "" marks from the characters
sed s/" "/""/g | # removes whitespace around values
awk -F',' '{if($10=="BAR"||$10=="BNS"||$10=="ELE"||$10=="FLA"||
$10=="GSH"||$10=="GUR"||$10=="HOK"||$10=="HPB"||$10=="JMA"||
$10=="LIN"||$10=="MOK"||$10=="ORH"||$10=="RCO"||$10=="RSK"||
$10=="SCH"||$10=="SCI"||$10=="SNA"||$10=="SPD"||$10=="SPO"||
$10=="SQU"||$10=="SSO"||$10=="STA"||$10=="SWA"||$10=="TAR"|| $10=="TRE"){print
$0 > "2017long30.csv" ;} }' #takes species
#(10th column) values in the list of the 25 desired species and
#prints the whole row in a file a file called 2017long30.csv
```

APPENDIX 4: AVAILABLE SURVEY DATA

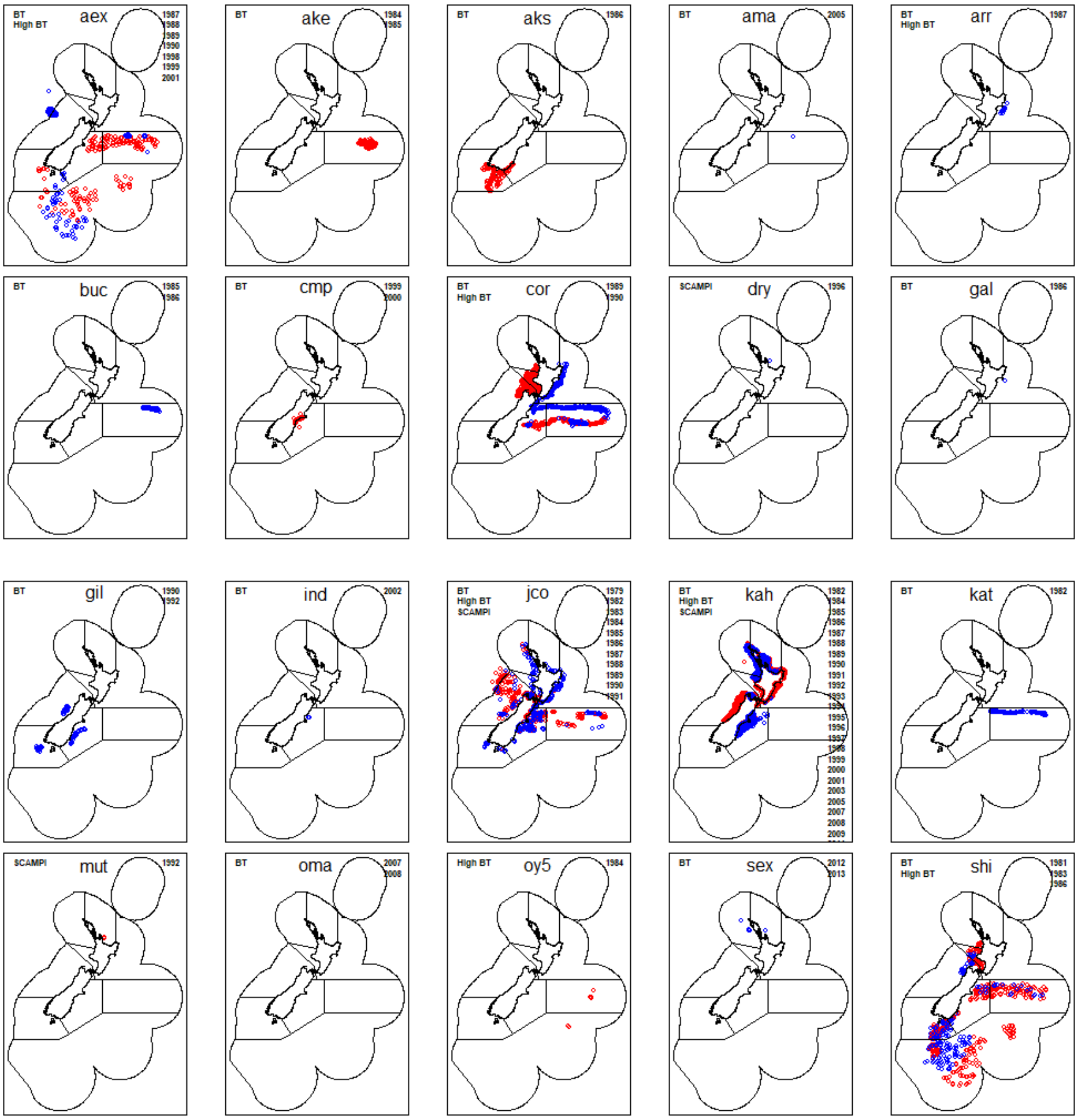

Figure A4.1: Spatial coverage of research trawls. Each panel represents a different vessel (vessel code centre top). Symbols are plotted at the locations of haul mid points. Year(s) in which the vessel was used are shown at right and gear type(s) used at left (BT:Bottom trawl; High BT:High opening bottom trawl; SCAMPI:Prawn/scampi trawl). Red indicates hauls performed between 1 November and 31 April, blue hauls performed between 1 May and 31 October. Polygons surrounding New Zealand are the Fisheries Management Areas.

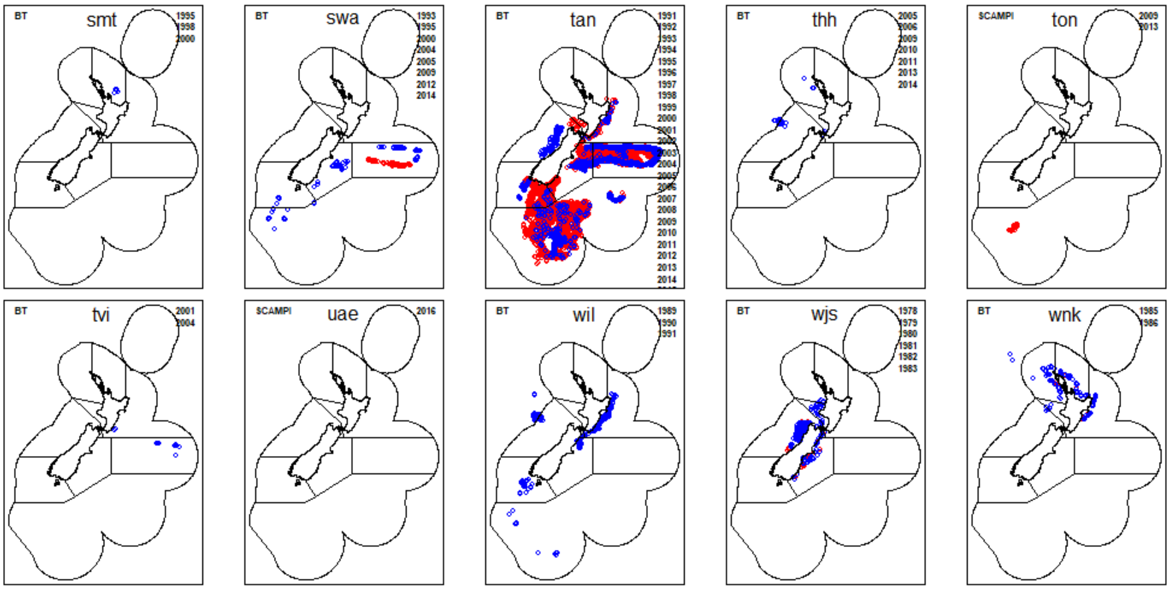

Figure A4.1 (cont): Spatial coverage of research trawls. Each panel represents a different vessel (vessel code centre top). Symbols are plotted at the locations of haul mid points. Year(s) in which the vessel was used are shown at right and gear type(s) used at left (BT:Bottom trawl; High BT:High opening bottom trawl; SCAMPI:Prawn/scampi trawl). Red indicates hauls performed between 1 November and 31 April, blue hauls performed between 1 May and 31 October. Polygons surrounding New Zealand are the Fisheries Management Areas.

APPENDIX 5: GAM DENSITY SURFACE FITS: ADDITIONAL RESULTS

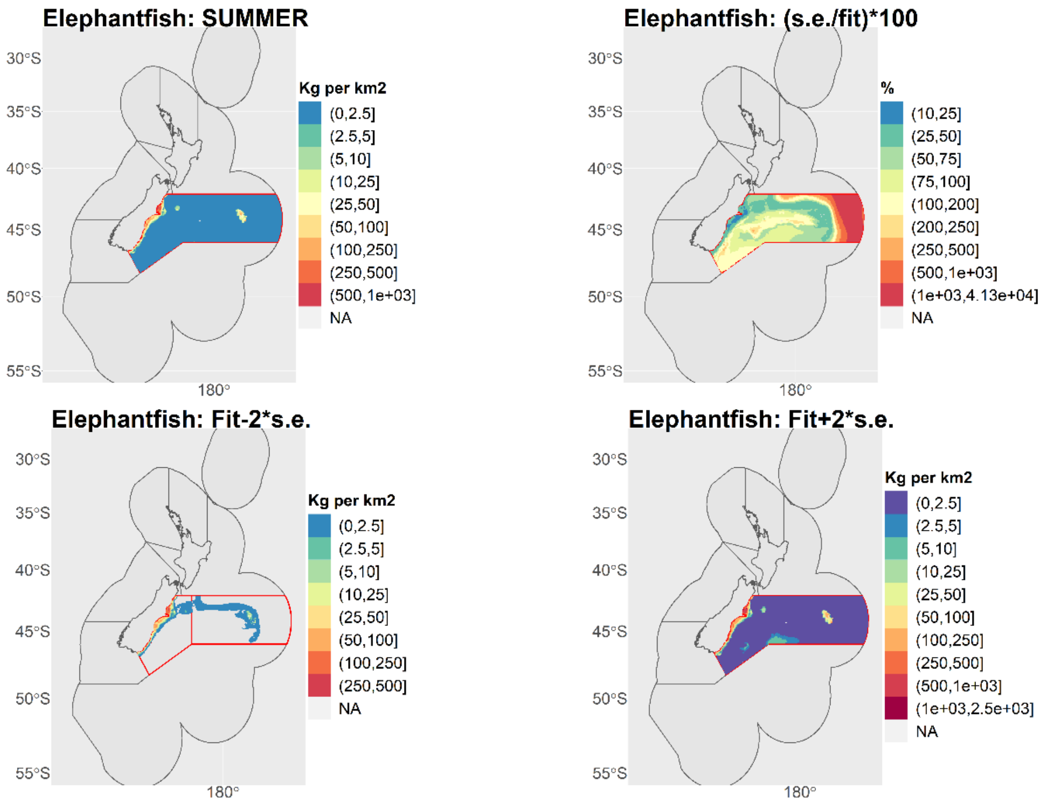

Figure A5.1. Elephant fish: Prediction of density surface over ELE 3 management area (FMAs 3 and 4). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

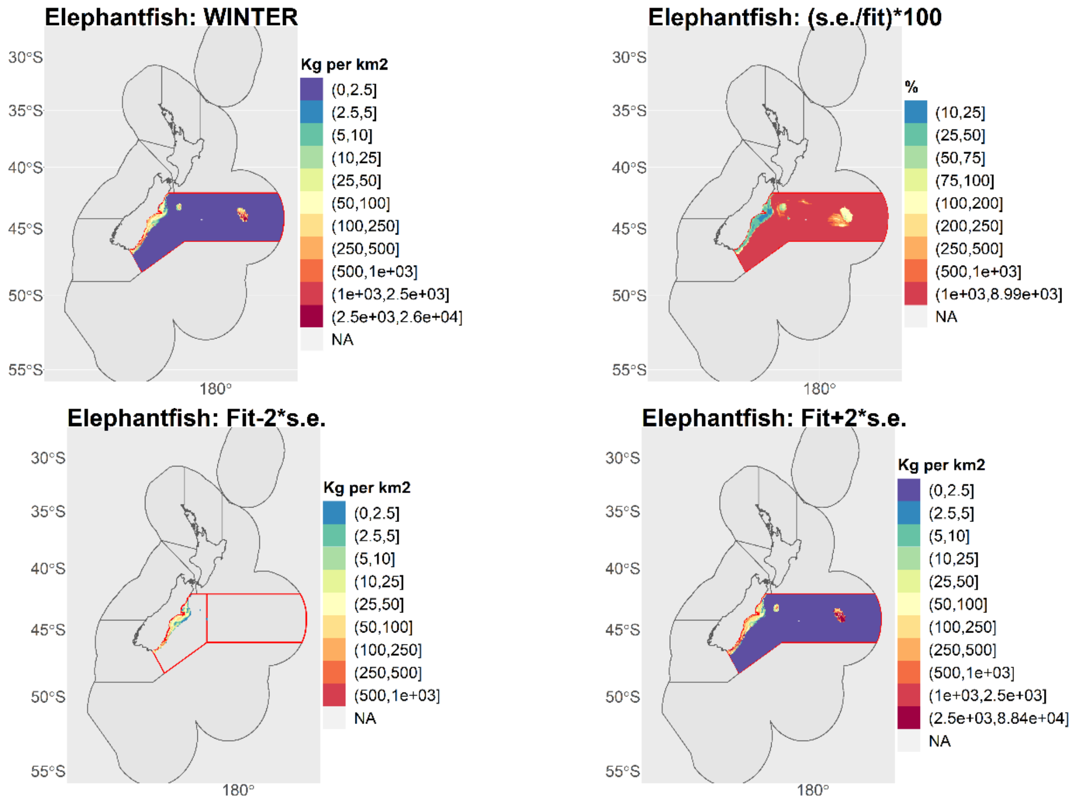

Figure A5.2. Elephant fish: Prediction of density surface over ELE 3 management area (FMAs 3 and 4). GAM fit using all years of survey data from ‘winter’ period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

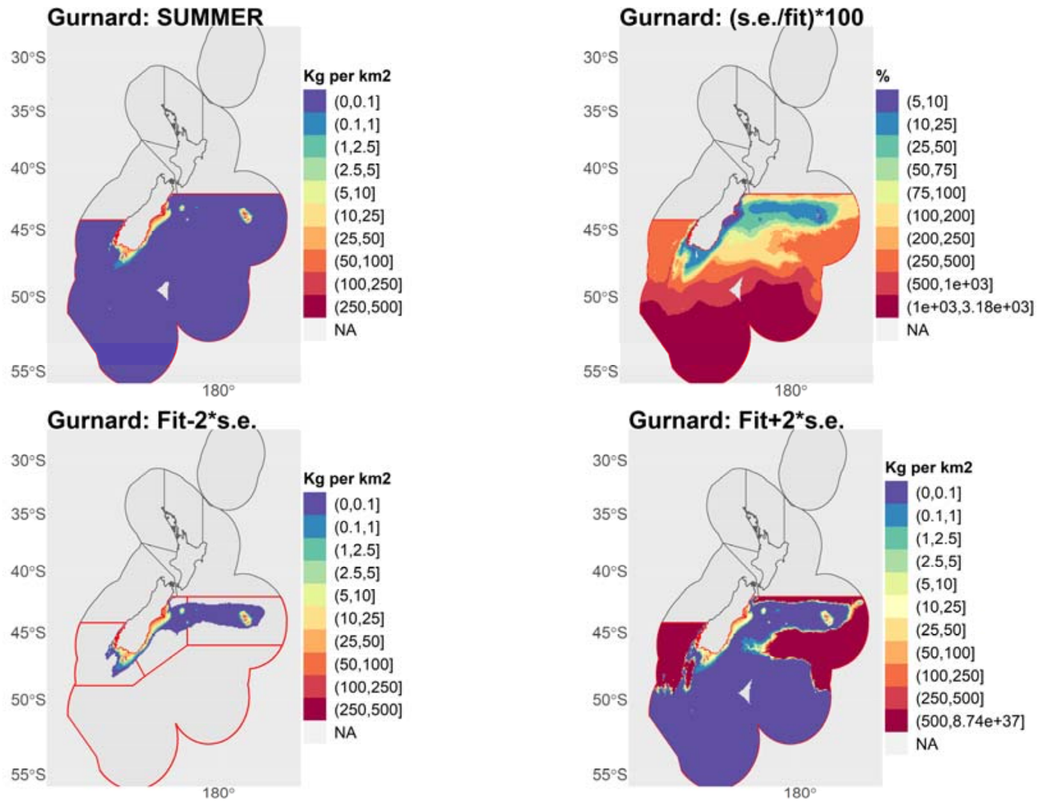

Figure A5.3. Red gurnard: Prediction of density surface over GUR 3 management area (FMAs 3, 4, 5 and 6). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

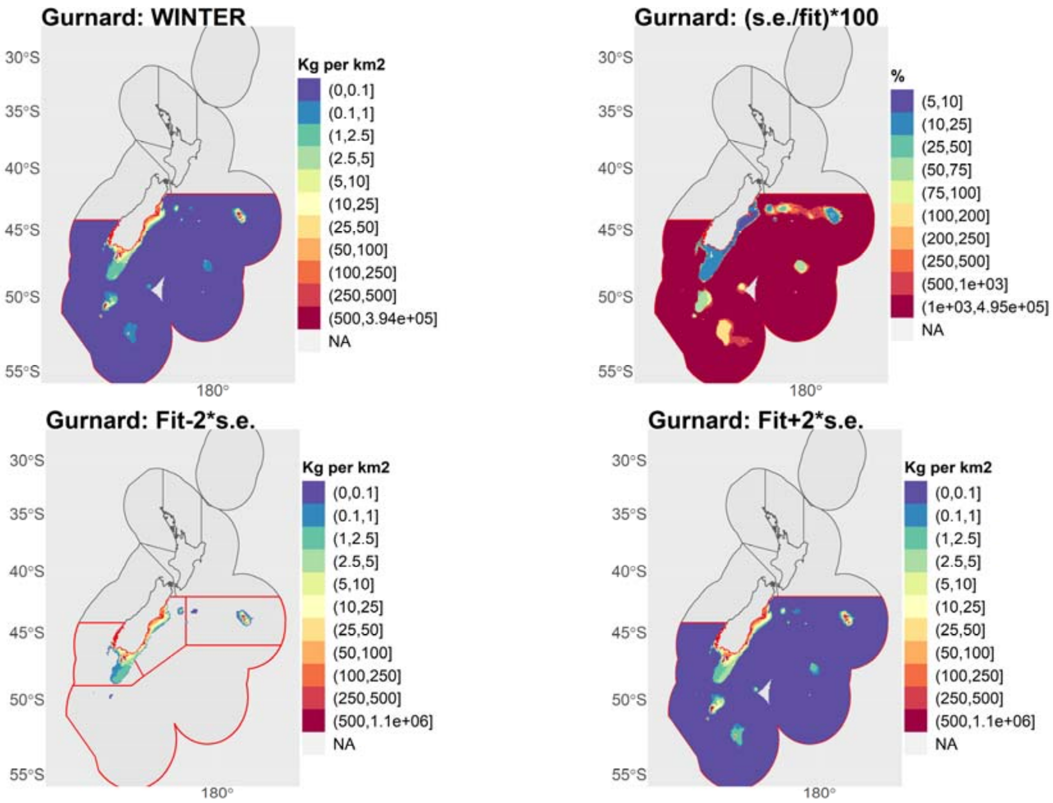

Figure A5.4. Red gurnard: Prediction of density surface over GUR 3 management area (FMAs 3, 4, 5 and 6). GAM fit using all years of survey data from 'winter' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

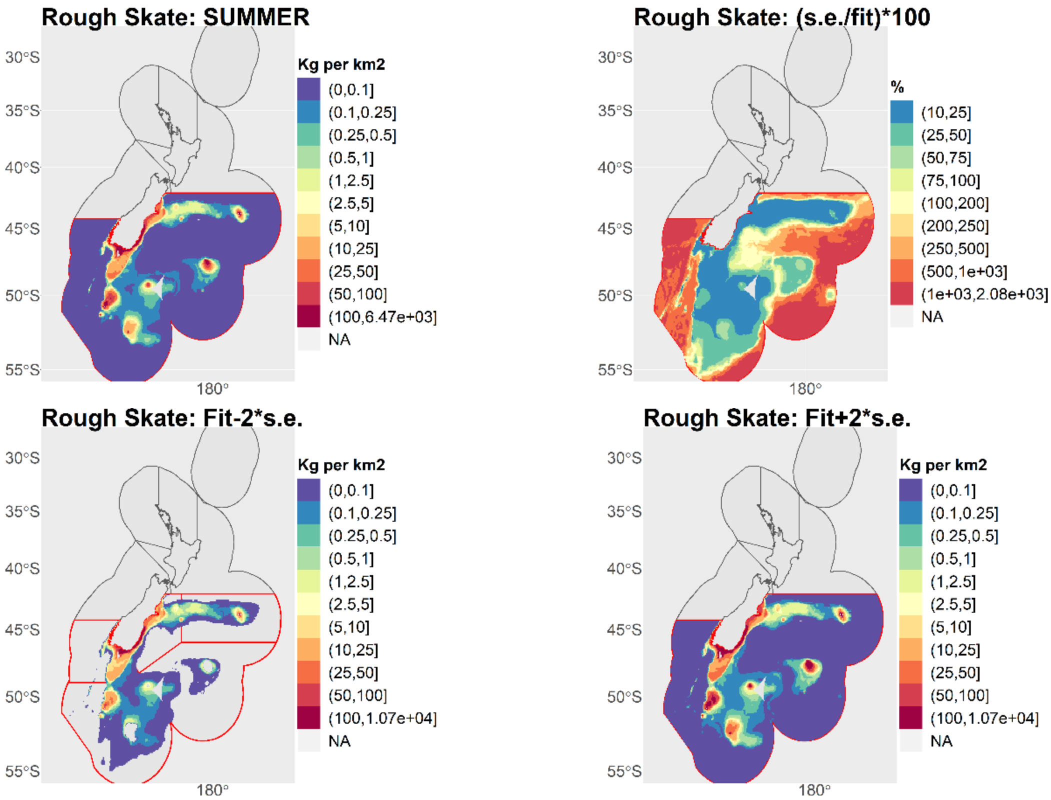

Figure A5.5. Rough skate: Prediction of density surface over RSK 3 management area (FMAs 3, 4, 5 and 6). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

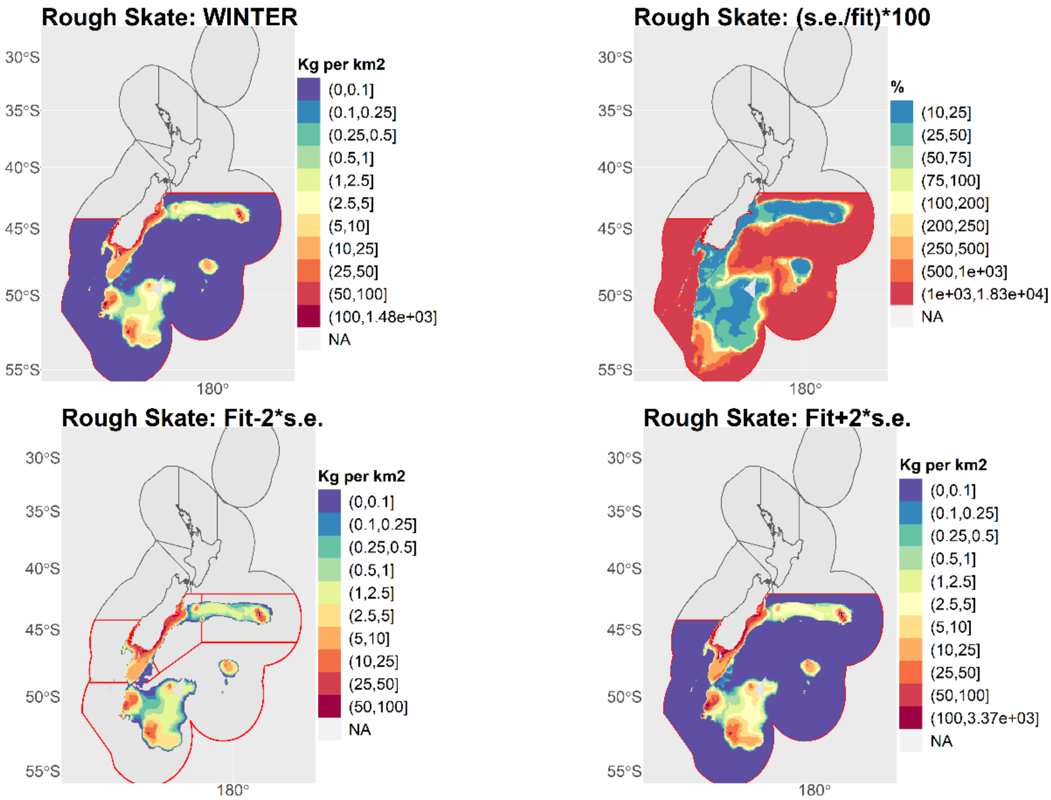

Figure A5.6. Rough skate: Prediction of density surface over RSK 3 management area (FMAs 3, 4, 5 and 6). GAM fit using all years of survey data from 'winter' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

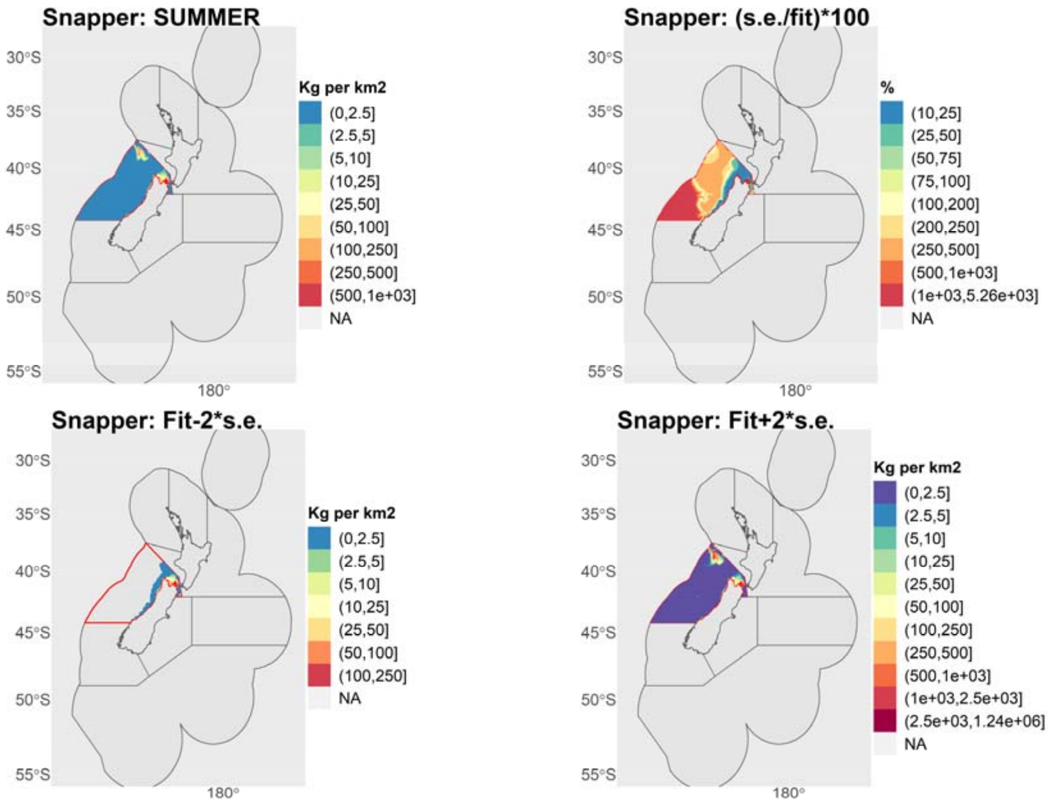

Figure A5.7. Snapper: Prediction of density surface over SNA 7 management area (FMA 7). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

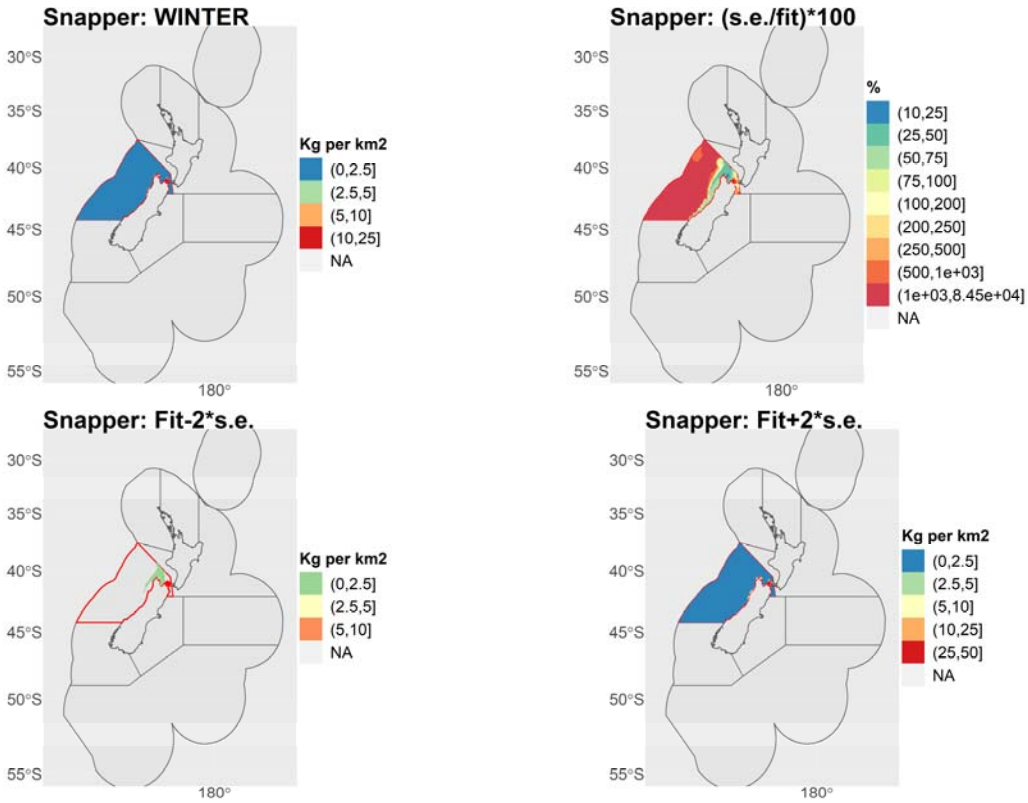

Figure A5.8. Snapper: Prediction of density surface over SNA 7 management area (FMA 7). GAM fit using all years of survey data from 'winter' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

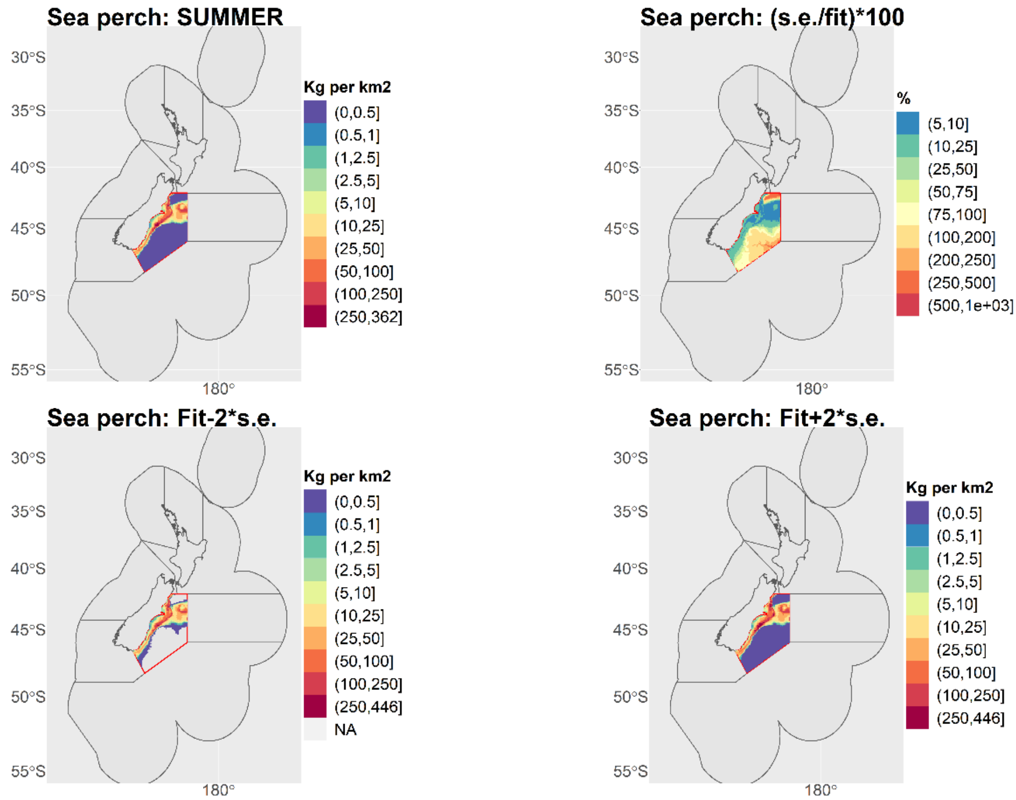

Figure A5.9. Sea perch: Prediction of density surface over SPE 3 management area (FMA 3). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

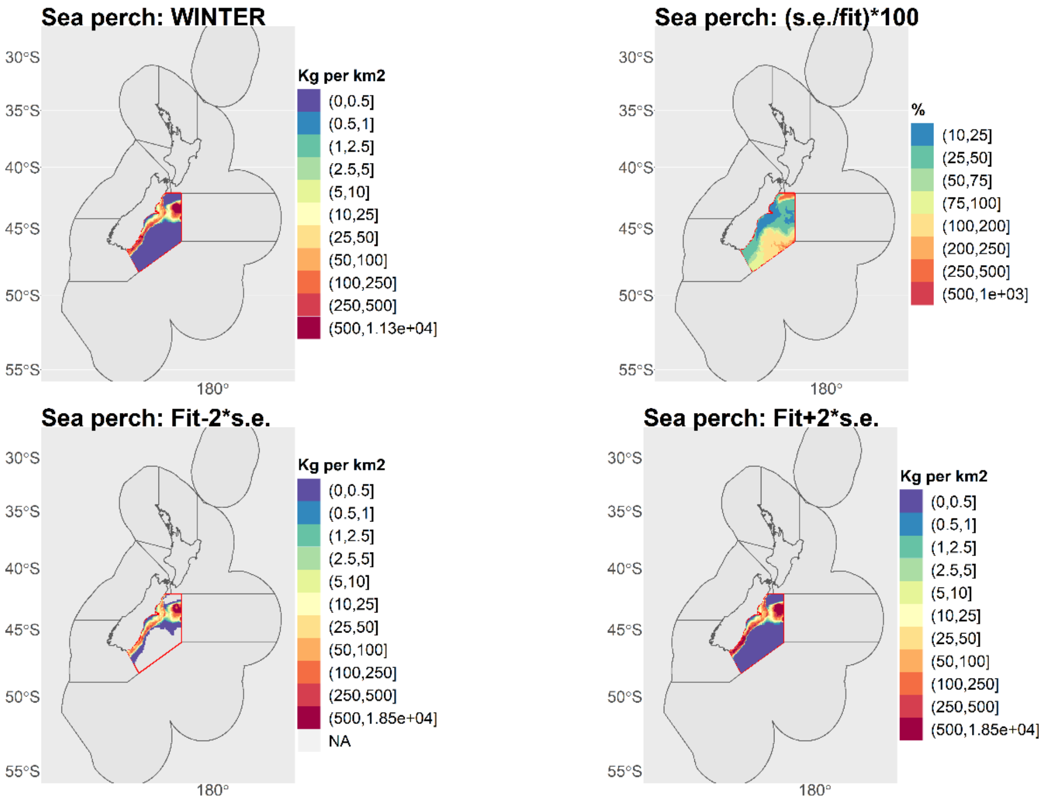

Figure A5.10. Sea perch: Prediction of density surface over SPE 3 management area (FMA 3). GAM fit using all years of survey data from 'winter' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

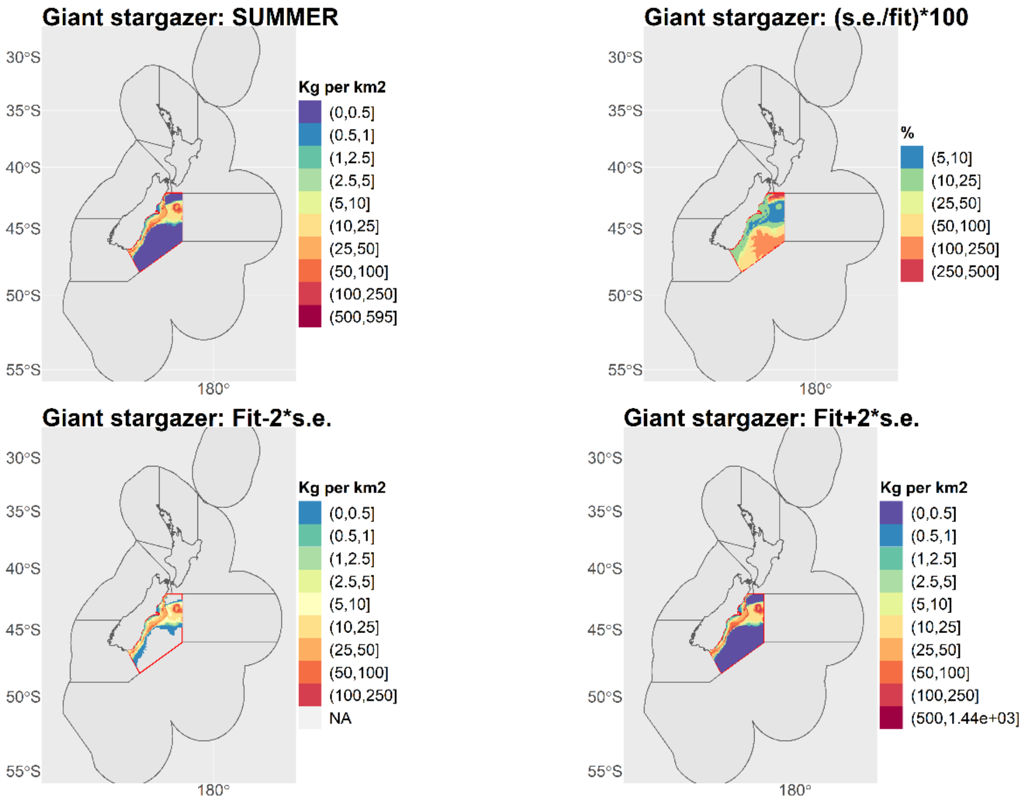

Figure A5.11. Giant stargazer: Prediction of density surface over STA 3 management area (FMA 3). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

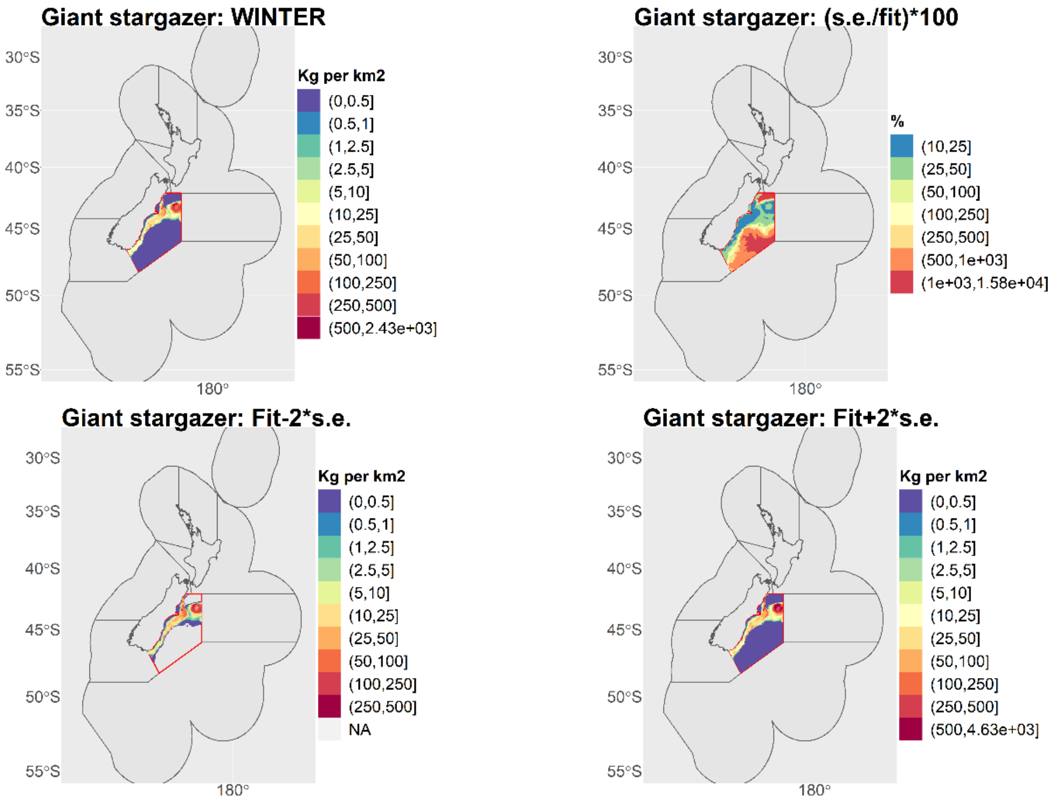

Figure A5.12. Giant stargazer: Prediction of density surface over STA 3 management area (FMA 3). GAM fit using all years of survey data from 'winter' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

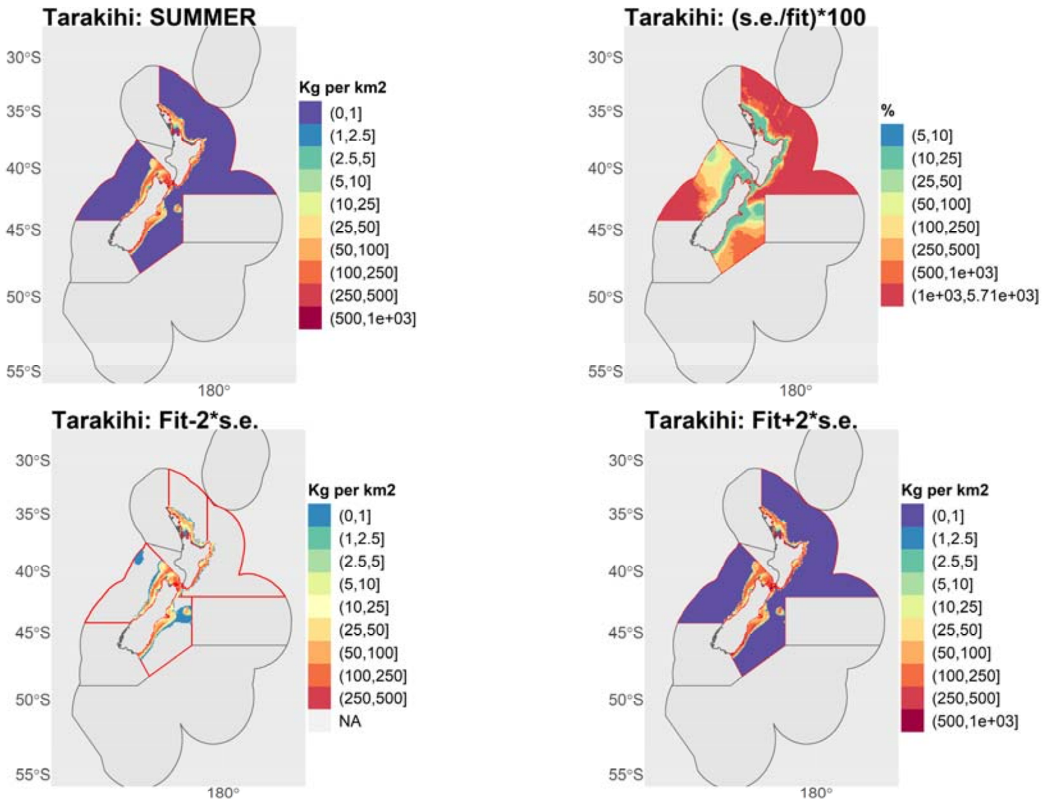

Figure A5.13. Tarakihi: Prediction of density surface over TAR 1-3 management area (FMAs 1, 2, 3 and 7[eastern Cook Strait]). GAM fit using all years of survey data from 'summer' period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

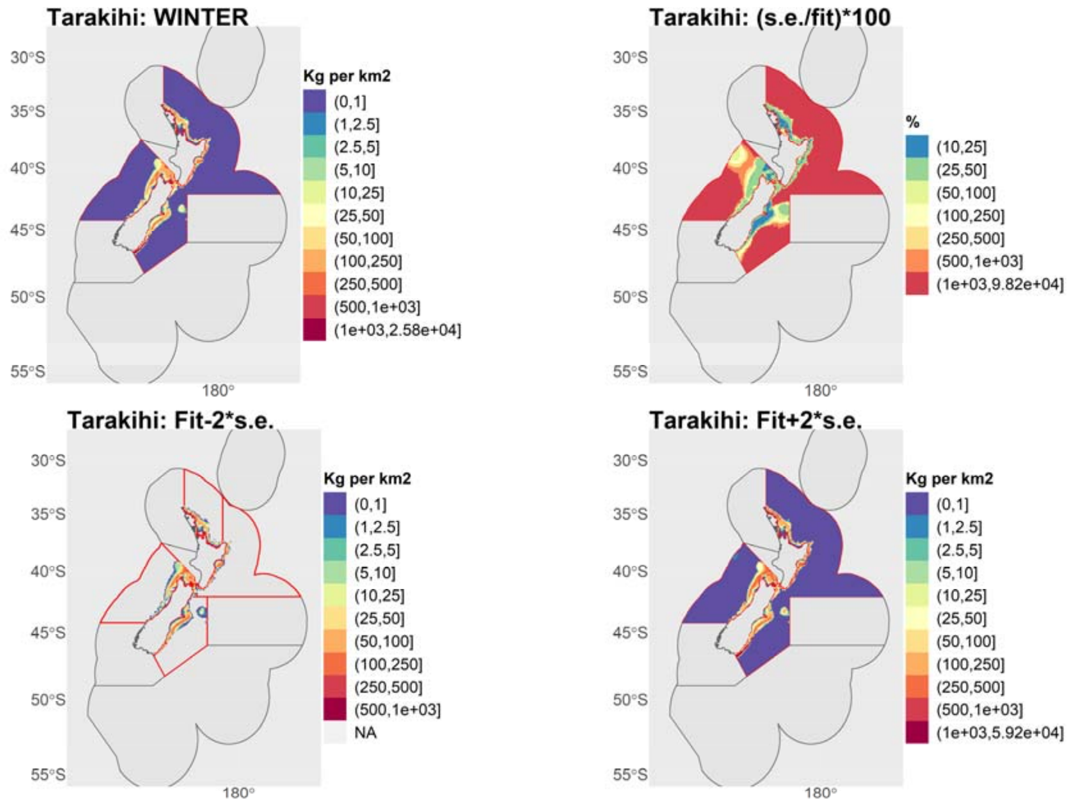

Figure A5.14. Tarakihi: Prediction of density surface over TAR 1-3 management area (FMAs 1, 2, 3 and 7[eastern Cook Strait]). GAM fit using all years of survey data from ‘winter’ period. Upper left: predicted densities (fit); upper right: s.e. of prediction as % of predicted value; lower left: density surface of (fit-2×s.e.); lower right: density surface of (fit+2×s.e.).

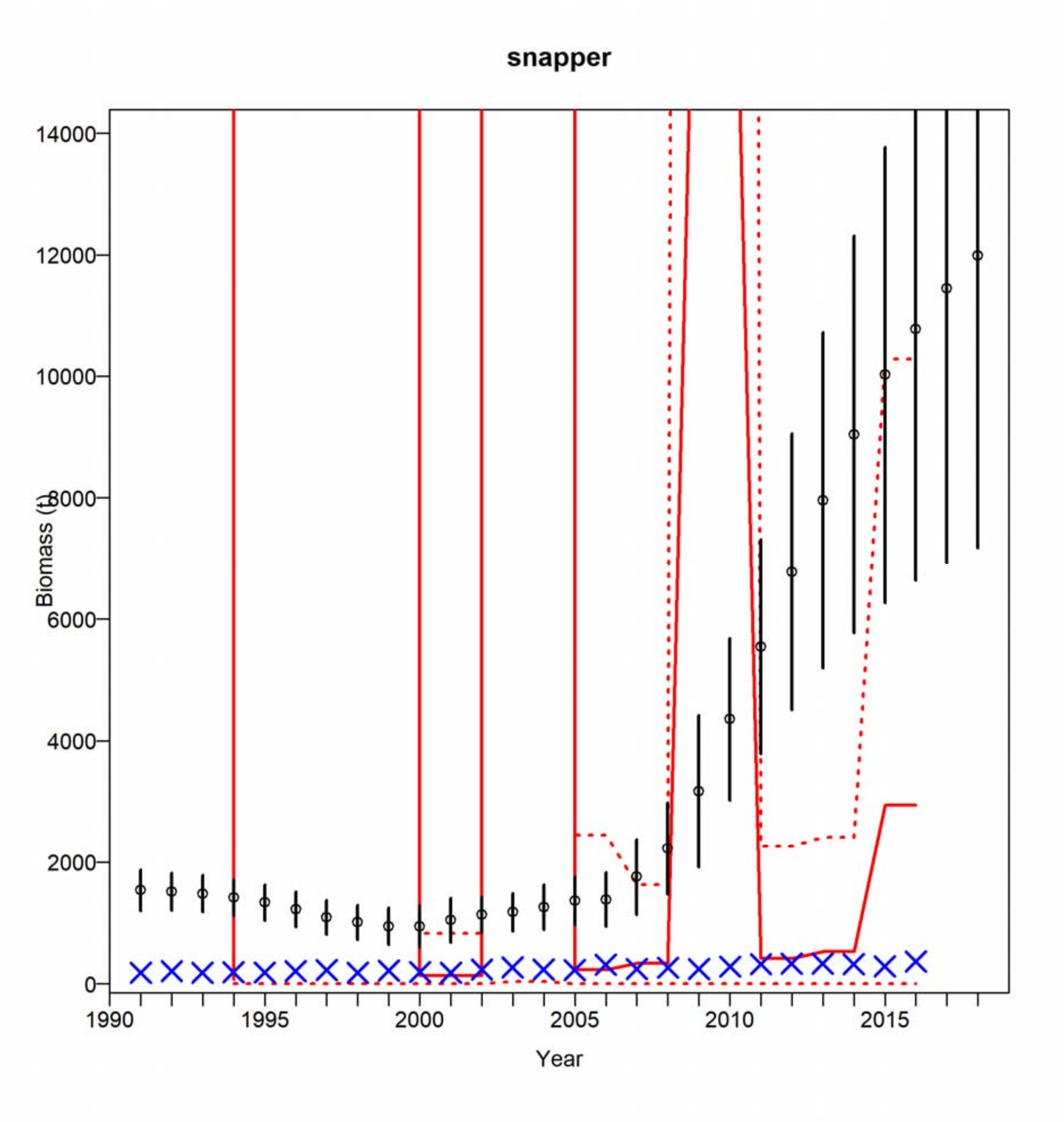

Figure A5.15 SNA 7: Total stock biomass estimates from integrated stock assessment (black circles with ± 2×std dev.) Red line (solid): Biomass estimates after GAM fitted to density data from individual WCSI surveys, (line is horizontal across years where no new survey data is available); Red lines (dashed): approximate confidence interval; lower value formed by summing values of density estimate – 2×s.e., upper value formed by summing values of density estimate + 2×s.e.; Blue crosses: estimated catch of snapper in FMA 7.

APPENDIX 6: ESAFE: ADDITIONAL FIGURES

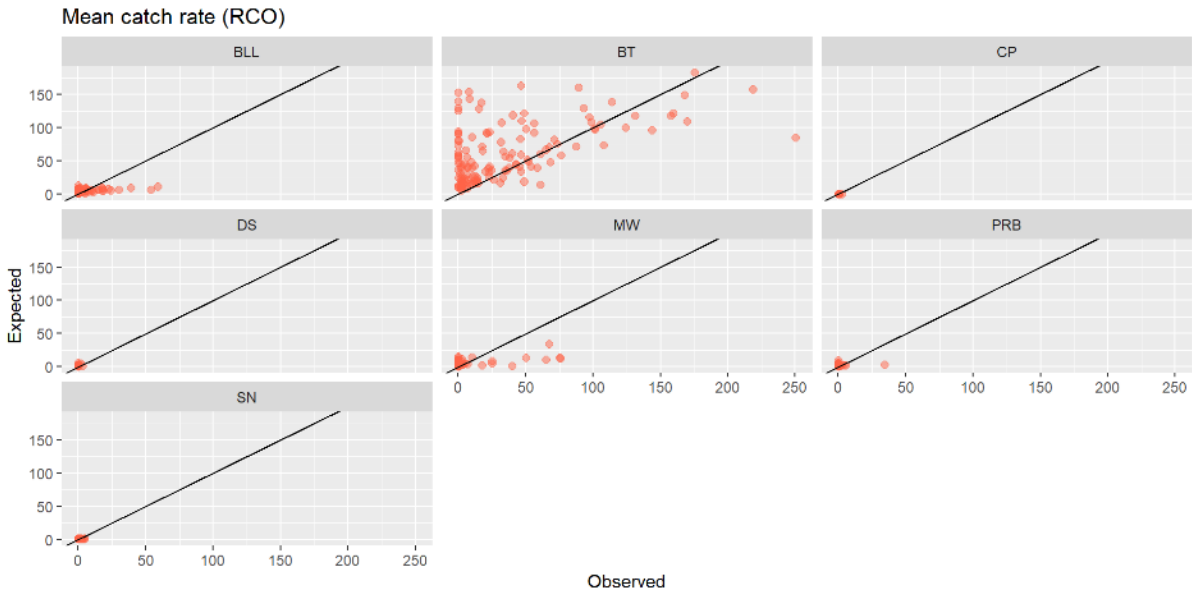

Figure A6.1. Comparison of observed and estimated catch values per density stratum for each gear type capturing RCO (red cod).

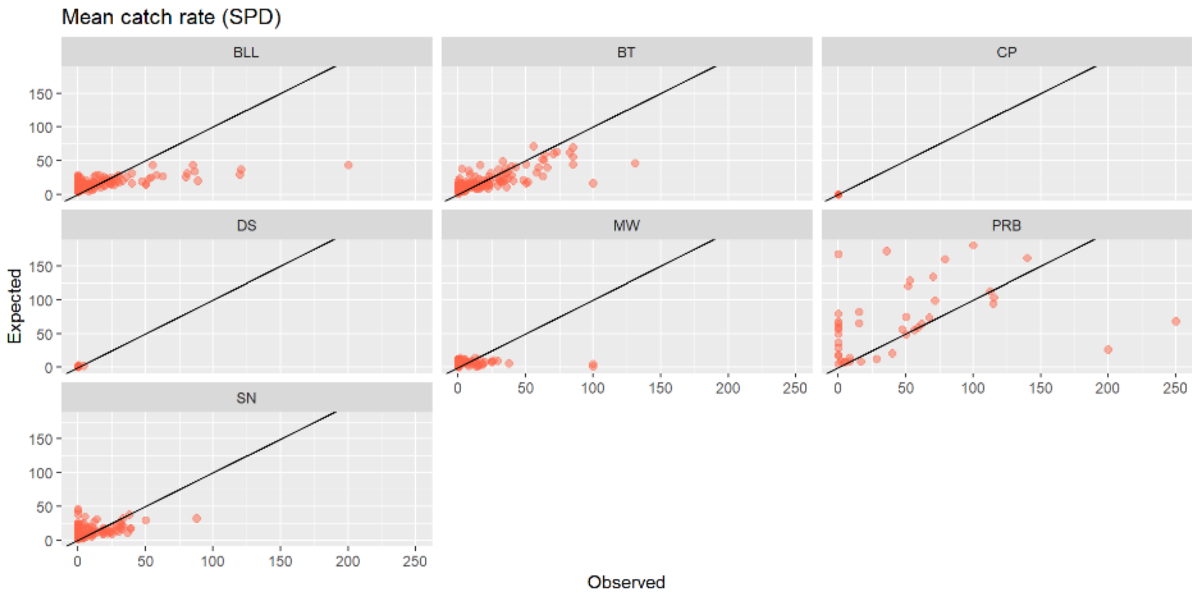

Figure A6.2. Comparison of observed and estimated catch values per density stratum for each gear type capturing SPD (spiny dogfish).

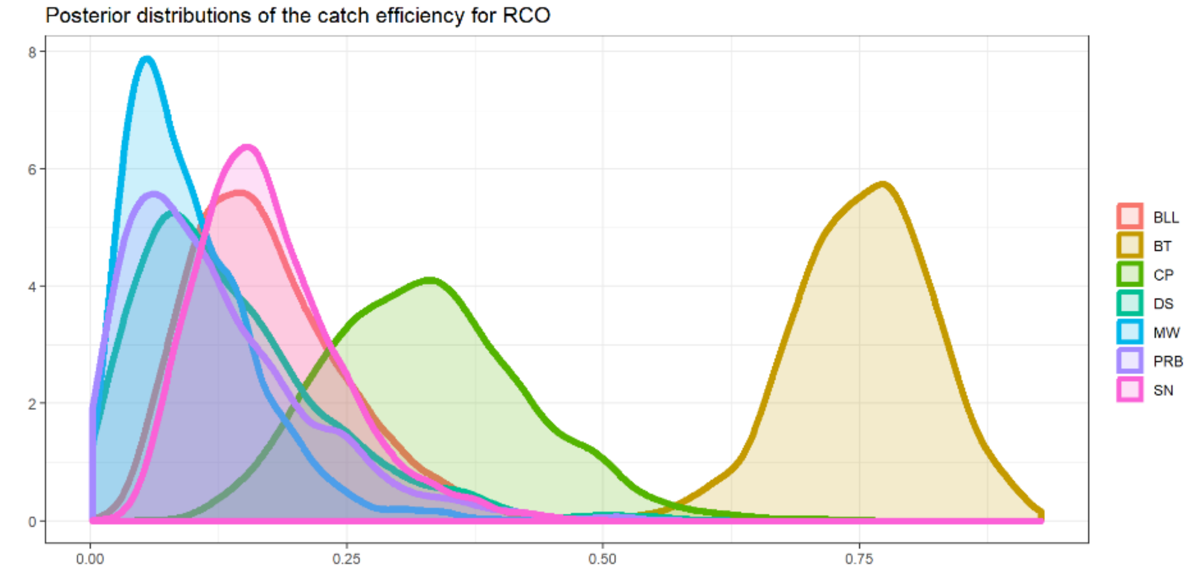

Figure A6.3. Posterior distributions of the gear efficiency for RCO (red cod) captured by each gear type.

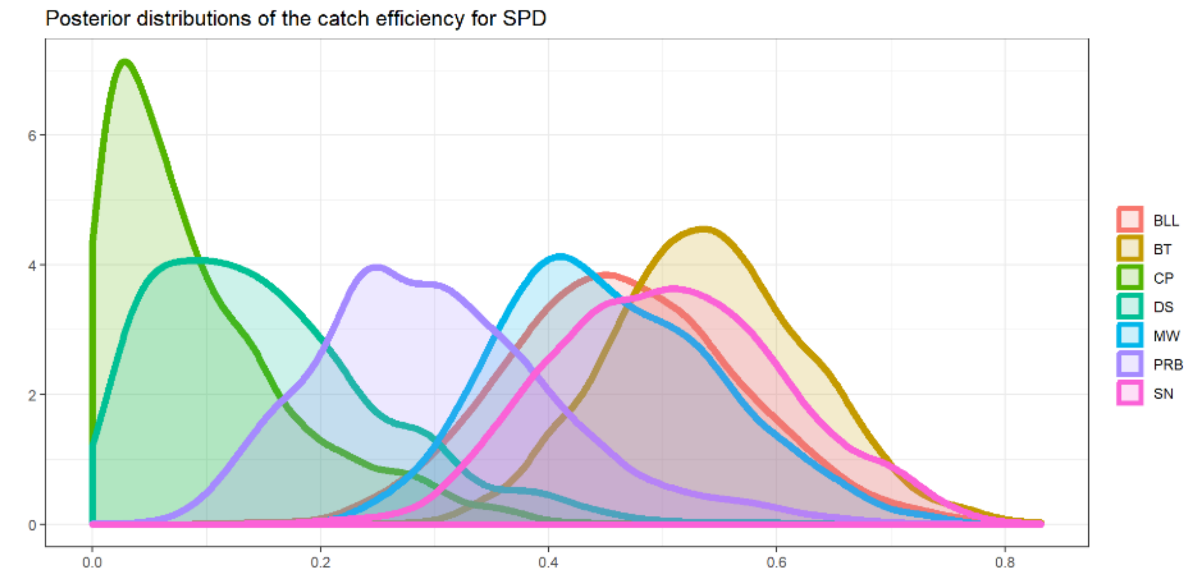

Figure A6.4. Posterior distributions of the gear efficiency for SPD (spiny dogfish) captured by each gear type.

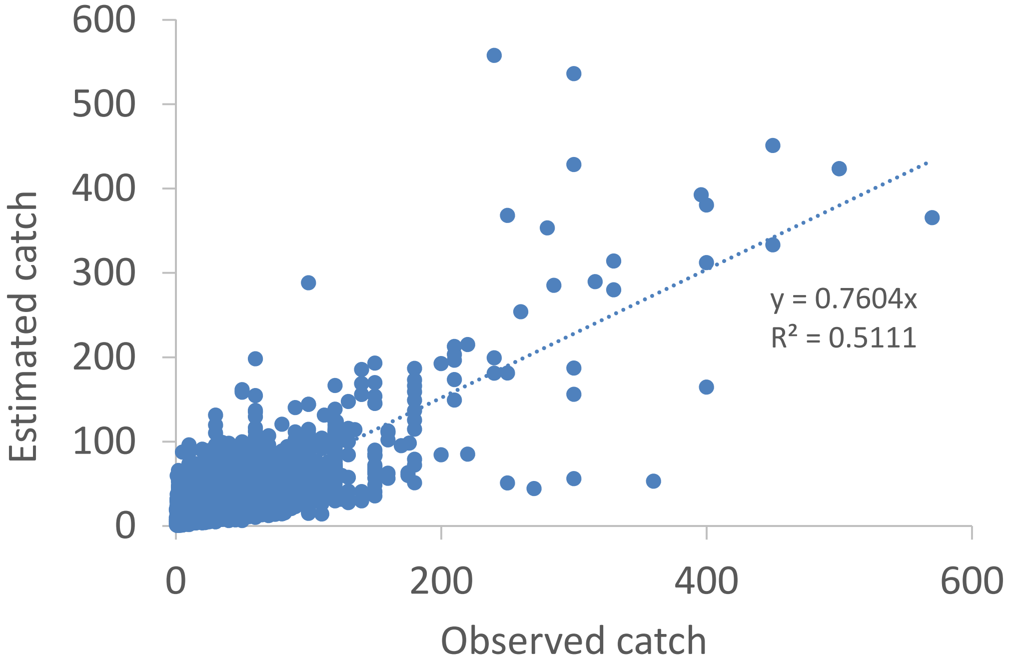

Figure A6.5. Comparison between estimated and observed catch for elephant fish (ELE) based on gear efficiency estimated by the original cross-sampling method using positive catch only.

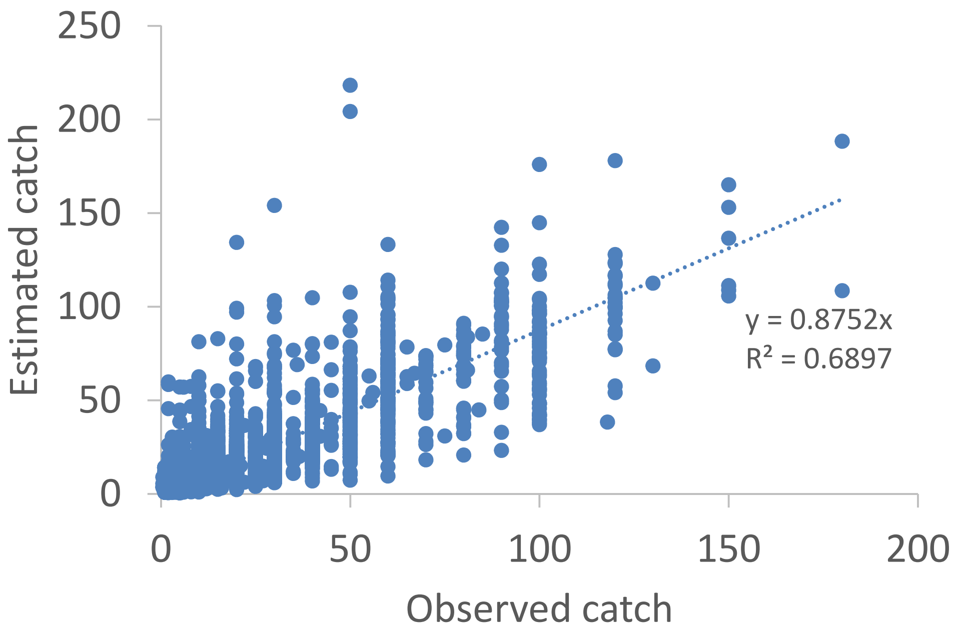

Figure A6.6. Comparison between estimated and observed catch for rough skate (RSK) based on gear efficiency estimated by the original cross-sampling method using positive catch only.

APPENDIX 7: CATCH ONLY METHODS: ADDITIONAL TABLES AND FIGURES

Table A7.1: life history parameter values and preferred water temperature values for species included in OCOM assessments.

Common Name	Scientific Name	Area or Stock	Sex	Reference	Linf	K	Amax	Preferred temp range (from Fishbase)
Barracouta	*Thyrsites atun*	Tasmania	both	Grant et al. (1978)	91.17	0.45		
		Tasmania	both	Grant et al. (1978)	91.01	0.42		
		Southland, New Zealand	F	Horn (2002)	89.3	0.259		
		Southland, New Zealand	M	Horn (2002)	81.1	0.336		
		all	both	Fisheries New Zealand (2019)			10	
		all	both	Fishbase				6.2 - 16 with mean 11.2
Elephant fish	*Callorhinchus milii*		F	M. Francis (unpubl. Data)	97.88	0.26		
			M	M. Francis (unpubl. Data)	75.03	0.34		
		all	both	Coutin (1992)			20	
		all	both	Fishbase				12.1 - 18.2 with mean 15.2

Table A7.1 (cont): life history parameter values and preferred water temperature values for species included in OCOM assessments.

Common Name	Scientific Name	Area or Stock	Sex	Reference	Linf	K	Amax	Preferred temp range (from Fishbase)
Red Cod	*Pseudophycis bachus*	RCO 3	F	Horn (1995)	76.5	0.41		
		RCO 3	M	Horn (1995)	68.5	0.47		
		RCO 7	F	Beentjes (2000)	79.6	0.49		
		RCO 7	M	Beentjes (2000)	68.2	0.53		
		all	both	Beentjes (1992)			6	
		all	both	Fishbase				7.9 - 13.5 with mean 11
Red Gurnard	*Chelidonichthys kumu*	GUR 3	F	Sutton (1997)	48.2	0.44		
		GUR 3	M	Sutton (1997)	42.2	0.49		
		GUR 7	F	Sutton (1997)	45.7	0.4		
		GUR 7	M	Sutton (1997)	40.3	0.37		
		GUR 3	F	Fisheries New Zealand (2019)			16	
		GUR 3	M	Fisheries New Zealand (2019)			13	
		GUR 7	both	Fisheries New Zealand (2019)			15	
		all	both	Fishbase				13.3 - 25 with mean 19.3

Table A7.1 (cont): life history parameter values and preferred water temperature values for species included in OCOM assessments.

Common Name	Scientific Name	Area or Stock	Sex	Reference	Linf	K	Amax	Preferred temp range (from Fishbase)
Rough skate	*Zearaja nasuta*	RSK 3	both	Francis et al. (2001)	91.3	0.16		
		RSK 3	both	Francis et al. (2004)	151.8	0.096		
		all	F	Francis et al. (2001)			9	
		all	both	Fishbase				7.4 - 12.6 with mean 9.2
Snapper	*Pagrus auratus*	SNA 1	both	Gilbert & Sullivan (1994)	58.8	0.102		
		SNA 2	both	NIWA (unpub)	68.9	0.061		
		SNA 7	both	MPI (unpub)	69.6	0.122		
		SNA 8	both	Gilbert & Sullivan (1994)	66.7	0.16		
		all	both	Fishbase			54	
		all	both	Fishbase				14 - 25.2 with mean 17.4
Sea perch	*Helicolenus barathri*	ECSI	F	Paul&Francis (2002)	40.7	0.128		
		ECSI	M	Paul&Francis (2002)	43.6	0.117		
		ECSI	F	Paul&Francis (2002)	37.9	0.13		
		ECSI	M	Paul&Francis (2002)	42.4	0.116		
		ECSI	both	Fisheries New Zealand (2019)			32	
		Chatham Rise	both	Fisheries New Zealand (2019)			43	
		all	both	Fishbase				2.5 - 7.1 with mean 4

Table A7.1 (cont): life history parameter values and preferred water temperature values for species included in OCOM assessments.

Common Name	Scientific Name	Area or Stock	Sex	Reference	Linf	K	Amax	Preferred temp range (from Fishbase)
Spiny dogfish	*Squalus acanthias*	SPD 3	F	Hanchet (1986)	120.1	0.069		
		SPD 3	M	Hanchet (1986)	89.5	0.116		
		ECSI	F	Fisheries New Zealand (2019)			26	
		ECSI	M	Fisheries New Zealand (2019)			21	
		all	both	Fishbase				4.2 - 18.7 with mean 9.9
Stargazer	*Kathetostoma giganteum*	STA 3	F	Sutton (1999)	78.11	0.14		
		STA 3	M	Sutton (1999)	61.49	0.2		
		STA 5	F	Sutton (1999)	73.92	0.18		
		STA 5	M	Sutton (1999)	59.12	0.19		
		STA 5	F	Sutton (2004)	72.61	0.17		
		STA 5	M	Sutton (2004)	60.76	0.18		
		STA 7	F	Manning & Sutton (2007)	85.74	0.13		
		STA 7	M	Manning & Sutton (2007)	71	0.15		
		all	both	Sutton (1999)			25	
		all	both	Fishbase				7.8 - 14.3 with mean 11.2

Table A7.1 (cont): life history parameter values and preferred water temperature values for species included in OCOM assessments.

Common Name	Scientific Name	Area or Stock	Sex	Reference	Linf	K	Amax	Preferred temp range (from Fishbase)
Tarakihi	*Nemadactylus macropterus*	TAR 3	F	Annala et al. (1990)	44.6	0.2009		
		TAR 3	M	Annala et al. (1990)	42.1	0.2085		
		TAR 4	F	Annala et al. (1989)	44.6	0.2205		
		TAR 4	M	Annala et al. (1989)	44.7	0.1666		
		TAR 7	F	Manning (2008b)	45.6	0.234		
		TAR 7	M	Manning (2008b)	42.7	0.252		
		all	both	Annala et al. (1990)			42	
		all	both	Fishbase				11.1-16 with mean 14

Table A7.2: Estimated key parameters from OCOM for the 12 stocks. Results using r and S priors taken from OCOM and CMSY with equal weight. Results obtained through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	BAR 1	K	50 221	73 148	**92 432**	120 003	165 460
3	BAR 1	r	0.19	0.30	**0.46**	0.68	1.36
3	BAR 1	MSY	7 894	8 925	**10 560**	12 483	17 025
3	BAR 1	S_{last}	0.14	0.24	**0.36**	0.54	0.91
3	BAR 1	B_{msy}	25 110	36 574	**46 216**	60 001	82 730
3	BAR 1	F_{msy}	0.10	0.15	**0.23**	0.34	0.68
3	BAR 1	B_{last}	13 774	23 017	**37 320**	50 354	71 786
3	BAR 1	F_{last}	0.13	0.19	**0.26**	0.41	0.69
3	BAR 1	B_{last}/B_{msy}	0.28	0.48	**0.71**	1.09	1.82
3	BAR 1	F_{last}/F_{msy}	0.31	0.86	**1.33**	2.06	3.78
3	BAR 4	K	11 138	14 192	**20 040**	35 125	135 496
3	BAR 4	r	0.20	0.30	**0.46**	0.69	1.35
3	BAR 4	MSY	1 360	1 698	**2 279**	4 048	14 302
3	BAR 4	S_{last}	0.20	0.27	**0.60**	0.81	0.95
3	BAR 4	B_{msy}	5 569	7 096	**10 020**	17 562	67 748
3	BAR 4	F_{msy}	0.10	0.15	**0.23**	0.34	0.67
3	BAR 4	B_{last}	3 585	4 390	**8 014**	26 517	127 102
3	BAR 4	F_{last}	0.02	0.10	**0.33**	0.59	0.73
3	BAR 4	B_{last}/B_{msy}	0.41	0.55	**1.20**	1.62	1.91
3	BAR 4	F_{last}/F_{msy}	0.10	0.40	**0.96**	2.61	4.57
3	ELE 3	K	9 548	13 093	**17 030**	23 488	40 731
3	ELE 3	r	0.06	0.14	**0.21**	0.29	0.44
3	ELE 3	MSY	638	809	**892**	964	1 054
3	ELE 3	S_{last}	0.11	0.23	**0.32**	0.44	0.56
3	ELE 3	B_{msy}	4 774	6 546	**8 515**	11 744	20 365
3	ELE 3	F_{msy}	0.03	0.07	**0.10**	0.15	0.22
3	ELE 3	B_{last}	1 792	3 409	**5 449**	8 283	16 536
3	ELE 3	F_{last}	0.07	0.13	**0.20**	0.32	0.61
3	ELE 3	B_{last}/B_{msy}	0.23	0.45	**0.65**	0.87	1.13
3	ELE 3	F_{last}/F_{msy}	1.01	1.41	**1.96**	2.90	5.98

Table A7.2 (cont). Estimated key parameters from OCOM for the 12 stocks. Results using r and S priors taken from OCOM and CMSY with equal weight. Results obtained through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	GUR 3	K	4 741	8 793	**13 685**	21 436	47 279
3	GUR 3	r	0.21	0.31	**0.49**	0.73	1.46
3	GUR 3	MSY	1 010	1 251	**1 558**	2 203	4 298
3	GUR 3	S_{last}	0.46	0.60	**0.71**	0.82	0.92
3	GUR 3	B_{msy}	2 370	4 396	**6 843**	10 718	23 640
3	GUR 3	F_{msy}	0.10	0.16	**0.24**	0.37	0.73
3	GUR 3	B_{last}	2 770	5 304	**9 054**	16 426	41 679
3	GUR 3	F_{last}	0.04	0.10	**0.17**	0.29	0.56
3	GUR 3	B_{last}/B_{msy}	0.91	1.20	**1.42**	1.63	1.83
3	GUR 3	F_{last}/F_{msy}	0.20	0.44	**0.71**	1.05	1.65
3	RCO 3	K	25 791	41 061	**54 429**	76 320	106 595
3	RCO 3	r	0.22	0.34	**0.53**	0.79	1.60
3	RCO 3	MSY	5 749	6 469	**7 247**	8 117	10 324
3	RCO 3	S_{last}	0.21	0.35	**0.50**	0.86	0.88
3	RCO 3	B_{msy}	12 895	20 531	**27 215**	38 160	53 298
3	RCO 3	F_{msy}	0.11	0.17	**0.27**	0.40	0.80
3	RCO 3	B_{last}	11 755	20 976	**27 631**	35 427	53 143
3	RCO 3	F_{last}	0.09	0.13	**0.16**	0.22	0.39
3	RCO 3	B_{last}/B_{msy}	0.41	0.69	**1.01**	1.73	1.77
3	RCO 3	F_{last}/F_{msy}	0.25	0.32	**0.67**	0.99	1.72
3	RSK 3	K	10 896	15 405	**21 660**	32 853	64 899
3	RSK 3	r	0.06	0.15	**0.24**	0.34	0.48
3	RSK 3	MSY	618	986	**1 214**	1 546	2 752
3	RSK 3	S_{last}	0.18	0.36	**0.55**	0.70	0.86
3	RSK 3	B_{msy}	5 448	7 703	**10 830**	16 427	32 450
3	RSK 3	F_{msy}	0.03	0.07	**0.12**	0.17	0.24
3	RSK 3	B_{last}	2 520	5 920	**11 160**	21 020	52 161
3	RSK 3	F_{last}	0.03	0.07	**0.14**	0.26	0.61
3	RSK 3	B_{last}/B_{msy}	0.37	0.73	**1.10**	1.40	1.72
3	RSK 3	F_{last}/F_{msy}	0.32	0.72	**1.19**	2.23	5.13

Table A7.2 (cont). Estimated key parameters from OCOM for the 12 stocks. Results using r and S priors taken from OCOM and CMSY with equal weight. Results obtained through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	RSK 7	K	676	1 595	**2 912**	4 970	11 050
3	RSK 7	R	0.06	0.14	**0.31**	0.58	1.35
3	RSK 7	MSY	87	156	**195**	268	494
3	RSK 7	S_{last}	0.46	0.60	**0.71**	0.82	0.91
3	RSK 7	B_{msy}	338	797	**1 456**	2 485	5 525
3	RSK 7	F_{msy}	0.03	0.07	**0.15**	0.29	0.68
3	RSK 7	B_{last}	397	981	**1 952**	3 677	9 766
3	RSK 7	F_{last}	0.02	0.04	**0.08**	0.17	0.42
3	RSK 7	B_{last}/B_{msy}	0.92	1.19	**1.43**	1.64	1.82
3	RSK 7	F_{last}/F_{msy}	0.18	0.38	**0.61**	0.90	1.83
3	SNA 7	K	6 703	11 259	**16 587**	23 278	31 727
3	SNA 7	R	0.06	0.11	**0.20**	0.35	0.74
3	SNA 7	MSY	462	640	**820**	994	1 234
3	SNA 7	S_{last}	0.05	0.14	**0.26**	0.36	0.87
3	SNA 7	B_{msy}	3 351	5 630	**8 293**	11 639	15 863
3	SNA 7	F_{msy}	0.03	0.05	**0.10**	0.18	0.37
3	SNA 7	B_{last}	698	2 187	**3 999**	5 986	10 835
3	SNA 7	F_{last}	0.04	0.06	**0.10**	0.17	0.55
3	SNA 7	B_{last}/B_{msy}	0.10	0.28	**0.51**	0.72	1.73
3	SNA 7	F_{last}/F_{msy}	0.18	0.65	**1.02**	1.82	5.46
3	SPD 3	K	48 370	66 744	**87 958**	127 815	291 862
3	SPD 3	R	0.02	0.04	**0.08**	0.11	0.18
3	SPD 3	MSY	569	1 184	**1 693**	2 226	4 641
3	SPD 3	S_{last}	0.23	0.37	**0.52**	0.69	0.88
3	SPD 3	B_{msy}	24 185	33 372	**43 979**	63 907	145 931
3	SPD 3	F_{msy}	0.01	0.02	**0.04**	0.06	0.09
3	SPD 3	B_{last}	14 013	25 316	**43 011**	81 891	249 051
3	SPD 3	F_{last}	0.01	0.02	**0.04**	0.07	0.12
3	SPD 3	B_{last}/B_{msy}	0.46	0.74	**1.04**	1.39	1.76
3	SPD 3	F_{last}/F_{msy}	0.21	0.61	**1.10**	1.98	4.60

Table A7.2 (cont). Estimated key parameters from OCOM for the 12 stocks. Results using r and S priors taken from OCOM and CMSY with equal weight. Results obtained through minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$

Method	Stock	Param	q0.05	q0.25	**q0.5**	q0.75	q0.95
3	SPE 3	K	3 725	7 019	**11 109**	17 789	39 944
3	SPE 3	r	0.06	0.12	**0.21**	0.37	0.80
3	SPE 3	MSY	317	475	**579**	694	1 532
3	SPE 3	S_{last}	0.23	0.37	**0.52**	0.68	0.89
3	SPE 3	B_{msy}	1 862	3 510	**5 554**	8 895	19 972
3	SPE 3	F_{msy}	0.03	0.06	**0.11**	0.19	0.40
3	SPE 3	B_{last}	1 452	2 856	**5 107**	9 823	33 573
3	SPE 3	F_{last}	0.02	0.06	**0.12**	0.21	0.41
3	SPE 3	B_{last}/B_{msy}	0.47	0.74	**1.04**	1.36	1.78
3	SPE 3	F_{last}/F_{msy}	0.22	0.64	**1.06**	1.70	3.13
3	STA 3	K	3 196	5 397	**8 083**	12 011	28 499
3	STA 3	r	0.14	0.26	**0.40**	0.61	1.10
3	STA 3	MSY	619	711	**766**	827	1 975
3	STA 3	S_{last}	0.24	0.39	**0.54**	0.75	0.92
3	STA 3	B_{msy}	1 598	2 699	**4 041**	6 005	14 249
3	STA 3	F_{msy}	0.07	0.13	**0.20**	0.30	0.55
3	STA 3	B_{last}	1 392	2 371	**3 843**	6 973	23 793
3	STA 3	F_{last}	0.03	0.11	**0.19**	0.31	0.53
3	STA 3	B_{last}/B_{msy}	0.47	0.77	**1.08**	1.50	1.84
3	STA 3	F_{last}/F_{msy}	0.20	0.60	**0.93**	1.35	2.26
3	TAR	K	22 974	49 427	**77 739**	135 642	226 377
3	TAR	r	0.06	0.12	**0.24**	0.41	0.98
3	TAR	MSY	3 418	4 217	**4 698**	5 104	5 629
3	TAR	S_{last}	0.12	0.25	**0.36**	0.48	0.71
3	TAR	B_{msy}	11 487	24 713	**38 870**	67 821	113 188
3	TAR	F_{msy}	0.03	0.06	**0.12**	0.21	0.49
3	TAR	B_{last}	7 553	14 489	**24 851**	45 311	95 158
3	TAR	F_{last}	0.05	0.10	**0.18**	0.31	0.60
3	TAR	B_{last}/B_{msy}	0.24	0.50	**0.71**	0.96	1.41
3	TAR	F_{last}/F_{msy}	0.57	1.01	**1.42**	2.08	4.45

Table A7.3. Integrated catch-only method (Method 3: r and S priors taken from OCOM and CMSY with equal weight).Incorporating CPUE data: Optimisation using both CPUE and saturation prior S (minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight). Dev. 2-1 is the relative deviation between optimisation option (ii) and option (i) (see also Table A7.2).

Method	Min	Stock	Param	q0.05	q0.25	q0.5	q0.75	q0.95	Dev. 2-1
3	2	ELE 3	K	9 653	12 994	16 901	24 157	43 559	0.00
3	2	ELE 3	r	0.06	0.14	0.21	0.29	0.44	0.00
3	2	ELE 3	MSY	673	818	887	955	1 051	-0.01
3	2	ELE 3	Slast	0.18	0.29	0.36	0.43	0.54	0.12
3	2	ELE 3	Bmsy	4 826	6 497	8 451	12 078	21 780	0.00
3	2	ELE 3	Fmsy	0.03	0.07	0.10	0.15	0.22	0.00
3	2	ELE 3	Blast	2 385	4 252	5 813	9 016	19 520	0.09
3	2	ELE 3	Flast	0.06	0.12	0.19	0.26	0.46	-0.08
3	2	ELE 3	Blast/Bmsy	0.36	0.58	0.72	0.86	1.08	0.12
3	2	ELE 3	Flast/Fmsy	1.12	1.43	1.77	2.23	3.54	-0.12
3	2	GUR 3	K	4 879	9 840	15 213	25 250	57 329	0.11
3	2	GUR 3	r	0.21	0.31	0.49	0.73	1.48	0.01
3	2	GUR 3	MSY	948	1 348	1 725	2 641	5 638	0.11
3	2	GUR 3	Slast	0.39	0.64	0.75	0.85	0.94	0.06
3	2	GUR 3	Bmsy	2 440	4 920	7 606	12 625	28 665	0.11
3	2	GUR 3	Fmsy	0.10	0.16	0.24	0.37	0.74	0.01
3	2	GUR 3	Blast	2 856	5 827	10 749	20 617	52 130	0.17
3	2	GUR 3	Flast	0.03	0.08	0.15	0.27	0.55	-0.15
3	2	GUR 3	Blast/Bmsy	0.79	1.28	1.50	1.71	1.87	0.06
3	2	GUR 3	Flast/Fmsy	0.15	0.35	0.61	0.91	2.06	-0.15
3	2	SNA 7	K	6 766	11 281	16 513	23 088	32 974	0.02
3	2	SNA 7	r	0.06	0.11	0.20	0.35	0.73	-0.03
3	2	SNA 7	MSY	474	650	823	994	1 229	-0.01
3	2	SNA 7	Slast	0.32	0.39	0.43	0.49	0.92	0.72
3	2	SNA 7	Bmsy	3 383	5 641	8 257	11 544	16 487	0.02
3	2	SNA 7	Fmsy	0.03	0.06	0.10	0.18	0.36	-0.03
3	2	SNA 7	Blast	4 268	5 755	7 171	8 954	12 448	0.87
3	2	SNA 7	Flast	0.03	0.04	0.05	0.07	0.09	-0.46
3	2	SNA 7	Blast/Bmsy	0.65	0.77	0.86	0.98	1.84	0.72
3	2	SNA 7	Flast/Fmsy	0.17	0.40	0.53	0.76	1.15	-0.48

Table A7.3 (cont). Integrated catch-only method (Method 3: r and S priors taken from OCOM and CMSY with equal weight).Incorporating CPUE data: Optimisation using both CPUE and saturation prior S (minimising $\left(\frac{B_{last}}{K} - S_{last}\right)^2$ and MSE_{cpue} together with equal weight). Dev. 2-1 is the relative deviation between optimisation option (ii) and option (i) (see also Table A7.2).

Method	Min	Stock	*Param*	q0.05	q0.25	**q0.5**	*q0.75*	q0.95	Dev 2-1
3	2	STA 3	K	3 460	5 555	**8 294**	*12 257*	29 448	0.02
3	2	STA 3	r	0.14	0.27	**0.41**	*0.61*	1.05	0.01
3	2	STA 3	MSY	630	722	**776**	*886*	1 990	0.01
3	2	STA 3	S_{last}	0.27	0.44	**0.64**	*0.79*	0.92	0.20
3	2	STA 3	B_{msy}	1 730	2 778	**4 147**	*6 128*	14 724	0.02
3	2	STA 3	F_{msy}	0.07	0.13	**0.20**	*0.31*	0.53	0.01
3	2	STA 3	B_{last}	1 605	2 957	**4 538**	*7 674*	24 269	0.16
3	2	STA 3	F_{last}	0.03	0.10	**0.16**	*0.25*	0.46	-0.14
3	2	STA 3	B_{last}/B_{msy}	0.54	0.87	**1.29**	*1.59*	1.84	0.20
3	2	STA 3	F_{last}/F_{msy}	0.20	0.53	**0.77**	*1.20*	1.98	-0.18
3	2	TAR	K	23 742	49 975	**77 594**	*133 224*	224 985	-0.02
3	2	TAR	r	0.06	0.13	**0.24**	*0.41*	0.95	0.03
3	2	TAR	MSY	3 461	4 207	**4 700**	*5 185*	5 612	0.00
3	2	TAR	S_{last}	0.19	0.29	**0.43**	*0.69*	0.71	0.19
3	2	TAR	B_{msy}	11 871	24 988	**38 797**	*66 612*	112 493	-0.02
3	2	TAR	F_{msy}	0.03	0.06	**0.12**	*0.21*	0.47	0.03
3	2	TAR	B_{last}	13 628	22 958	**33 318**	*45 932*	92 079	0.32
3	2	TAR	F_{last}	0.05	0.10	**0.14**	*0.20*	0.33	-0.24
3	2	TAR	B_{last}/B_{msy}	0.38	0.58	**0.86**	*1.37*	1.42	0.19
3	2	TAR	F_{last}/F_{msy}	0.57	0.64	**1.23**	*1.85*	2.90	-0.12

Table A7.4. Integrated catch-only method (Method 3: r and S priors taken from OCOM and CMSY with equal weight). Incorporating CPUE data: Optimisation on CPUE only (minimising MSE_{cpue} only); optimisation option (iii). Dev.3-1 and Dev. 3-2 are the relative deviation between option (iii) and option (i) (see also Table A7.2), and between options (iii) and (ii) (see also Table A7.3).

Method	Min	Stock	*Param*	q0.05	q0.25	**q0.5**	q0.75	q0.95	Dev.3-1	Dev.3-2
3	3	SNA 7	*K*	16,192	18,816	**22,698**	28,348	35,676	0.40	0.37
3	3	SNA 7	*r*	0.05	0.08	**0.12**	0.16	0.21	-0.43	-0.41
3	3	SNA 7	*MSY*	479	562	**665**	760	833	-0.20	-0.19
3	3	SNA 7	S_{last}	0.46	0.46	**0.48**	0.52	0.56	0.90	0.10
3	3	SNA 7	B_{msy}	8,096	9,408	**11,349**	14,174	17,838	0.40	0.37
3	3	SNA 7	F_{msy}	0.03	0.04	**0.06**	0.08	0.10	-0.43	-0.41
3	3	SNA 7	B_{last}	9,091	9,685	**10,755**	12,909	16,779	1.80	0.50
3	3	SNA 7	F_{last}	0.02	0.03	**0.04**	0.04	0.04	-0.64	-0.33
3	3	SNA 7	B_{last}/B_{msy}	0.91	0.92	**0.95**	1.03	1.12	0.90	0.10
3	3	SNA 7	F_{last}/F_{msy}	0.41	0.49	**0.60**	0.74	0.84	-0.41	0.14
3	3	STA 3	*K*	4,340	8,501	**14,358**	27,893	70,420	0.77	0.73
3	3	STA 3	*r*	0.30	0.38	**0.51**	0.68	1.10	0.25	0.24
3	3	STA 3	*MSY*	1,188	1,450	**1,815**	2,652	5,267	1.37	1.34
3	3	STA 3	S_{last}	0.86	0.89	**0.92**	0.94	0.97	0.70	0.42
3	3	STA 3	B_{msy}	2,170	4,250	**7,179**	13,946	35,210	0.77	0.73
3	3	STA 3	F_{msy}	0.15	0.19	**0.25**	0.34	0.55	0.25	0.24
3	3	STA 3	B_{last}	3,716	7,561	**13,138**	26,322	68,469	2.36	1.89
3	3	STA 3	F_{last}	0.01	0.03	**0.06**	0.10	0.20	-0.70	-0.65
3	3	STA 3	B_{last}/B_{msy}	1.71	1.78	**1.83**	1.89	1.94	0.70	0.42
3	3	STA 3	F_{last}/F_{msy}	0.07	0.15	**0.22**	0.29	0.36	-0.76	-0.71
3	3	TAR	*K*	97,733	141,287	**197,675**	253,102	510,917	1.50	1.55
3	3	TAR	*r*	0.05	0.08	**0.15**	0.21	0.26	-0.37	-0.39
3	3	TAR	*MSY*	3,338	3,737	**6,980**	9,318	15,066	0.49	0.48
3	3	TAR	S_{last}	0.34	0.37	**0.80**	0.86	0.92	1.21	0.85
3	3	TAR	B_{msy}	48,866	70,644	**98,837**	126,551	255,459	1.50	1.55
3	3	TAR	F_{msy}	0.03	0.04	**0.07**	0.10	0.13	-0.37	-0.39
3	3	TAR	B_{last}	63,113	79,251	**102,221**	199,063	470,000	3.06	2.07
3	3	TAR	F_{last}	0.01	0.02	**0.04**	0.06	0.07	-0.75	-0.67
3	3	TAR	B_{last}/B_{msy}	0.69	0.75	**1.60**	1.72	1.84	1.21	0.85
3	3	TAR	F_{last}/F_{msy}	0.16	0.28	**0.41**	1.76	1.82	-0.71	-0.67

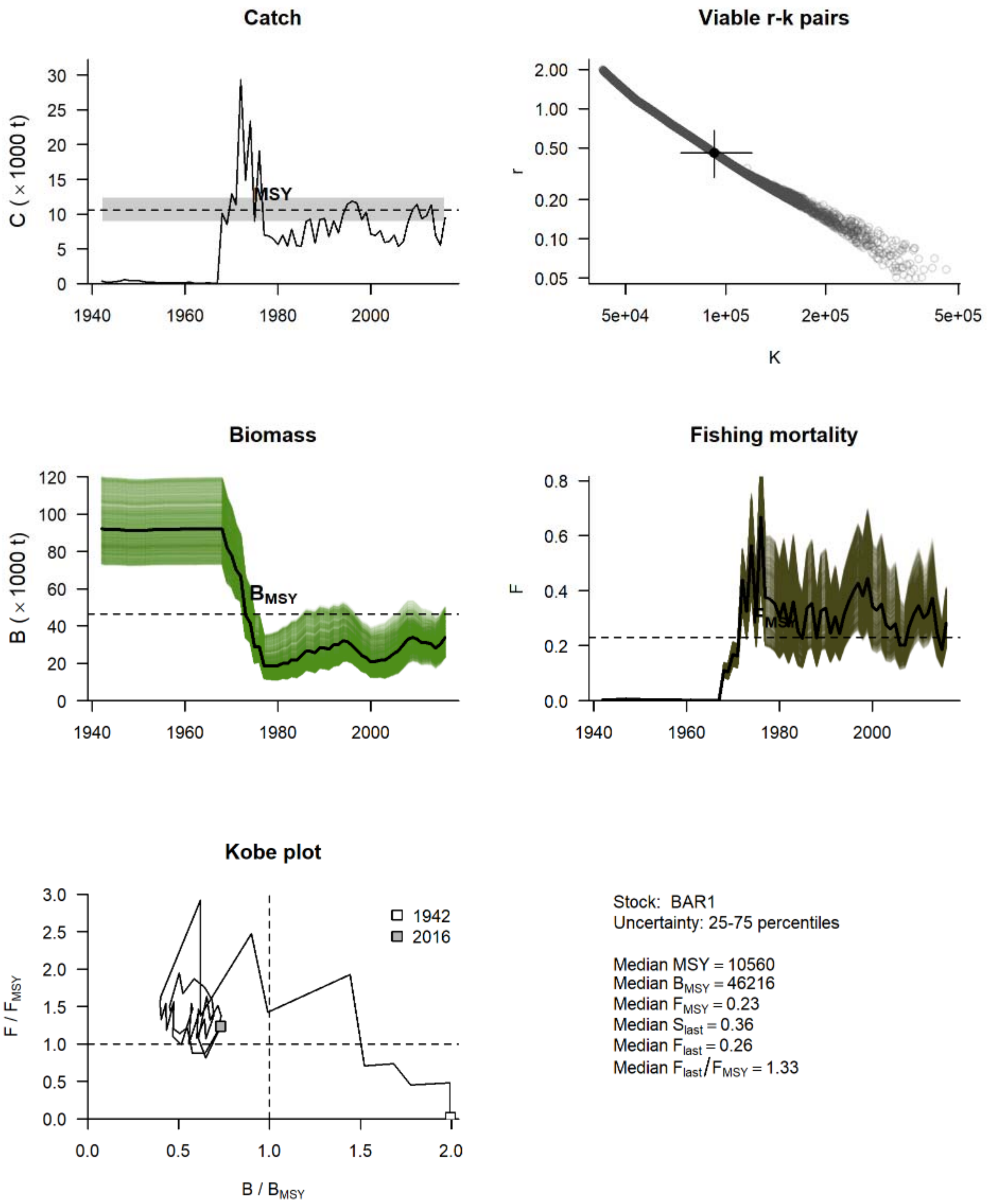

Figure A7.1. Result from the integrated catch-only method for BAR 1 (barracouta). Results using r and S priors taken from OCOM and CMSY with equal weight.

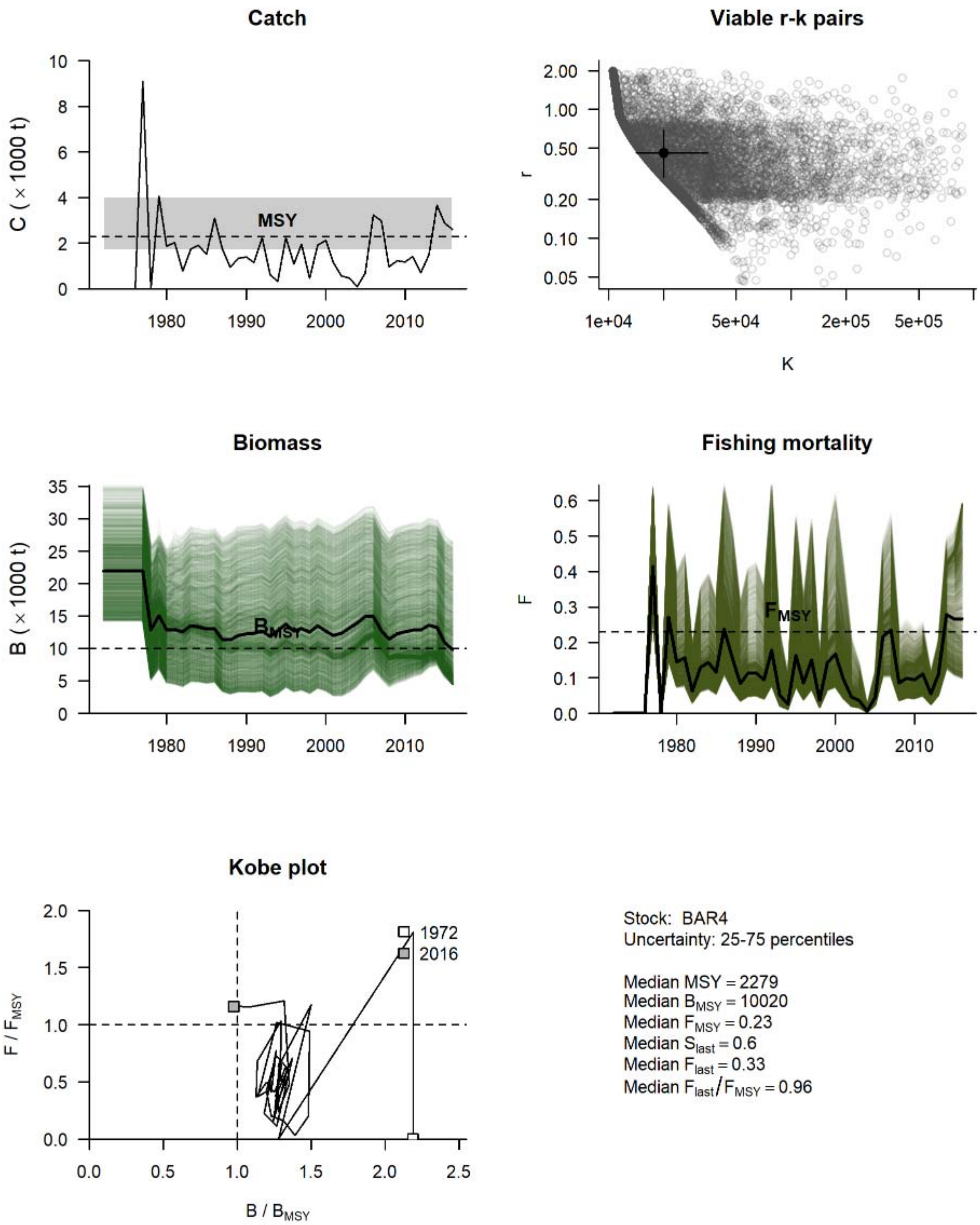

Figure A7.2. Result from the integrated catch-only method for BAR 4 (barracouta). Results using r and S priors taken from OCOM and CMSY with equal weight.

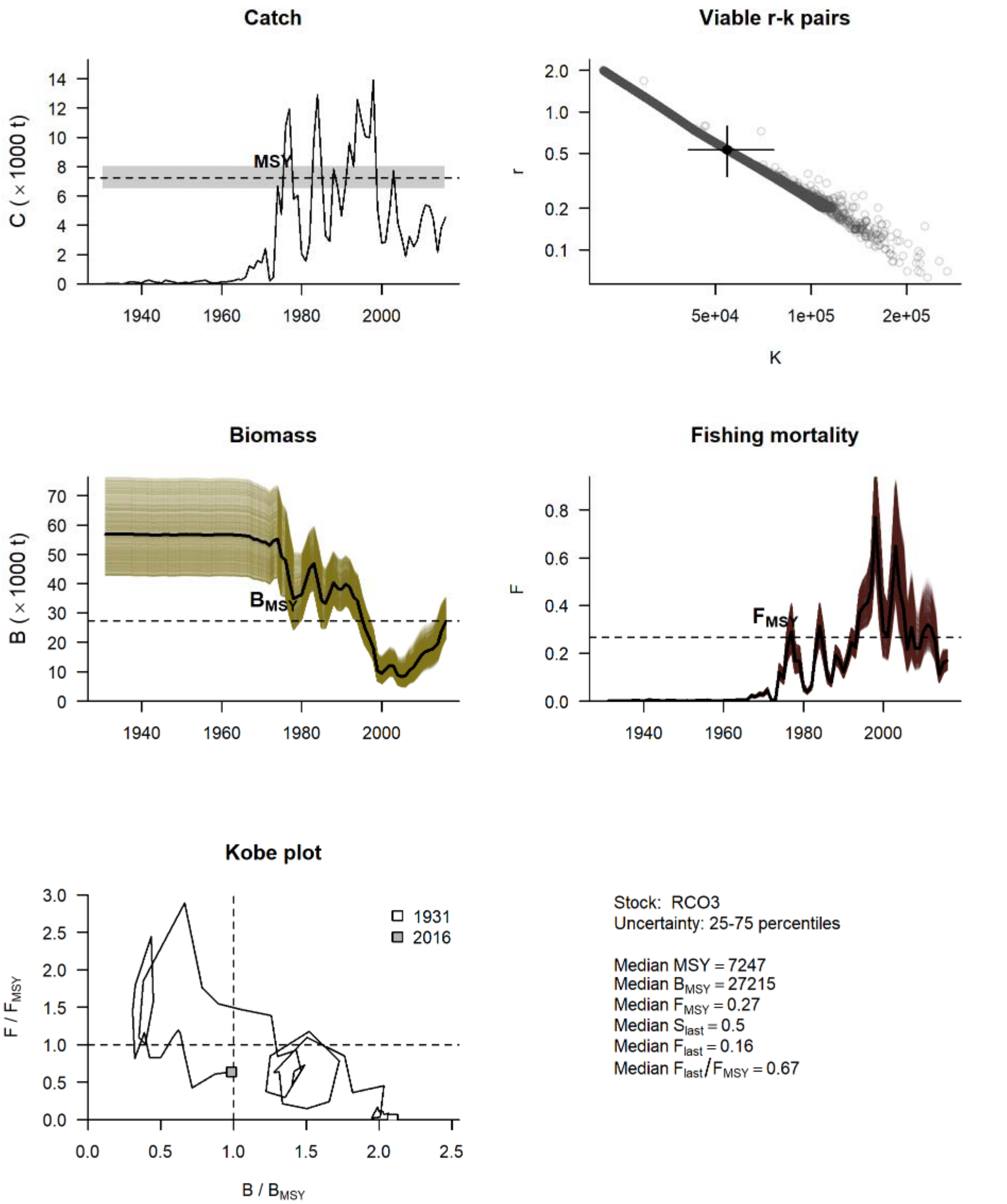

Figure A7.3. Result from the integrated catch-only method for RCO 3 (red cod). Results using r and S priors taken from OCOM and CMSY with equal weight.

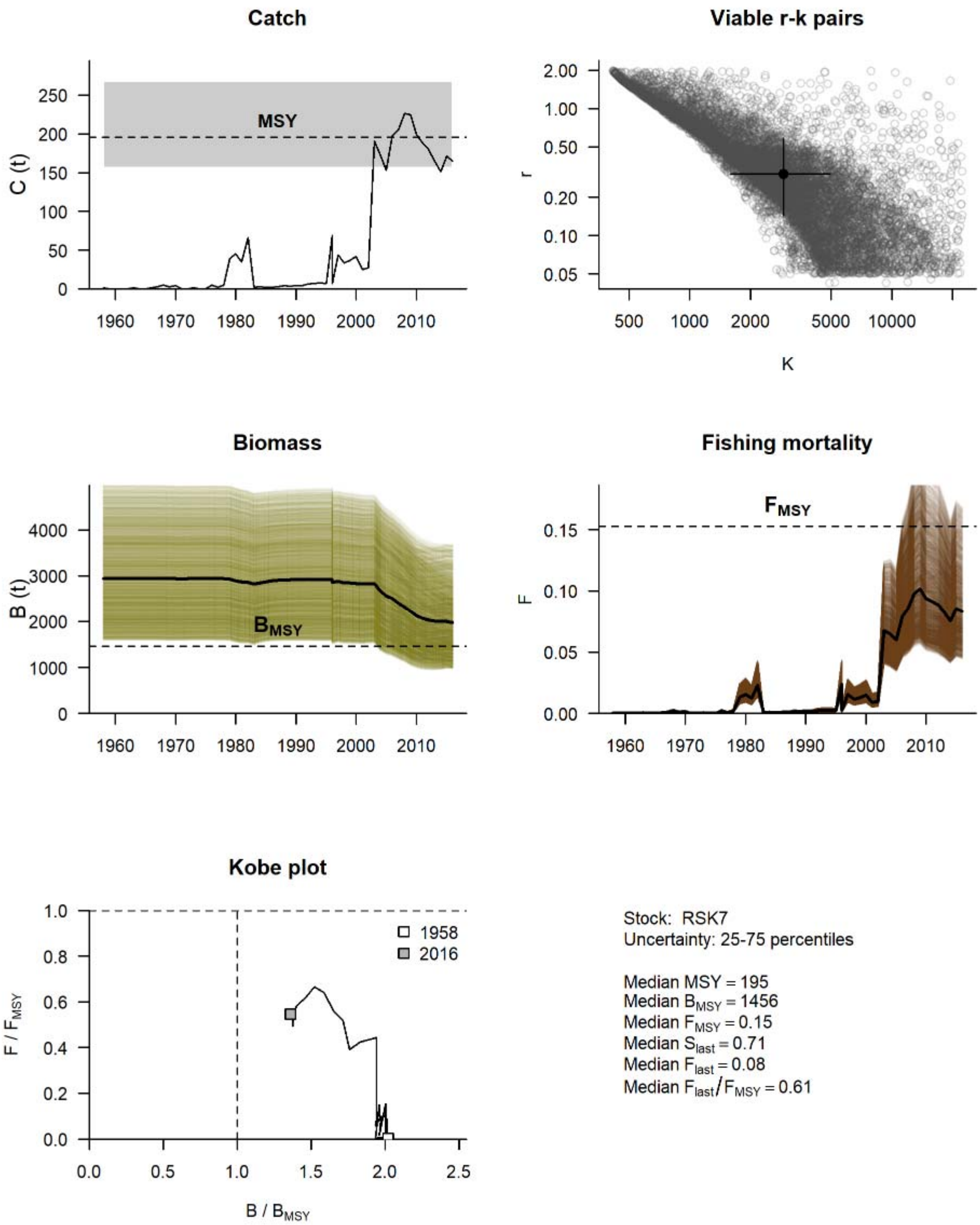

Figure A7.4. Result from the integrated catch-only method for RSK 7 (rough skate). Results using r and S priors taken from OCOM and CMSY with equal weight.

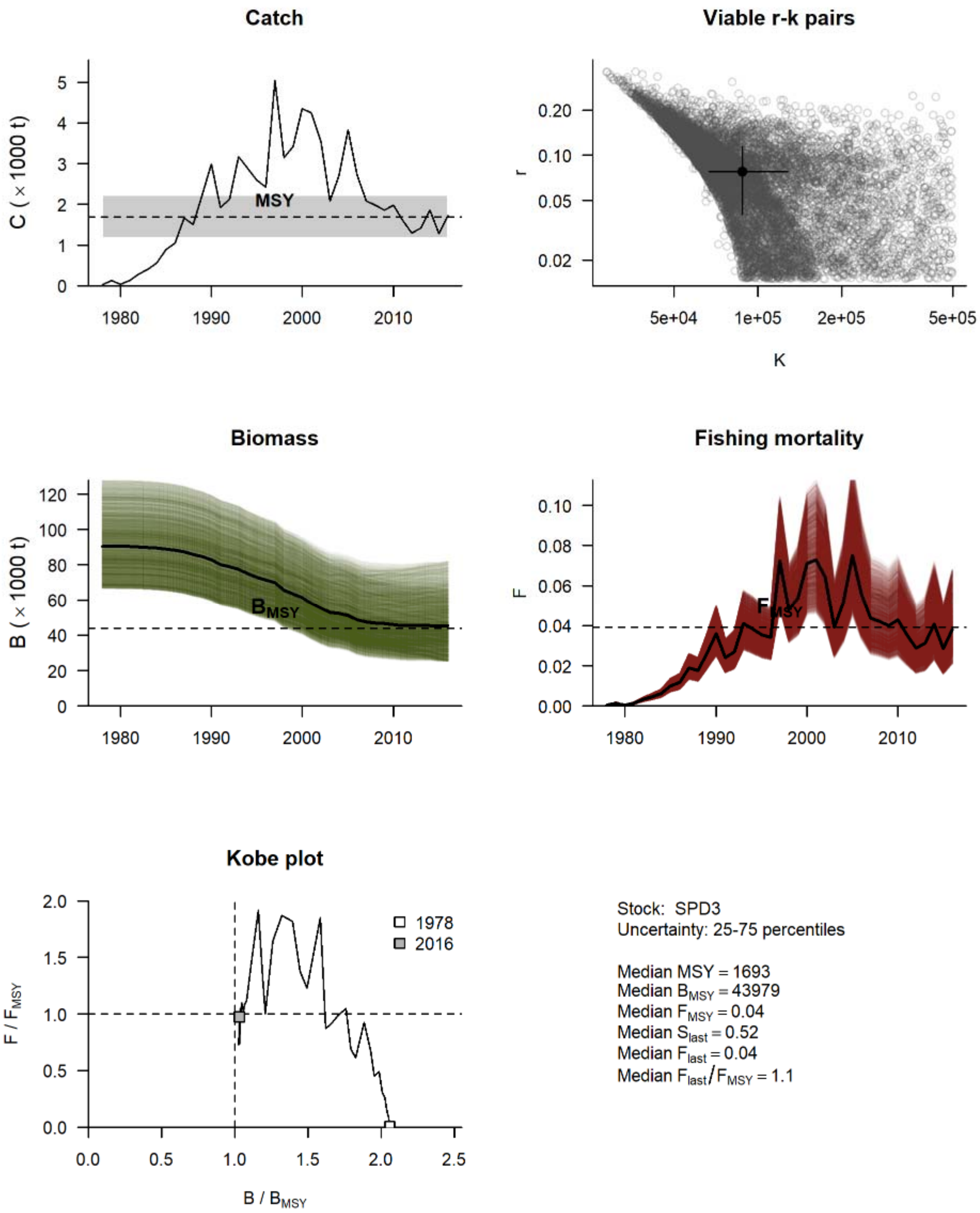

Figure A7.5. Result from the integrated catch-only method for SPD 3 (spiny dogfish). Results using r and S priors taken from OCOM and CMSY with equal weight.