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Characterisation and spatio-temporal CPUE standardisation of school shark in the NZ EEZ

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PLAIN LANGUAGE SUMMARY

This study on school shark analysed catch and effort data from 2008 to 2024, using commercial fishing data from three main fishing methods (set nets, bottom trawls, and bottom longlines) to estimate changes in relative abundance at several spatial scales.

The key findings were:

- school shark should be treated as one connected population throughout New Zealand waters;
- school shark numbers appear stable over recent years at about the level of the target reference period (2012–2018);
- school sharks move extensively around New Zealand waters. They were more common on the Chatham Rise and west coast of New Zealand in 2012–2014, but shifted toward the east coast in 2022–2024;
- the fishery has evolved from being mainly set nets (60% of catch in 1990) to a more balanced fishery of set nets, bottom trawls and longlines (about 30–40% each by 2024);
- the spatio-temporal modelling method provides more consistent population estimates than previous techniques, and lets us estimate CPUE indices for the population as whole, as well as regional and CPUE indices as required for management;
- the approach helps resolve conflicts between the CPUE indices estimated from different fishing methods and in different areas that have previously showed contradictory trends.

EXECUTIVE SUMMARY

Mormede, S.[1]; Dunn, A.[2] (2025). Characterisation and spatio-temporal CPUE standardisation of school shark in the NZ EEZ. New Zealand Fisheries Assessment Report 2025/33. 67 p.

The New Zealand school shark fishery has been operating since the 1940s, with catches relatively stable since the 1980s. The fishery itself has shifted from set net fishery (60% in 1990) to a more mixed fishery incorporating bottom trawl and bottom longline methods (each about 30% in 2024), reflecting broader changes in fishing practices.

This study characterised the school shark fishery and developed improved indices of vulnerable biomass for the entire school shark stock through spatio-temporal CPUE standardisation. The key conclusions are as follows:

1. Single stock hypothesis: The spatial analysis of length data supports treating school shark as a single stock across the New Zealand EEZ.
2. Methodological advancement: The spatio-temporal CPUE standardisation provides a superior methodology to derive abundance indices compared to traditional approaches, resolving previous conflicts between fishing methods and providing a New Zealand-wide index of school shark abundance.
3. Spatial patterns: The school shark distribution of vulnerable biomass shows high temporal variability, emphasising the species' mobility and the importance of a New Zealand-wide management approach.
4. Stock status: The school shark stock appears stable and at target levels based on the 2012–2018 reference period, with 2023–24 biomass estimates within the target range and the recent exploitation rate below the target exploitation rate.
5. Management boundaries: The current total allowable commercial catch allocation between QMAs broadly aligns with the estimated stock biomass distribution, noting that the QMA boundaries do not follow biological boundaries.
6. Assessment model simulations: The uncertainty in productivity estimates for school shark is very high as there are few reliable estimates of the key biological parameters. However, stock assessment model simulations using a range of plausible biological parameters suggested that the stock was unlikely to be at or below 40% B_0 without having extremely high variability in relative year class strengths. Model simulations suggested that exploitation rates of about 0.01–0.03 would lead to a stock status of 40% B_0 , but the evaluation of simple exploitation rate harvest strategies was hampered by the high level of uncertainty in the biological parameters and the lack of an estimate of absolute as opposed to relative abundance at the target reference point.

These findings provide a robust foundation for the assessment and sustainable management of school shark in New Zealand waters and demonstrate the value of spatio-temporal approaches for highly mobile marine species. The methods developed here could serve as a template for similar assessments of other low to medium information stocks in New Zealand and internationally.

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1. INTRODUCTION

School shark (*Galeorhinus galeus)* is a moderate-sized chondrichthyan with worldwide distribution and moderate productivity found in shallow waters extending to 600 m depth. In New Zealand, school shark has supported a fishery with consistent catches since the early 1980s; it is caught primarily by set net, bottom longline and bottom trawl. Whilst the New Zealand stock is deemed stable and listed as "Least Concern" when assessed using IUCN Red List Categories and Criteria, school shark has been overfished in many other parts of the world (Finucci et al. 2019).

School sharks in New Zealand are known to be highly mobile, moving between the North and South Islands, with a small proportion travelling as far as Australia (Hurst et al. 1999). Although school shark is deemed a single stock in the New Zealand Exclusive Economic Zone (EEZ), fishery areas were defined in 2014 based on gaps in catches and fisheries definition (Fisheries New Zealand 2024).

Between 2014 and 2024, management advice for school sharks was provided based on standardised catch per unit effort analyses (CPUE) by method and fishery areas (Fisheries New Zealand 2024), with the previous standardisation carried out in 2021 (Tremblay-Boyer 2021). Spatial parameters offered to these models were Statistical Area, or a cubic spline on longitude and latitude. In many fishery areas, trends in the standardised CPUE differed between fishing methods (Fisheries New Zealand 2021; Tremblay-Boyer 2021), raising concerns about the suitability of those indices for the management of this species.

The 2021 Plenary noted the following future research considerations with regards to stock structure and CPUE of school shark (Fisheries New Zealand 2021):

- *Further investigate the conflicts in SCH 2 & top of SCH 3 in a dedicated study that includes examination of whether conflicts are due to spatial or temporal structuring and augment this analysis through discussions with stakeholders. Similar analyses may be needed for other areas.*
- *Conduct further work to better understand stock structure and movements of stocks.*
    - *Collect more comprehensive information on the length and sex composition of school shark around New Zealand to obtain a clearer picture of the size and sex structuring of the population(s) by area.*
    - *Commercial length samples should be analysed under a modelling framework to identify environmental and operational covariates likely to influence length distributions and spatial structuring.*
    - *Conduct a feasibility study on the use of tags to determine more about stock movements and stock structure.*

As part of the development of spatially explicit fisheries risk assessment methodologies for chondrichthyans in the New Zealand EEZ, spatial distribution modelling methodologies were developed and tested on carpet shark, school shark, great white shark, and green turtle as well as on one simulated dataset (Mormede & Lyon 2023). Methods tested were either non spatially explicit standardisations using generalised additive models (GAM) or spatially explicit standardisations using vector autoregressive spatio-temporal models (VAST). A number of recommendations were made for future distribution modelling work, including in particular the need to include spatio-temporal interactions and to choose the fisheries data included wisely (Mormede & Lyon 2023). That project also compared the spatially explicit standardised CPUE indices for school shark in each of the fishery areas with existing CPUE indices and survey biomass series (Mormede & Lyon 2023, figure F.7 and figure F.8), showing many discrepancies.

This report provides a characterisation of school shark in New Zealand up to the 2024–25 fishing year, with an emphasis on spatio-temporal patterns. The characterisation also explores the spatial and temporal structure of the length data with a view to elucidating potential stock structures of school shark in New Zealand. A spatio-temporal CPUE standardisation for the entire NZ EEZ and for all methods combined is detailed. Results are compared with the outputs of the 2019 CPUE standardisation. We also report on the determination of reference points based on existing management processes and on a small simulation exercise to investigate potential alternative methods to determine reference points.

This report fulfils all Specific Research Objectives of Project SCH2024-01 funded by Fisheries New Zealand. The overall objective was: *To estimate stock abundance in SCH 1, 2, 3, 4, 5, 7, and 8*. The specific research objectives were:

1. To characterise the SCH 1, 2, 3, 4, 5, 7, and 8 fisheries.
2. To analyse existing commercial catch and effort data to the end of 2023–24 fishing year and undertake CPUE standardisations for each stock.
3. To complete partial quantitative stock assessments for all areas having accepted indices of abundance and reference points.
4. Broader outcomes.

2. METHODS

2.1 Data used

2.1.1 Available data

Commercial catch and effort data were extracted by Fisheries New Zealand for the period from 1st October 1989 to 30th September 2024 (extract on 9th December 2024, REPLOG 16308). The data extract included all data from trips where school shark was caught, processed or landed and all bottom longline, bottom trawl and set net effort reported on all forms. Various subsets of this effort data were considered for CPUE analyses.

Observer data for school shark from the Fisheries New Zealand observer sampling programme were also extracted, including all observer trips that reported school shark (extract on 9th December 2024, REPLOG 16308). In addition, biological and length frequency information from these trips were also extracted.

Seafood New Zealand authorised the use of sampling data collected by the Adaptive Management Programme (AMP); these were provided by Pisces Research Limited from a copy of the SeaFIC Data Management System database maintained by the Kahawai Collective.

Resource survey data (including data from the RV *Tangaroa* standardised trawl surveys and any other research voyages that reported school shark) were extracted, along with any biological and length frequency information (REPLOG 16308).

2.1.2 Data checks

Catch and effort data were corrected for errors using checking and imputation algorithms similar to those reported by Mormede et al. (2023a) and implemented in the software package *R* (R Core Team 2019). Individual tows were investigated, and errors were corrected using median imputation for start/finish latitude or longitude, fishing method, target species, tow speed, net depth, bottom depth, wingspread, duration, number of events, and headline height for each fishing day for a vessel. Range checks were defined for the remaining attributes to identify potential outliers in the data. The outliers were checked and corrected with median or mean imputation on larger ranges of data such as vessel, target species, and fishing method for a year or month.

Codes for hāpuku (*Polyprion oxygeneios*) and bass (*Polyprion americanus*) - i.e. BAS, HAP and HPB - were consolidated into a single HPB code, as well as flatfish codes (SFL, BRI, ESO, TUR, GFL, YBF, BFL, LSO) to the generic FLA code.

The fisheries areas used in 2021 (Fisheries New Zealand 2021; Tremblay-Boyer 2021) and statistical areas (Figure 1) were assigned based on the corrected positions or the reported statistical area where no specific location was available.

Landings were processed as in previous analyses (Tremblay-Boyer 2021). Specifically, non-landed destination codes and end-of-year codes were removed from the landings data, as well as shark fins if another code was also recorded for the landing. Duplicates and outliers were removed, and early conversion factors corrected. Estimated catch in the catch and effort data was scaled up to landings by trip and QMA for records within the top five species caught only.

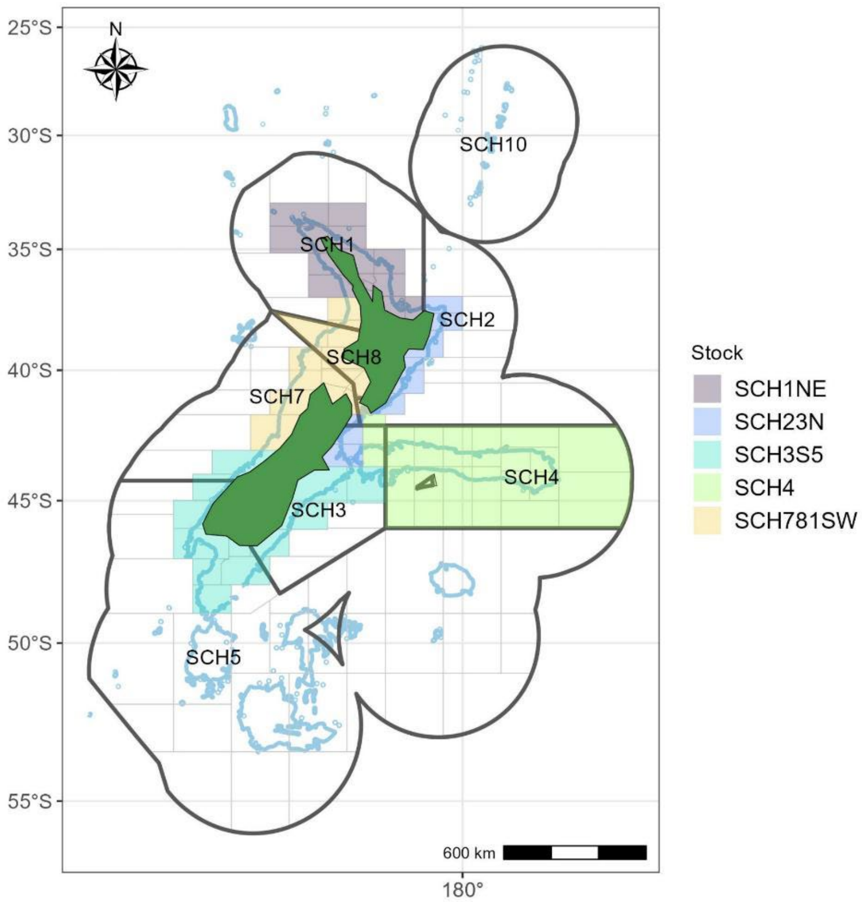

Figure 1: School shark quota management units (QMA – dark bold lines and names), bottom trawl / set net fishery areas from 2014 to 2024 ('Stock' - coloured areas), and statistical areas (grey lines).

2.2 Spatio-temporal analysis of length data

Modelling the spatial distribution of mean length and correcting for variables such as month and year (as in a CPUE standardisation), can help understand the spatial and temporal patterns in fish size/age. Looking at the data by method or region alone can result in biased conclusions because patterns of fish size/age could be different depending on when and where fishing occurred.

Integrated Nested Laplace Approximation (INLA) (Rue et al. 2009) was used to develop spatio-temporal models of fish length for bottom longline, bottom trawl and set net fisheries concurrently for school shark in the entire New Zealand EEZ, using data from observers, surveys and the AMP programme combined. A spatial mesh was developed using constrained Delaunay triangulation (Figure B.2). The mesh was limited to 3500 nodes (i.e., fewer nodes than data points). Each node becomes an estimated model parameter, constrained by the Stochastic Partial Differential Equation (SPDE) underpinning the INLA spatial smoothers. Records with unknown sex were dropped and length was rounded down to the nearest integer.

The length observations were fitted using a normal distribution (the minimum length was well away from zero and models specified using the normal distribution run much faster in INLA). The variables: year, month or season, sex, fishing method, depth, data source (observer, AMP or survey data), and spatial structure were offered to models for both data sets. Spatial structure was either constant, sex-specific, or season-specific. A limited set of plausible model structures was constructed. Both the deviance information criterion (DIC) and Watanabe-Akaike information criterion (WAIC) were used for model selection.

Finally, the R package *ClustGeo* was used to derive spatial fishery strata using hierarchical clustering with geographic constraints (Chavent et al. 2018). This package implements a clustering algorithm that includes soft contiguity constraints. The algorithm requires two dissimilarity matrices (D0 and D1) and a mixing parameter alpha. D0 is a matrix containing the Euclidean distance between all data points (i.e., the sizes of fish), and D1 is a matrix containing the distance in space (in metres) between all data points. The alpha parameter (a real value between 0 and 1) stipulates the relative importance of the data (D0) compared to space (D1).

The value of alpha can be somewhat subjective and can radically change the clusters. However, a semi-objective method for finding a good starting value for alpha involves:

1. Defining the number of clusters (e.g., K = 4 clusters).
2. Running the clustering algorithm for evenly spaced values of alpha between 0 and 1 (e.g., alpha = {0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}).
3. Examining a plot of the proportion of explained inertia of the partitions in K clusters for each alpha value and deciding on an alpha value.

The performance of the candidate strata was evaluated by calculating the scaled age frequency distributions of school shark for these strata and plotting the change in catches and in sex ratio of these candidate strata over time. The ideal stratum structure is one where the length frequency distributions and sex ratios remain constant over time and data are available for all strata.

2.3 Spatio-temporal CPUE standardisation

2.3.1 Resolution of the analysis

The data aggregation and model predictions were carried out to an equal area grid of 32 × 32 km (1024 km^2 area). The functions used to create such grids are provided by Mormede et al. (2022). The mean trawl length in the data selected was 18 km, so a grid of 32 km was deemed more adequate than a grid of 16 km. The mean bottom longline length was 6 km, and mean set net length under 2 km. This grid size was chosen as a natural balance between an overly optimistic precision of the model and an overly coarse result reducing the usefulness of the outputs. A sensitivity trial at 16 km scale was carried out on the model with bottom longline data only.

To avoid spurious distributions at the margins of the area fished and to remove any residual errors in location recorded, only cells within the total definition of the school shark fishery areas (Figure 1), and in which over 25 events were recorded in the CPUE dataset were used; sensitivity trials were carried out using a minimum of 10 or 1 records per cell. Each fishing event was assigned to a cell based on its mid position when start and end positions are available, or on start position otherwise.

2.3.2 Data selection for spatio-temporal CPUE standardisation

The spatio-temporal CPUE standardisation was carried out using data from 2008 to 2024 because prior to that time insufficient fine-scale spatial location data were available. In order to ensure data consistency over time across multiple reporting forms and requirements, events where school shark were not recorded in the top five caught species were given a ‘zero’ catch, and the remaining estimated catches were scaled up to the landings (see Section 2.1.2 above).

In previous analyses, the definition of the school shark fishery included all records that caught school shark or targeted one of 23 defined species (Tremblay-Boyer 2021 Table D.1, and Table A.1 in this document). However, because CPUE standardisations were carried out by fishing method and fishery area separately, only 3–5 target species were included in any standardisation. As the standardisation carried out in this analysis was for the entire NZ EEZ and all three fishing methods combined, using all 23 target species was not practical. Furthermore, it was expected that the catchability of school shark for any specific target species would differ between methods, requiring a method:target interaction component to the CPUE standardisation, which was not computationally feasible. Instead, the top five or ten target species for each of the fishing methods over the entire NZ EEZ were selected, and a method.target composite parameter created for the CPUE standardisation. Sensitivity trials were carried out with regards to the number of target species included in the analysis.

Even as defined with a reduced number of target species, the school shark fishery from 2008 to 2024 contained over two million records and over 400 vessels. Core vessels were defined as all vessels with at least 100 fishing records and 11 years in the fishery, retaining 212 vessels and over 80% of the school shark catch. Outliers in catch and effort parameters were also removed, leaving just over 700 000 records remaining in the CPUE analysis.

Spatio-temporal standardisations include a year:space interaction and are therefore computationally intensive. Further data aggregation was required and was carried out at the level of 32 km grid, month, vessel and method.target variable. Sensitivity trials were carried out using a daily aggregation. The catch and effort variables were summed over this aggregation, whilst latitude, longitude and speed were given their median value (mean was also tested but rejected by the Fisheries New Zealand Inshore Working Group at the time of the analysis). This resulted in a total of about 170 000 individual data points available to the models.

2.3.3 CPUE standardisation

Methods such as vector autoregressive spatio-temporal models (VAST, Thorson & Barnett 2017) apply a smoother to catch data (expressed in catch per area) in both time and space. Maunder et al. (2020) showed that spatio-temporal models were useful to derive indices of abundance and composition data when sampling intensity varies across the spatial domain—better accounting for variability in sampling over space and time that otherwise would violate the assumptions of time-invariant catchability and selectivity in stock assessment models. Ducharme-Barth et al. (2022) and Grüss et al. (2019) have also shown that spatio-temporal standardisation of CPUE was superior to traditional methodologies and Mormede & Lyon (2023) evaluated this approach on New Zealand school shark and on simulated data. This is particularly important for school shark as the standardised CPUE indices developed in 2021 showed diverging trends in the same area between fishing methods (Tremblay-Boyer 2021; Mormede & Lyon 2023), which was likely to be due to spatial differences in fishing location. These spatio-temporal CPUE standardisation methods have also been used in ling and hake characterisations to develop stock hypotheses (Dunn et al. 2021; Mormede et al. 2022, 2023b).

Standardised CPUE indices using best practice (e.g., see Hoyle et al. 2024 for a summary of good practice recommended for CPUE modelling) were carried out using spatio-temporal analyses following the recommendations of Mormede & Lyon (2023) and Thorson and others (Thorson 2019, Thorson et al. 2021):

- Although initial models included observer and survey data as well as commercial data, the final models only used commercial data as observer and survey data were too few and deemed unrepresentative of the school shark fishery.
- Models included bottom longline, bottom trawl, and set net fisheries together as these had different spatial and temporal distributions and none represented the entire stock. Sensitivity trials were carried out with alternative models for each fishing method separately.
- Spatio-temporal standardisation requires a measure of surface area. Because the bottom trawl width was considered unreliable, the measure of effort was defined as distance towed for bottom trawl, the total length of net for set nets and the total length of line for bottom longline. The width of bottom trawl and attraction distance for the other fishing methods was assumed constant and included in the 'method.target' parameter.
- The model distribution chosen was the delta-gamma distribution. The first component of a delta model (here a binomial distribution) estimates the probability of encountering a species at a given location and time, and the second component (here a gamma distribution) of the model estimates positive catch rates on condition that the species is encountered. The predicted biomass accounts for both the probability of presence and the catch rate given that the species is encountered. Delta-lognormal and Tweedie distributions were also tested but the models encountered convergence issues and these were not retained.
- The method used was '*grid*' and '*barrier*' to account for land barriers and refrain from smoothing over land.
- The number of knots used was 100. This was the maximum number of knots where the model still converged and provided marginal improvement in precision compared with 50 or 200 knots. Each knot represents the centre of each mesh cell used to split the space occupied by the fishery, whereby in this instance space was divided into 100 individual spatial areas with distinct underlying annual biomass.
- Spatial and temporal variation were assumed and estimated as random effects. Spatio-temporal effects were also estimated.

During model selection, potential explanatory variables were added to the models in a stepwise manner. Potential variables offered to the model were vessel as a random variable, a method.target combined parameter to allow for different target species for different fishing methods, season and speed (with a nominal speed for bottom longline and set net). The environmental parameters depth and turbidity were also tested as per Mormede & Lyon (2023), but were not retained in any model as they did not provide any improvement in fits and are not discussed further.

The model structure selected was a combination of 1) lower AIC, 2) highest deviance explained, and 3) no convergence or dispersion issues. A model was deemed to have no obvious convergence issues if no parameters hit a bound, the gradient of the marginal log-likelihood was less than 0.0001 for all fixed effects, and the Hessian matrix of second derivative of the negative log-likelihood was positive definite. Partial effect plots were also investigated to check for a significant effect.

2.3.4 Model outputs

Spatio-temporal standardisations provide a relative index of vulnerable biomass density per cell. Predicted relative biomass densities were carried out in the 32 km grid defined above, and relative biomasses were calculated by multiplying those densities by the surface area of each cell, taking into consideration part cells due to land masses. Relative estimates of biomass by fishery area, QMA or for the entire stock were then calculated by summing the local biomass in each cell for each area.

The models resulted in a single trend per area considered as opposed to a trend per fishing method and area as per the previous analysis. The trends were compared between areas, models and with previous analyses.

Because the spatio-temporal models were carried out at the scale of the entire New Zealand EEZ, they can be used to calculate the estimated proportion of the stock present in different areas. The proportion of school shark vulnerable biomass in each QMA was compared to the proportion of the total school shark TACC assigned to each of the QMAs.

2.4 Defining reference points

The Partial Quantitative Assessment of New Zealand school shark is based on an interpretation of the CPUE series, following the New Zealand Harvest Strategy Standard for low information stocks (Ministry of Fisheries 2011). Briefly, for each fishery area where a standardised CPUE series is accepted, a period of stable catch and CPUE is chosen as the reference point for the stock. This reference point might be deemed the target or limit level based on the rest of the CPUE series, catch history, survey information if available, and expert opinion of the working group. The status of each "stock" (fishery area) is then reported against this reference point (Fisheries New Zealand 2024).

Because up to 2024 some school shark fishery areas did not have an accepted CPUE series, they also did not have a reference point associated with them. With the development of spatio-temporal models at the scale of the New Zealand EEZ, standardised CPUE series for the entire school shark stock could be developed and a reference period could be defined.

2.5 Stock assessment model simulations

2.5.1 Introduction

Stock assessment model simulations using an age-structured assessment model were undertaken on school shark, with the objective of investigating operating models that could be used to inform exploitation rates and evaluate potential harvest strategies. We developed a preliminary pseudo-assessment model based on an age-sex structure model with a range of plausible biological parameters derived from published data and low information meta-analyses. Then, using these assumed biological parameters and the observed CPUE index, we simulated potential values of initial stock size and the resulting current stock status. These simulated models were then used to estimate current levels of exploitation and the level of exploitation required for the stock to be at the target reference point (i.e., 40% B_0). A simple constant exploitation rate harvest strategy was then applied.

2.5.2 Stock assessment model structure

A simple sex-age structured model was developed, with assumed biological parameters for school shark and implemented using Casal2 (Casal2 Development Team 2024). However, values for most of the biological parameters for school shark are not well known, including natural mortality (M), growth rates, maturity, and recruitment steepness, variability, and autocorrelation. While some data are available for these parameters, their uncertainty is high and stock-wide parameter values have not yet been developed for New Zealand school shark.

For the simulation study, potential uncertainty ranges for key biological parameters were derived from ether published estimates for New Zealand School Shark (i.e., the initial size in the growth curve, t_0) or from meta-analyses using the low-information methods of Thorson et al. (2017).

The initial size for the von Bertalanffy growth model was assumed to be t_0 = -1.6, based on pup size at birth of about 30 cm (Blackwell & Francis 2010). The remining biological parameters were estimated using the methods in Thorson et al. (2017). They introduced phylogenetic factor analysis to predict life-history parameters for fish species worldwide by analysing records of size, growth, maturity, and mortality parameters compiled from FishBase (Froese & Pauly 2000). This was implemented in the *R* package *Fishlife* (Thorson 2023) which can be used to provide an estimate of fish traits for all marine fish species globally based on an evolutionary model that approximates the co-evolution of life-history parameters representing adult growth, size, mortality, and maturity, as well as stock-recruit parameters. This incorporates phylogenetic dependencies and meta-analysis to help inform estimates of poorly defined or unknown life-history parameters across fish species.

Highly implausible values were truncated from these distributions (e.g., age of maturity greater than 25, steepness $h < 0.22$, and autocorrelation between annual recruitments > 0.5, and only considered values that were derived with a temperature range from 9–18° C, see Figure 2). While some parameters provided are unlikely to be realistic, the method does provide an approach to inform the range of parameter values when no other information is available. In addition, the simulations from Thorson et al. (2017) can be used to provide estimates of parameter correlations (Figure 3) that could also be used to inform the relationships between parameter estimates (Figure 3).

A total of 1000 simulated parameter sets were generated from the plausible values of biological parameters, and for each, a Casal2 model was constructed. These had a catch history based on the total catch of school shark over all areas, and an assumed length-based fishery selectivity. The fishery selectivity was based on the aggregated length distribution from the spatio-temporal analysis of length data above, and was assumed to be length-based (as the growth curve was unknown) and logistic shaped with parameters *a50*=75 cm and *ato95*=25 cm. We note that this is an approximation of the cumulative effect of setnet, trawl, and longline fisheries that occur on different components of the population, and specific selectivities, with associated catches, could be developed in future developments.

Five alternative model scenarios were run. In each case initial biomass (B_0) was estimated by fitting to the CPUE index and by freeing up estimation of year class strengths in the models:

- Model (01): The overall CPUE estimated from the spatial analysis was assumed to be an index of relative SSB, with mean = 0.4 SSB_0 for the period 2008–2012. This was to reflect the assumption that the index over the reference period (2008–2012) was when the stock was at the target (40% B_0).
- Model (02): The CPUE index was assumed to be a relative index of abundance (i.e., was not assumed to represent 40% B_0 over the reference period).
- Model (03): Model (01) but constraining h=0.5 to reduce the uncertainty in productivity as a sensitivity trial.
- Model (04): Model (01) but allowing YCS estimates to be estimated over the entire historical period.
- Model (05): Model (02) but allowing YCS estimates to be estimated over the entire historical period.

For each scenario, model estimates of B_0 (and YCS in the case of scenarios (ii) and (iv)) were calculated and estimates of current status and the SSB trajectory calculated. Then, for each scenario, an estimate of the harvest rate (a constant exploitation rate) was calculated to determine the optimum exploitation rate that would result in the stock being at 40% B_0. For these models, constant exploitation rate harvest strategies were applied, to determine whether the optimum exploitation rate could be estimated, and if so, how the models performed using this strategy.

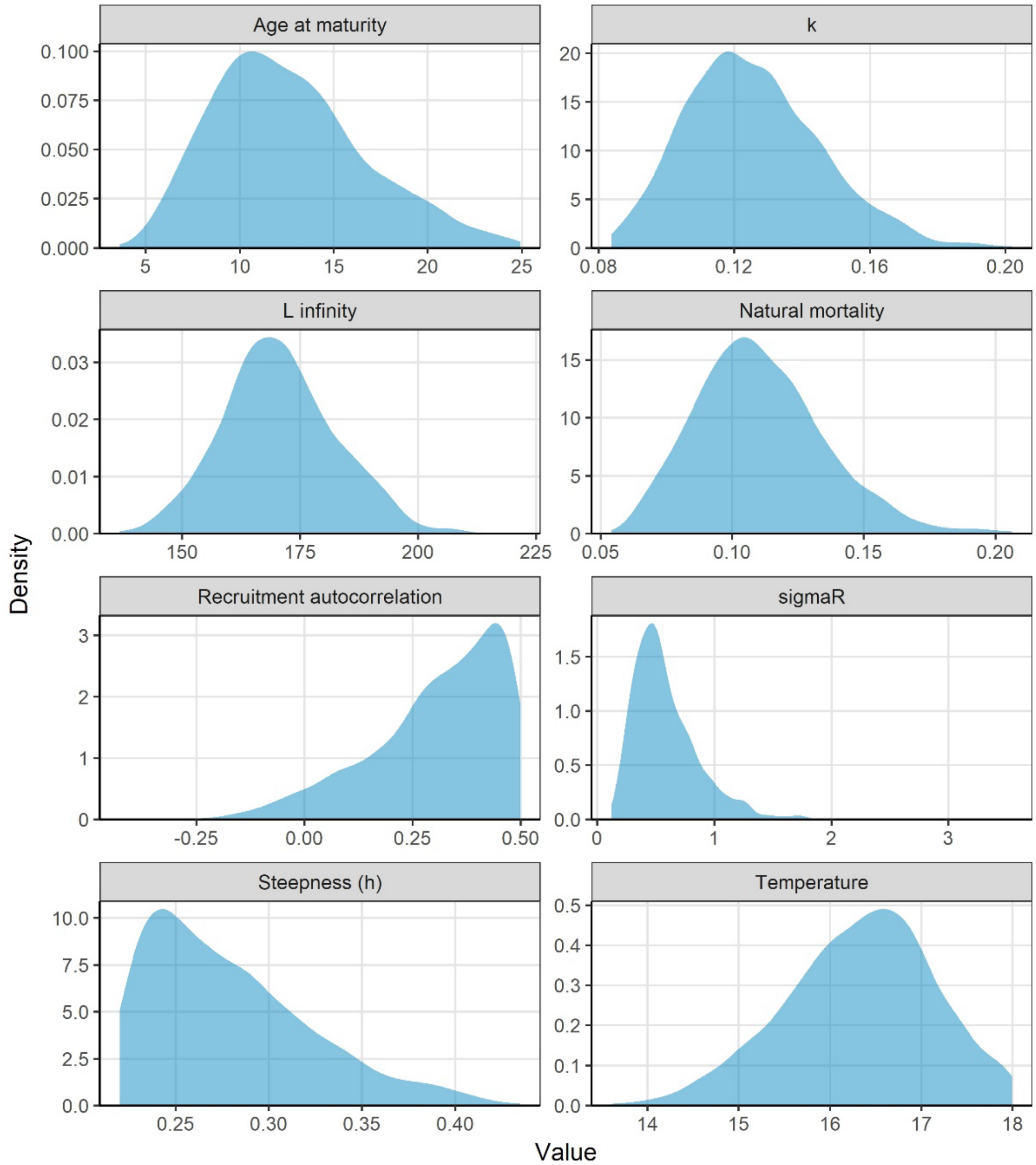

Figure 2: Potential biological parameter estimates from *Fishlife* meta-analysis for school shark.

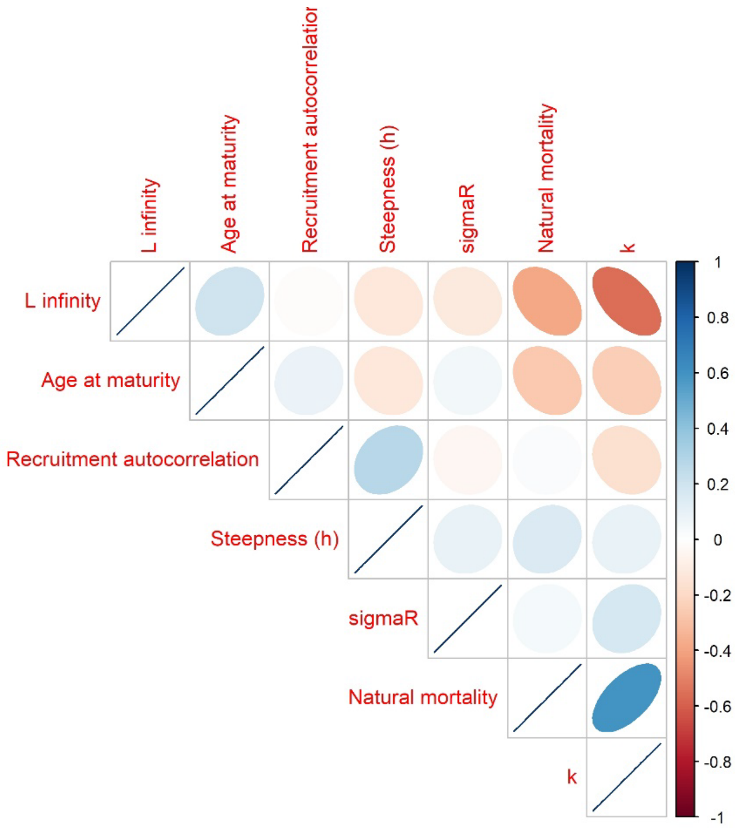

Figure 3: Correlations between biological parameter estimates from *Fishlife* meta-analysis for

3. RESULTS

3.1 Characterisation of the school shark fishery

School shark landings have been stable since the early 2000s: landings have been dominated by the landing code ‘dressed’ followed by ‘headed and gutted’ (Figure A.1); shark fins have consistently contributed to about 20% of landing records (Figure A.2) but less than 1% of annual total catch weight (Figure A.1). Furthermore, conversion factors have not changed since the early 1990s (Figure A.3). School shark was added to Schedule 6 in 2013, meaning that live school shark could be returned to the sea under certain circumstances but return declared using destination type X have been minimal (113 t since 2013). These returns have varied by QMA, with the majority of returns from SCH 3 and SCH 5 (Figure A.4).

Set net was historically the most important fishing method for school shark although the proportion of school shark caught annually by set net has dropped from about 60% in 1990 to under 40% in 2024. Conversely, the proportion of school shark caught by bottom trawl and bottom longline has increased to about 30% each in 2025. Catches by modular harvesting system (MHS) bottom fishing (reported as precision harvesting bottom fishing or PRB) have increased to about 8% in 2024, mostly from SCH 1 (Figure A.5). The proportion of catch by fishing method has been highly variable by QMA. For example SCH 4 is dominated by bottom longline while SCH 5 is dominated by set net (Figure A.6). School shark catches do not seem to be preferentially in harbours.

The majority of the school shark catch has come from set net and bottom longline fishing targeting school shark. Other target fisheries which have caught school shark were mainly the set net fishery for rig and the bottom longline fisheries for hāpuku, ling or snapper. School shark were also caught by bottom trawls targeting a multitude of species depending on location, including in order of decreasing total catch: tarakihi, gurnard, barracouta, school shark, stargazer and trevally (Figure A.7). The proportion of school shark by method and target species differed by QMA, in particular for bottom trawl (Figure A.8). School shark were typically in the top three recorded species for set net and bottom longline fishing, but their ranking was highly variable for bottom trawl (Figure A.9 to Figure A.11).

Catches of school shark have been highly seasonal for set net fishing in SCH 3, 5, 7 and 8, with most catches occurring in the summer season when school sharks are expected to be closer inshore. These trends were not as clear for bottom longline and not present in bottom trawl where a low proportion of the effort targeted school shark (Figure A.12).

The effort parameters for each fishing method have remained moderately stable, although the total set net length and corresponding number of sets per record dropped in 2020 when the electronic reporting system was introduced (ERS) and reporting requirements changed (Figure A.13 to Figure A.15).

Statistics and trends in target species during the 2019–20 to 2023–24 fishing years were as follows:

- SCH 1
    - About 41% of the total SCH 1 catch was taken by bottom trawl, followed by 28% by bottom longline, 19% by MHS bottom fishing, and 11% by setnet. The use of modular harvesting systems has been increasing in this fishery since 2015.
    - The method / target combinations of most importance were bottom trawl targeting tarakihi (23% of total catches), bottom longline targeting snapper (11%), and MHS bottom fishing targeting tarakihi (11%). Bottom longline, setnet and bottom trawl targeting school shark were the next highest catches at 9, 8 and 6% respectively of total school shark catches in SCH 1. Other method and target combinations each caught no more than 5% of total school shark catches in SCH 1.
- SCH 2
    - About 41% of the total SCH 2 catch were taken by setnet, followed by 27% by bottom trawl, 20% by bottom longline, and 10% by dahn line.
    - The method / target combinations of most importance were setnet targeting school shark (23% of total catches), bottom trawl targeting tarakihi (20%), bottom longline targeting school shark (7%), setnet targeting rig (7%), and bottom longline targeting hāpuku (6%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 2.
- SCH 3:
    - About 52% of the total SCH 3 catch were taken by setnet, followed by 28% by bottom trawl, and 17% by bottom longline.
    - The method / target combinations of most importance were setnet targeting school shark (24% of total catches) and rig (21%), and bottom longline targeting school shark (8%), hāpuku (7%), and bottom trawl targeting barracouta (7%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 3.
- SCH 4:
    - About 93% of the total SCH 4 catch were taken by bottom longline, and 6% by bottom trawl.
    - The method / target combinations of most importance were bottom longline targeting hāpuku (39% of total catches), school shark (28%), and ling (22%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 4.
- SCH 5:
    - About 75% of the total SCH 5 catch was taken by setnet, followed by 13% by bottom trawl and 11% by bottom longline.

    - The method / target combinations of most importance were setnet targeting school shark (71% of total catches) and bottom trawl targeting squid (20%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 5.
- SCH 7:
    - About 52% of the total SCH 7 catch were taken by bottom longline, followed by 43% by bottom trawl and 4% by setnet.
    - The method / target combinations of most importance were bottom longline targeting school shark (45% of total catches), and bottom trawl targeting tarakihi (10%), barracouta (8%) and gurnard (8%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 7.
- SCH 8:
    - About 41% of the total SCH 8 catch were taken by setnet, followed by 31% by bottom longline, 23% by bottom trawl, and 3% by MHS bottom fishing.
    - The method / target combinations of most importance were setnet targeting school shark (36% of total catches), bottom longline targeting school shark (24%), bottom trawl targeting tarakihi (7%), and bottom trawl targeting school shark (6%). Other method and target combinations each caught no more than 5% of total school shark catches in SCH 8.

Species caught as bycatch to the school shark fishery varied by fishing method. These are reported as a percentage of the school shark catch for those fisheries. Between 2020 and 2024,

- The only bycatch species of bottom longlines targeting school shark were hāpuku with a total weight of hapuku caught of 15% of the total school shark catch weight by those same bottom longlines targeting school shark, ling (14%), spiny dogfish (10%), and northern spiny dogfish (8%).
- The only bycatch species of setnet targeting school shark were rig (16% of school shark landed by setnet), spiny dogfish (10%) and carpet shark (7%).
- The main bycatch species of bottom trawl representing over 5% of the school shark catch landed by bottom trawl were tarakihi (98% of school shark landed by bottom trawl), ghost shark (32%), snapper (30%), spiny dogfish (26%), barracouta (26%), rig (25%), rattail (21%), gurnard (20%), john dory (16%), gemfish (15%), stargazer (14%), smooth skate (11%), spotted gurnard (11%), carpet shark (10%), trevally (8%), silver dory (7%), red cod (6%), and porcupine fish (6%). We note that the bottom trawl target fishery is small (Figure A.7).

3.2 Spatio-temporal analysis of length data

The unscaled observer length distribution of school shark by fishing method and QMA indicated that differences in sizes caught by the different fishing methods was more likely to be due to spatial effects rather than gear type (Figure B.1). Similar patterns were observed in the AMP data.

A spatio-temporal model of length data was carried out for school shark for the entire New Zealand EEZ caught by all three main fishing methods (bottom longline, bottom trawl and set net) and reported on all three data sources (observer, AMP and survey). Space was represented with about 3500 cells distributed over the entire area covered by the data (Figure B.2).

Both the DIC and WAIC suggested that the most complex models were the most parsimonious models for explaining length (Table B.1). The length model suggested that larger fish were predominantly on the Chatham Rise, around the north-east of the North Island and the south of the South Island, supporting the hypothesis of a single New Zealand stock (Figure 4). Clusters indicated differing parts of the population on the Chatham Rise, the south of the South Island, and then mostly inshore or offshore, with limited correspondence with the 2014–2024 school shark fishery areas or QMAs.

Partial effects plots indicated that set net fishing might catch slightly larger animals than bottom longline or bottom trawl, although this effect could be because set net fishing mostly targets school shark. The results also indicated that the survey might capture smaller animals, and that there is some level of inter-annual variability. (Figure B.3).

Interactions between space and sex were not significant, indicating that animals of same size did not seem to segregate spatially by sex. A season × space effect was significant and indicated an increase in smaller animals near Banks Peninsula in spring, although the extent to which this pattern might have been driven by sampling artefacts is unknown (Figure B.4)

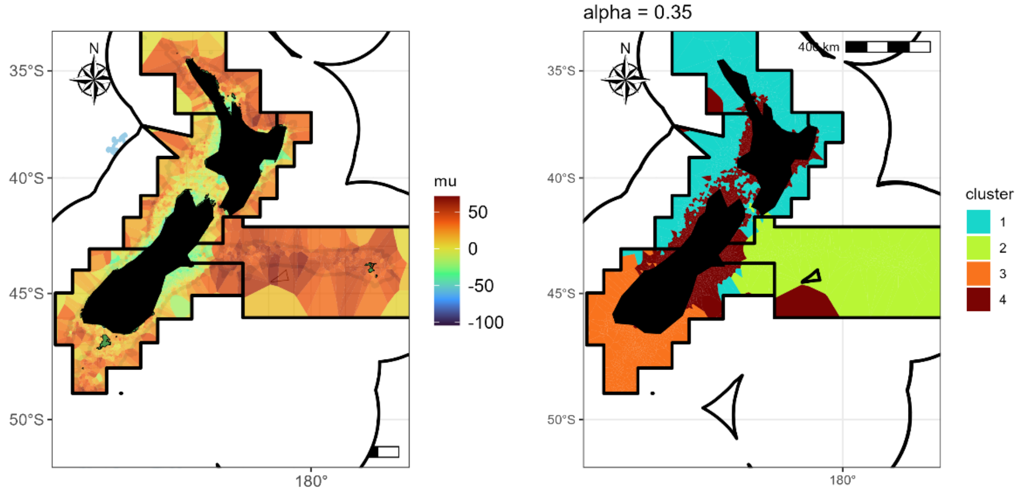

Figure 4: The spatial effect for the chosen model of Length ~ Intercept + Fishing method + Year + Sex + Season + Data source + Space (left) and resulting optimum clusters (alpha = 0.35). Mu is the deviance from the mean length. The 2014–2024 school shark fishery areas are represented by the black lines.

3.3 Spatio-temporal CPUE standardisation

3.3.1 Data selection for spatio-temporal CPUE standardisation

The target species to include in the spatio-temporal CPUE standardisation were selected by identifying the fisheries that represented the most cumulative catch of school shark and effort for each fishing method (Figure C.1). For set net and bottom longline, over 90% of the catch and 80% of the effort was represented by the top five target species. However, there has been very little school shark targeting by bottom trawl, and bottom trawl species targeting differs by area, so the top thirteen target species accounted for over 90% of the school shark catch and 80% of the bottom trawl effort within the school shark region. The top ten target species accounted for about 85% of school shark catches and 75% of effort by bottom trawl. The final data selection was the top five target species for set net and bottom longline independently, and the top ten for bottom trawl, with a sensitivity trial using the top thirteen species.

The characteristics of the three fishing methods also resulted in a very imbalanced dataset, in which most of the records came from the bottom trawl fishery which only represented a small fraction of the total school shark catch (Figure C.2). Spatio-temporal standardisation should be robust to such imbalance provided there is good spatial overlap between the methods.

Once the methods and their respective target species were selected, core vessel selection was carried out. With the aim of retaining 80% of the total catch with a stable fleet, core vessels were defined as those vessels with at least 100 records and 11 years in the fishery between 2008 and 2024 (Figure

C.3). These data were then aggregated at the 32 km scale as detailed in Section 2.3.1. The proportion of positive records for each fishery remained relatively stable over time, with about 20% of bottom trawl, 40% of bottom longline and 70% of set net records reporting catching school shark (Figure C.4).

An investigation into the spatio-temporal overlap of the final dataset indicated that at the 32 km scale, set net covered 59% of the total school shark area with an annual average of about 25%, whilst bottom longline and bottom trawl covered about 90% each, with an annual average in excess of 50% (Figure C.5). This is not surprising given that in this dataset set nets are typically limited to shallower depths closer to shore and targeted school shark (Figure C.6), while the bottom longline and bottom trawl fisheries extended much further out to sea (Figure C.7 and Figure C.8).

3.3.2 Developing the base case spatio-temporal CPUE model

The 100 knots for the model were distributed over the area covered by the data in proportion to data density (Figure C.9). The spatio-temporal distribution of the data was adequate (Figure C.10). The most parsimonious standardisation model included the year:space parameter and the method.target parameter only (Table C.1). Interestingly, the vessel parameter (offered as a random effect variable) was not significant even though it was often the most influential parameter in the previous non-spatially explicit CPUE standardisations of school shark (Tremblay-Boyer 2021), indicating that the vessel effect seen in previous standardisations was likely to have been an alias for spatial effects. Both the space and method.target parameters had a strong influence on the standardisation whilst none of the other parameters offered did (Figure C.11).

Partial effects plots of the method.target parameter indicated that bottom trawl had a lower probability of catching school shark, as indicated in the raw data (Figure C.4), but that the density given presence was driven by the target species rather than fishing method (Figure C.12). Spatio-temporal density distributions and relative density distributions indicated variable distribution of school shark over time (Figure C.13 and Figure C.14). Higher densities of school shark were expected on the Chatham Rise and west of New Zealand in 2008–2014, but on the east side of New Zealand in 2022–2024, indicating a highly mobile species. Scaled residuals were generally adequate, although they indicated that set net data might not be adequate for QMAs such as SCH 2 or SCH 7 (Figure C.15 and Figure C.16). Because the set net fishery is highly discrete and targets school shark specifically, it might not be representative of the entire population.

3.3.3 Sensitivity runs

The effect of the minimum number of records per cell (1, 10 or 25), aggregation time (daily or monthly) and number of target species for bottom trawl (10 or 13) was tested on the base case model. None of these had any significant effect on the standardised CPUE. Changing the aggregation calculation of continuous variables from mean as originally carried out to median as requested by the Inshore Working Group resulted in a small effect in the early and late years of the series, effectively flattening the series slightly.

Sensitivity runs were carried out in which the base model was rerun with a single fishing method at a time. Using only one fishing method at a time resulted in the reduction in the data included in the model and the spatial extent of that data. (Table C.2). The standardised CPUE series for the entire stock were similar between models, although the model with bottom longline only was more variable than the other series (Figure 5). However, there were differences by QMA reflecting, in particular, data availability and area coverage, for example in SCH 4 which has virtually no set net information (Figure C.17). Models by fishing method allowed the comparison of spatio-temporal standardisation with the previous standardisation by fishery area (Figure C.18).

Additional sensitivity runs were carried out on some of the models with a single fishing method. The model with bottom trawl only was rerun offering speed as an explanatory parameter, to investigate the impact of not including speed in the base model because of the bottom longline and set net data. Speed was not selected as an explanatory variable for the model with bottom trawl only. The bottom longline only model was also investigated further as it presented the most variable index over time. Removing the snapper fishery, adding vessel as a random effect or aggregating data at a 16 km scale were tested but did not result in any meaningful changes to the model output.

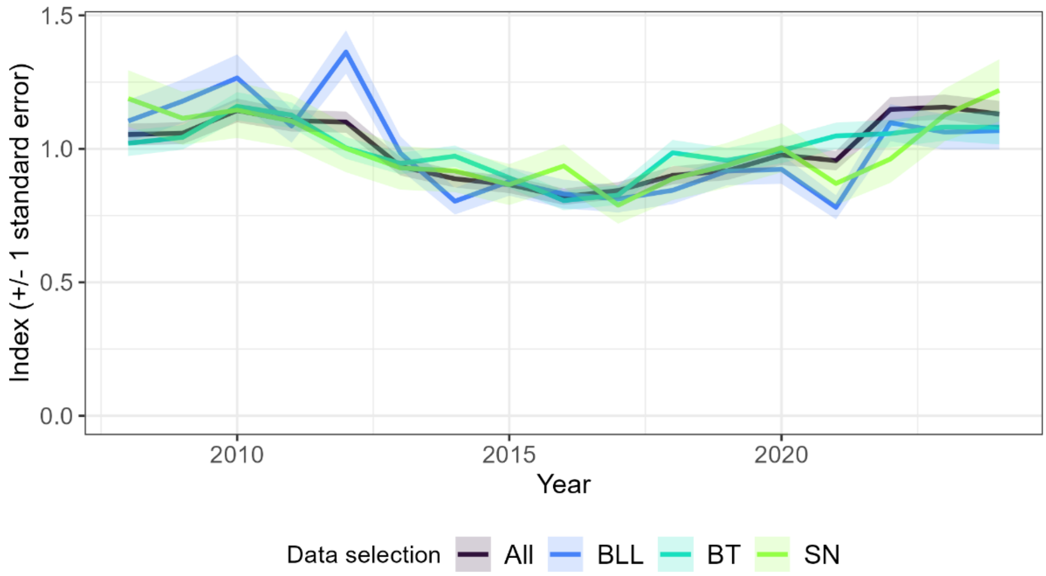

Figure 5: Relative index of vulnerable biomass of school shark for the models with data from all fishing methods (All), bottom longline only (BLL), bottom trawl only (BT) or set net only (SN).

3.3.4 Spatial distribution of the school shark population

One of the many advantages of developing spatio-temporal models of school shark catch and effort for the entire EEZ is that they can not only provide trends of vulnerable biomass by QMA (Figure C.19) but also relative biomass between the different QMAs (Figure C.20). For example, even though relative indices indicate a strong increase in the biomass in SCH 2, it represents a small proportion of the total stock and the increase could be explained by a small change in movement between SCH 1 and SCH 2.

The relative proportion of the vulnerable biomass of school shark in the different QMAs was compared with the current distribution of the total allowable commercial catch (TACC). Results indicate that the proportion of total TACC for each QMA are similar to the expected population distribution based on the base case model although the relative TACC between QMAs could be adjusted to better match the expected distribution of the school shark vulnerable biomass (Table C.3 and Figure C.21).

3.4 Status of the stock

The base model with all fishing methods and space:year and method.target parameters was chosen for management purposes, and applied to the entire stock (Fisheries New Zealand 2025). The period of 2012 to 2018 was chosen as the reference period because it had high stable catches and high stable relative abundance (Figure 6). Because of the stability of the catches over the entire fishery, this period was assumed to represent the target biomass, and mean relative fishing pressure for this period was used to calculate the overfishing threshold (Figure C.22). The relative biomass indices by QMA were also reported for management purposes (Figure C.23).

Although the assessment results were provided at the level of the entire stock, indices for the previously used fishery areas were also extracted from the base case model and compared with the previous assessment results (Figure C.24). The area of most change compared with previous assessment was SCH781W, which was previously based on a limited area survey index because of a lack of suitable standardised CPUE series (Fisheries New Zealand 2021).

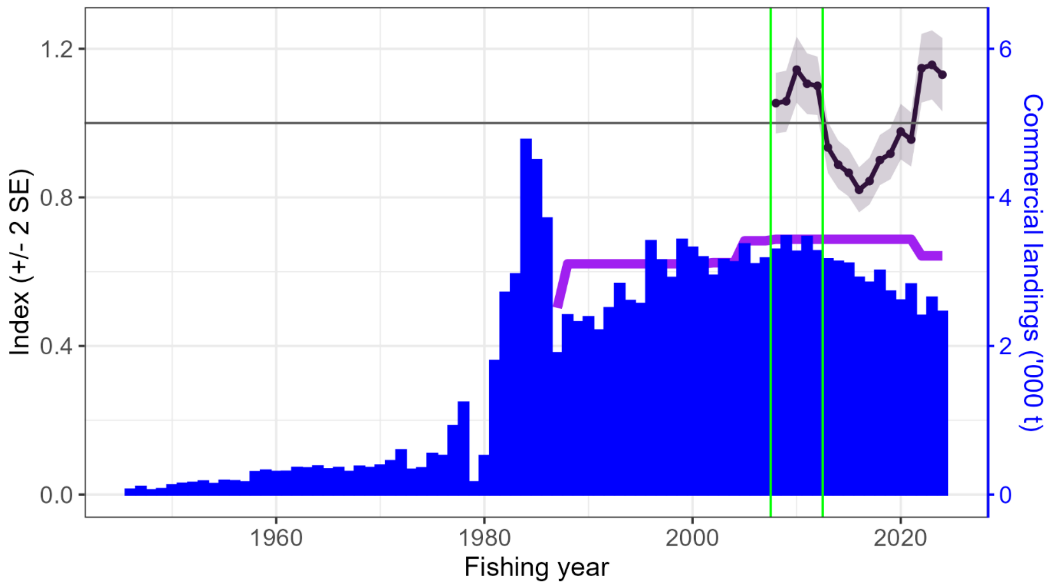

Figure 6: Relative vulnerable biomass of school shark for the entire stock (black line and dots) and 2 standard errors (grey area). Also included are total landings of school shark (blue bars) and total TACC (purple line). The target period (2008–2012) used for the assessment in 2025 is depicted by the green vertical lines.

3.5 Stock assessment model simulations

The stock assessment model simulations were run using the biological and selectivity parameters described above. Model fits to the CPUE index were poor for the model runs, with the pattern in CPUE unlikely given the model assumptions. In model (01), the decline in the index forced by the assumption that the stock was at 40% B_0 suggested that the current catch would have resulted in a continued decline (Figure 7). Model fits to the CPUE index were unable to reproduce the pattern in the estimated CPUE indices (Figure 8). This was similar to both model (02) (see Figure 9) and (03) where the year class strengths were assumed to fluctuate about an average of one. In the case of models (04) and (05), a strong pattern in the year class strength estimates were required to allow the stock to initially decline, then increase (Figure 10). In all cases, the uncertainty in the biological parameters led to wide bounds in estimates of the spawning stock biomass trajectory.

Estimation of the harvest rate for each model resulted in very low exploitation rates (U=0.01–0.03) that maintained the stock at target levels (40% B_0), and only extremely low exploitation rates that maintained the stock above 20% B_0 with a probability of at least 90%. The estimation of such low exploitation rates was due to the wide uncertainty in the biological parameters, specifically the values assumed for stock recruitment steepness (h), natural mortality (M) and the age of maturation.

Application of a constant exploitation rate harvest strategy was confounded by this level of uncertainty, and a lack of information on the true level of biomass led each to maintain the stock at or about the current levels (with wide bounds), rather than move towards a target level. Attempts to estimate a harvest strategy where the stock had a high probability of being above the 20% limit reference point failed — the underlying uncertainty in the biological parameters resulted in highly variable stock trajectories.

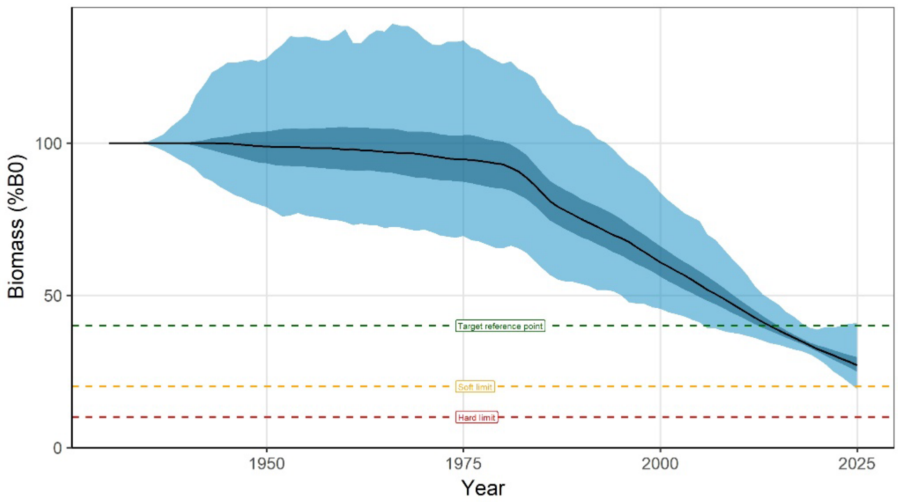

Figure 7: Estimated stock SSB trajectory for school shark, based on 1000 simulated biological parameters and assuming that the reference period (2008–2012) was 0.4 B_0 (model 01). The solid line indicates the median trajectory, with the interquartile range (dark shading) and 95% CIs (light shading). The target and limit reference (soft and hard) points are shown as horizontal dashed lines (green, yellow, and red respectively).

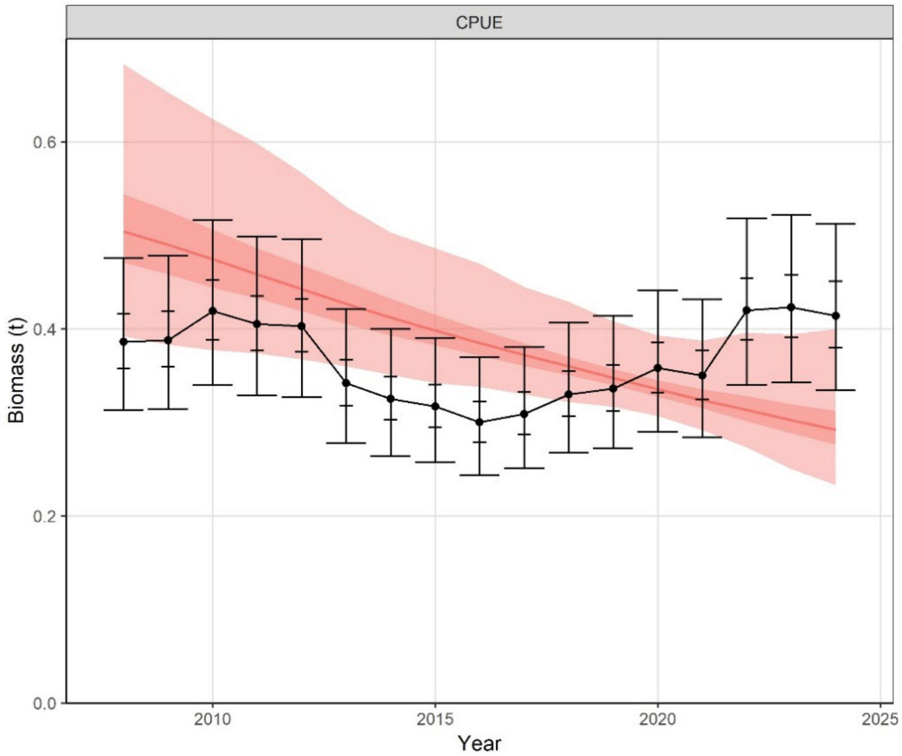

Figure 8: Estimated model fits to the CPUE index for school shark, based on 1000 simulated biological parameters and assuming that the reference period (2008–2012) was 0.4 B_0 (model 01). The black points represent the observed values, with black vertical lines indicating the observed CV (small ticks) and overall CV (large ticks, assuming 0.2 CV process error). The solid red line indicates the median trajectory, with the interquartile range (dark red shading) and 95% CIs (light red shading).

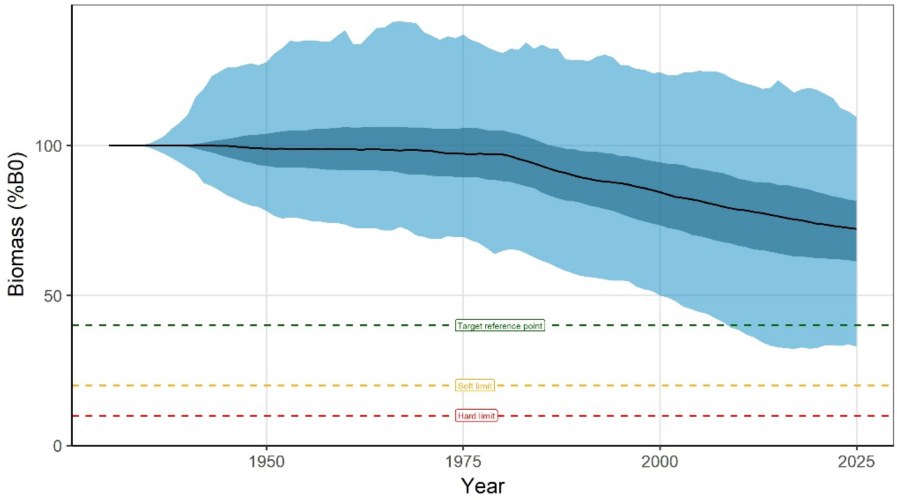

Figure 9: Estimated stock SSB trajectory for school shark, based on 1000 simulated biological parameters and fitting to the CPUE as a relative index of abundance (model 02). The solid line indicates the median trajectory, with the interquartile range (dark shading) and 95% CIs (light shading). The target and limit reference (soft and hard) points are shown as horizontal dashed lines (green, yellow, and red respectively).

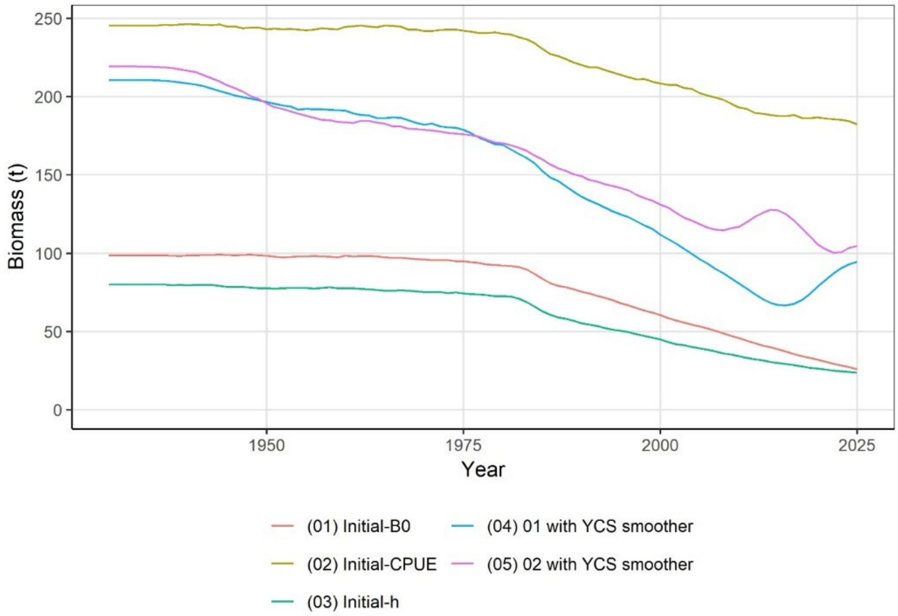

Figure 10: Median model trajectories for Models (01)–(05) for school shark, based on 1000 simulated biological parameters.

4. DISCUSSION

The results of this study provide important insights into the spatial and temporal patterns of school shark distribution and abundance in New Zealand waters. The spatio-temporal CPUE standardisation represents a significant advancement over previous non-spatially explicit approaches, addressing long-standing concerns about conflicting trends between fishing methods in the same fishery areas (Fisheries New Zealand 2021; Tremblay-Boyer 2021).

Preliminary simulations attempting to evaluate a harvest strategy highlighted the uncertainty in the biological parameters, suggesting that application of a harvest strategy that maintained the stock with a high probability of being above 20% B_0 and at the target of 40% B_0 would require refinement of the values of the underlying biological parameters for school shark, specifically stock recruitment relationship steepness (h) and natural mortality (M).

4.1 Fishery characterisation and temporal patterns

The characterisation confirms that the New Zealand school shark fishery has remained relatively stable since the early 2000s. The shift from set net dominance (60% in 1990) to a more mixed fishery incorporating bottom trawl and bottom longline methods (each about 30% in 2024) reflects broader changes in fishing practices, affecting the spatial distribution of catch and effort, particularly the impact of dolphin closures on the set-net fishery.

The seasonal patterns observed, particularly the increase in set net catches in SCH 3, 5, 7, and 8 in the summer and changes in length distributions in the different seasons, align with known school shark behaviour where animals move closer inshore during summer months (Hurst et al. 1999). The absence of strong seasonal patterns in bottom trawl catches is consistent with this method mostly targeting species other than school shark and with the broader spatial coverage.

4.2 Spatial distribution of lengths and stock structure

The spatio-temporal analysis of length data provides evidence supporting the hypothesis of a single New Zealand school shark stock, as larger fish were found predominantly on the Chatham Rise, around the northeast of the North Island, and south of the South Island. This distribution pattern suggests ontogenetic movements or size-based habitat preferences rather than separate school shark stocks around New Zealand. The lack of significance of the space × sex interaction parameter in the spatial length model indicates that size-based segregation is not sex-specific, further supporting a single stock hypothesis.

The clustering analysis revealed spatial groupings based on fish size that showed limited correspondence with the 2014–2024 fishery areas, suggesting that these might not have reflected biological population structure or stocks. This finding has important implications for future management strategies and supports the shift toward a New Zealand-wide assessment.

These results are in concordance with tagging studies which suggested a single biological stock in the New Zealand EEZ. An opportunistic tagging programme that examined school shark movements via satellite telemetry and mark recapture data was undertaken mainly on research trawlers starting in 1985 (Hurst et al. 1999; Blackwell & Francis 2010). A large proportion of tagged school sharks moved outside the QMA of release within 5 years, and a significant proportion eventually moved to Australia. Another tagging program was undertaken in 2020–2023, whereby large female school sharks were tagged with satellite tags in the Kaipara Harbour and observed to migrate between widely dispersed locations within and beyond the latitudinal extent of mainland New Zealand (Burton 2025).

4.3 CPUE standardisation

The performance of spatio-temporal models over traditional approaches is consistent with recent advances in fisheries science (Thorson & Barnett 2017; Grüss et al. 2019; Ducharme-Barth et al. 2022; Mormede & Lyon 2023). Modelling multiple methods in the same spatio-temporal framework is not new (e.g., Grüss et al. 2017; Edwards 2023; Proudfoot et al. 2024). It allows the different spatial and temporal distributions of data to be integrated into a single assessment to cover the entire range of school shark. It does assume that the three fishing methods sample the same underlying population component when in the same location, meaning that there is little difference in terms of selectivity of the different fishing methods. The similar selectivity patterns across fishing methods, as indicated by the length analysis, support this assumption (Figure B.1 and Figure B.3).

Sensitivity trials were carried out in which models were developed for each fishing method independently. Although these had generally the same overall trend in biomass, none of these models covered the entire area of school shark and therefore could not provide reliable local area biomass indices for all QMAs. Furthermore, the discrete nature of the set net fishery and its specific targeting of school shark may limit its representativeness of the broader population, as suggested by the residual patterns in some QMAs.

The only parameter of significance to the models, additional to the space and year interaction, was the method.target combined parameter. The finding that vessel effects, previously identified as highly influential in non-spatial standardisations (Tremblay-Boyer 2021), were not significant in the spatio-temporal models, suggested that these effects were largely aliasing spatial patterns. This result demonstrates the importance of explicitly accounting for spatial structure in CPUE standardisations, particularly for highly mobile species like school shark, as recommended by Mormede & Lyon (2023).

The spatio-temporal modelling approach combining all fishing methods provides several advantages for the assessment of school shark. First, it generates a single trend for the entire stock rather than potentially conflicting trends by fishing method and area. Second, it allows the estimation of the proportion of vulnerable biomass in different areas, enabling the evaluation of current TACC allocations against estimated stock distribution.

The comparison between model-estimated biomass proportions and current TACC allocations (Table C.3) suggests that the existing quota distribution broadly reflects stock distribution patterns, although some fine-tuning may be warranted. The relatively close alignment provides confidence in both the model outputs and existing management frameworks.

Management advice was provided based on the model combining all three fishing methods, for the entire school shark stock together. 2012–2018 was selected as the reference period given the stability and high values for both catches and relative abundance during this time. Given the long history of the school shark fishery in New Zealand with stable catches, this period is likely to represent a maximum sustainable exploitation level, supporting its use as a target reference point under New Zealand's low-information stock harvest strategy standard (Ministry of Fisheries 2011).

The current assessment suggests that school shark stock is at or near the target level, with the 2023–24 biomass estimate within the target range established from the 2012–2018 reference period. The stability of the fishery over recent decades, combined with the spatio-temporal analysis showing no evidence of range contraction or major abundance declines, supports the current "Least Concern" conservation status when assessed using the IUCN Red List Categories and Criteria (Finucci et al. 2019). However, the highly mobile nature of school shark, demonstrated by both the spatial analysis and previous tagging studies (Hurst et al. 1999), emphasises the importance of continued monitoring and adaptive management approaches.

4.4 Model Performance and Limitations

The spatio-temporal models demonstrated good convergence properties and explained a high proportion of deviance (88.9% for the base case model). The inclusion of the method-target parameter was crucial for model performance, highlighting the importance of accounting for different catchability rates between target species and fishing methods.

Several limitations should be acknowledged. The uneven spatial coverage of different fishing methods, particularly the nearshore limitation of set nets, may affect model predictions in data-sparse areas. The aggregation of data to monthly intervals and 32 km spatial resolution, while computationally necessary, may smooth over finer-scale patterns, particularly for bottom longline and set net which operate at a much finer scale. Additionally, the assumption of constant selectivity across methods and over time, while supported by the length analysis, may not hold under all circumstances.

The residual patterns, suggesting potential inadequacy of set net data for representing the entire population in some QMAs, warrant further investigation. Future work might benefit from developing hierarchical models that account for different representativeness of fishing methods. The validity of using all three methods within a single modelling framework could also be investigated through a simulation framework.

4.5 Comparison with Previous Assessments

The spatio-temporal indices show broad consistency with previous assessments where data were adequate, providing confidence in the new approach. The most significant change was for area SCH781W, which previously relied on limited survey data due to inadequate commercial CPUE series (Fisheries New Zealand 2021). The new approach provides more robust abundance indices for all areas by leveraging the full spatial extent of commercial data.

4.6 Future Research Considerations

This assessment was reviewed by the Stock Assessment Plenary in May 2025. The Plenary identified the following future research consideration related to CPUE modelling of school shark:

Spatio temporal modelling of abundance

- *Investigate the statistical validity of using multiple fishing methods with different selectivities in a single spatio-temporal CPUE standardisation model using simulations. {relevant for multiple species}*
- *Explore other model structures and data sources for SCH including*
  - *QMA-scale spatio temporal models (as a sensitivity test of the assumptions of the nationwide model)*
  - *modelling of residual variance by method.target, following the approach presented in Grüss & Thorson (2019)*
  - *putting an autoregressive structure (ideally a first-order autoregressive structure) on spatio temporal variation to account for large changes in the spatial footprint of fishing methods from one year to another*
  - *QMA specific method.target terms*
  - *incorporating DHARMa residuals and other spatio temporal modelling advances*
  - *aggregating data with mean positional data*
  - *inclusion or exclusion of different data sets (e.g., survey series, SN data, non-target fisheries)*
  - *using smaller grid sizes (particularly for SN and BLL)*
  - *the potential of a statistical area resolution model starting in the 1990s*
- *Investigate the potential for bias in the indices if the spatial effect aliases for vessel effect in spatio temporal CPUE analysis.*
  - *Identify more rigorously the reasons why vessel ID is not influential in the spatio-temporal model.*

5. FULFILMENT OF BROADER OUTCOMES

As required under Government Procurement rules[3], Fisheries New Zealand considered broader outcomes (secondary benefits such as environmental, social, economic, or cultural benefits) that would be generated by this project.

Whakapapa links all people back to the land, sea, and sky, and our obligations to respect the physical world. This research aims to ensure the long-term sustainability of tupere (school shark) stocks, for the good of the wider community (including stakeholders and the public) and the marine ecosystems that they inhabit.

This project supports regional businesses, diversity and inclusion, and our research is inextricably linked to the moana from the work it carries out and the tangata whenua it supports. All researchers and companies involved are New Zealand owned, based and operated. As part of this project, the team has continued to build capacity and capability in fisheries science and stock assessment.

The team is committed to zero waste and carbon neutrality, environmental stewardship and social responsibility. Ocean Environmental and soFish Consulting are net zero emission companies.

6. ACKNOWLEDGEMENTS

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[3] https://www.procurement.govt.nz/procurement/principles-charter-and-rules/government-procurement-rules/planning-your-procurement/broader-outcomes/

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8. APPENDIX A – Characterisation

Table A.1: Species codes, common names and scientific names for the target species part of the 2021 definition of the school shark fishery.

Species code	Common name	Scientific name
BAR	Barracouta	*Thyrsites atun*
BNS	Bluenose	*Hyperoglyphe antarctica*
ELE	Elephant fish	*Callorhinchus milii*
FLA	Flats	
GUR	Gurnard	*Chelidonichthys kumu*
HOK	Hoki	*Macruronus novaezelandiae*
HPB	Hapuku & bass	*Polyprion oxygeneios & P americanus*
JDO	John dory	*Zeus faber*
LIN	Ling	*Genypterus blacodes*
MOK	Moki	*Latridopsis ciliaris*
RCO	Red cod	*Pseudophycis bachus*
SCH	School shark	*Galeorhinus galeus*
SKI	Gemfish	Rexea *spp.*
SNA	Snapper	*Pagrus auratus*
SPO	Rig	*Mustelus lenticulatus*
SQU	Arrow squid	*Nototodarus sloanii & N. gouldi*
STA	Giant stargazer	*Kathetostoma spp.*
SWA	Silver warehou	*Seriolella punctata*
TAR	Tarakihi	*Nemadactylus macropterus & N. rex*
TRE	Trevally	*Pseudocaranx georgianus*
WAR	Common warehou	*Seriolella brama*

Table A.2: Species codes, common names and scientific names for the other species included in this analysis.

Species code	Common name	Scientific name
ABR	Shortsnouted lancetfish	*Alepisaurus brevirostris*
AER	Aeneator recens	*Aeneator recens*
ALB	Albacore tuna	*Thunnus alalunga*
APL	Pelagic thresher	*Alopias pelagicus*
BCA	Barracudina	*Magnisudis prionosa*
BCO	Blue cod	*Parapercis colias*
BDA	Barracuda	*Sphyraena novaehollandiae*
BLU	Bluefish	*Girella cyanea*
BPE	Butterfly perch	*Caesioperca lepidoptera*
BUT	Butterfish	*Odax pullus*
BYX	Alfonsino & long-finned beryx	*Beryx splendens & B. decadactylus*
CAR	Carpet shark	*Cephaloscyllium isabellum*
CDL	Cardinalfish	*Epigonidae*
CRA	Rock lobster	*Jasus edwardsii*
EMA	Blue mackerel	*Scomber australasicus*
FLO	Flounder	
GMU	Grey mullet	*Mugil cephalus*
GSH	Ghost shark	*Hydrolagus novaezealandiae*
HAK	Hake	*Merluccius australis*
HHS	Hammerhead shark	*Sphyrna zygaena*
JGU	Spotted gurnard	*Pterygotrigla picta*
JMA	Jack mackerel	*Trachurus declivis, T. murphyi, T. novaezelandiae*
KAH	Kahawai	*Arripis trutta, A. xylabion*
KIN	Kingfish	*Seriola lalandi*
KOH	Koheru	*Decapterus koheru*
LDO	Lookdown dory	*Cyttus traversi*
LEA	Leatherjacket	*Meuschenia scaber*
MDO	Mirror dory	*Zenopsis nebulosa*
ORH	Orange roughy	*Hoplostethus atlanticus*
OSD	Other sharks and dogs	*Selachii*
PAD	Paddle crab	*Ovalipes catharus*
PIP	Pipefish	*Syngnathidae*
PMA	Pink maomao	*Caprodon longimanus*
POR	Porae	*Nemadactylus douglasii*
RBY	Rubyfish	*Plagiogeneion rubiginosum*
REC	Red rock crab	*Guinusia chabrus*
RIB	Ribaldo	*Mora moro*
RPE	Red perch	
RRC	Red scorpion fish	*Scorpaena cardinalis & S. papillosus*
RSK	Rough skate	*Zearaja nasuta*
RSN	Red snapper	*Centroberyx affinis*
SCI	Scampi	*Metanephrops challengeri*
SDO	Silver dory	*Cyttus novaezealandiae*
SFI	Starfish	*Asteroidea & Ophiuroidea*
SND	Shovelnose spiny dogfish	*Deania calcea*
SPD	Spiny dogfish	*Squalus acanthias*
SPE	Sea perch	Helicolenus *spp.*
SPZ	Spotted stargazer	*Genyagnus monopterygius*
STG	Stargazer	
SWO	Broadbill swordfish	*Xiphias gladius*
THR	Thresher shark	*Alopias vulpinus*
TRA	Roughies	*Trachichthyidae*
TRU	Trumpeter	*Latris lineata*
WRA	Longtailed stingray	*Dasyatis thetidis*
WWA	White warehou	*Seriolella caerulea*

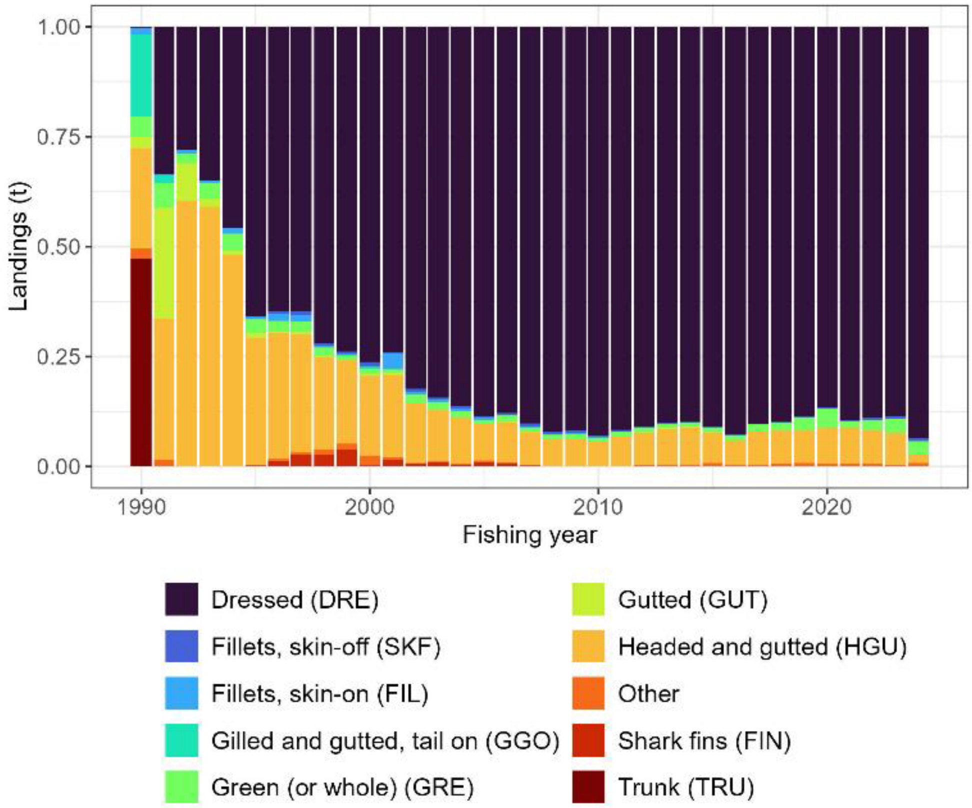

Figure A.1: School shark landings (t) by state code over time.

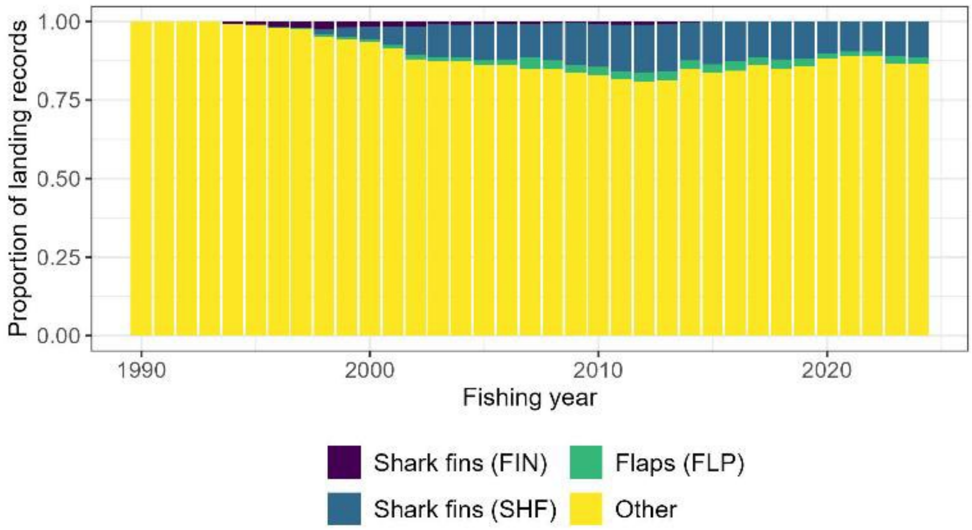

Figure A.2: Proportion of school shark landing records as fins.

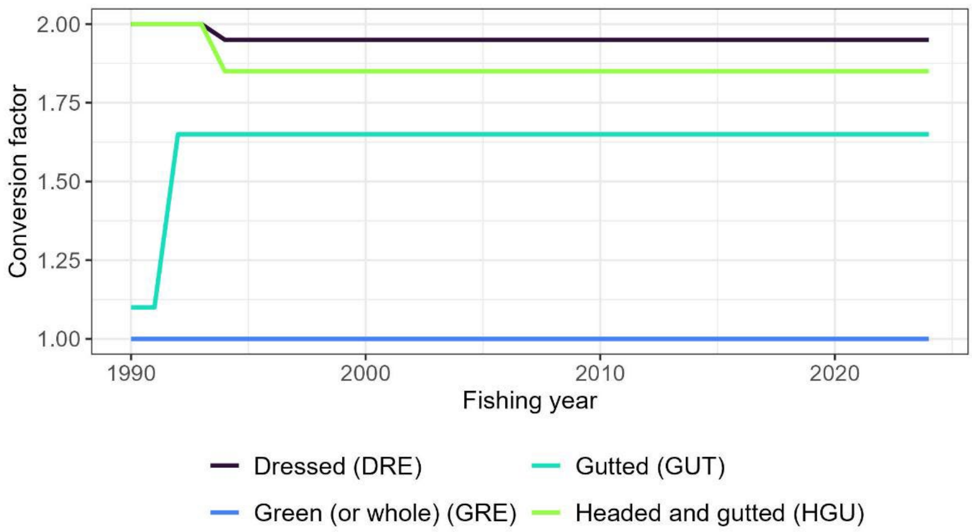

Figure A.3: Average reported conversion factor over time per landed state.

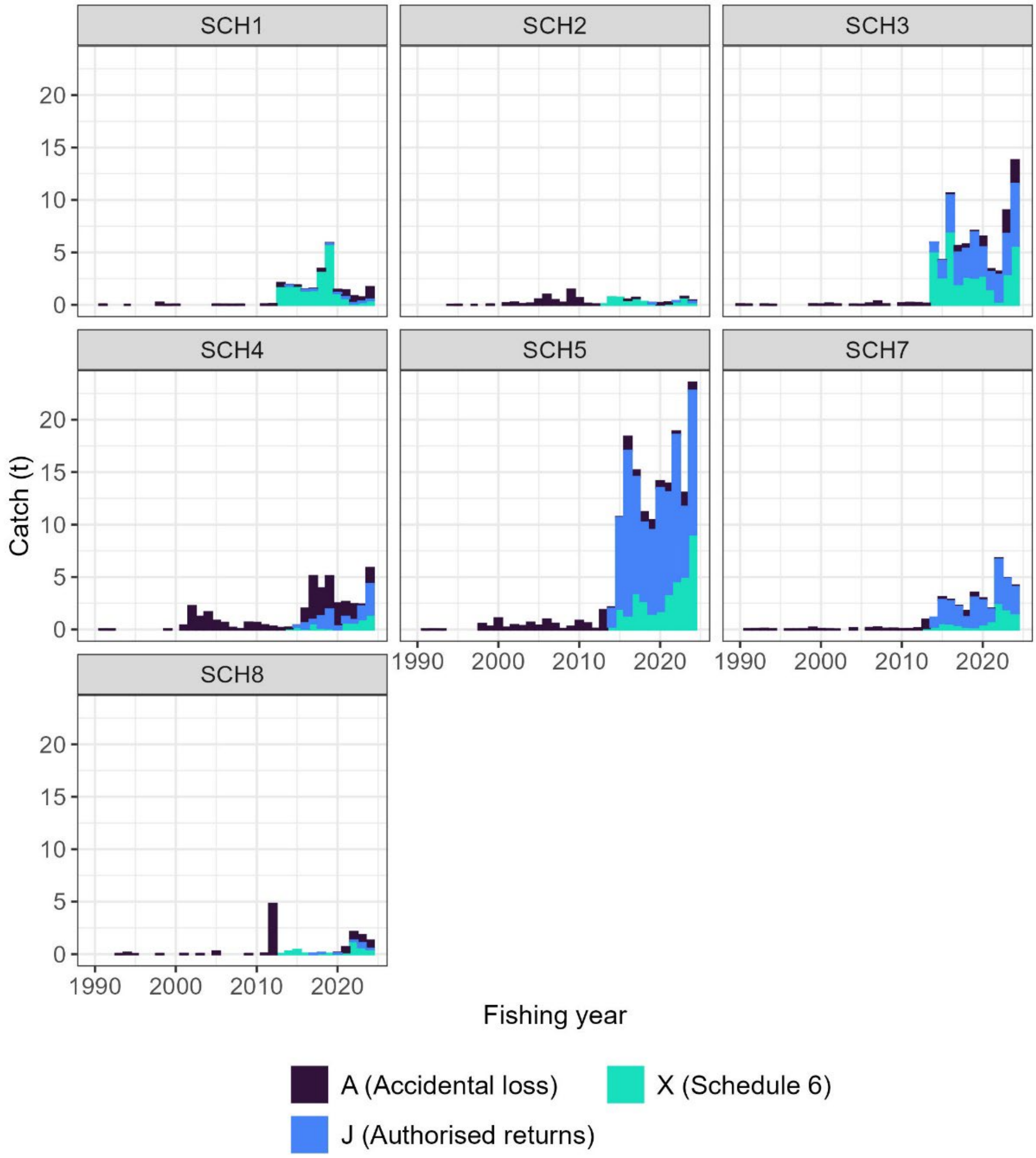

Figure A.4: Reported releases of school shark under Schedule 6, by year, QMA and reported code.

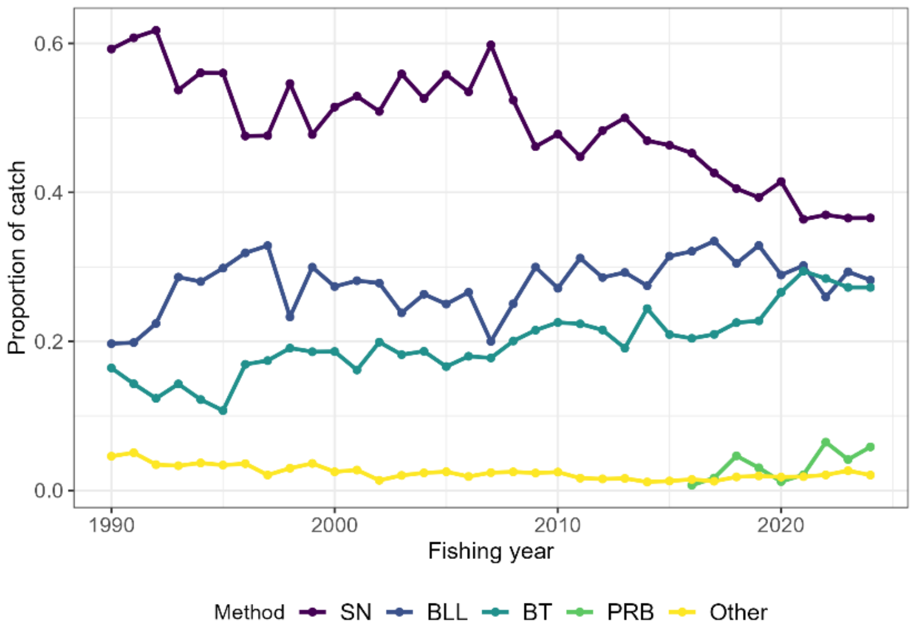

Figure A.5: Proportion of the estimated school shark catch by set net (SN), bottom longline (BLL), bottom trawl (BT), precision harvesting bottom trawl (PRB) and other fishing methods (Other) by fishing year for all QMA combined.

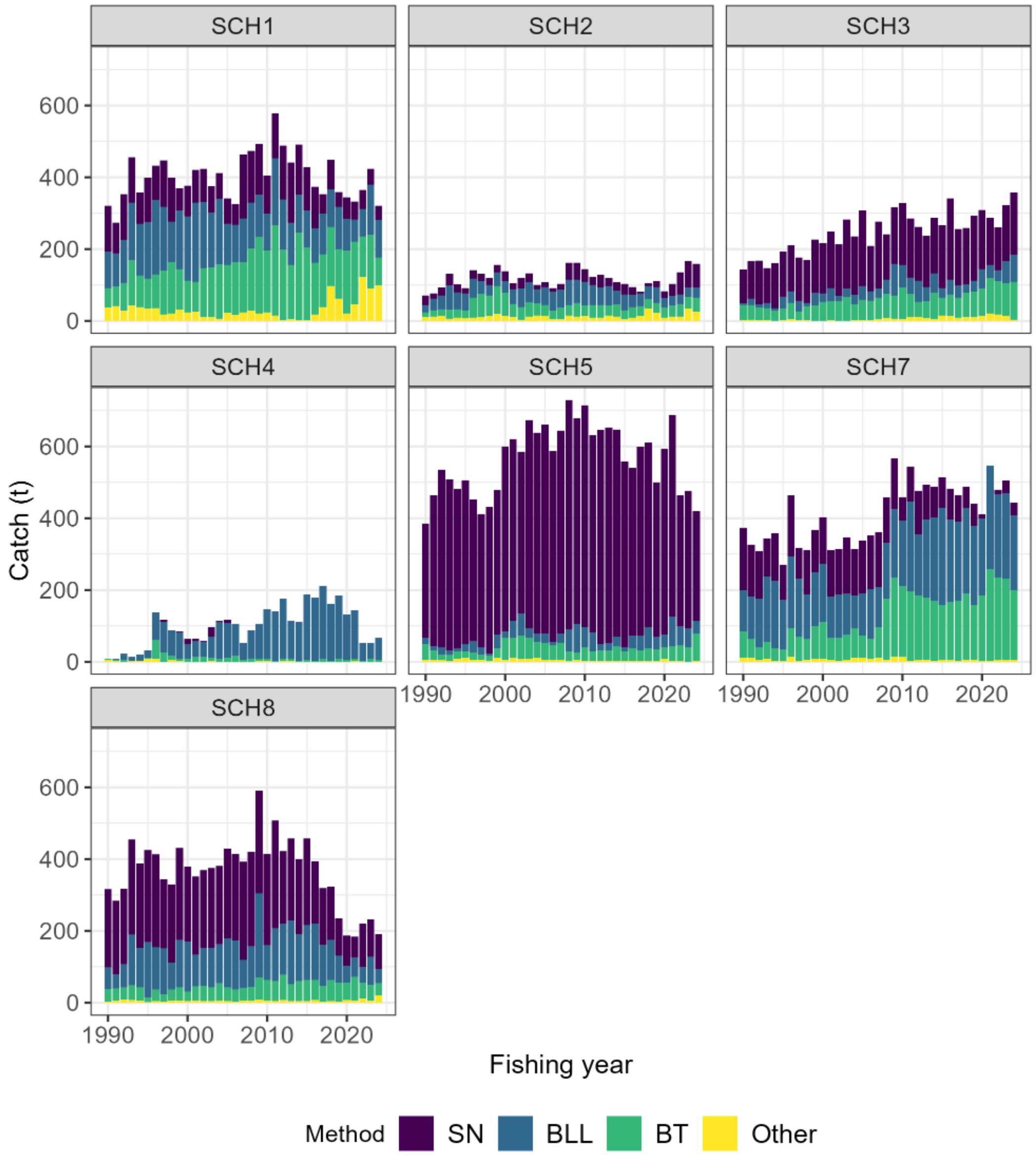

Figure A.6: Estimated school shark catch (t) by set net (SN), bottom longline (BLL), bottom trawl (BT), and other fishing methods (Other) by fishing year and QMA.

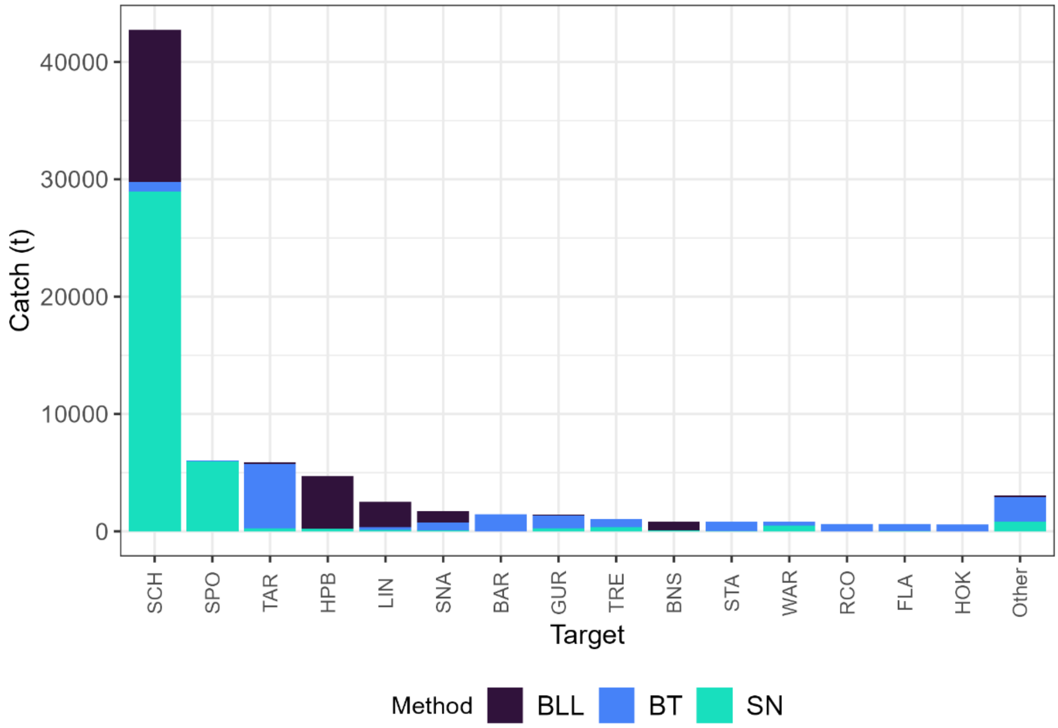

Figure A.7: Estimated school shark catch (t) by set net (SN), bottom longline (BLL), bottom trawl (BT) and by target species. Only the top six target species per method are reported. Species codes are detailed in Table A.1 and Table A.2.

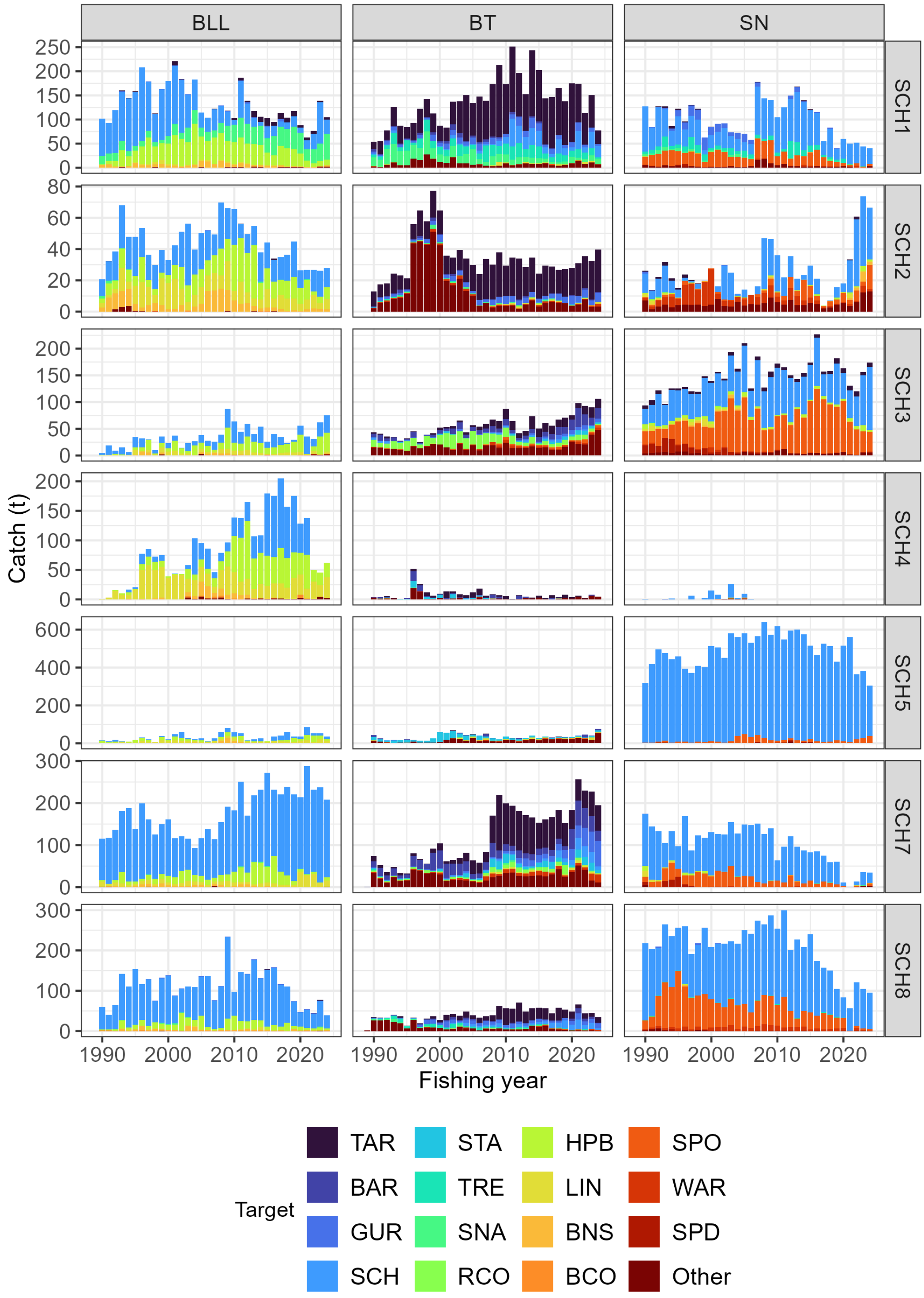

Figure A.8: Estimated school shark catch (t) by set net (SN), bottom longline (BLL), bottom trawl (BT) and by target species by fishing year and QMA. Only the top six target species per method are reported. Species codes are detailed in Table A.1 and Table A.2.

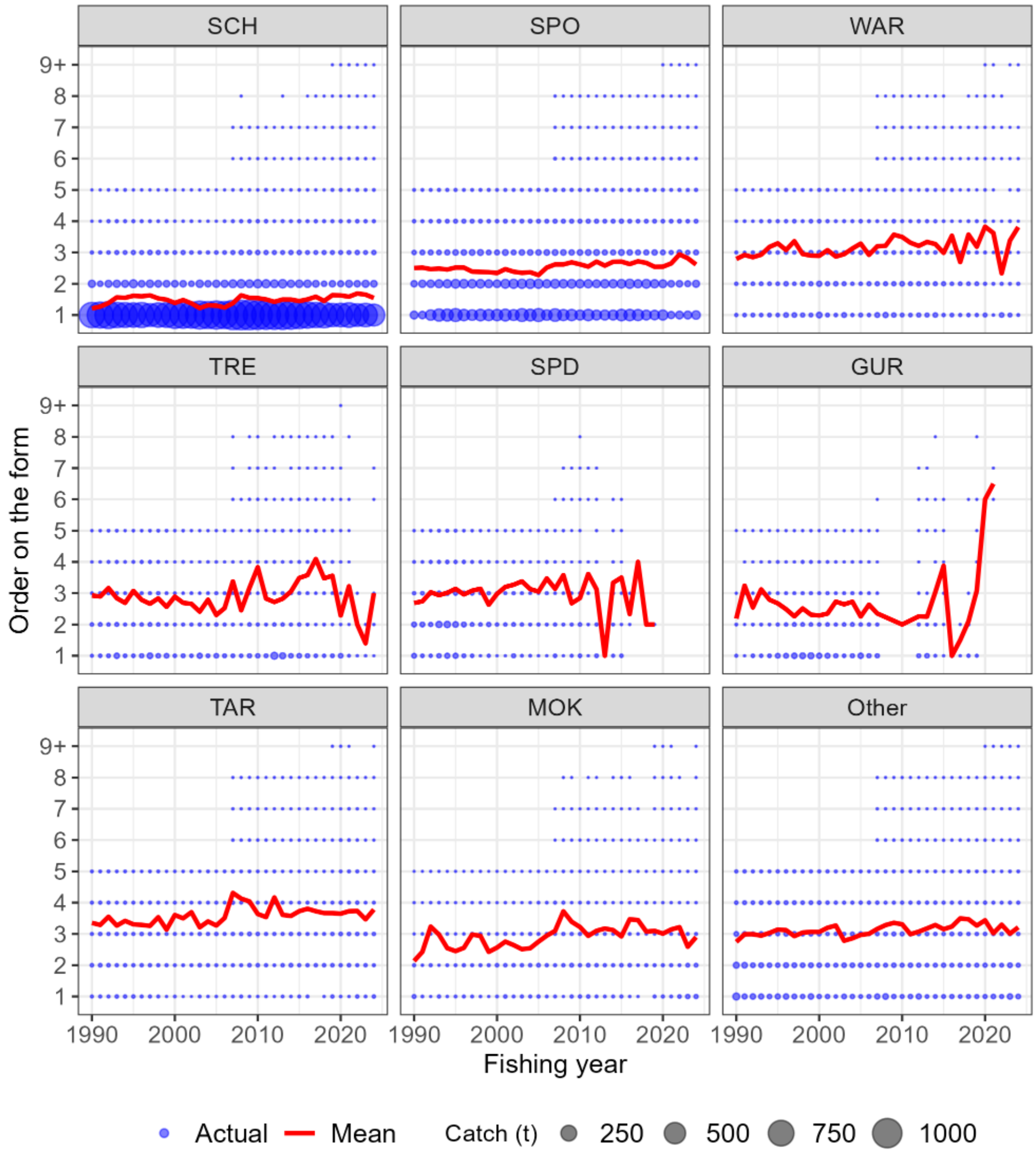

Figure A.9: Set net estimated school shark catch (t) by reporting order and target species (circles) and weighted mean reported order on the form. The target species are ordered in decreasing total school shark catch. Species codes are detailed in Table A.1 and Table A.2.

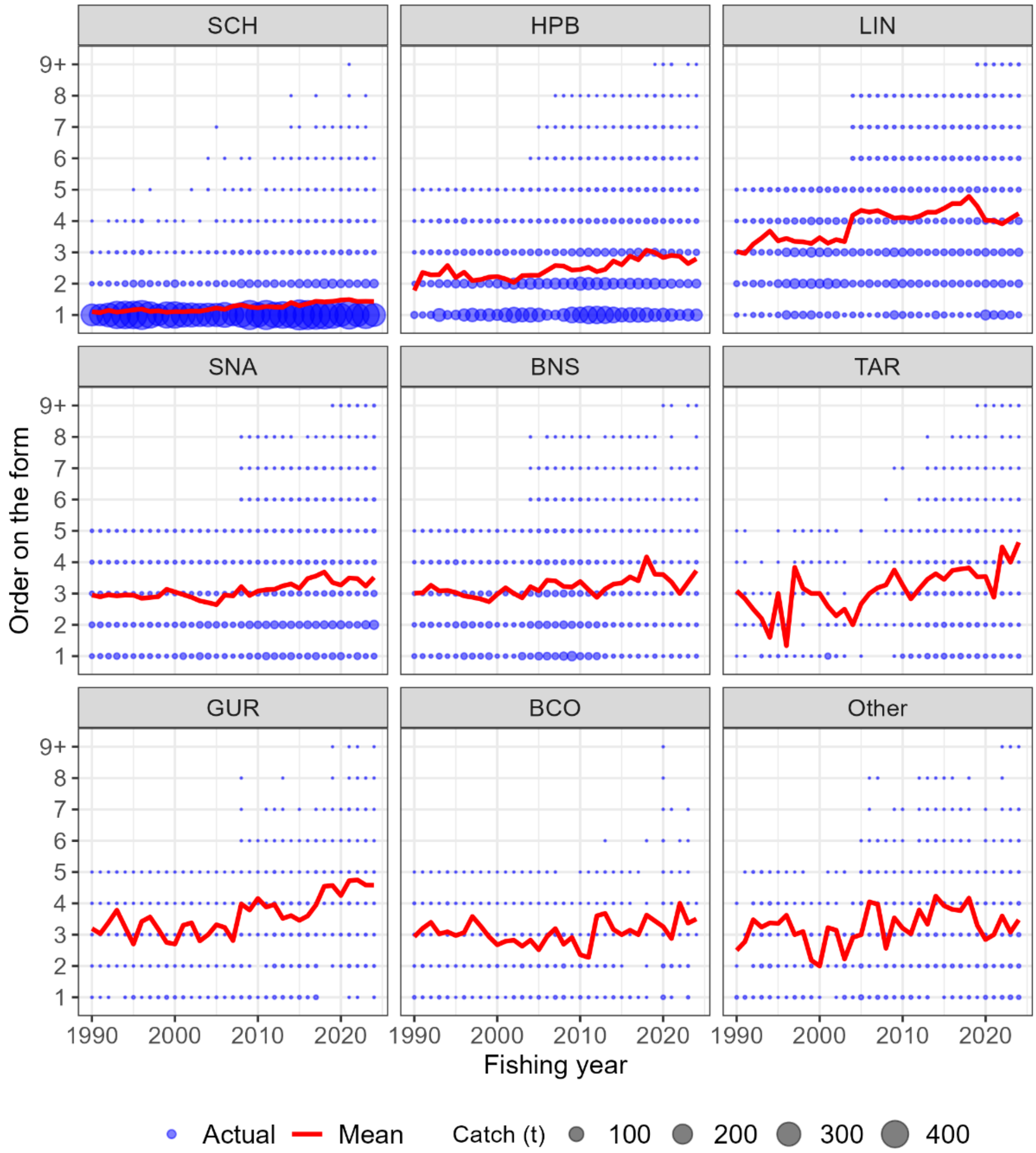

Figure A.10: Bottom longline estimated school shark catch (t) by reporting order and target species (circles) and weighted mean reported order on the form. The target species are ordered in decreasing total school shark catch. Species codes are detailed in Table A.1 and Table A.2.

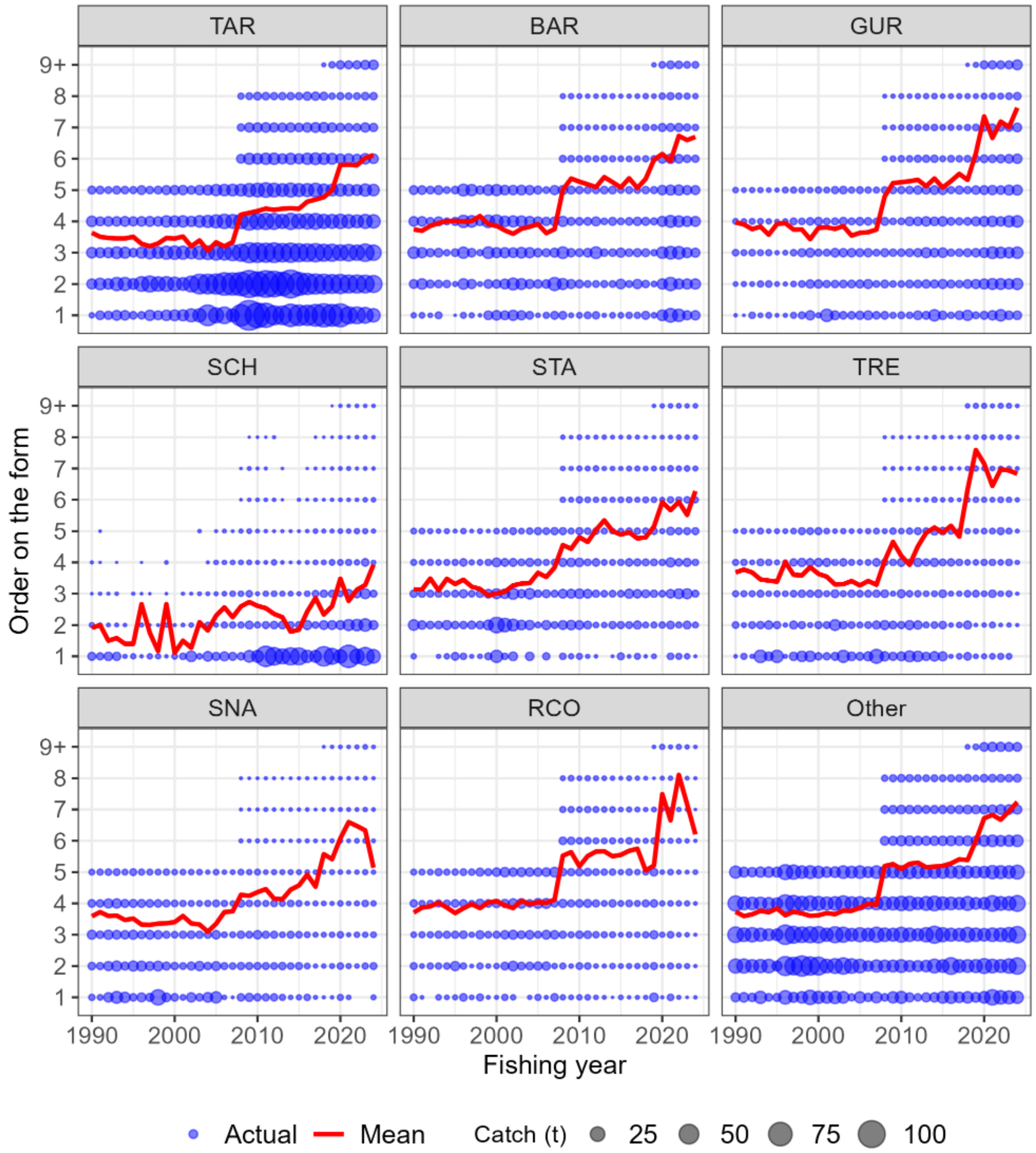

Figure A.11: Bottom trawl estimated school shark catch (t) by reporting order and target species (circles) and weighted mean reported order on the form. The target species are ordered in decreasing total school shark catch. Species codes are detailed in Table A.1 and Table A.2.

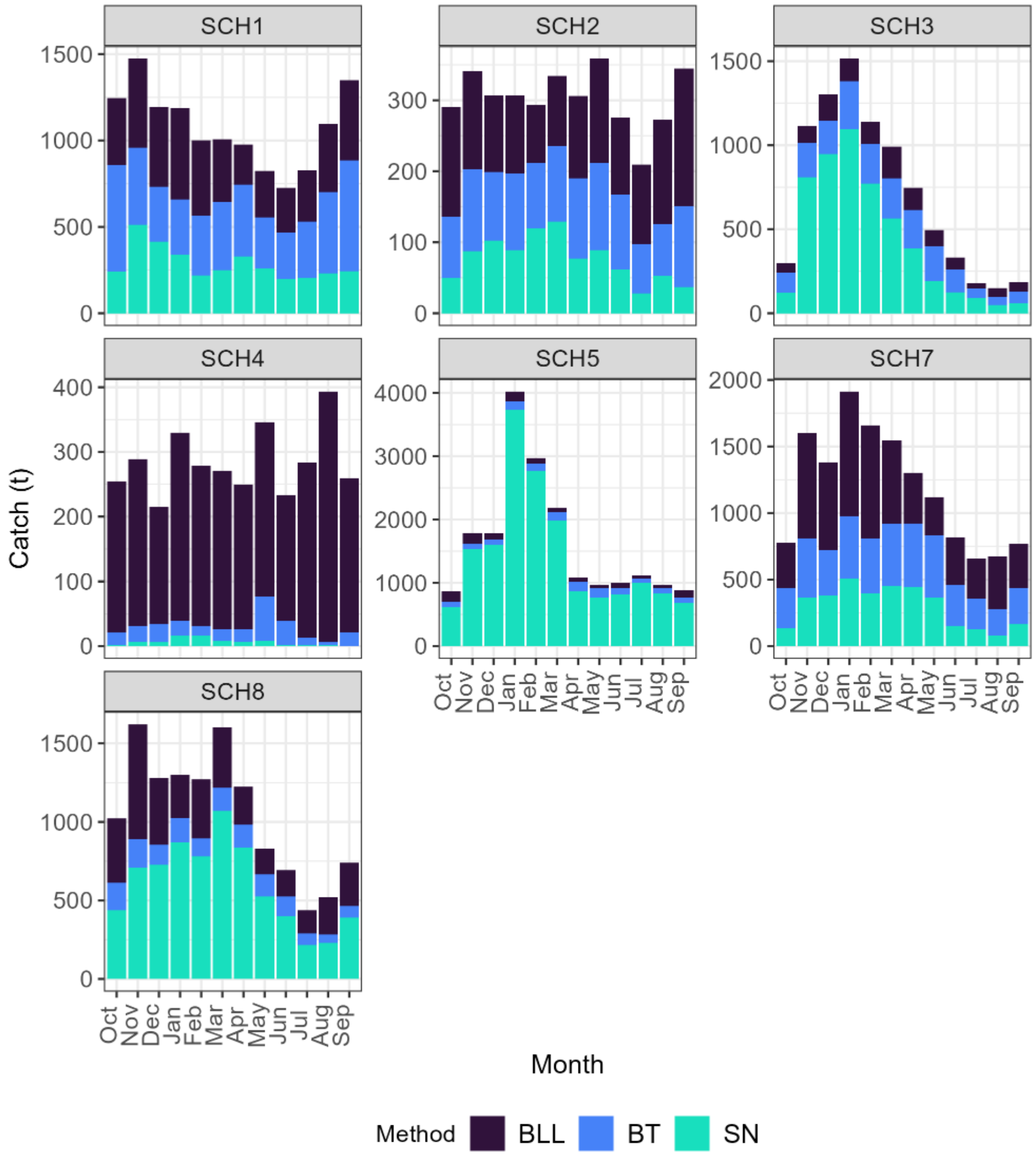

Figure A.12: Estimated school shark catch (t) by set net (SN), bottom longline (BLL), bottom trawl (BT) by month and QMA.

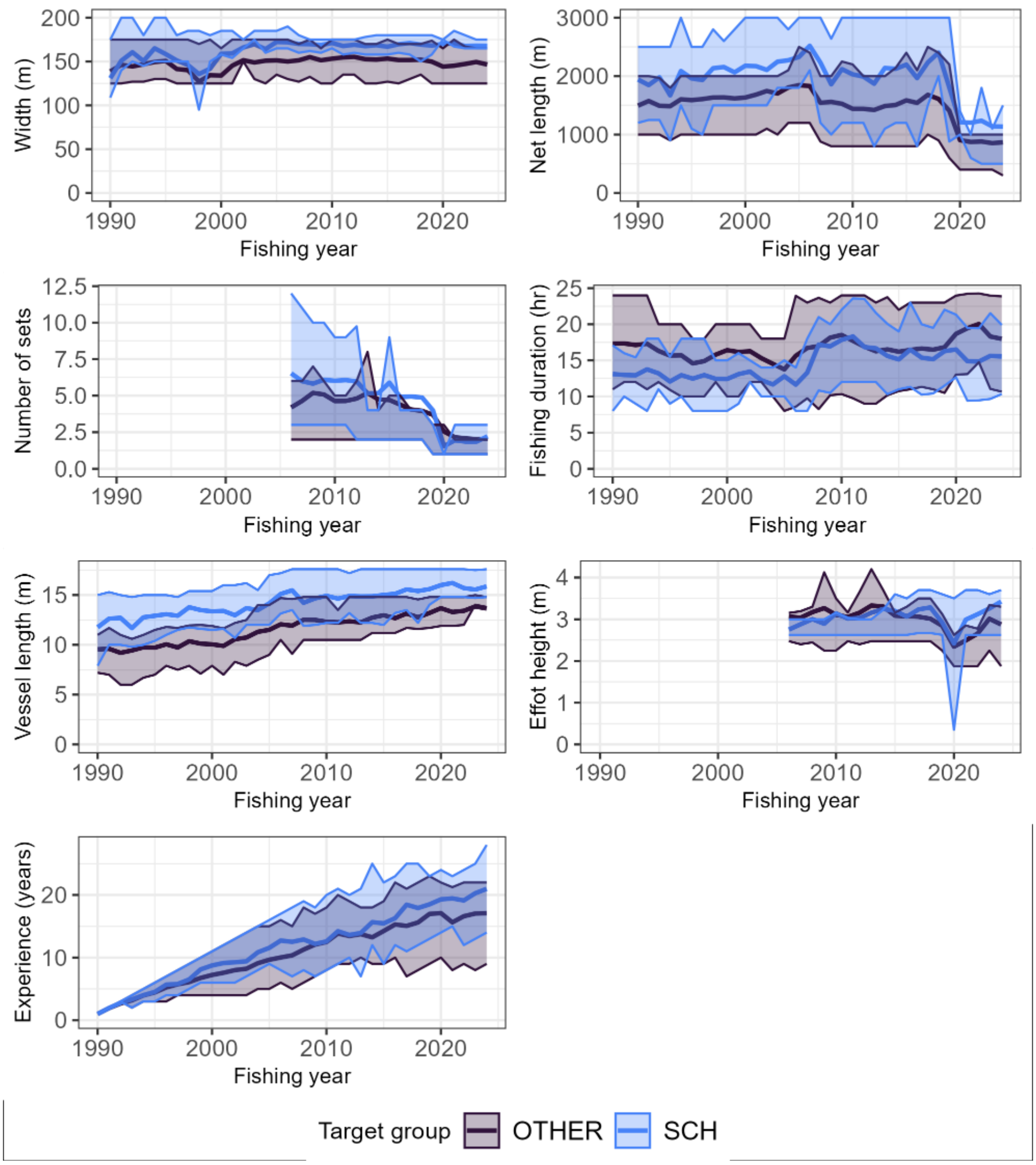

Figure A.13: Change in effort characteristics over time by school shark target (SCH) or other of the set net school shark fishery. Median and interquartile range are shown.

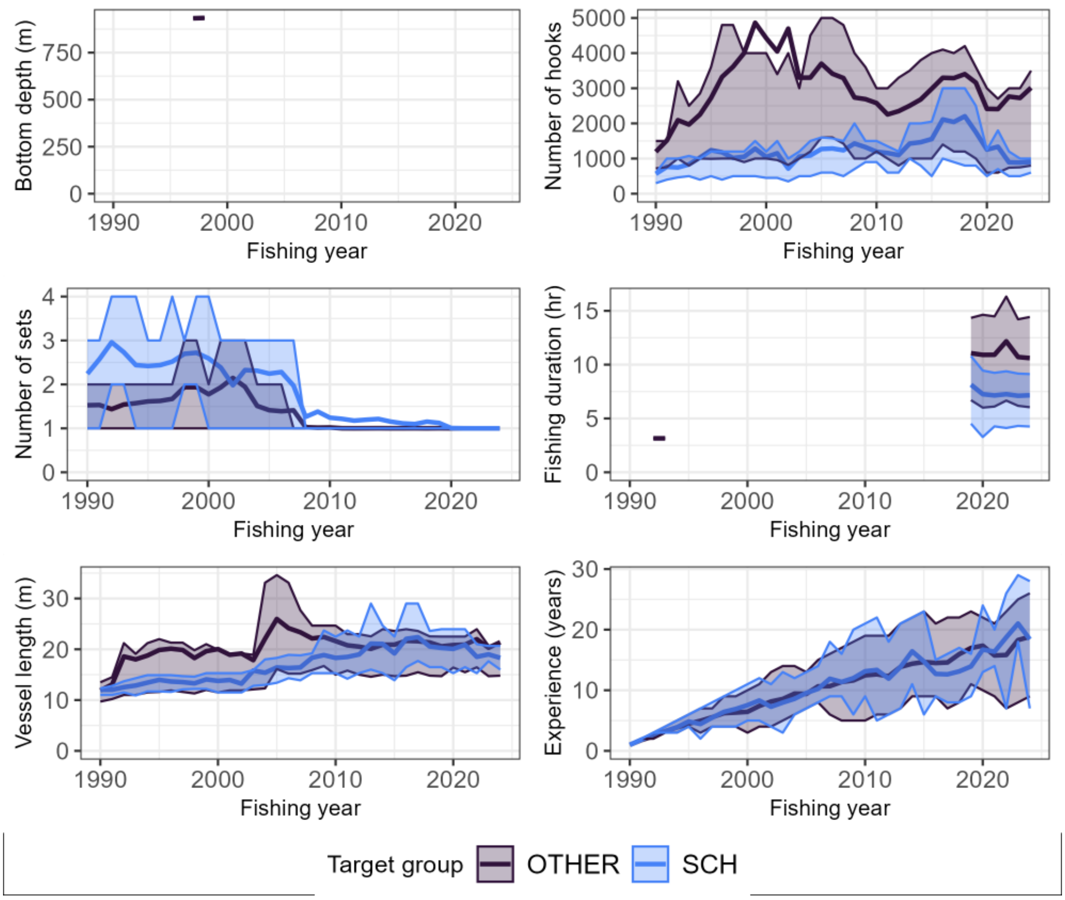

Figure A.14: Change in effort characteristics over time by school shark target (SCH) or other species in the bottom longline school shark fishery. Median and interquartile range are shown.

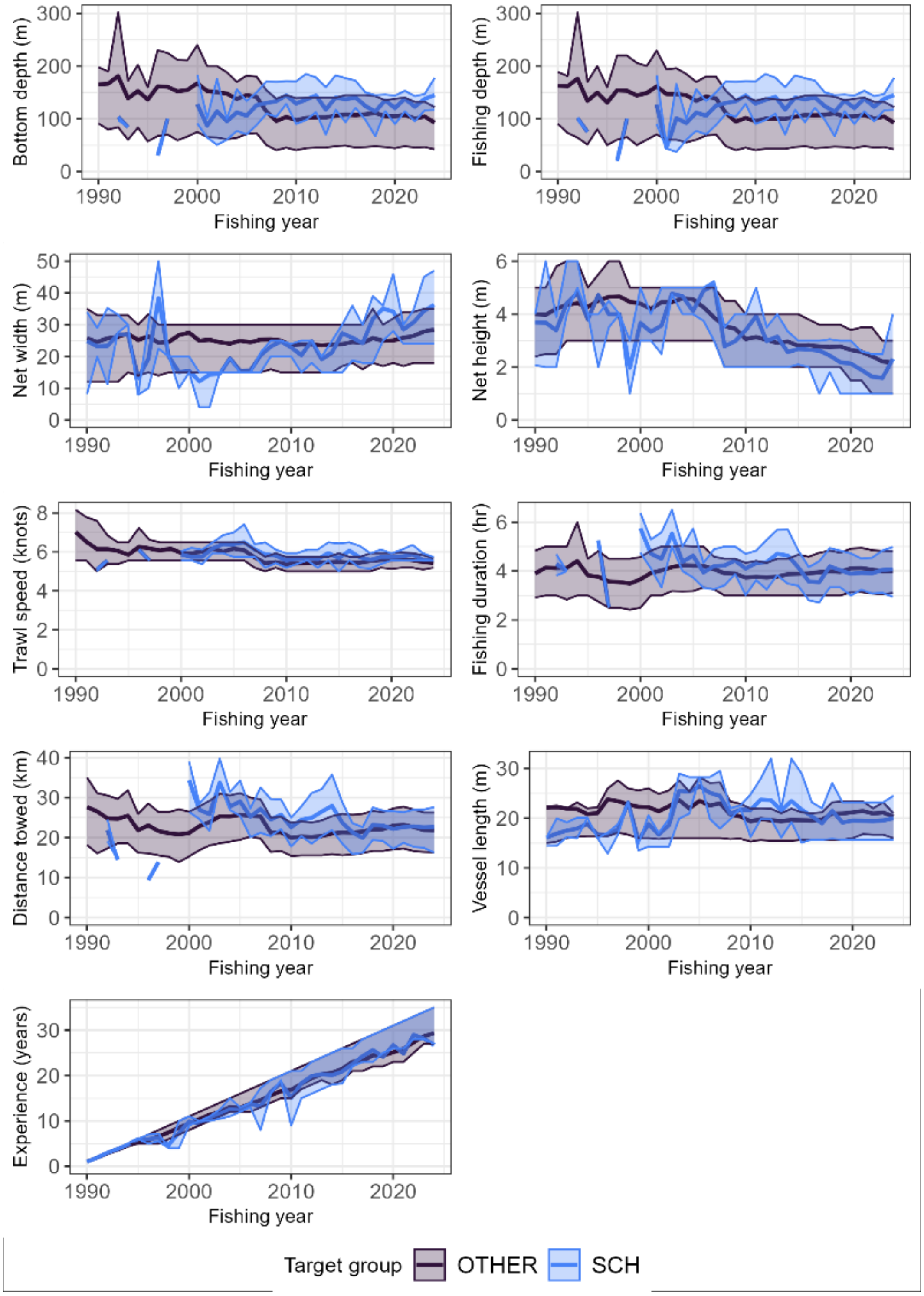

Figure A.15: Change in effort characteristics over time by school shark target (SCH) or other species in the bottom trawl school shark fishery. Median and interquartile range are shown.

9. APPENDIX B – spatio-temporal analysis of length data

Table B.1: Model comparison Watanabe-Akaike Information Criterion (WAIC) for each of the model runs of mean length of school shark. The model term 'Space' refers to the INLA SPDE term.

Model	WAIC
Length ~ Intercept + Space	588 805
Length ~ Intercept + Fishing method + Space	584 057
Length ~ Intercept + Fishing method + Year + Space	582 545
Length ~ Intercept + Fishing method + Year + Sex + Space	582 491
Length ~ Intercept + Fishing method + Year + Sex + Season + Space	582 267
Length ~ Intercept + Fishing method + Year + Sex + Season + Data source + Space	**580 596**

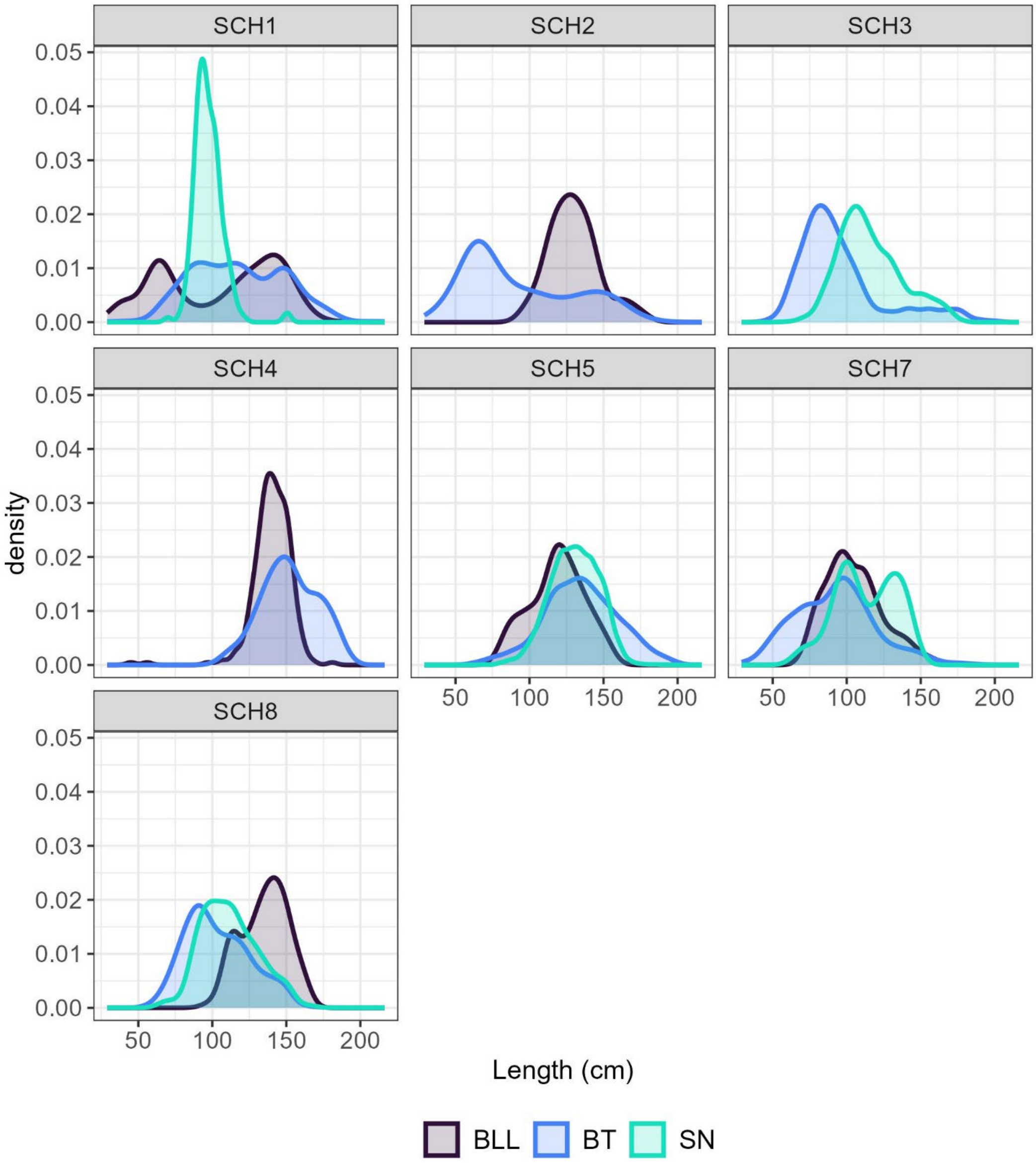

Figure B.1: Unscaled length frequency distribution of school shark by set net (SN), bottom longline (BLL), bottom trawl (BT) and QMA from observer data.

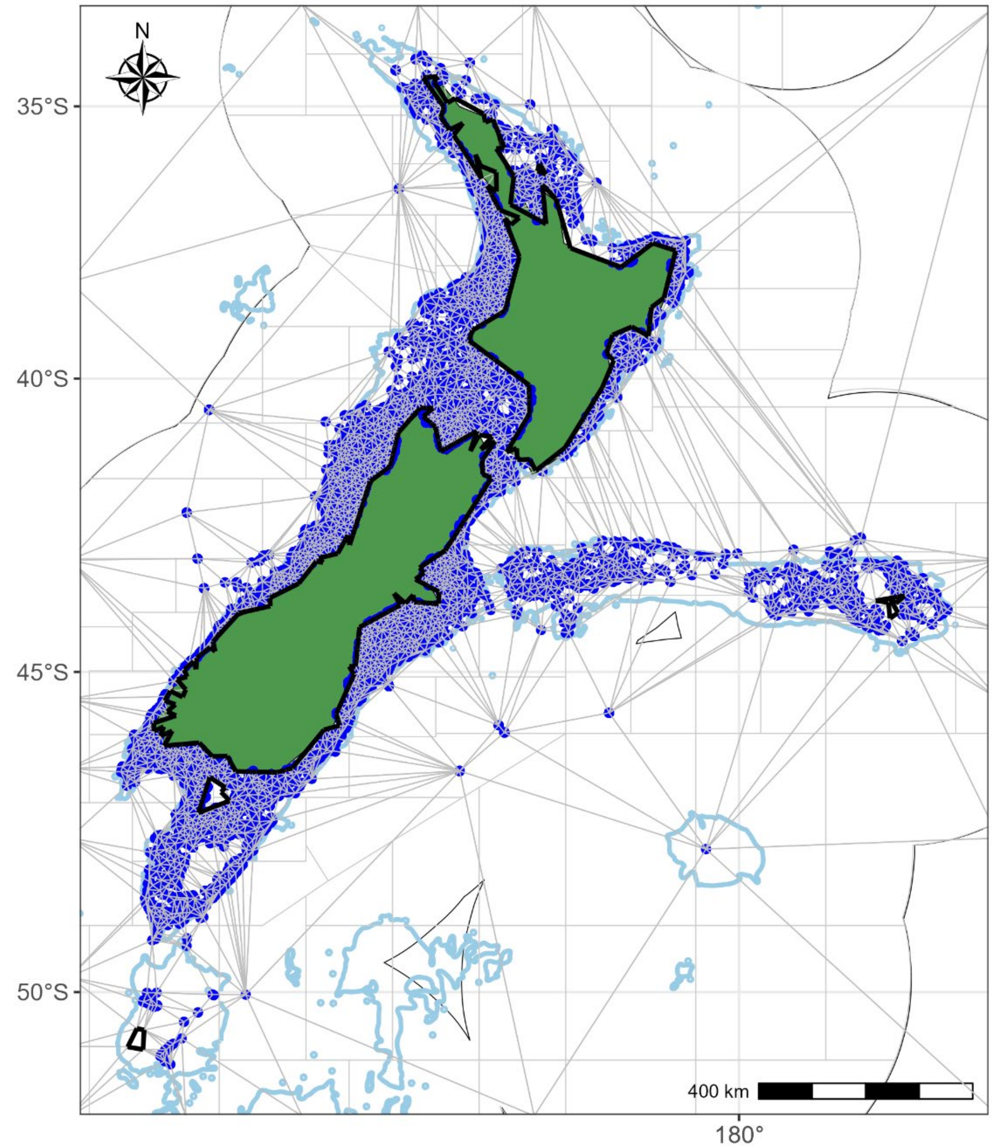

Figure B.2: Spatial mesh for school shark spatio-temporal length models showing the locations of length data (blue points), the spatial mesh (grey lines), the extent of the spatial model (thick black lines).

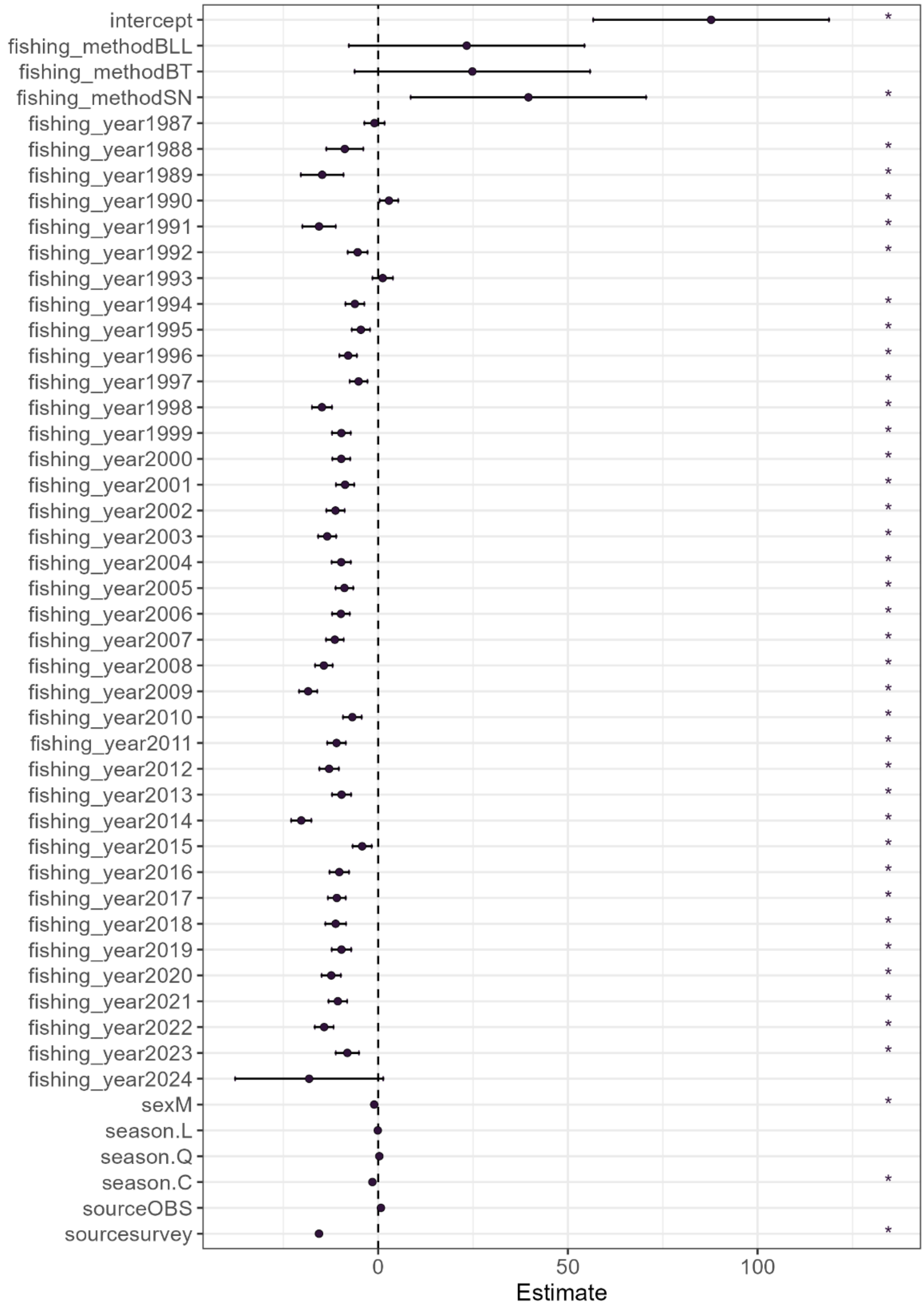

Figure B.3: The partial effects plots for the chosen model of Length ~ Intercept + Fishing method + Year + Sex + Season + Data source + Space. * denotes a statistically significant parameter.

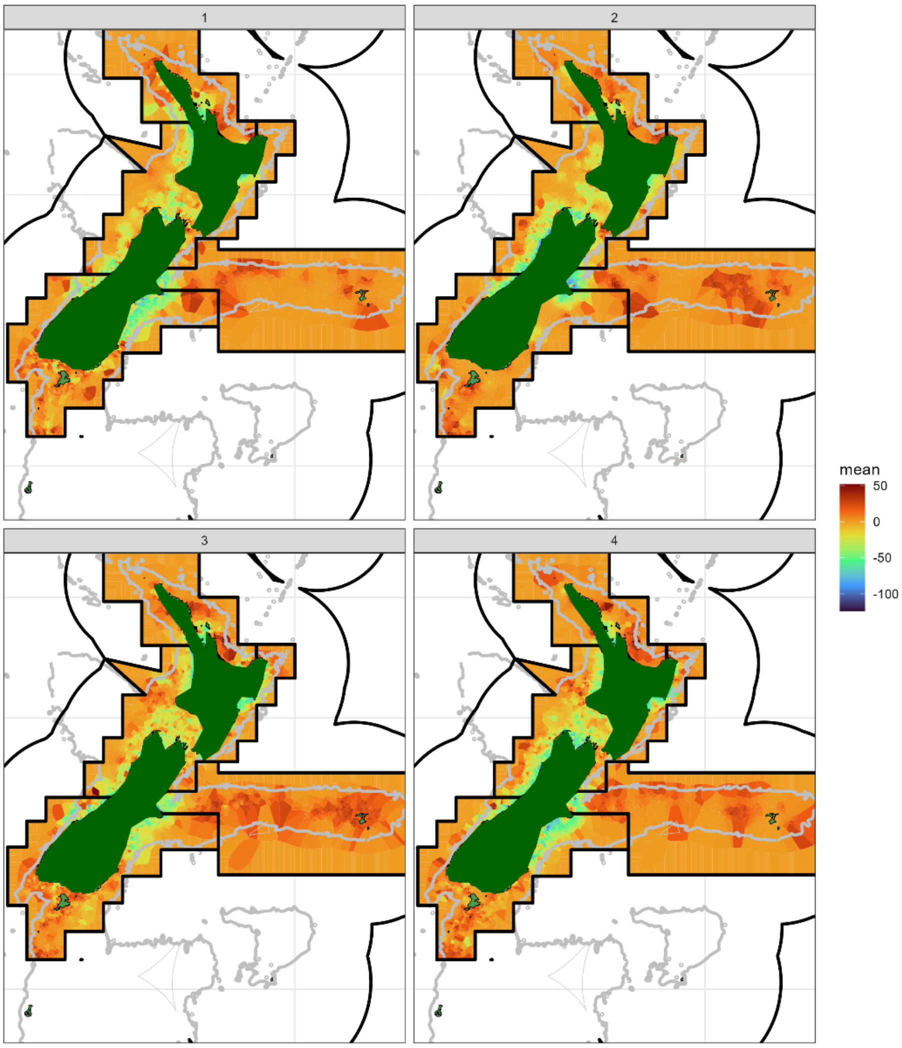

Figure B.4: The spatial effect for model of Length ~ Intercept + Fishing method + Year + Sex + Season + Data source + Space x Season, where 1 is spring. 'mean' is the deviation from the mean length.

10. APPENDIX C – Spatio-temporal CPUE standardisation

Table C.1: Models investigated for the spatio-temporal CPUE standardisation. The preferred model is indicated in bold. Tests for convergence are reported.

Model	% Deviance	Converges
year:space	77.5	yes
year:space + vessel	77.6	yes
year:space + method.target	**88.9**	**yes**
year:space + vessel + method.target + season	88.9	yes
year:space + vessel + method.target + poly(speed, 3)	89.0	yes

Table C.2: Data available to the different sensitivity models run using a single fishing method at a time.

Initial data / model	Number of cells in model	Number of records
Model with all fishing methods	468	168 890
Model with set net only	284	12 424
Model with bottom trawl only	411	130 662
Model with bottom longline only	418	25 804

Table C.3: Model estimate of the proportion of the vulnerable biomass (mean over all years and range of the values in each individual year) and proportion of the 2025 total allowable catch (TACC) in each QMA.

QMA	SCH1	SCH2	SCH3	SCH4	SCH5	SCH7	SCH8
Model	27 (23–32)	5 (4–7)	11 (9–12)	10 (7–12)	14 (12–17)	23 (19–26)	10 (8–11)
TACC	22	6	12	7	16	20	17

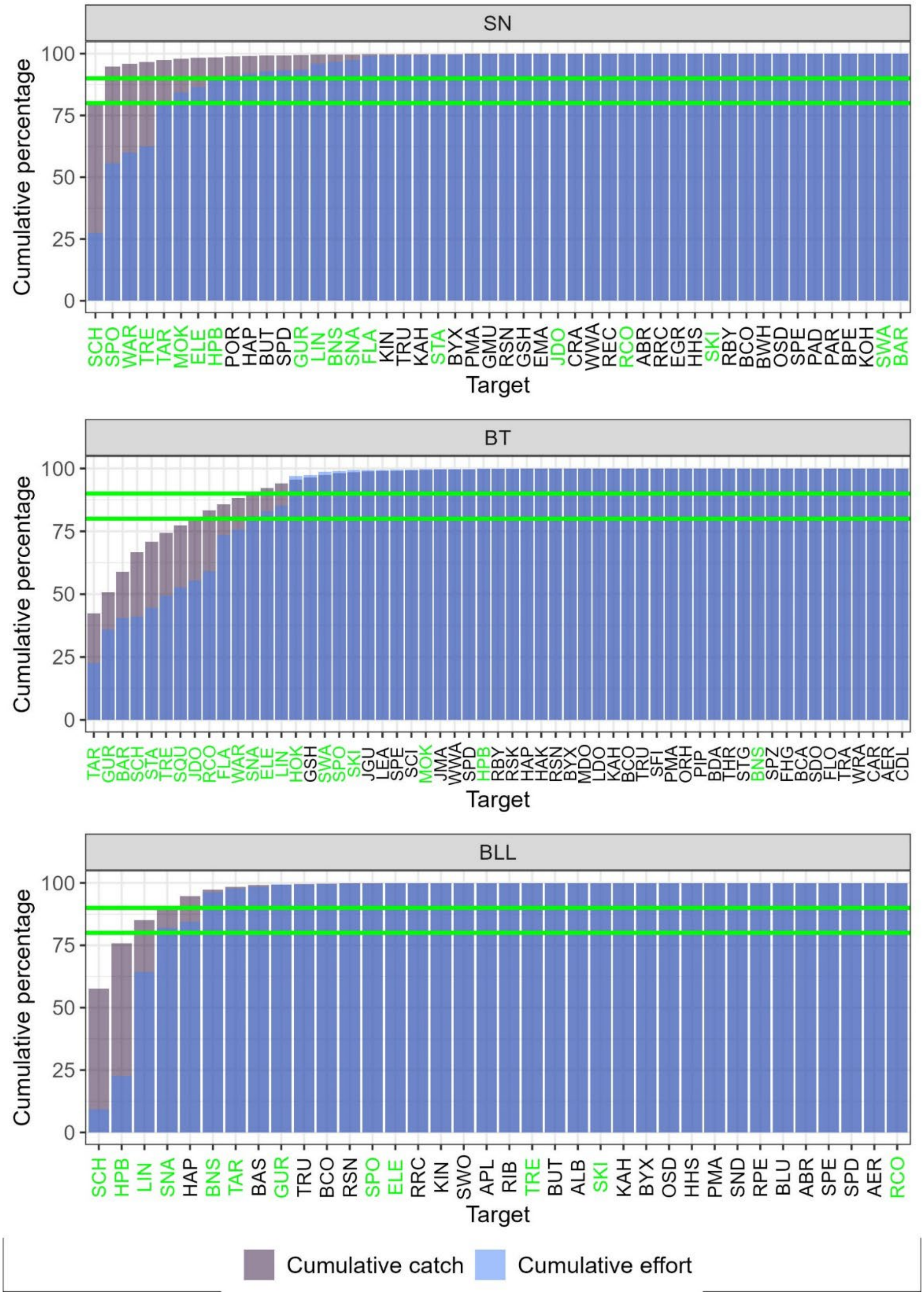

Figure C.1: Cumulative percentage of total catch (grey) and effort (blue) of the school shark fishery in 2008–2024 by set net (SN), bottom longline (BLL), bottom trawl (BT) and target species. The target species are ordered in decreasing total school shark catch. Species codes are detailed in Table A.1 and Table A.2. The target species in green belong to the 2021 definition of the school shark fishery (Table A.1). The horizontal green lines are arbitrarily set at 80% and 90%.

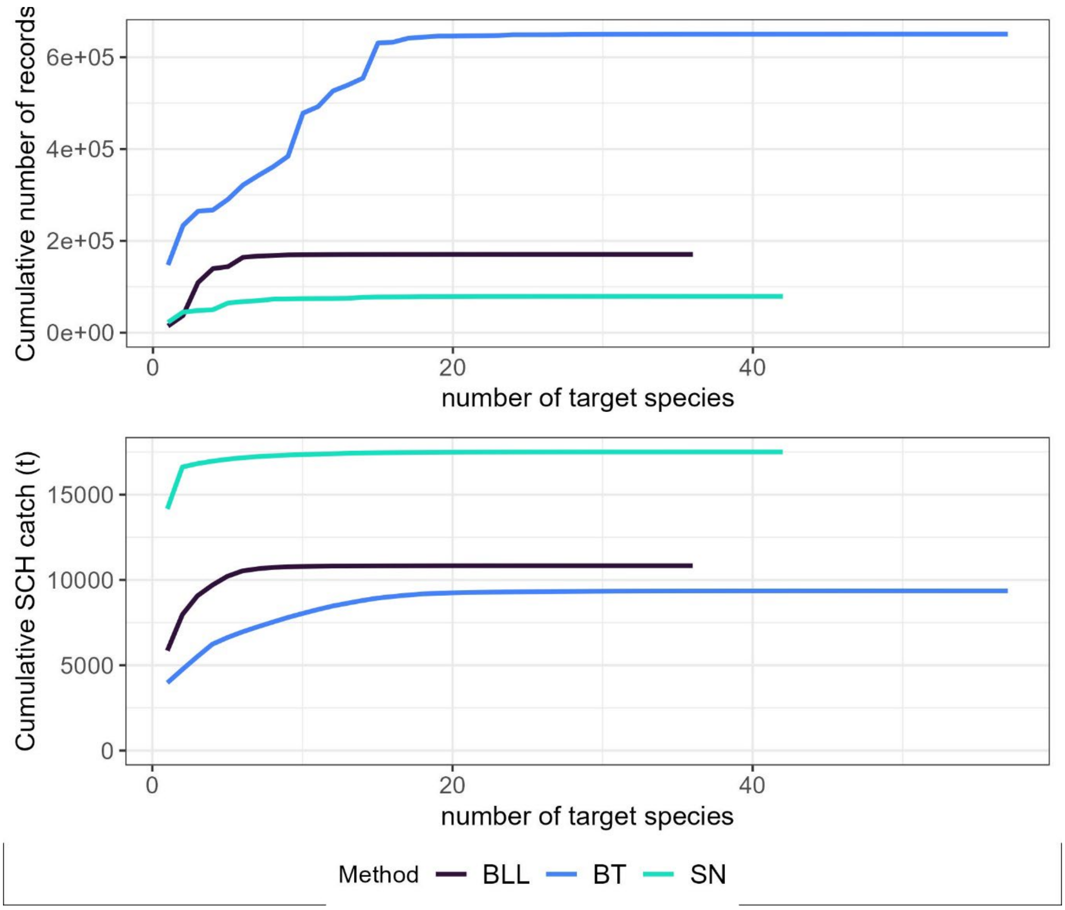

Figure C.2: Cumulative number of records (top) and catch (t, bottom) of the school shark fishery in 2008–2024 by set net (SN), bottom longline (BLL), bottom trawl (BT) and number of target species included. The target species are ordered in decreasing total school shark catch for each fishing method independently.

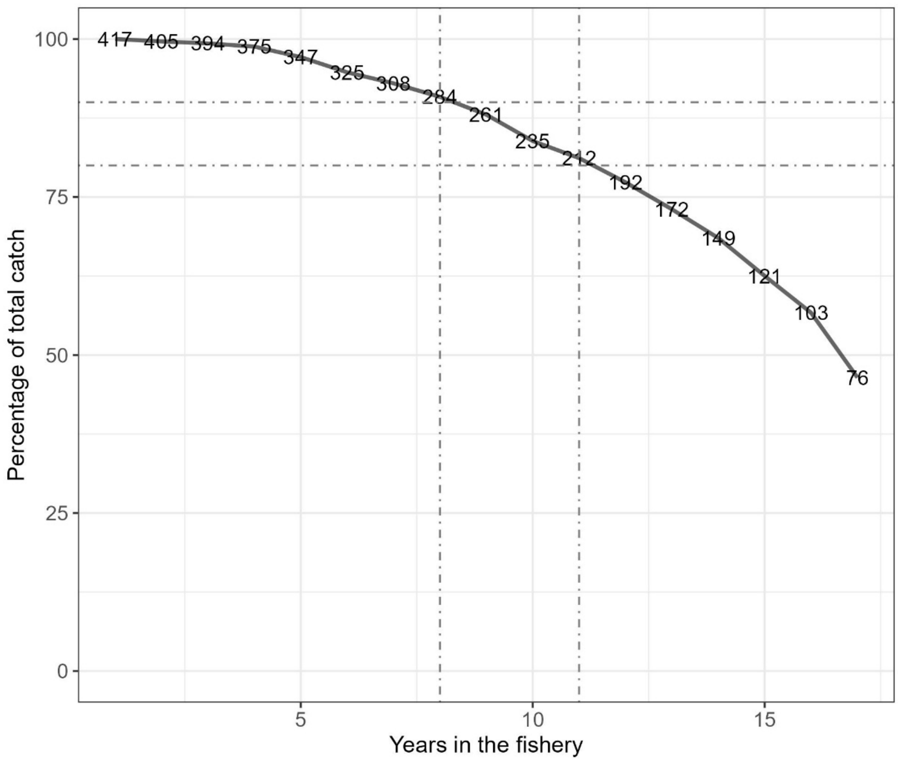

Figure C.3: Core vessel selection: proportion of total catch by vessel experience for the school shark fishery in 2008–2024.

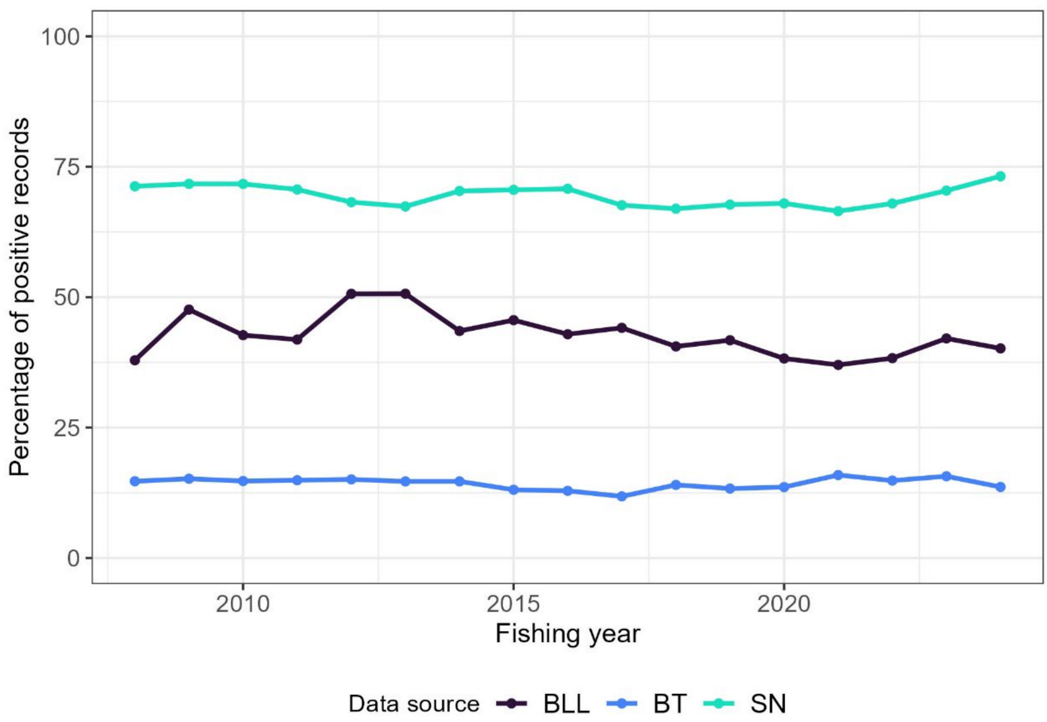

Figure C.4: Core vessel selection: proportion of positive records (reporting a school shark catch) for set net (SN), bottom longline (BLL), bottom trawl (BT) for the school shark fishery in 2008–2024.

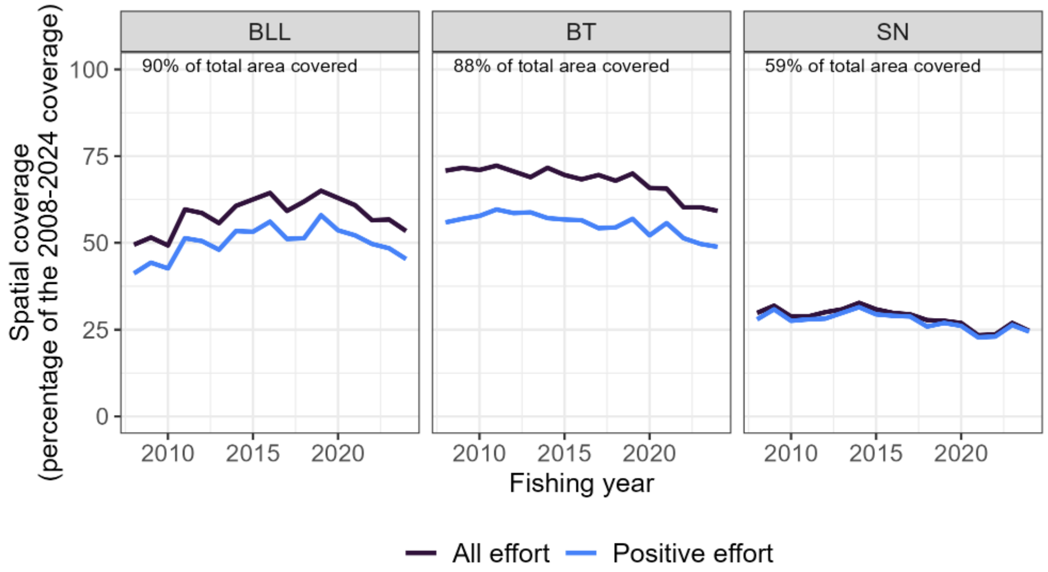

Figure C.5: Spatial annual coverage of the set net (SN), bottom longline (BLL) and bottom trawl (BT) fisheries, expressed as the percentage of the 2008–2024 total number of 32 km cells covered by all three methods for the entire dataset (all effort) or the data where catches occurred (positive effort).

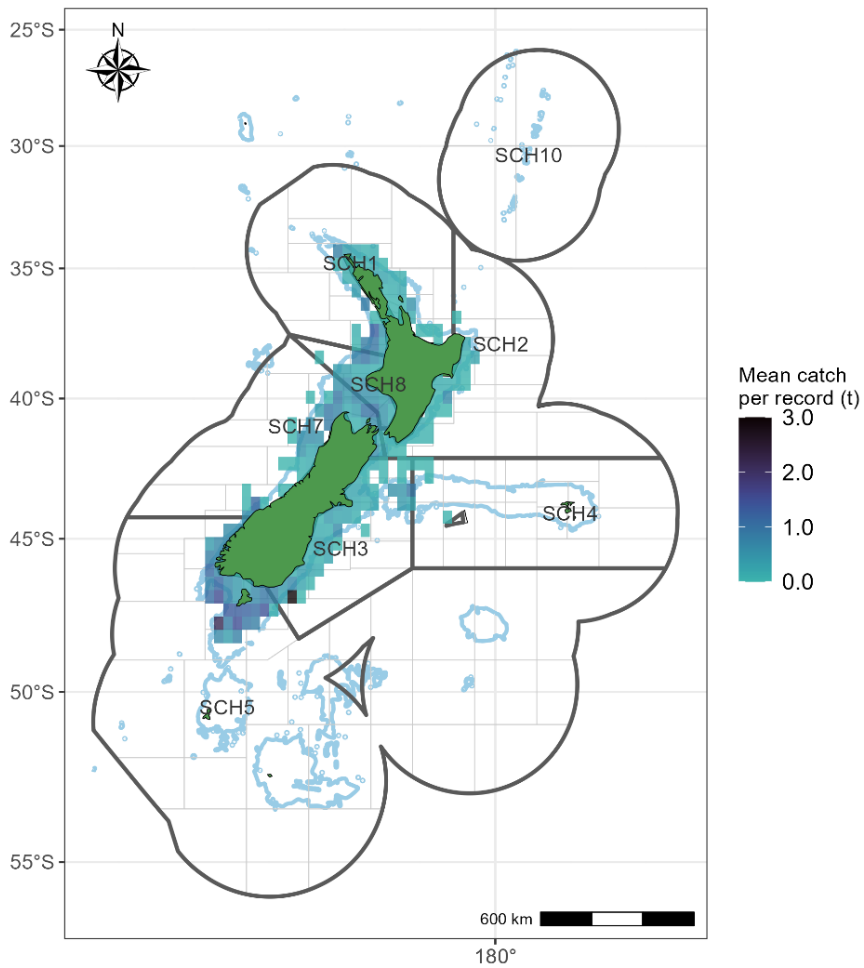

Figure C.6: Set net raw CPUE (expressed as catch per record) averaged over the 2008–2024 period.

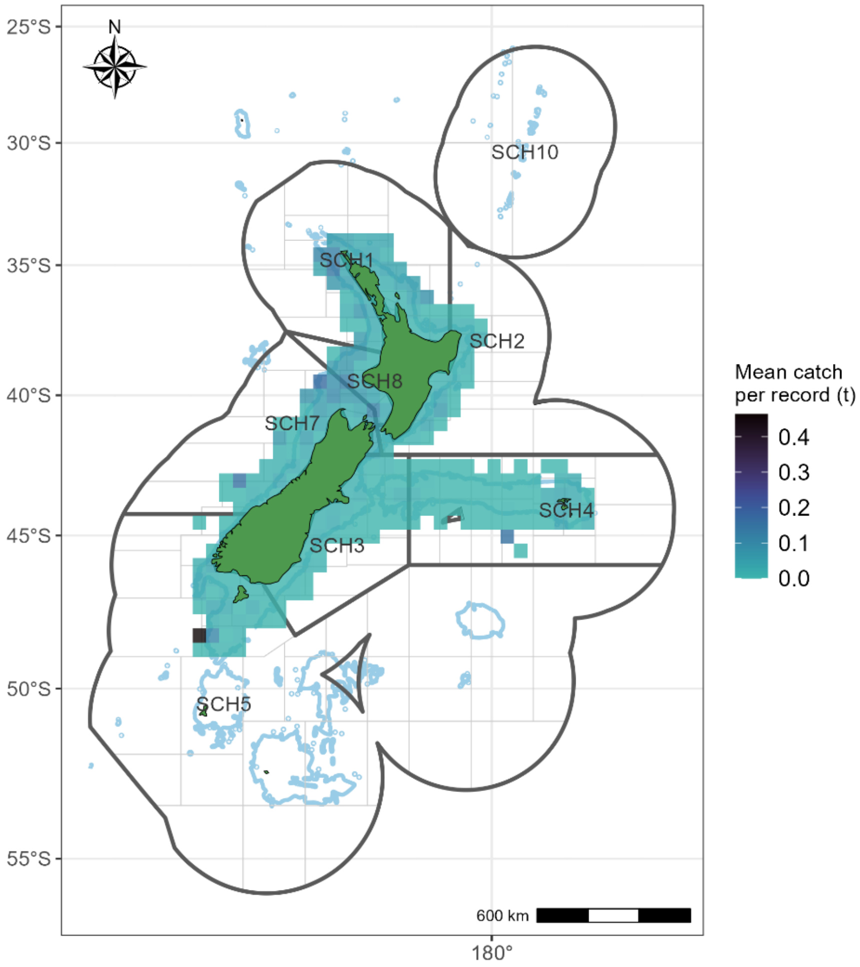

Figure C.7: Bottom trawl raw CPUE (expressed as catch per record) averaged over the 2008–2024 period.

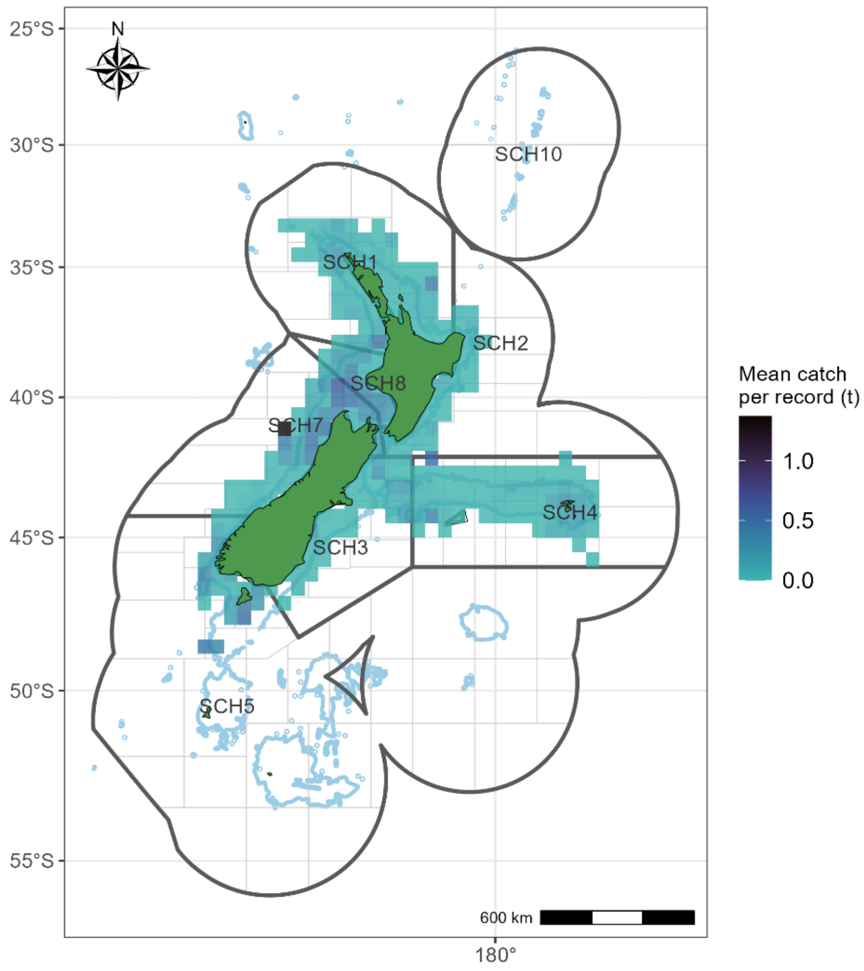

Figure C.8: Bottom longline raw CPUE (expressed as catch per record) averaged over the 2008–2024 period.

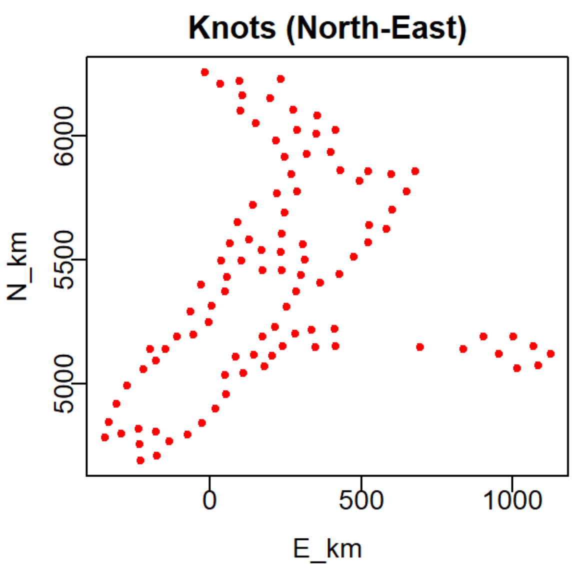

Figure C.9: Distribution of the spatial knots for the base case spatio-temporal model.

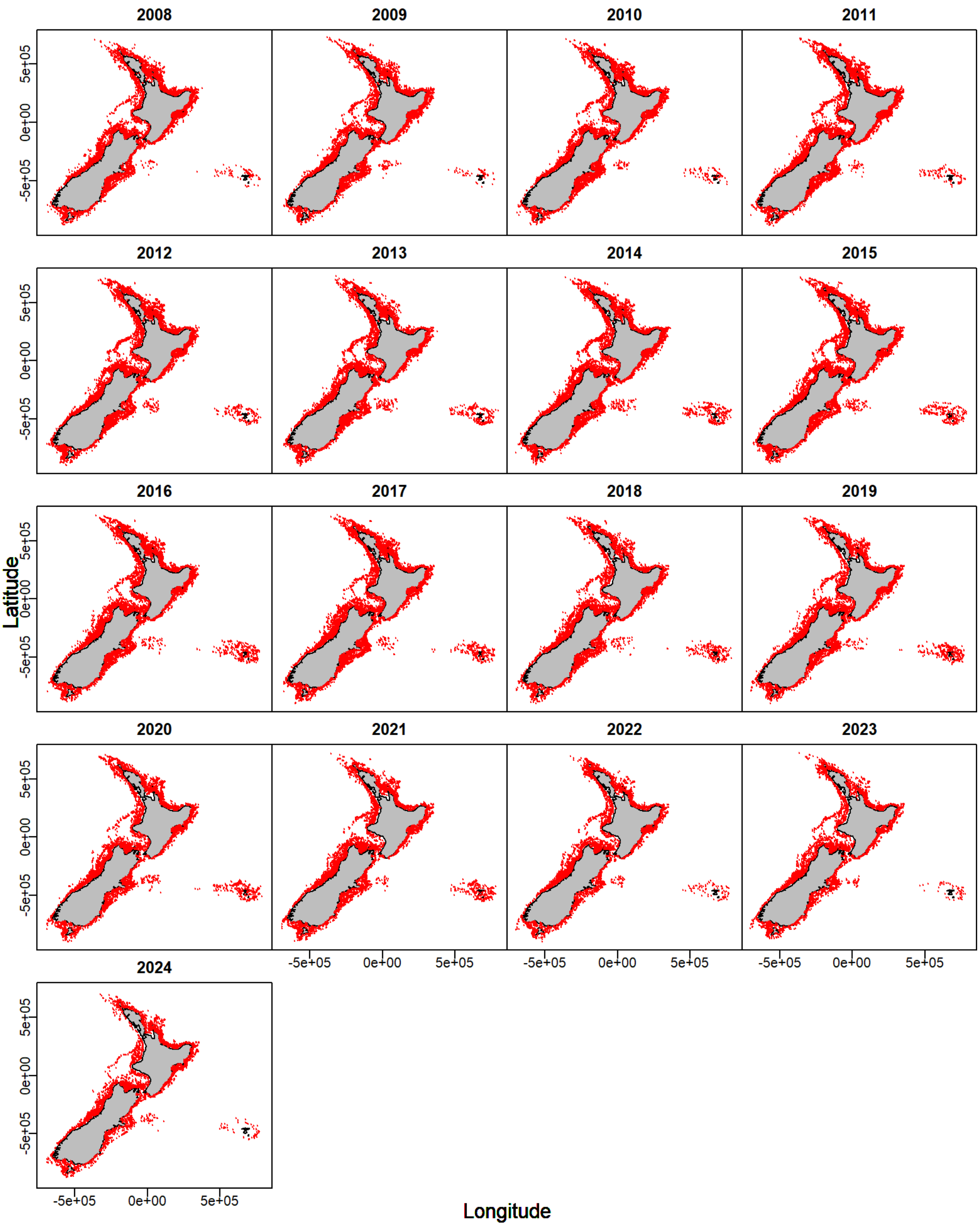

Figure C.10: Spatio-temporal distribution of the data included in the base case spatio-temporal model.

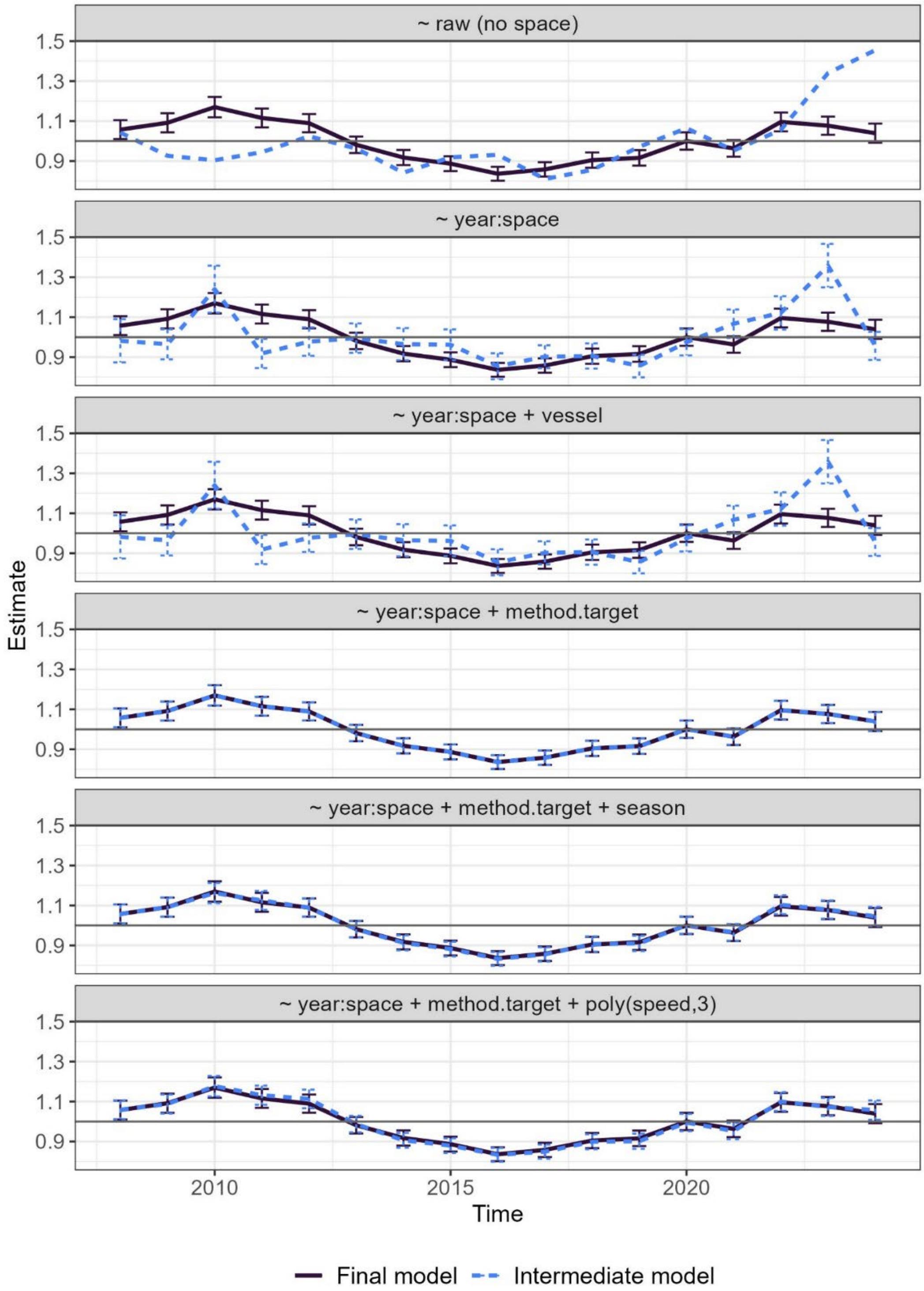

Figure C.11: Unstandardised and standardised CPUE indices for the various models tested (Intermediate model) compared with the final model (CPUE ~ year:space + method.target). The error bars represent ±1 standard error. Time is fishing year.

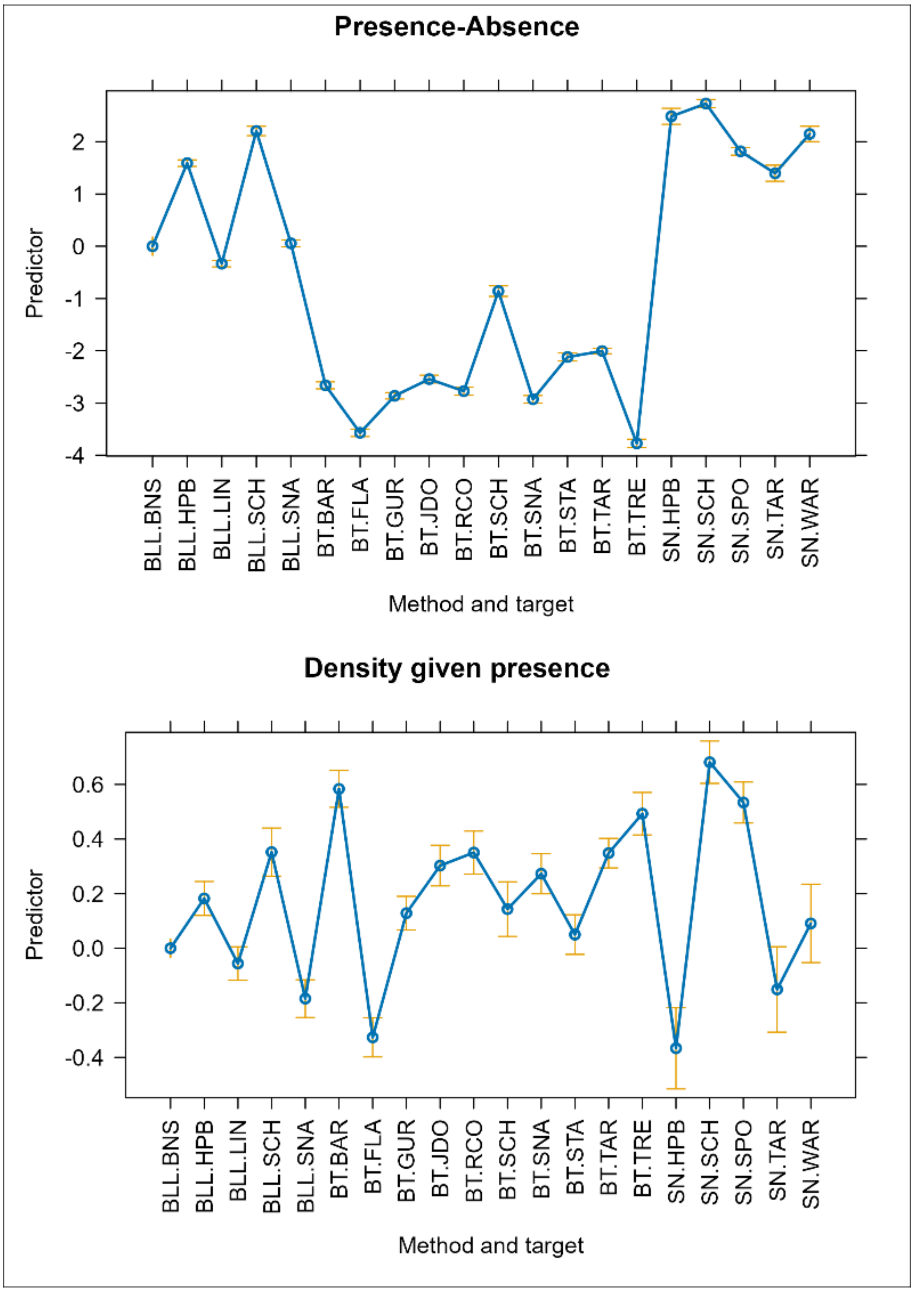

Figure C.12: Partial effects plots of the method.target parameter for the final model (CPUE ~ space:year + method.target). The error bars represent ±1 standard error for the set net (SN), bottom longline (BLL) and bottom trawl (BT) fisheries. Species codes are detailed in Table A.1 and Table A.2.

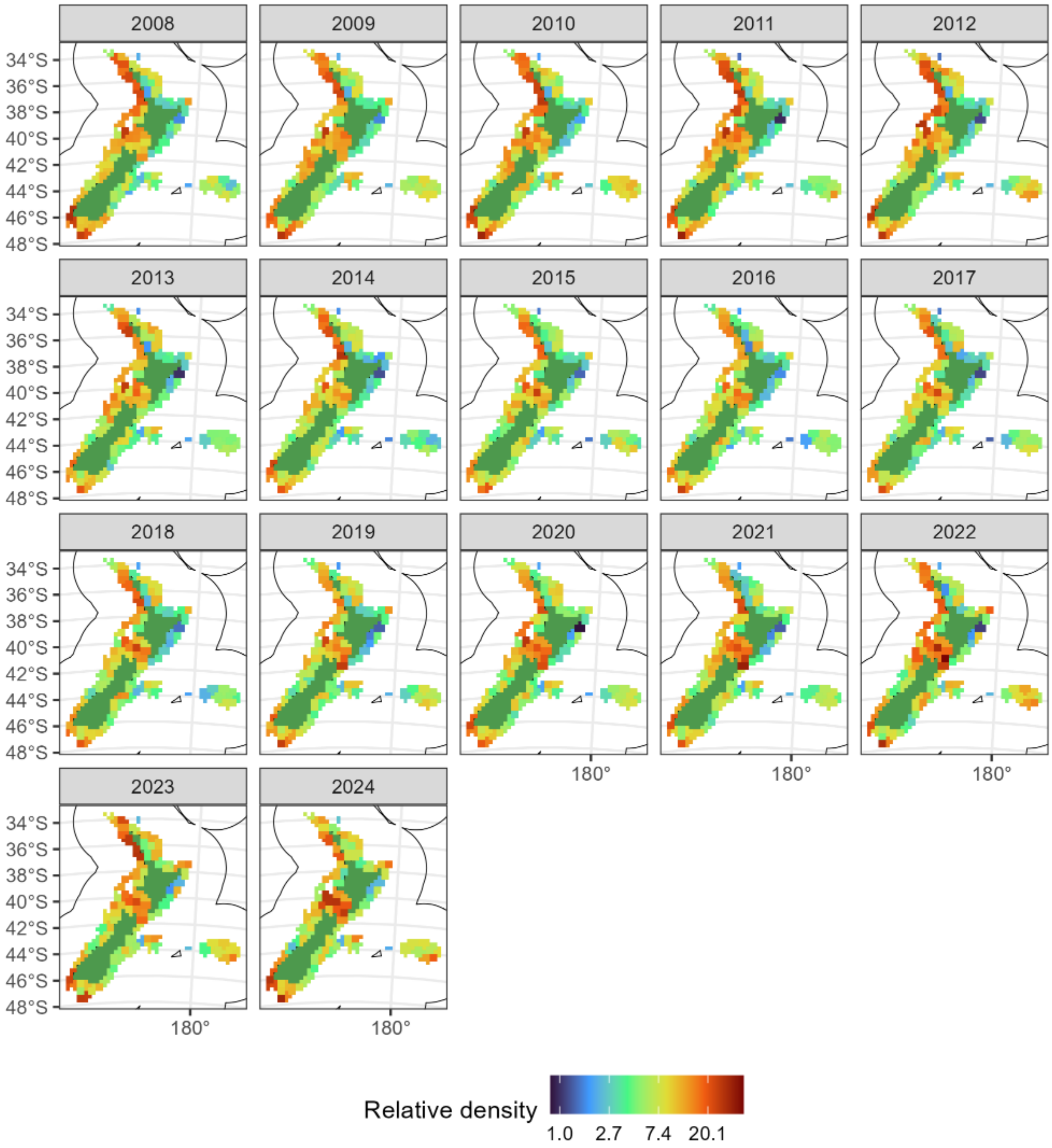

Figure C.13: Relative spatio-temporal biomass density of school shark.

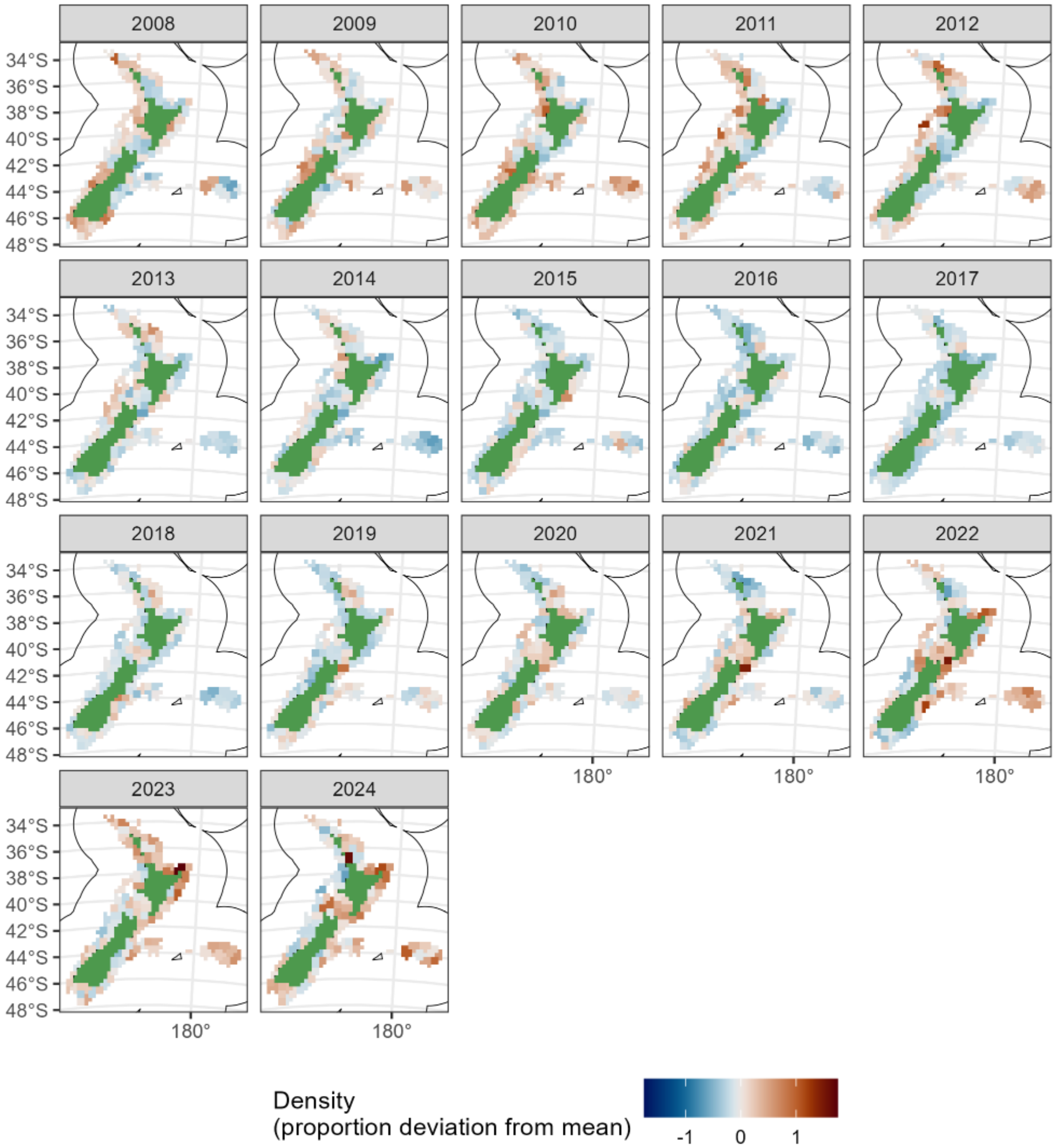

Figure C.14: Relative spatio-temporal variability in biomass density of school shark, expressed as a deviation from the series mean for each individual cell.

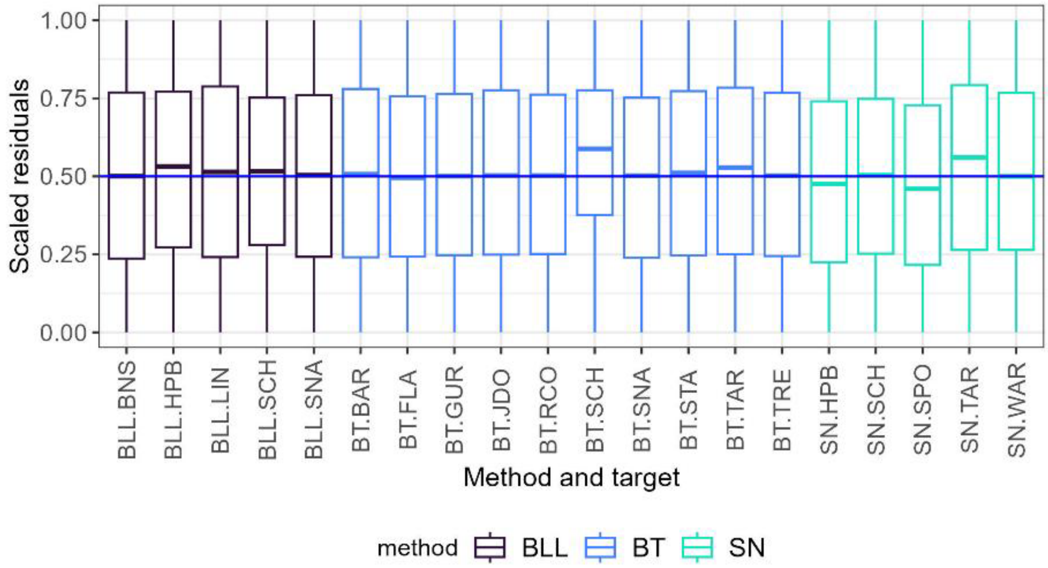

Figure C.15: Scaled residuals by target and fishing method for the set net (SN), bottom longline (BLL) and bottom trawl (BT) fisheries for the base case model. Species codes are detailed in Table A.1 and Table A.2.

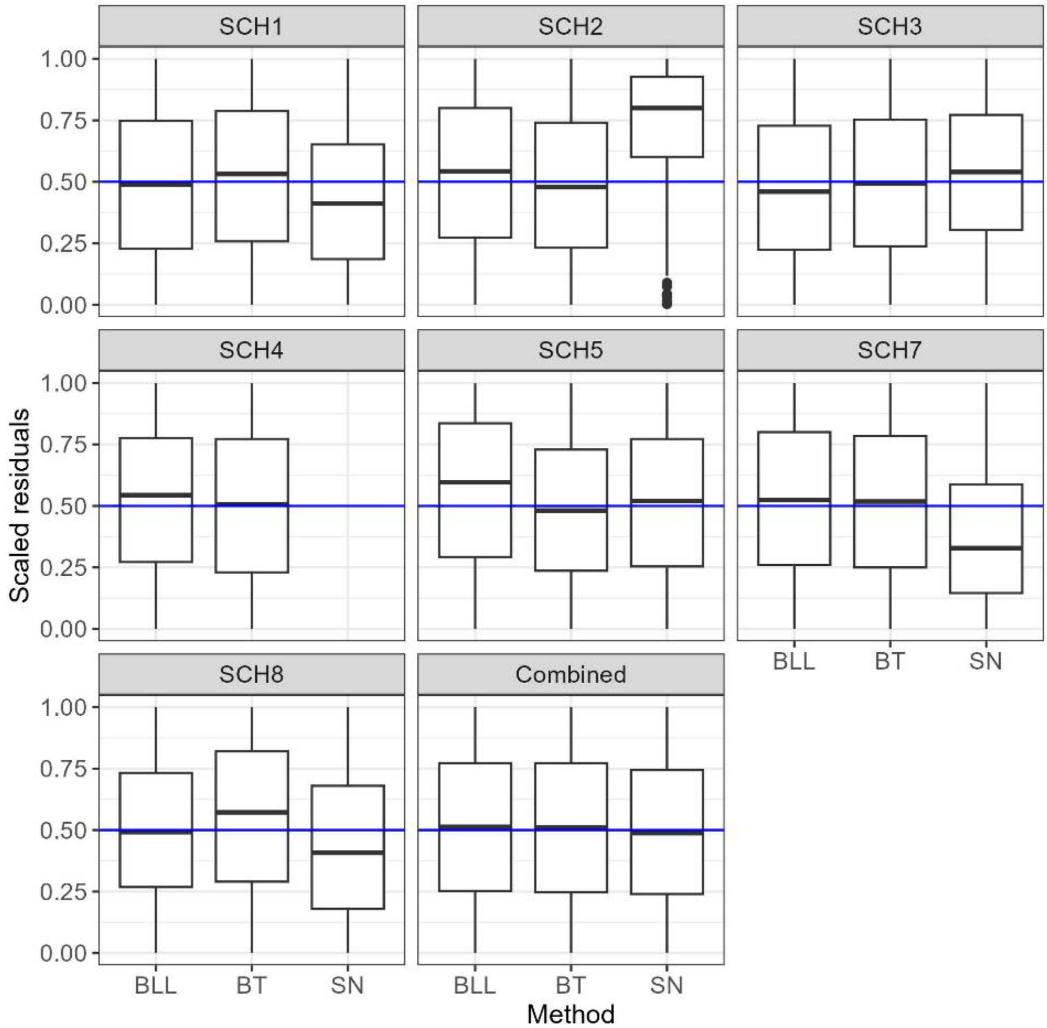

Figure C.16: Scaled residuals by QMA and fishing method for the set net (SN), bottom longline (BLL) and bottom trawl (BT) fisheries for the base case model.

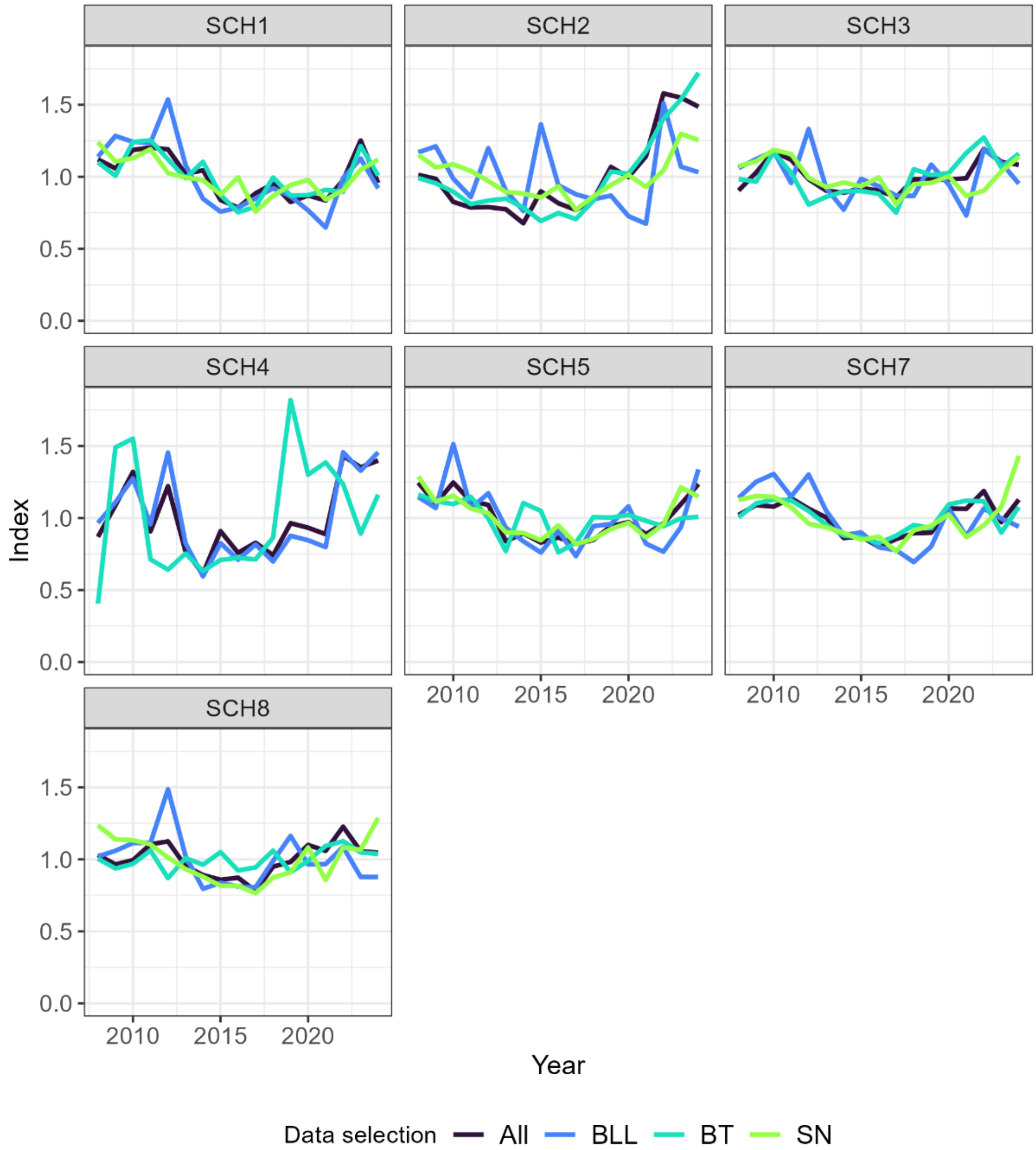

Figure C.17: Spatially and temporally standardised CPUE for the model with data from all fishing methods (All), bottom longline only (BLL), bottom trawl only (BT) or set net only (SN) by QMA.

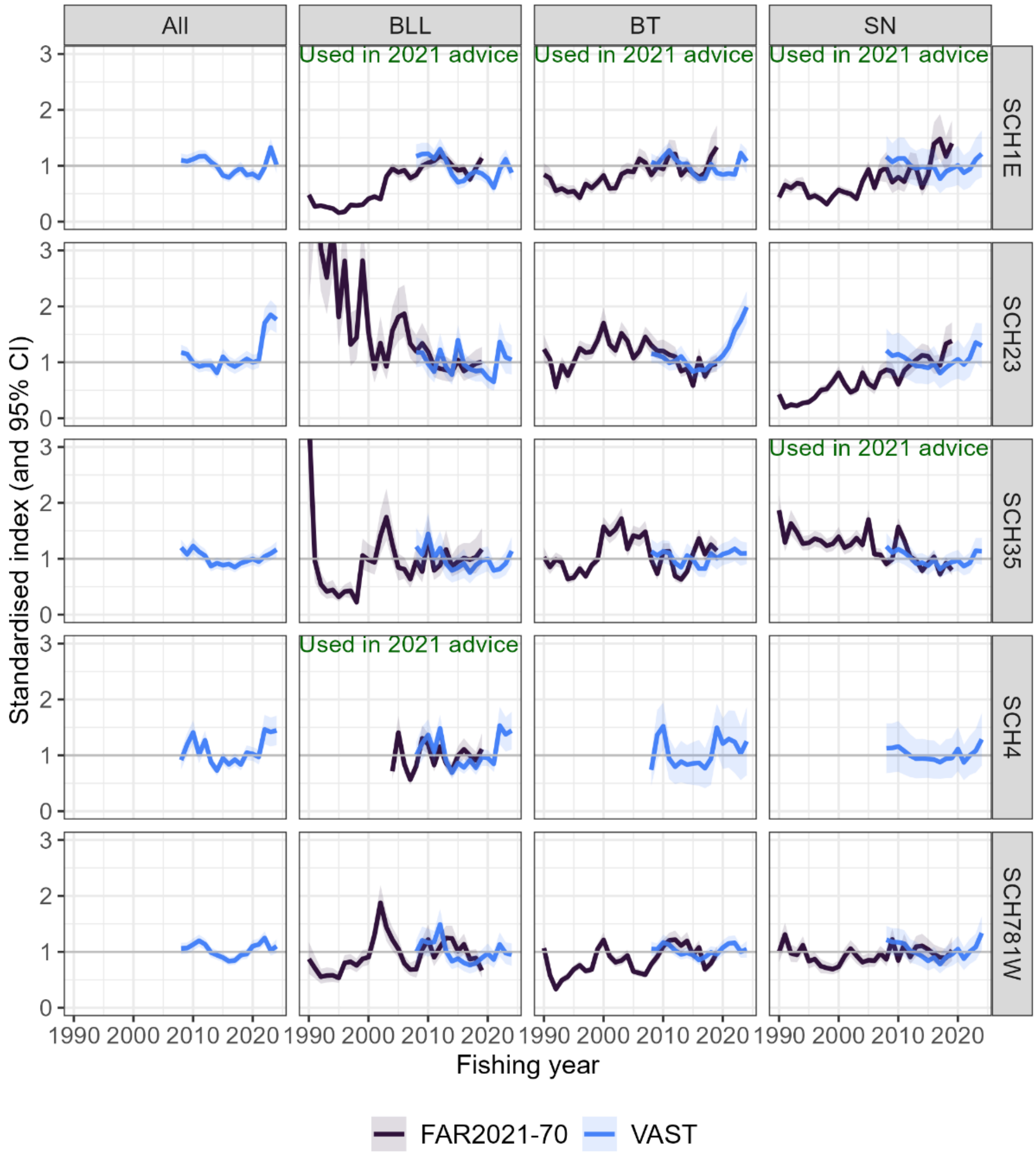

Figure C.18: Spatially and temporally standardised CPUE by fishery area from this analysis (VAST) for the model with data from all fishing methods (All), bottom longline only (BLL), bottom trawl only (BT) or set net only (SN) compared with the 2021 model results (FAR 2021/70, Tremblay-Boyer 2021) by fishery area. The series used in the 2021 management advice are noted (Fisheries New Zealand 2021).

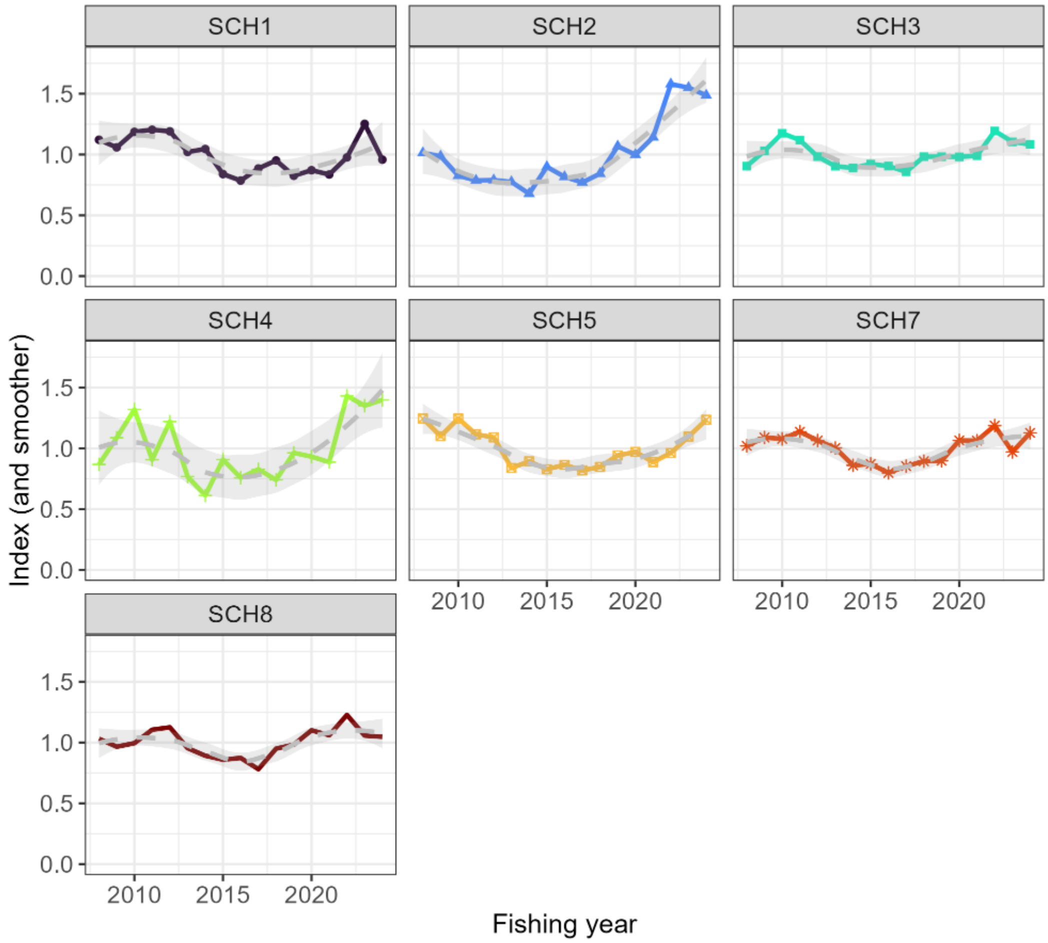

Figure C.19: Relative vulnerable biomass trends of school shark by QMA, with each series standardised to a mean of 1. A smoother is plotted for each series (95% credible interval of a loess smoother with 0.75 span).

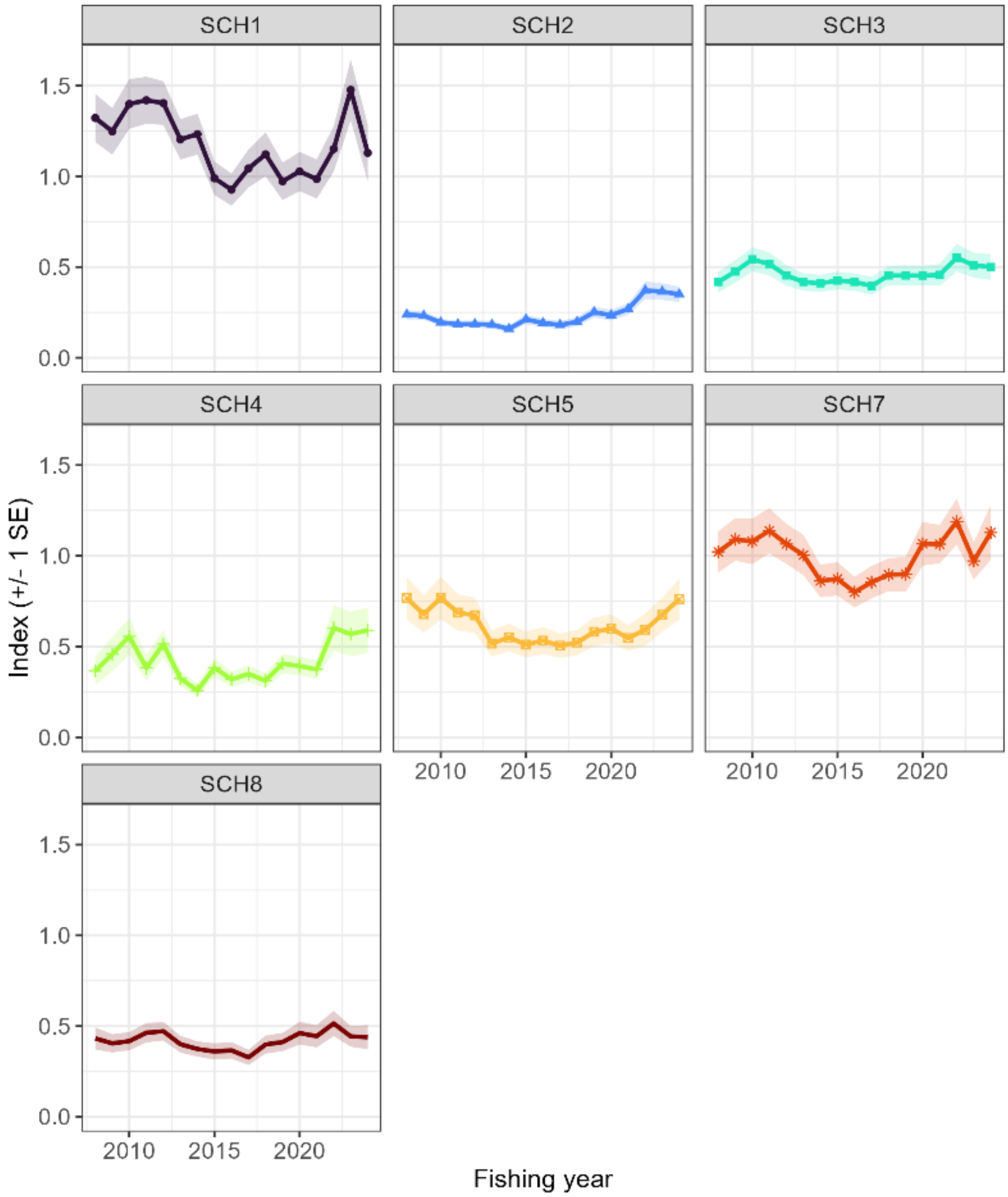

Figure C.20: Relative vulnerable biomass trends of school shark by QMA with ±1 standard error interval (shade), with the proportion between QMAs maintained.

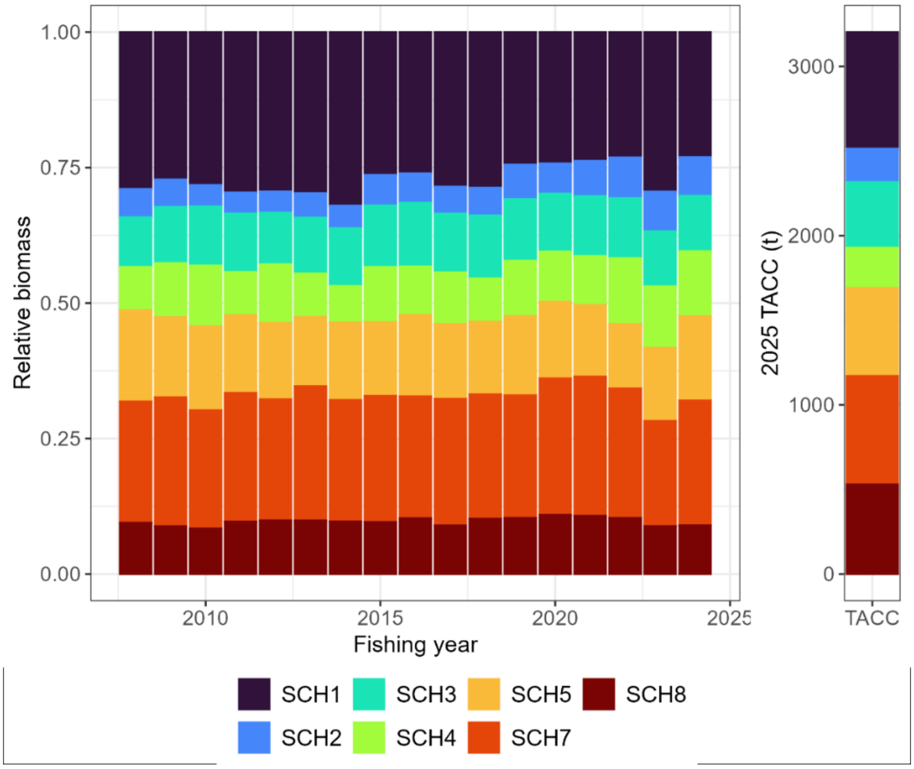

Figure C.21: Proportion of relative vulnerable biomass of school shark in the different QMAs, and the proportion of the 2025 total allowable commercial catch by QMA (TACC).

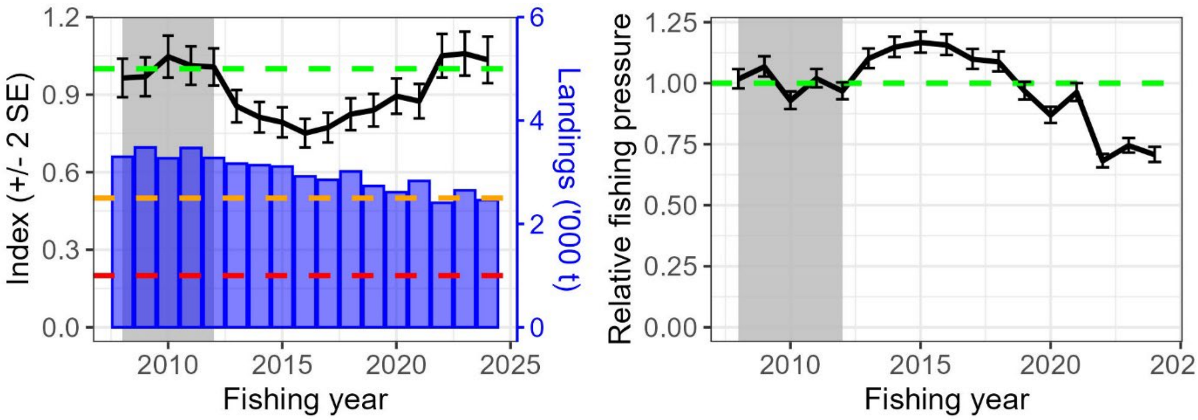

Figure C.22: Left panel: Biomass index for the entire school shark stock as the spatially and temporally standardised CPUE using commercial data from setnet, bottom longline, and bottom trawl (black line and ± 2 standard error). Also shown is the trajectory of total landed SCH by all methods (blue bars). Horizontal lines represent the target (green dashed line), the soft limit (yellow dashed line), and hard limit (red dashed line). The reference period is shown in grey. Right panel: Annual relative exploitation rate for entire school shark stock from the spatially and temporally standardised CPUE series and ± 2 standard error. The interim FMSY-compatible target is shown by the green dashed line and the reference period in grey.

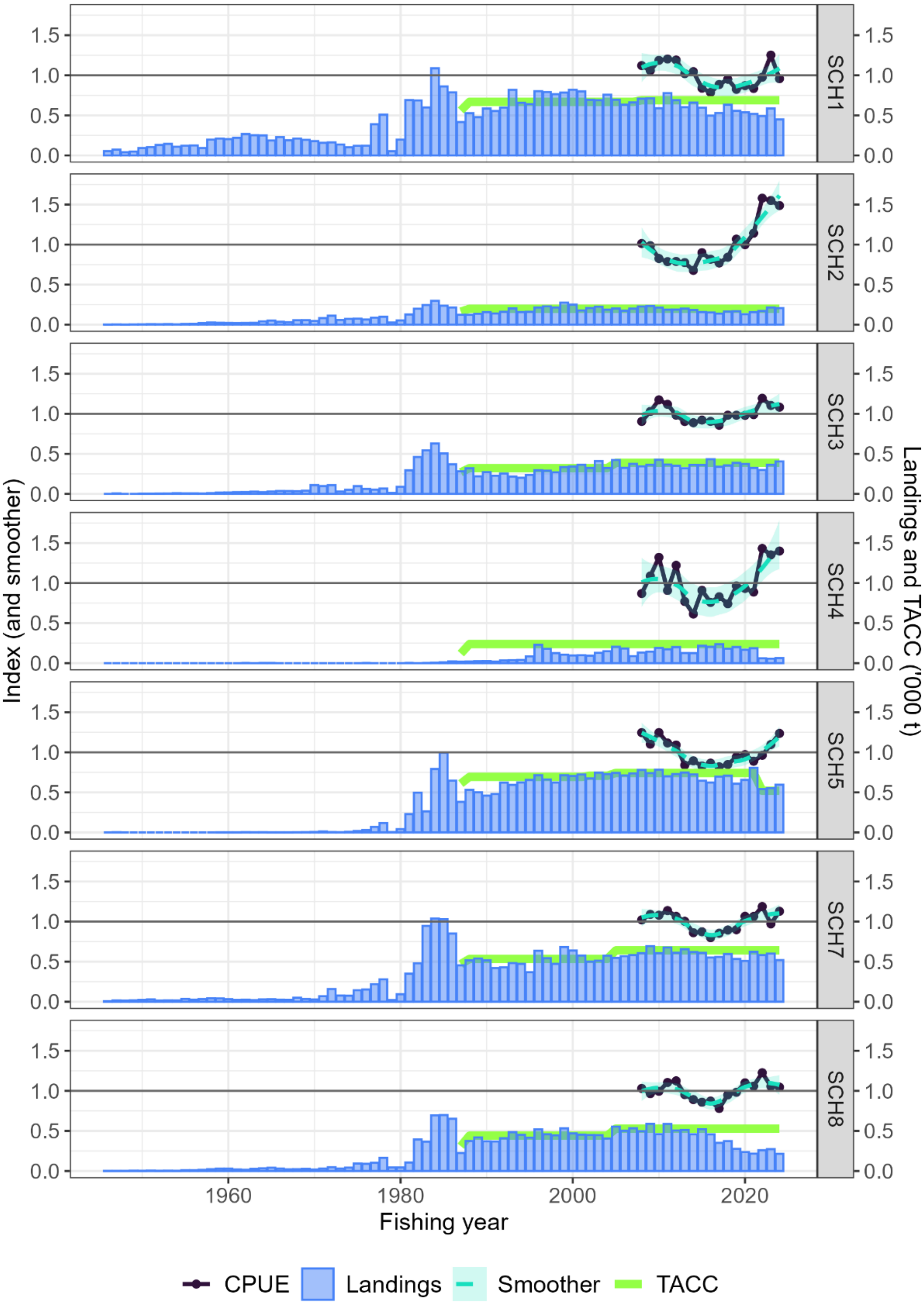

Figure C.23: Relative vulnerable biomass of school shark, summarised and standardised by stock (black line and dots) and smoother (blue line and area). Also landings of school shark by QMA (blue bars) and TACC by QMA (green lines).

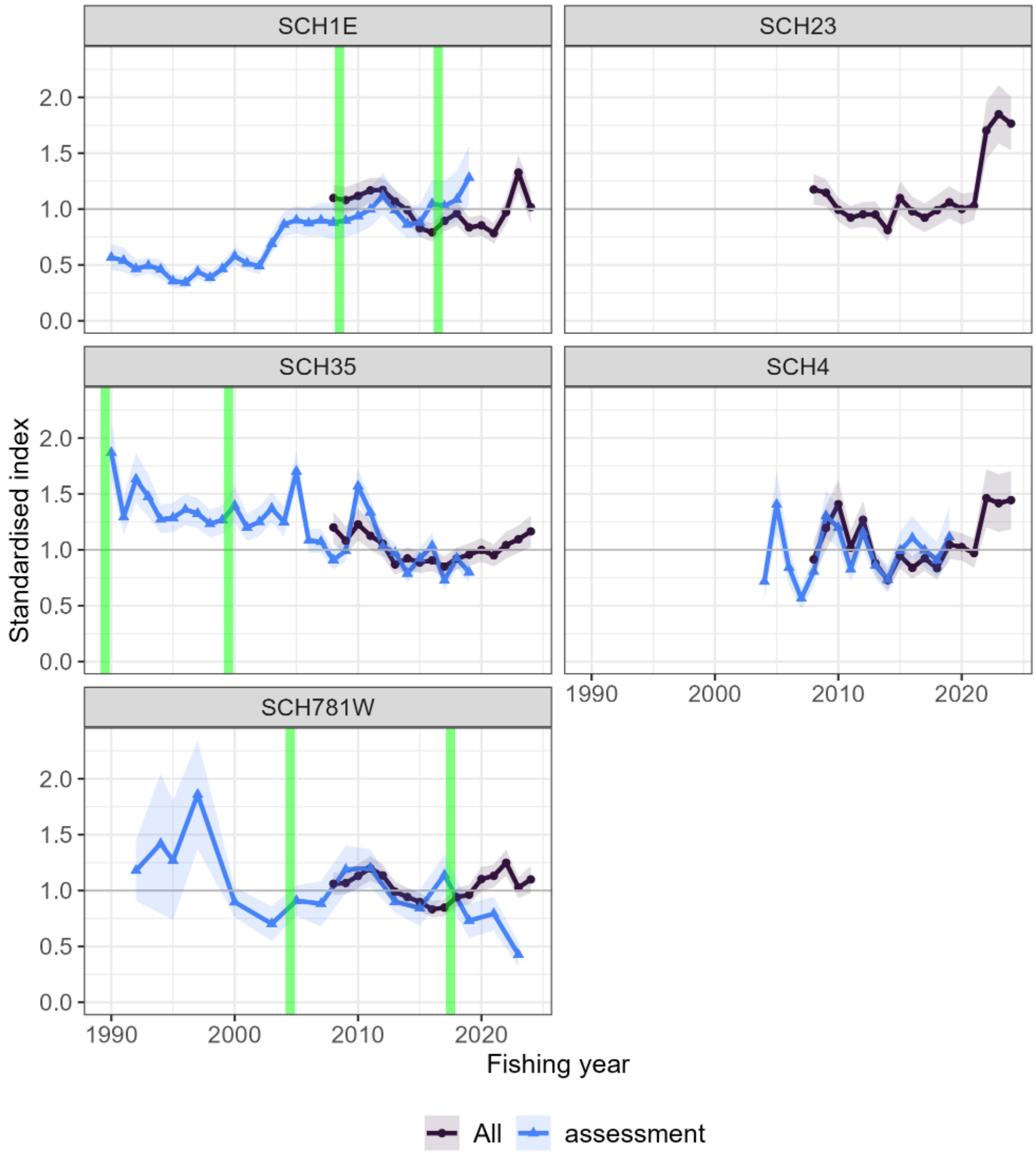

Figure C.24: Relative index of vulnerable biomass of school shark by 2014–24 fishery area (All) compared with the previously used indices for management advice (assessment) and previously used reference period for each fishery area where management advice was accepted (green vertical lines).