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Analysing Potential Inputs to the 2025 Stock Assessment of Western and Central Pacific Oceanic Whitetip Shark (*Carcharhinus longimanus*)

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EXECUTIVE SUMMARY

Oceanic whitetip sharks (*Carcharhinus longimanus*) are caught as bycatch in longline and purse seine fisheries in the Western and Central Pacific ocean (WCPO). Previous assessments indicated the stock was overfished and overfishing was occurring, and the recent assessment highlighted issues associated with some of the inputs.

This report documents Phase 1 of the current project which investigates the potential methods for catch reconstruction, CPUE and length compositions for use in the stock assessment for oceanic whitetip shark in 2025 (Phase 2). This study used model developments made in the context of other shark assessments to develop a set of potential inputs for the upcoming assessment.

Different subsets of longline CPUE observer data showed similar trends, with the exception of the distant water fleet index. Overall, the indices showed a consistent decline from a high in 1999 that flattens around 2005. The indices remained fairly low post-2005, but seemed to increase slightly in the most recent years. Purse seine CPUE indices showed different standardisation effects between set-types, but both free-school and associated indices showed an increase in CPUE in recent years (2009–2020). These indices were corrected for climatic conditions expressed by the NINA4 index.

Predicting longline interactions across the WCPO indicated that the total predicted interactions have declined since 1999, a trend that is consistent with previous analyses. Overall, for both purse seine fisheries, the predicted total interactions declined since the late 1990s and have remained comparably low since then.

Length compositions trends were inconsistent among years and months for models associated with catch and CPUE. However, area effects in longline length data were observed, with smaller fish in the equatorial regions and larger fish at higher latitudes.

The following recommendations are made:

- There are likely to be sufficient data and a sufficiently consistent signal in the different datasets, especially from longline, to conduct a stock assessment.
- We suggest that a fully integrated assessment could be attempted, based on the consistency of datasets developed herein. We suggest that our updated analyses of input data should be compared with previous assessment models in a stepwise fashion.
- As year effects are relatively minor in the longline fisheries, future catch reconstruction attempts could extrapolate interactions further back in time to avoid complications with assuming or estimating initial fishing mortalities in the assessments.

- Alternative assessment methods (for example surplus production assessments) should be run in parallel with an integrated assessment. Length-based or hybrid length-based spatial assessments provide an alternative approach that is independent of recent longline data, and allows for multi-model inference that can strengthen conclusions and potential management advice from an integrated approach.

1. INTRODUCTION

This project investigates methods for reconstructing overall catch, standardised CPUE and length compositions for use in a potential stock assessment for oceanic whitetip shark in the Western and Central Pacific Ocean (WCPO), which is scheduled for 2025.

Oceanic whitetip sharks (*Carcharhinus longimanus*) are wide ranging across the tropical and sub-tropical Pacific Ocean. They are caught as bycatch in tropical and sub-tropical longline fisheries targeting tuna, billfish and blue sharks throughout the WCPO. Oceanic whitetip sharks are also caught in the purse seine fisheries of the WCPO. Unlike blue shark, where some target fisheries exist in the South Pacific Ocean, no target fisheries exist for oceanic whitetip sharks (Williams and Ruaia 2021). While oceanic whitetip sharks were caught as bycatch and were retained in large numbers historically, since January 2013 oceanic whitetip sharks within the WCPFC have been required to be released (WCPFC 2011). However, a recent review documented that the non-retention Conservation Management Measure (CMM) was unevenly applied across WCPFC Members, Cooperating Non-Members and Participating Territories (CCMs), and some oceanic whitetip shark individuals were still observed as being retained (Rice 2018).

The first stock assessessment of oceanic whitetip shark (*Carcharhinus longimanus*) in the WCPO (and in the Pacific) was in 2012 (Rice and Harley 2012) followed by a second assessment in 2019 (Tremblay-Boyer et al. 2019). In addition, in 2019, alternative assessment methods for oceanic whitetip shark (including catch-only simulations, general spatial risk assessment model, Bayesian dynamic surplus production model) were investigated allowing a comparison with the age-structured integrated stock assessment (Neubauer et al. 2019). The variety of models provided similar results, and all methods suggested that there was a substantial risk that current fishing mortality remained above F_{crash}, the fishing mortality that would lead to extinction in the long-term.

Management advice from SC08 informed by the 2012 assessment suggested that the WCPO oceanic whitetip shark stock was in an overfished state and overfishing was occurring. That advice was upheld by SC15 after the 2019 assessment. SC15 considered that the integrated stock assessment (compared to the other models) estimated slightly higher overall fishing mortality, with lower productivity and stock status, and therefore provided the most pessimistic view of current fishing mortality and sustainable fishing mortality. Further, while SC15 noted that the 2019 stock assesment also estimated a slight recovery in stock biomass in 2013-2016, it remained unclear as to what trajectory the stock status would take in the future. A slight recovery in stock status of oceanic whitetip sharks estimated in the 2019 asessment may be considered an indication of the effect of the implementation of CMMs that prohibited the retention of oceanic whitetip sharks (WCPFC 2011 and WCPFC 2019). This lead Brouwer et al. (2024) to recommend that the hypothesis that oceanic whitetip shark fishing related mortality has decreased since 2015 be tested as part of the 2025 stock assessment.

The 2012 and 2019 oceanic whitetip assessments and associated SC management advice continue to highlight data limitations, leading to a wide range of uncertainties considered for the assessment, as is commonly observed across WCPO shark assessments in general. Most WCPO shark fisheries data are characterised by poor historic logsheet reporting and, while recent reporting has improved, mandatory release policies have further complicated the information available from catch data (Brouwer et al. 2024). As a result, historic catch for sharks is ambiguous, and catch histories often need to be reconstructed rather than relying on reported or observed catch (Peatman et al. 2018, Neubauer et al. 2021a, Large et al. 2022, Neubauer et al. 2023). Brouwer and Hamer (2020) also note that past management interventions may complicate the CPUE standardisation, along with the impact of regulatory changes on fishery dependent data; generally low observer coverage in longline fleets particularly in the high seas; and, for most fleets after the oceanic whitetip shark CMM (CMM2011-04) came into force, most oceanic whitetip sharks have been released and not all are reported on logsheets nor seen by observers.

The catch reconstruction prepared as input to the 2019 oceanic whitetip shark assessment introduced the use of discard mortality (DM) scenarios in the historical catches, a key step to account for the potential impacts of the non-retention measures for oceanic whitetip shark (Tremblay-Boyer and Neubauer 2019). This, along with other structural improvements to the catch reconstruction process implemented in successive WCPO shark assessments since, have lead to modelling approaches that better account for non-representative distribution of observed effort in the extrapolation of observed catch rates to WCPO-wide effort. Weighted cross-validation model selection was introduced in the 2022 WCPO mako shark catch reconstruction (Large et al. 2022), followed by the addition of Bayesian hierarchical stacking to the model weighting used in the 2023 WCPO silky shark catch reconstruction (Neubauer et al. 2023), have further progressed the methodology to reconstract past catch histories from non-representative observer data. The catch history was considered a key uncertainty in the 2019 assessment (Tremblay-Boyer et al. 2019), therefore the latest catch reconstruction methods developed for WCPO shark species will be applied to oceanic whitetip shark data prepared for the 2025 assessment.

For the 2019 assessment, the SPC 2019 Pre-Assessment Workshop (PAW) (Pilling and Brouwer 2019) agreed to focus on developing standardised CPUE indices for oceanic whitetip shark in the longline bycatch fleet, as the underlying data were deemed the most reliable of those available, and also covered the greatest extent within the assessment region. The 2012 assessment included standardised indices for other fleets, but these indices were not used in the reference model or the uncertainty grid. In the

2019 assessment, the CPUE for longline bycatch fleet pointed to a general decline in abundance over time since 1999 (with highly variable and imprecise estimates for the earlier part of time series), and a slight increase from 2013 but with the series considered less reliable in later years due to the introducion of CMMs. Tremblay-Boyer et al. (2019) found that there was a conflict between the key input datasets of standardised CPUE and catch-at-length compositions, where the CPUE showed a steep decline over the assessment's duration but the catch-at-length showed no concurrent decline in mean length that would have been indicative of a degradation of the age structure due to overfishing.

Tremblay-Boyer and Neubauer (2019) noted a number of issues associated with the quality and availability of composition data for the 2019 assessment: length data are sparse over time, and the number of length measurements has markedly declined over the recent period of the assessment due to the number of individuals not being brought on board; and, with uneven sampling between fleets, the compositional data may not be representative of catch-at-length for all fleets over time. Additionally, the 2019 assessment was unable to standardise for the distinct north-south increase in mean length, and consequently these data were downweighted in the assessment. However, Tremblay-Boyer and Neubauer (2019) also note this data input could potentially become more informative with further analysis.

As with catch reconstruction methods, developments in compositional data analysis have also been undertaken in subsequent WCPO shark assessments since 2019. These include scaled model-predicted length compositions to address the lack of spatial and temporal representative coverage of length measurement sampling for sharks from both purse seine and longline fisheries. Neubauer et al. (2023) note that down-weighting composition data may not be sufficient to eliminate false signals that can occur due to lack of representative sampling across key sources of variability, and they used a standardisation model for composition data that adjusts the length-frequency samples based on spatial and temporal variability. A similar approach will be applied to oceanic whitetip shark length data for input into the 2025 assessment.

This report also investigates standardised CPUE analyses for both the longline and purse seine fleets, with the addition of data since the 2019 assessment, for consideration by SC20 as likely input into the 2025 assessment.

2. METHODS

2.1 Description of datasets

We used a range of data-sources held by the Pacific Community (SPC) who are the custodians of data supplied to the WCPFC by Members, Cooperating Non-Members and

Participating Territories (CCMs). These datasets were extracted by SPC upon request, and analysed by the assessment team.

The following datasets were used for analysis:

- **L-BEST:** SPC's best (raised) estimates of longline effort (in hooks) for fleets in the WCPFC Convention Area, available at the 5°× month × year × flag × fleet resolution.
- **S-BEST:** SPC's best (raised) estimates of purse-seine effort (in sets) for fleets in the WCPFC Convention Area, available at the 1°× month × year × flag × set-type × fleet resolution.
- **Observer programmes for the WCPO longline fleet:** The observer dataset for the WCPFC longline fleet available to SPC was used for the analysis, including data from the SPC's Regional Observer Program and national observer programmes. Records collected by longline observers that are relevant to this assessment are key fishing event attributes (including date and time, location), as well as information on gear and catch:
  - gear/set characteristics (hooks between floats, total number of hooks fished);
  - species;
  - fate code of the catch (e.g., discarded or retained);
  - condition at capture and at release (if not retained); and
  - length and the sex of the individual.
- **Logsheet-reported [1] operational data for WCPO purse-seine and longline fleets:** Reported by day, flag, EEZ, latitude and longitude, set type, vessel, catch and effort. Oceanic whitetip shark were not reported consistently on log-sheets for either purse-seine or longline fisheries before the introduction of CMM2011-04.

Previous stock assessments for oceanic whitetip shark focused on observer data, since operational data was not deemed suitable for deriving indices of abundance or catch information. In contrast, recent stock assessments for blue and mako sharks used a range of indices derived from logsheet-reported data, from a subset for vessels and flags that have reporting consistently through time (Neubauer et al. 2021b, Large et al. 2022). However, the latter relied on consistent reporting from a small set of flags (mainly JP, EU, NZ and AU) in high latitudes. For oceanic whitetip shark and other tropical species (such as silky shark), which are caught across a number of EEZs and in the tropical

[1] Note: Not all logsheet and observer data are available for stock assessments of elasmobranchs. As a result, the SPC could not release logsheet or observer data from some WCPFC CCMs in some years for the oceanic whitetip stock assessment and related analyses.

high-seas, data from these flags with relatively consistent reporting likely represents too small a proportion of catch and effort to be useful for estimating abundance trends. We therefore did not attempt to use logsheet data for this analyses.

2.2 Estimating fishery interactions from observer data

As with the 2019 oceanic whitetip assessment, we opted to estimate interactions from observer data. While this procedure is potentially biased by conservation measures in place since 2013 (CMM2011-04), there are few useful alternatives available. Trade-based catch reconstructions were developed for the 2019 assessment to provide an alternative catch scenario, but only the observer-based catch reconstruction was used as input into that assessment (due, in part, to the problematic assumption of a constant WCPO oceanic whitetip shark proportion in the global fin trade). Tremblay-Boyer et al. (2019) discuss the substantial problems associated with time-series based on fin-trade sampling. The greatest challenge was the inability to scrutinise such estimates on the basis of data — they essentially represent assumptions about species compositions and fin-trade volumes that are extrapolated in time, and are unlikely to be correct in recent times given non-retention measures in place in the WCPFC and in many EEZs.

Trade based estimates of catch will not be revisited for the 2025 assessment. Instead, we aimed to try and develop a better understanding of recent catch-rates, especially in longline fleets where retention measures may lead to a substantial number of sharks going unnoticed or unidentified by observers if they are cut free before being within a distance that would allow observers to identify the animals.

2.2.1 Estimation of catch rates from observed sets

Observer data from longline and purse-seine data were used to analyse trends in catch rates as well as to extrapolate observed catch rates to best estimates of over-all fishing effort in the WCPO in order to estimate over-all interaction rates. Catch-rate models were similar, but not identical, for the two tasks: catch rate models for prediction require the use of variables that are available for the over-all effort datasets; these are restricted to vessel flag, month, year, and estimated catch of main tuna and billfish target species. Observer data for CPUE can be analysed using observer-program and gear factors as standardising variables.

CPUE analyses also provide a way to inspect consistency of trends among gear types, and to understand the impact of non-retention measures on composition data and extrapolated catch estimates from longline data. Specifically, by analysing observer CPUE along a number of strata, we can gain an understanding of the likely change in reporting along these strata using a comparative approach. While this approach doesn't allow for an estimation of the absolute levels of reporting changes across the whole fleet (i.e., all fleets may be affected to some degree), we can get a relative estimate that can provide insights into potential solutions for reconstructing total interaction levels.

Catch rates were standardised using a progression of models aimed at exploring the importance of oceanographic and gear factors on CPUE (Tables 9 and 10). Models were similar between longline and purse-seine, with both models using a negative-binomial model with over-dispersion adjustment (Tremblay-Boyer & Neubauer 2019). The model used the number of hooks (or sets) as an offset. In the case of longline CPUE, we estimated smooth effects for the number of hooks (effectively allowing for non-linear catch rates with the number of hooks) and hooks between floats (HBF). For purse-seine, analyses were split between associated and un-associated sets given differences in length-composition for these gear-types.

For longline, we applied CPUE models to four distinct subsets for analysis.

1. Full dataset - We used all observer data available for the tropical WCPO. This dataset includes observations from tuna, billfish and blue shark target fisheries, but an observer-program-year interaction specified as a random effect allows for deviations from a global annual trend for each observer program. This dataset was used to test for over-all consistency among observer programs, without an expectation of deriving a useful index.

2. Observer program dataset - A dataset of observer programs was prepared following Tremblay-Boyer and Neubauer (2019), using observer data from FMOB, HWOB, FJOB, PFOB, NCOB, ASOB, KIOB and MHOB.

3. Additional observer program dataset - Loosely based on the dataset as above (HWOB, PFOB, NCOB, FJOB, FMOB), with observer data from TWOB, TOOB and CNOB.

4. Distant water fleets only - A dataset with only distant water fishing fleets, which accounted for the majority of recent observer data in the tropical WCPO.

Clarke et al. (2018), in the 2018 silky shark assessment, suggested variations in catchability with ENSO (specifically, the NINA4 index; Figure 1) may be driving catchability in WCPFC longline fisheries for silky shark, and a time-varying catchability formulation was adopted for the accepted model. This aspect was incorporated in the 2024 silky shark assessment (Neubauer et al. 2023) by including the NINA4 index in two ways, and we have made the same addition for the oceanic whiteip assessment. First, a main effect for the NINA4 index was applied as the mean over the preceding three years for indices based on associated purse seine catch, or four years for all free-school and longline indices. This reflects an approximate time-frame over which indices might integrate. Secondly, an interaction term with observer-program was added, to investigate if region specific trends in catchability (or local abundance) driven by NINA4 could alter the over-all index.

A series of models were run from a simple non-standardised model for annual catch rate, and sequentially adding effects to the model, with the full model taken as the standardisation model for each analysis.

The full longline CPUE model was given by:

```
obs_int | hooks ~ (1|yy) +
                  (1|program_code*yy) +
                 s(log(hooks)) +
                 s(log(HBF)) +
                  (1|vessel_id)) +
                  (1|mm) +
                 s(SST) +
                   NINA4_MA(3/4) +
                  (1+NINA4_MA(3/4)|program_code) +
                t2(lon5,lat5)
```

with all variables added sequentially according to the formula above. The base model for longline observer effort included year, month, SST, chlorophyll-a, distance to coast and the amount of swordfish catch. Alternative models added non-linear effects for hooks, flag, NINA4 indices and various spatio-temporal terms. The corresponding model for purse-seine excluded swordfish catch but added set-type-year interactions (Table 11).

The same approach was taken for purse-seine by set type (Table 12), omitting any hook related variables and vessel id (the latter was not available in the data extract). All models were fitted with brms using full Bayesian inference from MCMC, with four chains run for 1000 iterations each, discarding 500 iterations as burn-in and retaining 2000 iterations for inference across the four chains.

2.2.2 Extrapolation of observed catch rates to WCPO-wide effort

A difficult aspect of extrapolating observer catch-effort, beyond potential issues due to non-retention measures, is the non-representative distribution of observed effort. Relative to over-all effort, observer effort in both longline and purse-seine has only been relatively widespread in recent years (Tables 1–6).

The lack of representative effort makes it difficult to develop models on the basis of model selection, which will favour models that best predict the observed interactions, but may not perform optimally across effort that is poorly observed. To counter this potential bias in selected models, Large et al. (2022) used-cross validation by flag weighted by the total effort. However, this method is computationally intensive, and evaluating cross-validation for a large number of strata (e.g., vessel flags), or a range of different strata (flags, latitude) for a number of candidate models is prohibitive.

To circumvent the high computational overhead of the previous method, and to allow more flexibility in the variables used to judge model performance, Neubauer et al. (2023) cast the model weighting as a linear-modelling problem, estimating predictive capacity of individual models as a function of covariates, which can be used to predict model weights for prediction datasets that are not well represented in the training set. Specifically, Bayesian hierarchical stacking is used, a model-based estimation of stacking weights (Yao et al. 2022). The procedure uses the expected log-posterior predictive density estimate per model and data point (Yao et al. 2018), and then uses a logistic-linear model to estimate the effect of covariates on the predictive ability of individual models. The corresponding stacking model was written in Stan (Appendix B), using flag, year, latitude and set-type (for purse-seine) as covariates, and producing corresponding predictions over the full effort data for longline and purse-seine datasets.

Previous catch reconstruction models for sharks in the tropical WCPO separated short-lived target shark fisheries in the western tropical Pacific from non-target fisheries (Tremblay-Boyer & Neubauer 2019). The main difference in approaches for these fisheries was that fishery-year effects were assumed constant for target fisheries, effectively assuming that fisheries in the area continued to catch sharks at high (target) catch rates throughout their existence. Such a treatment may no longer be appropriate since there is no indication of continued high shark catches from these fisheries, and we therefore included these fisheries in our over-all model, using model formulations with flag-year interactions and spatial/spatio-temporal terms, as well as model selection to fit the model.

2.3 Model-based scaling of length composition data

Length composition data for sharks from both purse-seine and longline data have not been collected in a representative manner across the fleets over time and space (Figures 2, 3). This poses a problem in that the lack of representative sampling across key sources of variability can lead to biased estimates of catch compositions. Biased compositions can, in turn, lead to false signals if composition data is not reflective of biological processes represented in the assessment model (Minte-Vera et al. 2017), and even down-weighting composition data may not be sufficient to eliminate such signals (Wang & Maunder 2017). It is therefore important to get an unbiased representation of composition data that corrects for biased sampling and appropriately scales composition data.

The present study used a standardisation model for composition data. The model is similar to the one developed in Neubauer and Kim (in press). The procedure adjusts the length-frequency samples based on spatial and temporal variability, similar to CPUE standardisation. However, unlike CPUE, rather than removing variation across strata, it predicts length-compositions across catch (or CPUE for index fisheries). This procedure has the advantage that reasonably smooth length-frequency distributions (i.e., filtering out variance from highly multi-modal length-frequency distributions that result from low sample numbers) for sparsely sampled strata can be extracted, even if individual samples in those strata are unlikely to provide a reliable estimate of the actual length frequencies. Random effects formulations ensure the sharing of information across strata.

The formulation is an extension of the multinomial GLM, which was developed for estimating length frequencies of New Zealand rock lobster removals (D. Webber, unpublished analysis). The extension here was achieved by factorising the multinomial distribution into independent Poisson distributions for total measurements (N_s) in sample s, and a second Poisson distribution with mean $\lambda_{i,s}$ over draws $n_{i,s}$ for the number of fish in length category i in sample s. Length proportions π can then be recovered by setting $\pi_i = \lambda_i / \sum_j(\lambda_j)$. This setting allows the formulation as a straightforward Poisson GLM, using the total counts N_s in sample s as an offset term.

We implemented this model using vessel flag, area (defined as 10°x 10°bins) and year, as well as set-type for purse seine data. For each term, an interaction with year effects allows prediction of area-flag-year (and set-type) specific length compositions from available data, with predictions reflecting the amount of information and variability within strata. There was little evidence for sex-bias in any of the data (Figure 24), and we therefore did not include sex in the analysis.

Analyses were run independently for longline and purse seine observer data, and restricted to the tropical WCPO (-20°S to 20°N) The model was implemented in brms and run via:

```
tot_by_bin ~ offset(log(n)) +
             (1 | bin) +
             (1 | bin:area) +
             (1 | bin:yy) +
             (1 | bin:mm) +
             (1 | bin:area:yy) +
             (1 | bin:flag_id) +
             (1 | bin:flag_id:yy).
```

where tot-by-bin is the total observations by length bin, modeled with a Poisson error distribution, n is the total observations across length bins in a stratum, and all factors are included as interactions with length bins.

A corresponding model was developed for standardising compositions for potential index fisheries, by using variables used in the CPUE standardisation, and scaling compositions by predicted CPUE across index data:

```
tot_by_bin ~ offset(log(n)) +
             (1 | bin) +
             (1 | bin:area) +
             (1 | bin:yy) +
             (1 | bin:mm) +
             (1 | bin:area:yy) +
             (1 | bin:program_code) +
             (1 | bin:program_code:yy) +
             t2(meiv2, bin, k = c(5, 10)).
```

The model can be used to obtain predictions for corresponding strata in catch or CPUE data (or predictions), and scaled using relative catch in each stratum when aggregating to larger scales. For example, predictions and scaling can be achieved at an area-flag-year stratum for longline data, with scaled estimates combined to an annual predicted composition. The analysis above was carried out for longline data; purse seine analyses were attempted, however there were low number of length samples for purse seine (1400 observations in total across set types), which proved insufficient to fit models.

3. RESULTS

3.1 Models of catch rates based on observer data

3.1.1 Longline observer indices

Different subsets of longline CPUE observer data resulted in similar trends for most of the indices developed for longline (Figure 4), except for the index for distant water fleets, which showed fluctuations without a clear trend. With the exception of the distant water fleet index (which starts in 2009), overall the estimated year effects were highly variable and uncertain at the start of the time series (prior to 2000), and showed a consistent decline from a high in 1999 that flattens around 2005.

The scale of the initial CPUE was not independent of the subset of observer programs used. The index used by Tremblay-Boyer et al. (2019) and the full dataset showed a very high initial CPUE, with large fluctuations. The index with additional observer programs was markedly lower, and less noisy (albeit still uncertain), during the first 5 years.

The indices remained low post-2005, but appeared to increase slightly in the recent time period from 2018, including for the dataset based on the previous assessment for oceanic whitetip shark (Tremblay-Boyer et al. 2019).

Based on the Tremblay-Boyer et al. (2019) subset, there were very minimal standardisation effects (Figure 5), but also a high degree of inconsistency among observer programs (Figure 6). Early CPUE, in particular, was highly inconsistent, with estimates from KIOB being clearly wrong. The alternative index, without KIOB and with additional programs, again showed little standardisation effect (Figure 7), but showed a higher degree of consistency between observer programs, and a lower initial CPUE (Figure 8). Complete diagnostics for all the longline observer indices developed are in Appendix B.

3.1.2 Purse seine observer indices

Purse seine CPUE indices showed different results between set types (Figure 9). For both indices there was a standardisation effect associated with the addition of the NINA4 covariate to the model (Figures 10 and 11). The standardisation effect on the free-school sets index flattened the index from a strongly increasing unstandardised trend (Figures 10 and 12), to an index with minimal increase. There was a high degree of consistency between observer programs in raw CPUE and the standardised CPUE index.

In contrast, the object-associated index had a lesser standardisation effect from the NINA4 covariate relative to the free-school sets (Figures 11 and 14). Even so, the relative value was lower post-2016, and slightly higher in the earlier time period. The addition of observer program into the model had a standardisation effect on this index that removed the steep declining pattern around 2020 (Figure 11). The overall CPUE index for the object-associated sets showed an increase over the same time period, with a notable increase in catch rates in recent years. While not as consistent as CPUE for unassociated sets, there was a reasonable degree of consistency between observer programs in raw CPUE and the standardised CPUE index for object-associated sets. Complete diagnostics for purse seine observer indices are also in Appendix B.

3.2 Predicting catch across the WCPO

3.2.1 Longline catch of oceanic whitetip shark across the WCPO

Across the candidate models, two models had the highest weights (Figures 16a and b). The main model accounted for the majority of the effort between latitudes -30°and -20°S (Figure 16c). This model included spatial terms (lat/long), and flag-year catch. Both models with the highest weights did not include NINA4 based formulations. Overall, there was little change in the predicted model weights from the inputs to the prediction dataset (Figure 16d). Model diagnostics suggested good fits across all strata (Appendix C.1).

Predictions based on effort (Figures 17 and 18) revealed high predicted total catch mainly in the southern equatorial region of the Pacific (between -20°S and the Equator); CPUE was relatively high throughout most of the Pacific (except for some north-western areas) (Figure 18).

Overall, total predicted catch has declined since 1999 (Figure 19) from around 200 000 individuals to around 50 000 per year. This decline is comparable to figures predicted by Peatman et al. (2018), but lower than total catch predicted by Tremblay-Boyer et al. (2019), especially in the early 2000s when the latter analysis suggested catches in excess of 500 000 individuals.

The decline can be associated with the predicted interaction trends of the distant water fleet nations vessels (KR, TW, CN and JP) (Figure 20). A large proportion of the total catch, particularly in the predicted peak year (1999) were attributed to the KR flagged vessels, with a high random effect estimate for that year. Predicted total catch declined post-1999, but increased again around 2005 (Figure 19), corresponding with the increased predicted catch from TW and CN flagged vessels (Figure 20). Thereafter, catch steadily declined.

3.2.2 Purse seine catch with oceanic whitetip shark across the WCPO

Much like the longline models, there were two purse seine models with high weights, neither of which include NINA4 based formulations. However, the main model included spatio-temporal terms for spatial fields by month and flag-year catch (Figure 21a and b). This model performed well for the effort across the Pacific, but slightly better for the effort in the equatorial Pacific (-10°S to 10°N) (Figure 21c). Model weights had little change from the inputs to the prediction datasets (Figure 21d), and model diagnostics showed relatively good fits across all strata (Appendix C.2).

For both object-associated and free-school sets, fishing effort is concentrated in the western equatorial Pacific, and high predicted total catch generally occurred in that area (Figure 22).

Overall, for both purse seine fisheries, the predicted total catch declined since the late 1990s and remained comparably low for the rest of the time series (Figure 23). Post-2010, the total catch for free-school sets is predicted to have increased steadily until recent times.

3.3 Length frequency compositions

Longline length data showed no consistent trend (Figures 24–26), and length compositions showed no strong month or year effects for models designed to scale compositions by catches and CPUE (Figures 27 and 28). Most of the variation in the composition data is explained by location of fishing effort (area) and vessel-flags or observer program, with some of the variability explained by the corresponding interaction terms with the year variable.

The models were able to fit the data relatively well across all the strata (Figures 29, 30, 31, 32, 33, 34). However, the estimated year effects showed no trends (Figure 35).

The vessel-flag effects revealed a high proportion of small sharks (length $<$100 cm) were caught by US flagged vessels (Figure 36), with other vessel-flags exhibiting similar patterns of proportions of small to average sized individuals (e.g. CN, KR, PG). Some vessel-flags caught larger individuals, such as NC, SB, PF, KI.

Longline fisheries across the northern and southern equatorial regions (10°N – -10°S) tended to catch higher proportions of smaller oceanic whitetip sharks, with bigger sharks caught further south (-20°S). Scaled length frequencies, by area, also exhibited this north-south size trend, with mostly small to average sized sharks caught around the equatorial region, with larger sharks caught in fisheries in southern latitudes (Figure 38).

The modal length (upper jaw fork length, UL) of scaled length frequencies was around $\sim$110 cm in the longline fisheries, particular for the distant water fleet nation flags, which accounted for most of the catch (Figures 39 and 40). Similarly, standardised length frequencies by CPUE show only very slight variations (Figure 33), and appeared unimodal with a peak at lengths of $\sim$110 cm UL.

Purse seine length data were not analysed beyond simple extraction and plotting of data, which confirmed sparse composition data for these fisheries (Appendix D).

4. DISCUSSION

Our analyses for oceanic whitetip datasets largely followed methods employed for these datasets in the last stock assessment (Tremblay-Boyer & Neubauer 2019). We explored the sensitivity of some of the inputs to subsetting of the data, and employed updated analyses developed for recent shark assessments.

While there were clear similarities between our results and the previous assessment inputs, some important differences and nuances remain. Specifically, the reconstructed catches in our analysis showed a more steady decline at an over-all lower level since the mid-1990s (assuming the 1999 spike in Korean catch is due to a reporting error rather than an abnormally high catch that year). The over-all level of catch predicted from our analysis was more akin to that predicted by Peatman et al. (2018), albeit still slightly below those estimates in early years.

The key difference between our present analysis and the previous one is the explicit inclusion of smooth representation of space in the model. The previous analysis only contained a flag and flag-year effect which, in effect, would apply the same catch rate for flags within a given year regardless of location. Given poor spatial observer coverage for longline fleets, this assumption possibly leads to very high estimates for parts of the fleet that fish in waters with low oceanic whitetip shark abundance. In addition, our model-based stacking provides a way to adjust the model choice for non-representative sampling, which should lead to more reliable predictions. While the true scale of catches remain unknown, a steady decline appears *a priori* more plausible than a sharp increase for a population that had likely been subject to longline fisheries since the second half of the 1900s.

The lower and more steady decline in early catch mirorred an over-all lower level of CPUE seen in our analysis across alternative CPUE datasets. The high initial CPUE seen in previous analyses and our initial CPUE based on previously used observer records, leads to a sharp decline from the late 1990s from a relatively flat CPUE for the first five years. Given the exploitation history of the stock, and slow life history of oceanic whitetip shark, a more steady decline appears more plausible *a priori*. We therefore suggest that, at a minimum, alternative indices should be explored for the upcoming stock assessment.

The previous stock assessment employed an integrated stock assessment (Tremblay-Boyer et al. 2019), and a natural first assessment step will be to update the assessment in a step-wise manner with updated data, and (potentially) standardised length compositions for index fleets. Secondly, given difficulties with shark assessments in many areas, we recommend that a surplus production assessment approach should also be attempted. Other assessment approaches may not be needed, but could provide a multi-model approach to ensure that the assessment is robust.

The following recommendations are made:

- There are likely to be sufficient data and a sufficiently consistent signal in the different datasets, especially from longline, to conduct a stock assessment.
- We suggest that a fully integrated assessment could be attempted, based on the consistency of datasets developed herein. We suggest that our updated analyses of input data should be compared with previous assessment models in a stepwise fashion.
- As year effects are relatively minor in the longline fisheries, future catch reconstruction attempts could extrapolate interactions further back in time to

avoid complications with assuming or estimating initial fishing mortalities in the assessments.

- Alternative assessment methods (for example surplus production assessments) should be run in parallel with an integrated assessment. Length-based or hybrid length-based spatial assessments provide an alternative approach that is independent of recent longline data, and allows for multi-model inference that can strengthen conclusions and potential management advice from an integrated approach.

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TABLES

6.1 Observer data availability

6.1.1 Longline observer data

Table 1: Number of observer - reported oceanic whitetip shark interactions by flag in the data extract from the SPC observer database for longline fishing events.

Year	AU	BZ	CK	CN	FJ	FM	JP	KI	KR	MH	NC	NZ	PF	PG	PW	SB	TO	TV	TW	US	VN	VU	WF	WS
1990	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	22	0	0	0	0	0	32	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	28	0	0	3	0	0	15	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0
1994	69	0	0	7	1	0	42	0	0	0	0	0	0	0	0	0	0	0	27	19	0	0	0	0
1995	11	0	0	75	36	0	34	0	0	0	0	0	0	0	0	0	11	0	69	57	0	0	0	0
1996	41	0	1	61	10	5	16	0	0	0	42	3	0	0	0	3	0	0	17	117	0	0	0	0
1997	18	0	0	84	51	4	93	0	0	0	0	0	27	0	0	31	0	0	27	79	0	0	0	0
1998	0	0	0	56	0	6	15	0	48	0	11	3	0	0	0	131	116	0	738	192	0	0	0	4
1999	0	0	0	40	63	1	22	0	187	0	2	0	0	476	0	667	11	0	419	145	0	0	0	1
2000	0	0	0	77	0	5	26	0	0	0	0	1	0	2	1	20	16	0	65	325	0	0	0	0
2001	0	0	0	75	2	3	3	0	0	0	1	2	0	200	0	24	0	0	380	639	0	0	0	10
2002	24	0	0	0	16	0	2	0	59	0	17	0	57	449	0	73	0	0	175	685	0	0	0	0
2003	21	0	0	0	70	0	0	0	0	0	19	5	93	4	0	53	0	0	4	239	0	0	0	0
2004	19	0	0	122	61	28	2	0	0	0	11	2	52	33	0	21	231	0	179	537	0	0	0	0
2005	3	0	0	39	298	42	13	0	69	0	2	1	39	299	0	0	10	0	0	163	0	0	0	0
2006	8	0	2	252	115	18	0	0	152	0	6	0	50	222	0	0	127	0	25	198	0	0	0	2
2007	13	0	0	348	71	38	0	0	3	0	1	2	23	145	0	0	44	0	0	170	0	0	0	0
2008	6	0	0	81	124	47	0	3	0	7	2	1	23	161	0	0	64	0	7	93	0	0	0	0
2009	3	0	11	109	86	0	0	0	0	3	5	0	42	0	0	0	11	0	27	172	0	9	0	0
2010	2	0	10	10	18	0	0	0	0	0	3	1	68	255	0	0	1	0	44	224	0	35	0	0
2011	21	0	8	10	34	0	0	0	6	0	7	0	18	14	0	1	0	0	208	156	0	54	0	0
2012	15	0	0	193	8	0	0	0	42	0	7	0	17	402	0	28	0	0	647	143	0	0	0	0
2013	28	0	12	112	69	19	0	5	119	0	3	0	29	279	0	45	0	0	99	201	0	85	0	4
2014	37	0	10	38	46	15	2	0	49	0	12	0	70	76	0	5	6	0	164	244	0	15	0	0
2015	20	0	26	3	102	15	18	3	84	0	1	0	78	0	0	42	11	0	103	314	0	21	0	0
2016	0	0	0	222	120	18	34	15	38	6	15	0	122	9	0	0	3	13	141	260	0	16	0	0
2017	0	0	37	371	83	0	25	21	53	8	17	0	74	0	0	0	5	0	212	106	0	0	0	26
2018	0	0	12	87	246	3	80	7	72	14	17	2	37	0	0	5	5	13	172	147	0	41	0	0
2019	0	0	27	111	229	5	62	27	160	12	40	0	57	0	0	7	22	5	250	286	0	32	0	11
2020	0	0	0	292	168	1	0	7	36	0	33	0	65	0	0	0	5	0	188	214	0	0	0	0
2021	0	0	0	302	103	2	2	1	50	19	11	0	58	0	0	0	19	0	313	260	0	0	0	0
2022	0	0	1	37	161	2	0	10	163	0	40	0	86	0	0	0	18	0	281	353	0	0	2	0

Table 2: Proportion of observer effort by flag in the data extract from the SPC observer database for longline fishing events.

Year	Obs. sets	AU	JP	KR	NC	NZ	CN	PF	TW	FJ	FM	US	CK	TO	PG	SB	WS	PW	KI	MH	VU	VN	TV	BZ	WF
1990	305	0.14	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1991	790	0.38	0.62	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1992	920	0.36	0.61	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1993	1235	0.45	0.50	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1994	1173	0.26	0.45	0.00	0.00	0.01	0.02	0.00	0.08	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1995	1063	0.19	0.35	0.00	0.00	0.07	0.09	0.00	0.06	0.03	0.00	0.18	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1996	1101	0.14	0.25	0.00	0.05	0.13	0.07	0.00	0.05	0.01	0.01	0.26	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	1497	0.10	0.18	0.00	0.00	0.26	0.07	0.04	0.05	0.02	0.02	0.21	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	1408	0.00	0.08	0.05	0.02	0.28	0.06	0.00	0.16	0.00	0.02	0.23	0.00	0.05	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	1059	0.00	0.05	0.05	0.02	0.32	0.08	0.00	0.10	0.05	0.02	0.16	0.00	0.02	0.04	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2000	1417	0.00	0.04	0.00	0.00	0.20	0.05	0.00	0.06	0.00	0.03	0.47	0.00	0.02	0.05	0.06	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2001	2219	0.02	0.01	0.00	0.01	0.21	0.05	0.00	0.04	0.01	0.01	0.51	0.00	0.00	0.09	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2002	4018	0.10	0.02	0.04	0.01	0.08	0.00	0.02	0.03	0.01	0.01	0.51	0.00	0.00	0.05	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2003	3368	0.12	0.01	0.00	0.03	0.14	0.01	0.06	0.01	0.05	0.00	0.42	0.00	0.00	0.04	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2004	4540	0.10	0.01	0.00	0.02	0.10	0.04	0.04	0.03	0.03	0.01	0.50	0.00	0.02	0.05	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2005	5036	0.10	0.03	0.02	0.01	0.07	0.04	0.05	0.00	0.09	0.01	0.51	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2006	5810	0.09	0.01	0.03	0.01	0.05	0.12	0.05	0.01	0.06	0.02	0.48	0.00	0.02	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007	5111	0.07	0.01	0.02	0.01	0.08	0.11	0.03	0.01	0.06	0.01	0.56	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008	4740	0.11	0.00	0.00	0.02	0.05	0.03	0.04	0.03	0.07	0.01	0.56	0.01	0.02	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009	5055	0.08	0.00	0.00	0.04	0.08	0.04	0.09	0.03	0.04	0.00	0.56	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
2010	4501	0.05	0.00	0.00	0.05	0.06	0.02	0.10	0.04	0.04	0.00	0.59	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00
2011	5654	0.05	0.00	0.02	0.03	0.04	0.01	0.06	0.22	0.05	0.00	0.42	0.01	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.04	0.02	0.00	0.00	0.00
2012	7971	0.03	0.00	0.05	0.02	0.03	0.09	0.05	0.27	0.02	0.00	0.32	0.00	0.00	0.08	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2013	11939	0.02	0.00	0.06	0.01	0.02	0.09	0.04	0.33	0.06	0.01	0.21	0.01	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00
2014	10788	0.01	0.01	0.03	0.01	0.03	0.07	0.04	0.33	0.15	0.03	0.23	0.01	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
2015	10723	0.01	0.17	0.04	0.01	0.03	0.00	0.03	0.29	0.16	0.02	0.17	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00
2016	13268	0.00	0.13	0.02	0.01	0.02	0.07	0.02	0.28	0.17	0.03	0.18	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.02	0.01	0.00	0.01	0.00	0.00
2017	16189	0.00	0.09	0.04	0.01	0.02	0.13	0.03	0.35	0.11	0.00	0.15	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00
2018	18394	0.00	0.08	0.04	0.01	0.02	0.09	0.01	0.34	0.15	0.01	0.14	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.02	0.03	0.00	0.00	0.00	0.00
2019	20175	0.00	0.11	0.06	0.01	0.01	0.13	0.02	0.29	0.13	0.02	0.14	0.01	0.00	0.00	0.03	0.01	0.00	0.01	0.01	0.02	0.00	0.00	0.00	0.00
2020	14794	0.00	0.01	0.05	0.01	0.01	0.21	0.03	0.37	0.13	0.02	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
2021	12812	0.00	0.00	0.03	0.02	0.01	0.15	0.04	0.41	0.09	0.00	0.21	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
2022	12787	0.00	0.00	0.06	0.02	0.01	0.08	0.05	0.35	0.14	0.00	0.26	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00

Table 3: Proportion (in number of hooks) of longline effort coverage based on observer effort by flag in the data extract from the SPC observer database for longline fishing events.

Year	Hooks (millions)	AU	CK	CN	FJ	FM	JP	NZ	TW	US	NC	PG	TO	PF	KR	WS	PW	KI	MH	VU	SB	TV
1995	36.18	0.06	0.01	0.00	0.01	0.00	0.01	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1996	30.26	0.09	0.07	0.00	0.00	0.01	0.00	0.05	0.00	0.02	0.04	0.02	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	30.82	0.05	0.00	0.01	0.01	0.03	0.00	0.24	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	42.31	0.00	0.00	0.00	0.00	0.01	0.00	0.16	0.00	0.02	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	49.13	0.00	0.00	0.00	0.01	0.01	0.00	0.10	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2000	35.94	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.00	0.06	0.00	0.01	0.01	0.00	0.00	0.03	0.04	0.00	0.00	0.00	0.00	0.00
2001	46.80	0.00	0.00	0.01	0.00	0.01	0.00	0.08	0.00	0.08	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2002	63.71	0.00	0.01	0.00	0.00	0.01	0.00	0.05	0.00	0.10	0.02	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2003	54.90	0.00	0.00	0.00	0.01	0.01	0.00	0.11	0.00	0.07	0.03	0.02	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2004	55.69	0.00	0.00	0.00	0.01	0.02	0.00	0.12	0.00	0.11	0.03	0.00	0.07	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2005	39.64	0.00	0.00	0.01	0.03	0.05	0.00	0.15	0.00	0.10	0.01	0.05	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2006	59.38	0.00	0.01	0.00	0.02	0.12	0.00	0.13	0.00	0.10	0.02	0.05	0.08	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007	65.86	0.00	0.00	0.01	0.02	0.01	0.00	0.21	0.00	0.09	0.02	0.01	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008	52.34	0.00	0.01	0.00	0.02	0.02	0.00	0.11	0.00	0.10	0.03	0.06	0.09	0.00	0.00	0.00	0.00	0.09	0.02	0.00	0.00	0.00
2009	66.51	0.00	0.01	0.00	0.01	0.00	0.00	0.22	0.00	0.11	0.08	0.00	0.07	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2010	55.54	0.00	0.00	0.00	0.01	0.00	0.00	0.13	0.00	0.13	0.09	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2011	73.00	0.00	0.02	0.00	0.00	0.00	0.00	0.08	0.00	0.11	0.07	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
2012	78.03	0.00	0.00	0.01	0.00	0.00	0.00	0.12	0.00	0.11	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00
2013	71.98	0.00	0.05	0.02	0.00	0.02	0.00	0.14	0.00	0.13	0.00	0.06	0.00	0.00	0.00	0.01	0.00	0.03	0.00	0.00	0.23	0.00
2014	72.91	0.00	0.08	0.00	0.00	0.00	0.00	0.14	0.00	0.11	0.00	0.04	0.02	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
2015	75.98	0.00	0.00	0.00	0.00	0.04	0.08	0.15	0.00	0.09	0.00	0.05	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
2016	66.41	0.00	0.04	0.02	0.00	0.05	0.08	0.12	0.00	0.10	0.00	0.07	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.15
2017	70.30	0.00	0.11	0.04	0.00	0.00	0.07	0.15	0.00	0.10	0.00	0.00	0.04	0.00	0.04	0.00	0.00	0.04	0.04	0.01	0.00	0.06
2018	69.96	0.00	0.09	0.03	0.00	0.02	0.07	0.11	0.07	0.11	0.00	0.01	0.02	0.03	0.03	0.00	0.00	0.02	0.07	0.04	0.03	0.07
2019	77.14	0.00	0.07	0.05	0.12	0.03	0.11	0.08	0.00	0.10	0.00	0.00	0.04	0.04	0.04	0.02	0.00	0.06	0.04	0.03	0.05	0.03
2020	62.87	0.00	0.00	0.05	0.11	0.03	0.01	0.08	0.06	0.08	0.07	0.00	0.11	0.04	0.02	0.00	0.00	0.02	0.01	0.00	0.00	0.00
2021	56.49	0.00	0.02	0.03	0.09	0.01	0.00	0.11	0.07	0.09	0.07	0.00	0.18	0.00	0.01	0.00	0.00	0.04	0.04	0.00	0.00	0.00

6.1.2 Purse seine observer data

Table 4: Number of observer - reported oceanic whitetip shark interactions by flag in the data extract from the SPC observer database for purse seine fishing events.

Year	CK	CN	EC	ES	FM	ID	JP	KI	KR	MH	NR	NZ	PG	PH	SB	SV	TK	TV	TW	US	VU
1997	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	159.00	0.00
1998	0.00	0.00	0.00	0.00	183.00	0.00	0.00	34.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	920.00	0.00
1999	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.00	0.00	0.00	0.00	0.00	846.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.00	0.00	1.00	0.00	0.00	0.00	0.00	295.00	0.00
2001	0.00	0.00	0.00	0.00	5.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	185.00	0.00
2002	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	8.00	0.00	0.00	0.00	0.00	94.00	0.00
2003	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	3.00	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	351.00	3.00
2004	0.00	0.00	0.00	0.00	14.00	0.00	0.00	0.00	0.00	6.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	162.00	6.00
2005	0.00	0.00	0.00	0.00	16.00	0.00	0.00	0.00	0.00	9.00	0.00	0.00	7.00	2.00	3.00	0.00	0.00	0.00	0.00	15.00	36.00
2006	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	10.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	19.00	5.00
2007	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	7.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	16.00	3.00
2008	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	84.00	5.00
2009	0.00	4.00	0.00	0.00	0.00	0.00	1.00	2.00	17.00	3.00	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	0.00	15.00	2.00
2010	0.00	4.00	4.00	41.00	43.00	0.00	21.00	2.00	79.00	4.00	0.00	38.00	8.00	0.00	0.00	0.00	0.00	3.00	66.00	172.00	21.00
2011	0.00	5.00	5.00	1.00	0.00	0.00	76.00	9.00	32.00	13.00	0.00	0.00	0.00	0.00	0.00	4.00	0.00	0.00	32.00	154.00	49.00
2012	0.00	5.00	1.00	1.00	4.00	0.00	16.00	3.00	11.00	4.00	0.00	0.00	7.00	6.00	0.00	0.00	0.00	1.00	20.00	45.00	4.00
2013	0.00	17.00	13.00	22.00	3.00	0.00	7.00	7.00	25.00	5.00	0.00	2.00	5.00	1.00	0.00	2.00	0.00	0.00	44.00	96.00	4.00
2014	0.00	11.00	5.00	5.00	8.00	0.00	15.00	13.00	17.00	60.00	0.00	0.00	54.00	2.00	0.00	10.00	0.00	0.00	45.00	129.00	8.00
2015	0.00	0.00	1.00	4.00	27.00	0.00	3.00	43.00	25.00	21.00	0.00	0.00	43.00	7.00	0.00	2.00	0.00	0.00	38.00	121.00	5.00
2016	0.00	1.00	0.00	3.00	12.00	0.00	15.00	49.00	43.00	27.00	0.00	1.00	63.00	7.00	2.00	0.00	0.00	2.00	46.00	153.00	0.00
2017	0.00	2.00	3.00	3.00	30.00	0.00	29.00	43.00	35.00	40.00	0.00	2.00	73.00	1.00	11.00	10.00	0.00	2.00	50.00	107.00	0.00
2018	0.00	15.00	10.00	10.00	43.00	0.00	16.00	125.00	66.00	57.00	2.00	1.00	95.00	1.00	24.00	1.00	0.00	6.00	172.00	183.00	4.00
2019	1.00	5.00	23.00	30.00	58.00	0.00	48.00	124.00	68.00	60.00	22.00	0.00	95.00	1.00	41.00	3.00	0.00	1.00	169.00	166.00	20.00
2020	0.00	0.00	11.00	4.00	32.00	0.00	3.00	55.00	44.00	8.00	19.00	0.00	14.00	0.00	2.00	1.00	0.00	7.00	39.00	50.00	4.00
2021	0.00	0.00	0.00	9.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2022	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	8.00	10.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	11.00	0.00

Table 5: Proportion of total observer effort by flag in the data extract from the SPC observer database for purse seine fishing events.

Year	Obs. sets	US	FM	KI	SB	PG	MH	VU	PH	CN	ES	JP	KR	NZ	SV	TV	TW	EC	ID	NR	CK	TK
1995	747	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1996	1273	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	923	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	904	0.91	0.06	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	634	0.94	0.02	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2000	789	0.91	0.00	0.01	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2001	976	0.91	0.03	0.00	0.00	0.04	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2002	1086	0.74	0.08	0.03	0.04	0.07	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2003	1178	0.44	0.10	0.03	0.02	0.05	0.11	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2004	1839	0.38	0.09	0.01	0.00	0.08	0.12	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2005	1394	0.32	0.10	0.00	0.04	0.14	0.16	0.20	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2006	1578	0.20	0.03	0.02	0.02	0.18	0.10	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007	1646	0.21	0.04	0.01	0.00	0.14	0.10	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008	1776	0.57	0.08	0.01	0.02	0.05	0.10	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009	5577	0.37	0.02	0.02	0.00	0.08	0.07	0.12	0.06	0.02	0.00	0.07	0.08	0.01	0.01	0.00	0.06	0.00	0.00	0.00	0.00	0.00
2010	18437	0.28	0.02	0.02	0.00	0.07	0.04	0.08	0.00	0.05	0.01	0.11	0.15	0.01	0.01	0.01	0.12	0.02	0.00	0.00	0.00	0.00
2011	19155	0.25	0.03	0.03	0.01	0.07	0.05	0.07	0.01	0.05	0.01	0.14	0.14	0.01	0.01	0.01	0.12	0.02	0.00	0.00	0.00	0.00
2012	22615	0.27	0.02	0.04	0.00	0.07	0.05	0.07	0.02	0.04	0.01	0.13	0.11	0.01	0.00	0.01	0.13	0.01	0.00	0.00	0.00	0.00
2013	26613	0.21	0.00	0.03	0.00	0.05	0.06	0.07	0.06	0.06	0.02	0.12	0.13	0.01	0.01	0.01	0.14	0.02	0.00	0.00	0.00	0.00
2014	28016	0.23	0.02	0.06	0.00	0.07	0.07	0.03	0.11	0.04	0.01	0.09	0.11	0.01	0.01	0.00	0.13	0.01	0.00	0.00	0.00	0.00
2015	27278	0.19	0.05	0.10	0.00	0.13	0.08	0.01	0.11	0.01	0.01	0.06	0.13	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00
2016	25449	0.14	0.06	0.10	0.02	0.13	0.05	0.00	0.13	0.01	0.01	0.09	0.12	0.01	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00
2017	27693	0.14	0.08	0.08	0.02	0.17	0.05	0.01	0.09	0.00	0.01	0.09	0.13	0.00	0.00	0.00	0.11	0.01	0.00	0.00	0.00	0.00
2018	31854	0.14	0.07	0.10	0.01	0.13	0.05	0.01	0.09	0.01	0.01	0.09	0.13	0.00	0.00	0.01	0.13	0.01	0.00	0.00	0.00	0.00
2019	32601	0.13	0.09	0.10	0.02	0.10	0.06	0.02	0.08	0.00	0.01	0.08	0.14	0.00	0.00	0.00	0.14	0.01	0.00	0.02	0.00	0.00
2020	12413	0.09	0.10	0.10	0.01	0.05	0.03	0.04	0.21	0.00	0.00	0.06	0.14	0.00	0.00	0.01	0.08	0.02	0.00	0.06	0.00	0.00
2021	3291	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.72	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2022	2098	0.02	0.03	0.01	0.01	0.01	0.03	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.01

Table 6: Proportion (in number of sets) of purse seine effort coverage based on observer effort by flag in the data extract from the SPC observer database for purse seine events.

Year	Sets (1000s)	US	FM	KI	SB	PG	MH	VU	PH	CN	ES	JP	KR	NZ	SV	TV	TW	EC	ID	NR	CK	TK	AU	FR	PA
1995	32.07	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1996	33.19	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1997	34.10	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1998	35.88	0.18	0.13	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	31.62	0.18	0.04	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2000	35.05	0.20	0.00	0.05	0.09	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2001	33.98	0.23	0.04	0.00	0.00	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2002	37.58	0.17	0.14	0.18	0.16	0.02	0.05	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2003	39.27	0.17	0.12	0.25	0.07	0.01	0.15	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2004	40.86	0.27	0.17	0.13	0.00	0.03	0.20	0.58	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2005	45.77	0.19	0.15	0.00	0.10	0.03	0.23	0.20	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2006	42.61	0.17	0.12	0.27	0.05	0.04	0.18	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007	47.05	0.18	0.16	0.13	0.00	0.03	0.19	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008	53.35	0.16	0.24	0.11	0.07	0.01	0.24	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2009	53.00	0.25	0.16	0.19	0.02	0.06	0.43	0.70	0.03	0.04	0.01	0.06	0.07	0.08	0.34	0.16	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2010	56.36	0.63	0.40	0.57	0.04	0.17	0.45	1.00	0.00	0.37	0.59	0.23	0.39	0.16	1.00	0.58	0.28	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2011	59.75	0.78	0.54	0.44	0.12	0.16	0.46	1.00	0.02	0.28	0.25	0.18	0.41	0.22	0.76	0.40	0.32	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2012	63.82	0.70	0.37	0.46	0.07	0.18	0.61	1.00	0.07	0.47	0.51	0.23	0.36	0.36	0.16	0.47	0.40	0.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2013	62.62	0.72	0.10	0.43	0.00	0.16	0.76	1.00	0.23	0.49	1.00	0.27	0.52	0.24	0.63	0.39	0.46	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2014	63.63	0.68	0.55	0.62	0.00	0.22	0.85	1.00	0.35	0.44	0.86	0.24	0.47	0.33	0.86	0.51	0.45	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2015	50.98	0.70	0.84	0.81	0.03	0.53	0.80	1.00	0.47	0.27	0.48	0.24	0.59	0.11	0.65	0.45	0.49	0.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2016	49.44	0.71	0.77	0.67	0.22	0.36	0.75	1.00	0.58	0.41	1.00	0.33	0.54	0.30	0.77	0.78	0.53	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2017	54.61	0.83	0.75	0.56	0.29	0.38	0.83	0.74	0.50	0.13	1.00	0.33	0.57	0.37	1.00	0.70	0.47	0.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2018	53.12	0.84	0.67	0.72	0.26	0.36	0.81	0.76	0.92	0.63	1.00	0.44	0.63	0.35	0.73	0.70	0.64	1.00	0.00	0.63	0.00	0.00	0.00	0.00	0.00
2019	56.64	0.86	0.64	0.61	0.33	0.40	0.70	0.67	0.59	0.95	1.00	0.37	0.60	0.00	1.00	0.73	0.63	1.00	0.00	0.72	1.00	0.00	0.00	0.00	0.00
2020	53.26	0.36	0.25	0.30	0.10	0.09	0.20	0.39	0.41	0.00	0.26	0.10	0.27	0.00	0.46	0.37	0.19	1.00	0.00	0.28	0.43	0.00	0.00	0.00	0.00
2021	52.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.51	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2022	53.03	0.03	0.01	0.00	0.02	0.00	0.03	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.13	0.00	0.00	0.00

6.2 Logsheet data availability

Table 7: Number of reported oceanic whitetip shark captures by flag in the data extract from the SPC logsheet database for longline fishing events.

Year	AS	AU	BZ	CK	CN	ES	FJ	FM	GU	ID	JP	KI	KR	MH	NC	NU	NZ	PF	PG	PH	PT	PW	SB	SN	TO	TV	TW	US	VN	VU	WS
1997	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	0	391	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	0	578	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	0	1194	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	502	0	0	0
2002	0	1376	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1604	0	0	0
2003	0	1676	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1967	0	0	0
2004	0	786	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1873	0	0	0
2005	0	947	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	107	0	0	0
2006	0	697	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	0	298	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2417	0	0	3
2008	0	187	0	0	0	65	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1821	0	0	0
2009	0	263	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	151	1924	0	0	0
2010	0	315	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	232	1587	0	0	4
2011	0	340	0	7	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	1591	0	0	70
2012	0	300	0	111	198	0	695	3	0	0	0	0	35	0	2	0	0	0	0	0	0	0	0	0	0	4	4	1471	0	2	48
2013	0	506	0	452	198	0	669	54	0	38	0	0	18	0	0	0	0	0	35	0	0	0	0	0	0	0	69	1139	0	29	47
2014	0	539	0	190	201	0	84	63	0	0	183	0	173	0	0	0	0	992	275	0	0	0	0	0	0	0	13	1394	0	1	14
2015	0	1158	0	287	352	0	136	184	0	0	526	0	3216	0	16	0	0	3922	43	0	0	0	0	0	0	0	0	1677	0	0	42
2016	0	1225	0	623	278	0	225	948	0	0	805	28	96	17	72	0	0	6112	0	0	0	0	0	0	83	0	8	1885	0	0	41
2017	0	1354	0	595	367	0	1179	861	0	0	2091	3	6737	69	142	0	0	10516	2	0	0	1	0	0	0	47	5590	981	0	29	5
2018	0	806	0	1850	724	0	4054	3033	0	0	1941	67	3	211	207	0	0	4714	0	0	0	14	0	0	0	1	0	918	0	171	15
2019	0	1073	0	1224	477	0	6970	1274	0	0	1382	0	77	140	238	0	0	4213	0	0	0	0	0	0	2	0	0	994	0	9	130
2020	0	1082	0	871	1102	0	3162	1568	0	0	375	63	13	157	314	0	0	3835	0	0	0	0	0	0	0	0	0	852	0	9	11
2021	0	1633	0	73	287	0	3002	1733	0	0	181	0	20	252	103	0	0	5360	0	0	0	0	3	0	7	0	0	1134	0	27	27
2022	0	740	0	1	947	0	1941	563	0	0	20	2	149	100	352	0	0	4256	0	0	0	6	0	0	0	0	0	479	0	0	64

Table 8: Reported oceanic whitetip shark captures (in mt) by flag in the data extract from the SPC logsheet database for purse seine fishing events.

Year	CK	CN	EC	ES	FM	FR	ID	JP	KI	KR	MH	NR	NZ	PA	PG	PH	SB	SV	TV	TW	US	VN	VU
1996	0.00	0.00	0.00	0.00	20.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
2004	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2005	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00
2006	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
2008	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.04	20.00	0.00	0.00
2009	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2010	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.35	0.00	0.04
2011	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.06
2012	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.22	0.07	0.00	0.00	0.00	0.00	0.46	0.00	0.00
2013	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.00
2014	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.22	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.20	0.40	0.00	0.00
2015	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.07	0.08	0.00	0.10	0.00	0.01	0.00	0.07	0.00	0.00	0.00	0.00	0.39	0.56	0.00	0.00
2016	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.03	0.04	0.28	0.09	0.00	0.00	0.00	1.50	0.00	0.00	0.00	0.00	0.25	0.59	0.00	0.00
2017	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.09	0.18	0.05	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.58	0.68	0.00	0.05
2018	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.07	0.24	0.06	0.20	0.00	0.00	0.00	0.27	0.00	0.14	0.00	0.00	0.12	0.65	0.00	0.02
2019	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.28	0.00	0.07	0.00	0.14	0.00	0.01	0.00	0.03	0.23	0.00	0.58	1.15	0.00	0.15
2020	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.36	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.19	0.54	0.00	0.00
2021	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.03	0.11	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	1.65	0.00	0.11
2022	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.08	0.00	0.00	0.60	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.68	0.00	0.00

6.3 CPUE models

Table 9: Table of models used for multi-model predictions of longline CPUE with oceanic whitetip shark in the tropical WCPO . All models were run with and without over-dispersion adjustment for the negative binomial variance (see Tremblay-Boyer and Neubauer (2019)).

<table>
<tr><th>Model</th><th>Model terms</th></tr>
<tr><td>CPUE.yy</td><td>(1|yy)</td></tr>
<tr><td>CPUE.yy.progyy</td><td>(1|yy) + (1|program-code) + (1|program-code:yy)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF</td><td>CPUE.yy.progyy + s(log(hooks)) + s(HBF)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves</td><td>CPUE.yy.progyy + s(log(hooks)) + s(HBF) + (1|vessel-id)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves.mm</td><td>CPUE.yy.progyy + s(log(hooks)) + s(HBF) + (1|vessel-id) + (1|mm)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves.mm.sst</td><td>CPUE.yy.progyy + s(log(hooks)) + s(HBF) + (1|vessel-id) + (1|mm) + s(SST)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves.mm.sst.nina</td><td>CPUE.yy.progyy + s(log(hooks)) + s(HBF) + (1|vessel-id) + (1|mm) + s(SST) + NINA4-MA4</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves.mm.sst.nina.progint</td><td>(1|yy) + (1|program-code:yy) + s(log(hooks)) + s(HBF) + (1|vessel-id) + (1|mm) + s(SST) + NINA4-MA4 + (1+NINA4-MA4|program-code)</td></tr>
<tr><td>CPUE.yy.progyy.hooks.HBF.ves.mm.sst.nina.progint.latlong</td><td>(1|yy) + (1|program-code:yy) + s(log(hooks)) + s(HBF) + (1|vessel-id) + (1|mm) + s(SST) + NINA4-MA4 + (1+NINA4-MA4|program-code) + t2(lon5,lat5, bs=c(”cr”,”cr”), k=c(5,5))</td></tr>
</table>

Table 10: Table of models used for multi-model predictions of purse seine CPUE with oceanic whitetip shark in the tropical WCPO. All models were run with and without over-dispersion adjustment for the negative binomial variance (see Tremblay-Boyer and Neubauer (2019)).

Model	Model terms
CPUE.yy	(1|yy)
CPUE.prog.yy	(1|yy) + (1|program-code) + (1|program-code:yy)
CPUE.prog.yy.mm	CPUE.prog.yy + (1|mm)
CPUE.prog.yy.mm.sst	CPUE.prog.yy + (1|mm) + s(SST)
CPUE.prog.yy.mm.sst.nina	CPUE.prog.yy + (1|mm) + s(SST) + NINA4-MA4
CPUE.prog.yy.mm.sst.nina.progint	(1|yy) + (1|program-code:yy) + (1|mm) + s(SST) + NINA4-MA4 + (1+NINA4-MA4|program-code)
CPUE.prog.yy.mm.sst.nina.progint.latlong	(1|yy) + (1|program-code:yy) + (1|mm) + s(SST) + NINA4-MA4 + (1+NINA4-MA4|program-code) + t2(lon5,lat5, bs=c("cr","cr"), k=c(5,5))

6.4 Catch rate estimation models

Table 11: Table of models used for multi-model predictions of longline interactions with oceanic whitetip shark in the tropical WCPO. All models were run with and without over-dispersion adjustment for the negative binomial variance (see Tremblay-Boyer and Neubauer (2019)).

Model	Model terms
base	(1 | yy) + (1 | mm) + s(SST) + s(chla) + s(swo-n) + s(dist2coast)
base.flag	base + (1 | flag-id)
base.hooks	base + s(log(hooks))
base.flag.hooks	base + s(log(hooks)) + (1 | flag-id)
base.space	base + t2(lon5,lat5)
base.space.hooks	base + t2(lon5,lat5) + s(log(hooks))
base.space.hooks.flag	base + t2(lon5,lat5) + s(log(hooks)) + (1 | flag-id)
base.space.flagyy	base + t2(lon5,lat5) + (1 | flag-id) + (1 | flag-id:yy)
base.space.hooks.flagyy	base + t2(lon5,lat5) + s(log(hooks)) + (1 | flag-id) + (1 | flag-id:yy)
base.spacetime	base + t2(lon5,lat5,mm)
base.spacetime.hooks	base + t2(lon5,lat5,mm) + s(log(hooks))
base.spacetime.hooks.flag	base + t2(lon5,lat5,mm) + s(log(hooks)) + (1 | flag-id)
base.spacetime.flagyy	base + t2(lon5,lat5,mm) + (1 | flag-id) + (1 | flag-id:yy)
base.spacetime.hooks.flagyy	base + t2(lon5,lat5,mm) + s(log(hooks)) + (1 | flag-id) + (1 | flag-id:yy)
base.spacetime.yy	base + t2(lon5,lat5,yy)
base.spacetimehooks.yy	base + t2(lon5,lat5,yy) + s(log(hooks))
base.hooks.spacetime.yy.flag	base + t2(lon5,lat5,yy) + s(log(hooks)) + (1 | flag-id)
base.spacetime.nina	base + t2(NINA4,lon5,lat5)
base.spacetimehooks.nina	base + t2(NINA4,lon5,lat5) + s(log(hooks))
base.hooks.spacetime.nina.flag	base + t2(NINA4,lon5,lat5) + s(log(hooks)) + (1 | flag-id)

Table 12: Table of models used for multi-model predictions of purse seine interactions with oceanic whitetip shark in the tropical WCPO. All models were run with and without over-dispersion adjustment for the negative binomial variance (see Tremblay-Boyer and Neubauer (2019)).

Model	Model terms
base	(1+set-type|yy) + (1|mm) + s(SST) + s(chla) + s(dist2coast)
base.flag	base + (1|flag-id)
base.space	base + t2(lon5, lat5)
base.space.flag	base + t2(lon5, lat5) + (1|flag-id)
base.space.flagyy	base + t2(lon5, lat5) + (1|flag-id) + (1|flag-id:yy)
base.spacetime	base + t2(lon5, lat5, mm)
base.spacetime.flag	base + t2(lon5, lat5, mm) + (1|flag-id)
base.spacetime.flagyy	base + t2(lon5, lat5, mm) + (1|flag-id) + (1|flag-id:yy)
base.spacetime.nina	base + s(NINA4)
base.spacetime.nina.flag	base + t2(NINA4,flag-id)
base.spacetime.nina.flagyy	base + s(NINA4) + (1|flag-id) + (1|flag-id:yy)
base.spacetime.nina	base + t2(NINA4, lon5, lat5)
base.spacetime.nina.flag	base + t2(NINA4, lon5, lat5) + (1|flag-id)
base.spacetime.nina.flagyy	base + t2(NINA4, lon5, lat5) + (1|flag-id) + (1|flag-id:yy)

FIGURES

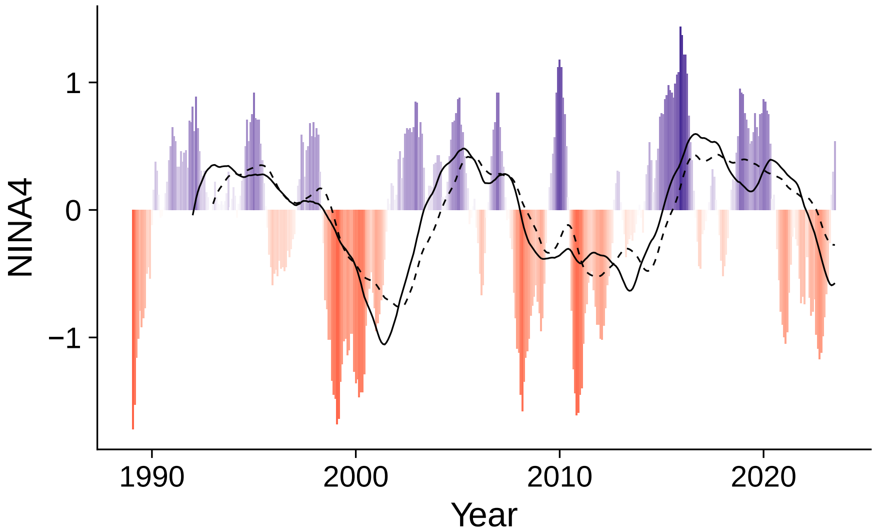


Figure 1: NINA4 index by year - month and associated 36 month (solid line) and 48 month (dashed line) lagged moving average timeseries, used for fisheries catching predominantly small and a mix of small and large sharks, respectively.

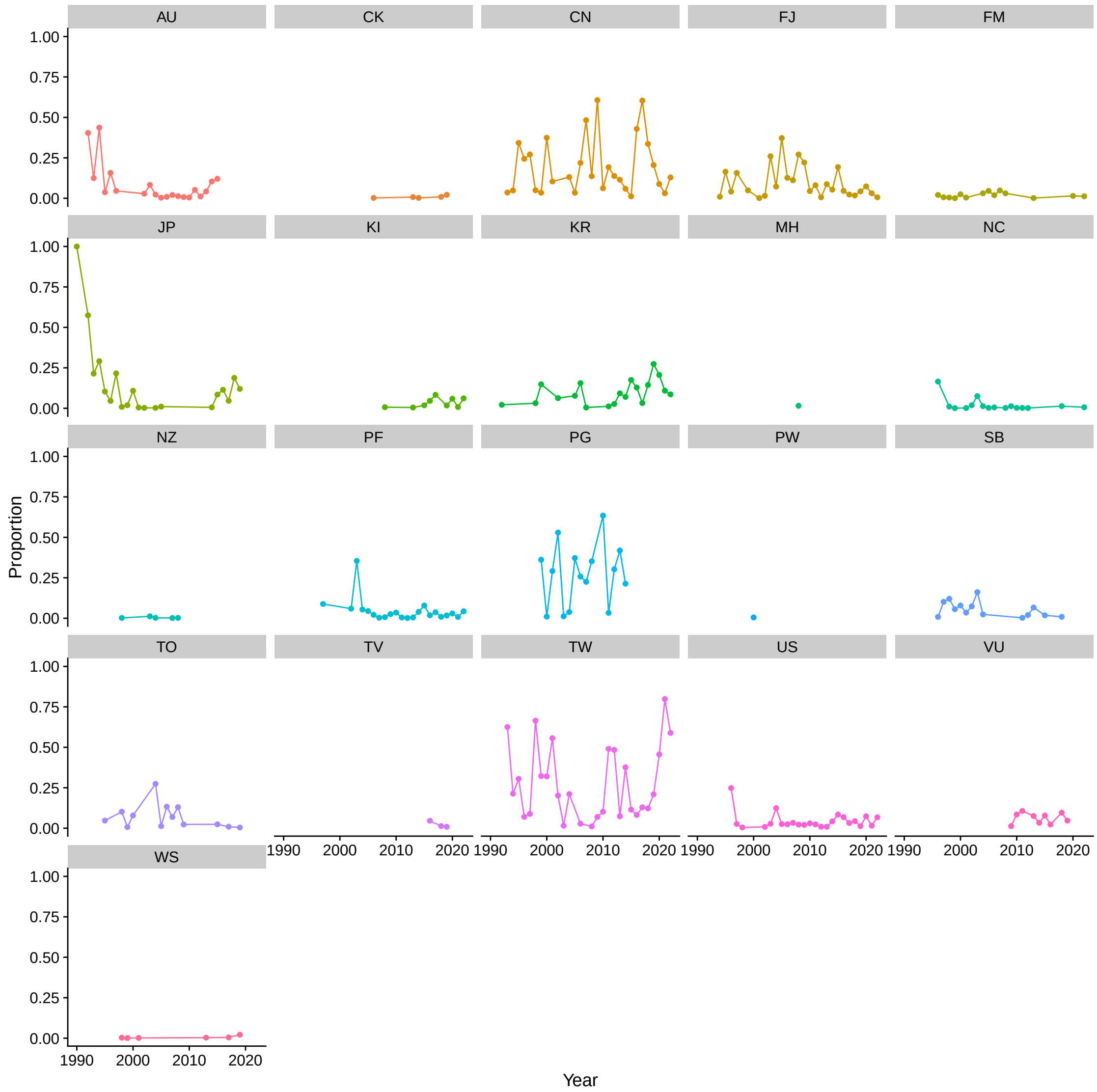


Figure 2: Proportion of length samples by vessel flag and year.

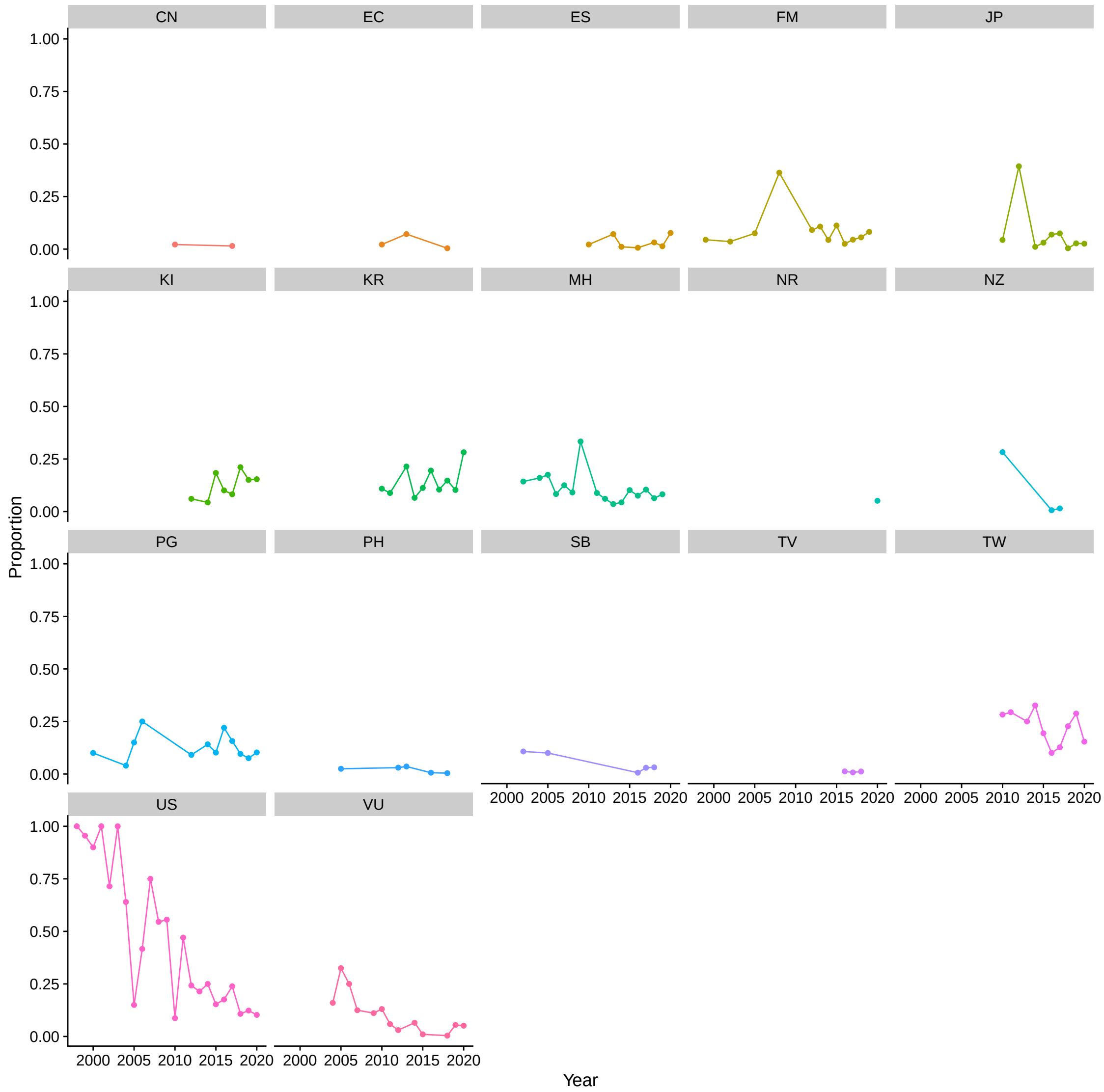


Figure 3: Proportion of length samples by vessel flag and year

6.5 CPUE figures

6.5.1 Longline CPUE

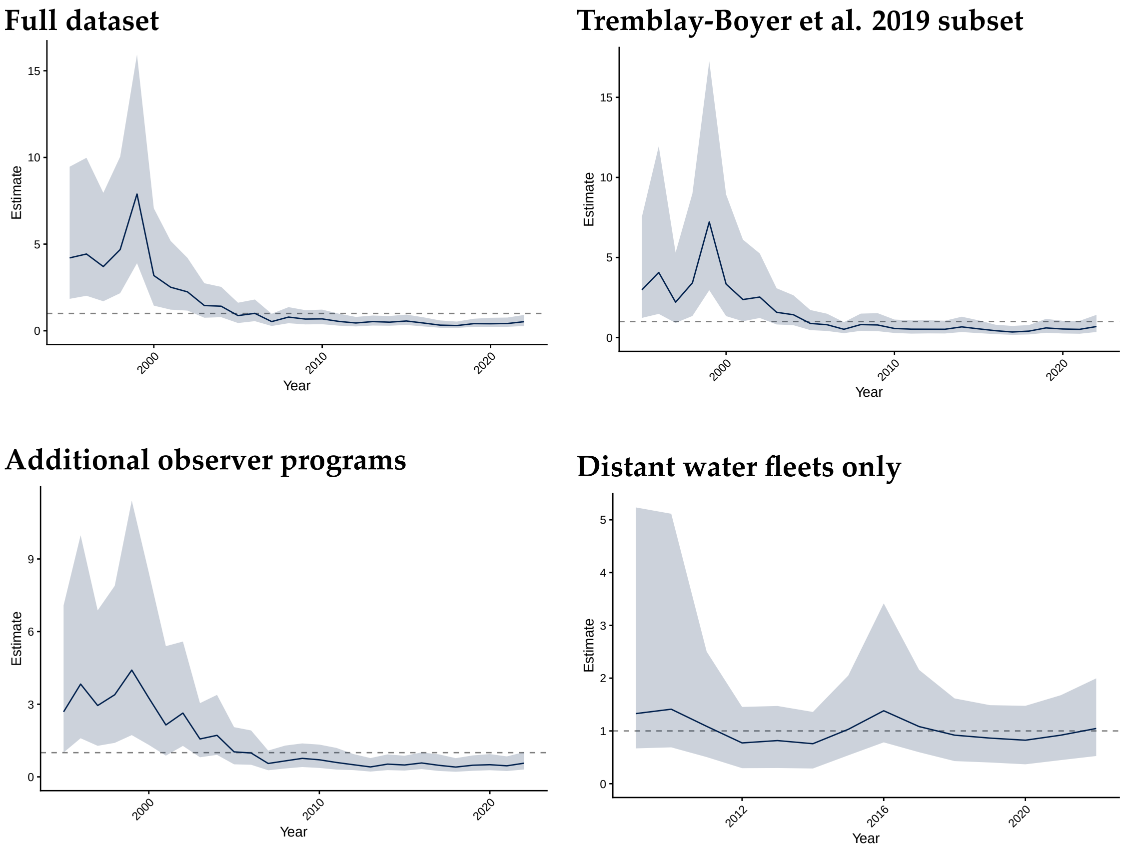


Figure 4: Longline CPUE across four distinct data-sets. Shown is the posterior median and 95% credible interval for the year effect, standardised for regional trends and operational and environmental variables.

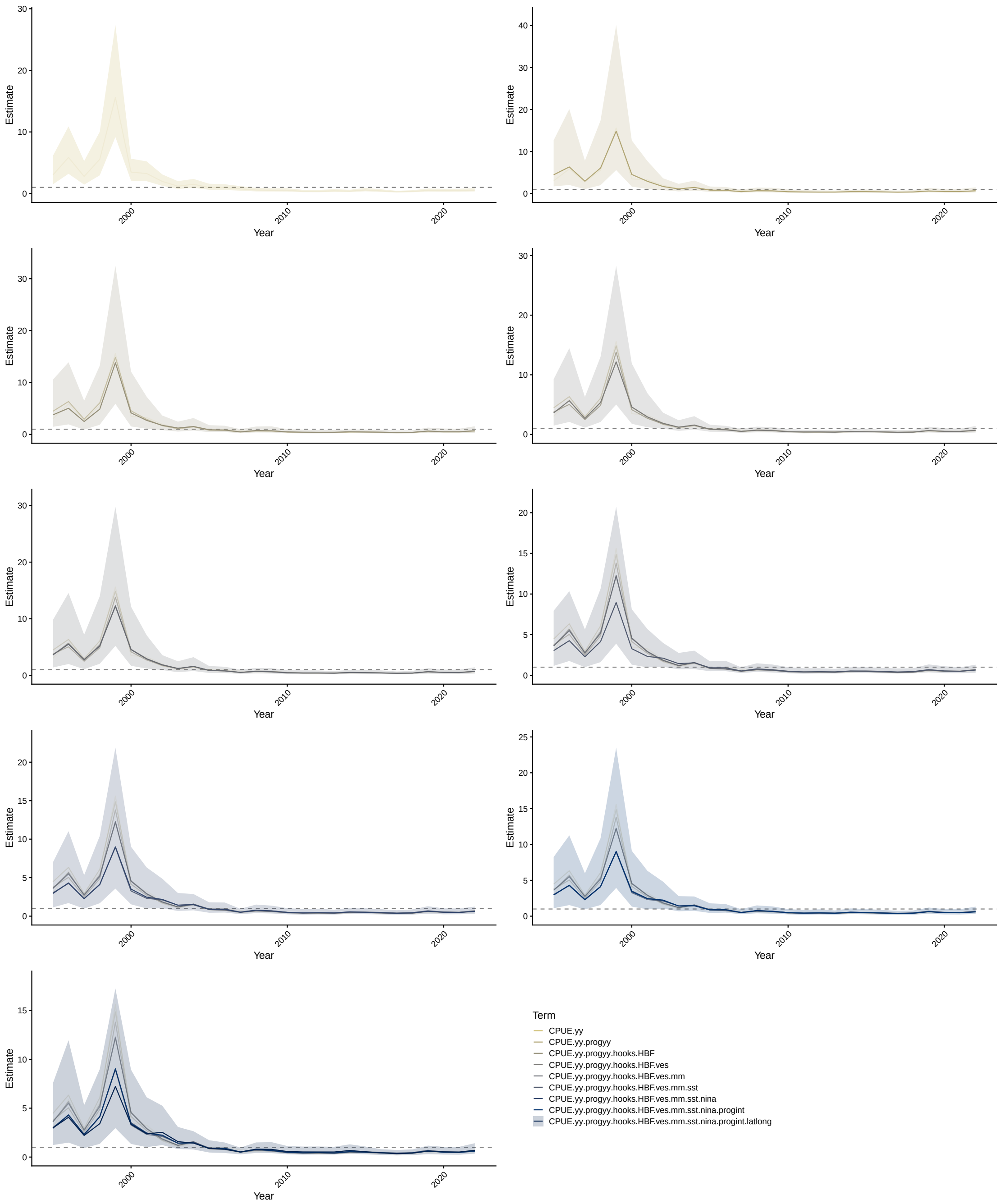


Figure 5: CPUE standardisation effects for longline for data based on Tremblay-Boyer et al. 2019 observer programs. Each row of plots corresponds to the addition of a variable. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

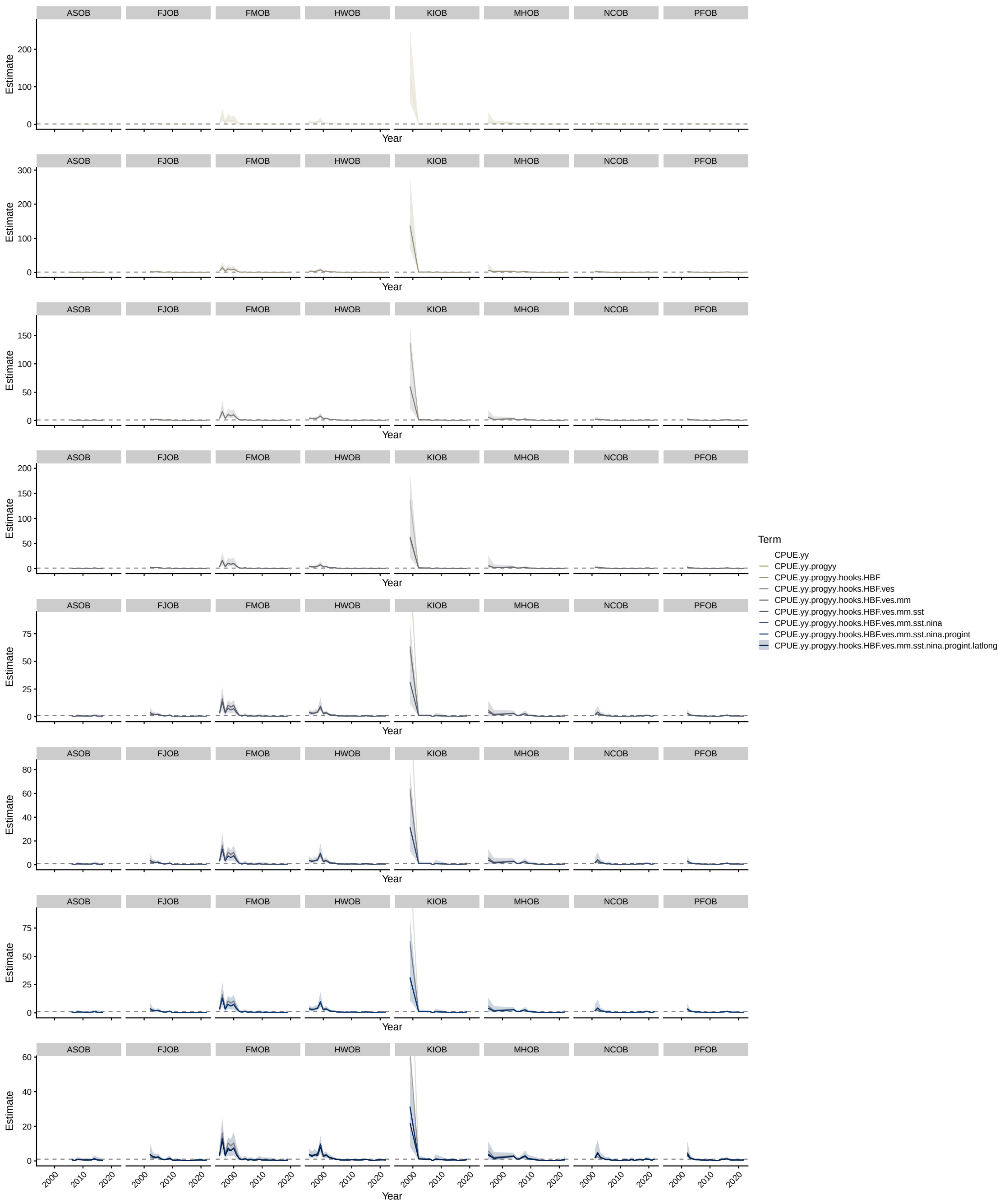


Figure 6: Longline CPUE standardisation effects by observer-program for data based on Tremblay-Boyer et al. 2019 observer programs. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year catch. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

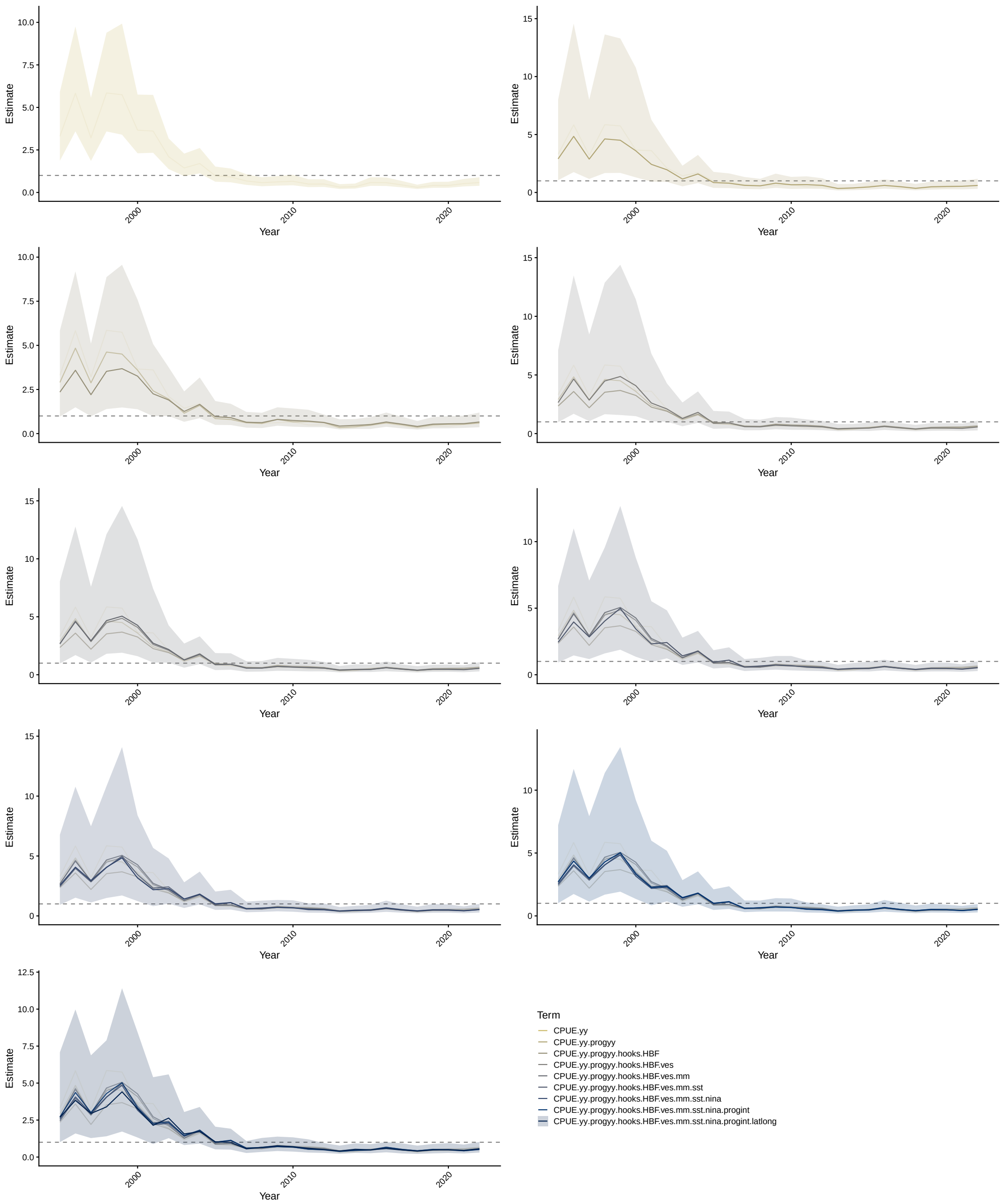


Figure 7: CPUE standardisation effects for longline for the dataset loosely based on Tremblay-Boyer et al. 2019 dataset with the addition of TWOB, TOOB and CNOB observer programs and removal of KIOB. Each row of plots corresponds to the addition of a variable. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

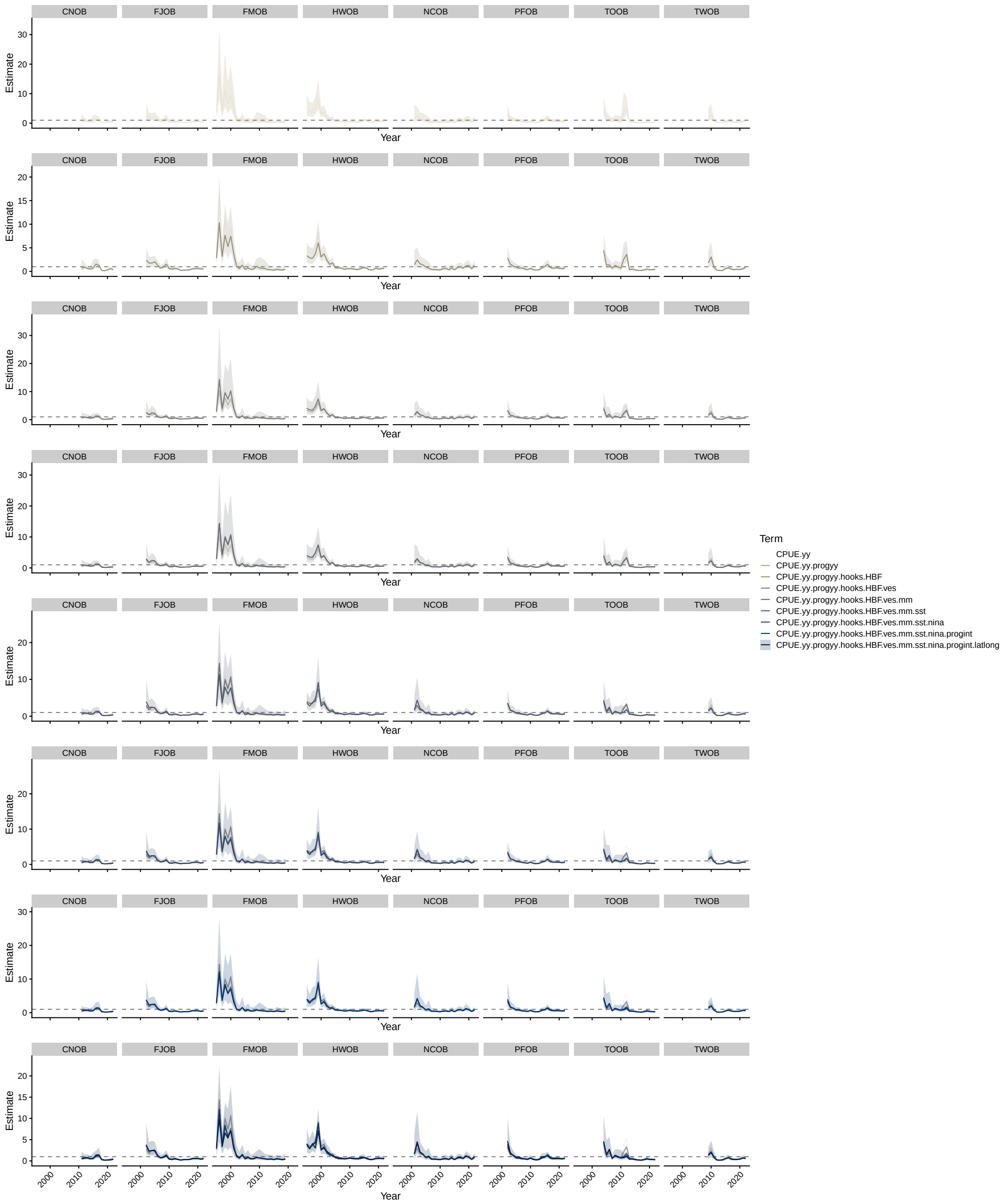


Figure 8: Longline CPUE standardisation effects by observer-program for the dataset loosely based on Tremblay-Boyer et al. 2019 with the addition of TWOB, TOOB and CNOB observer programs and removal of KIOB. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year catch. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

6.5.2 Purse seine CPUE

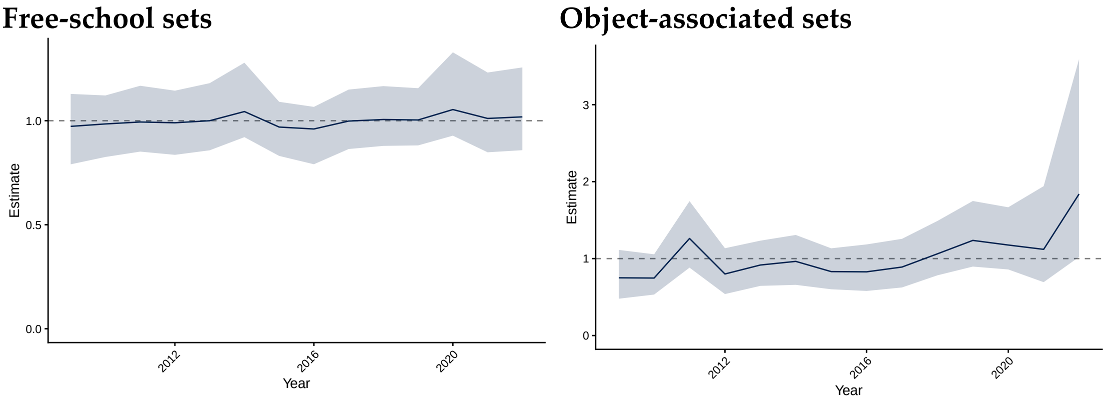


Figure 9: purse seine CPUE index by set - type. Shown is the posterior median and 95% credible interval for the year effect, standardised for regional trends and environmental variables.

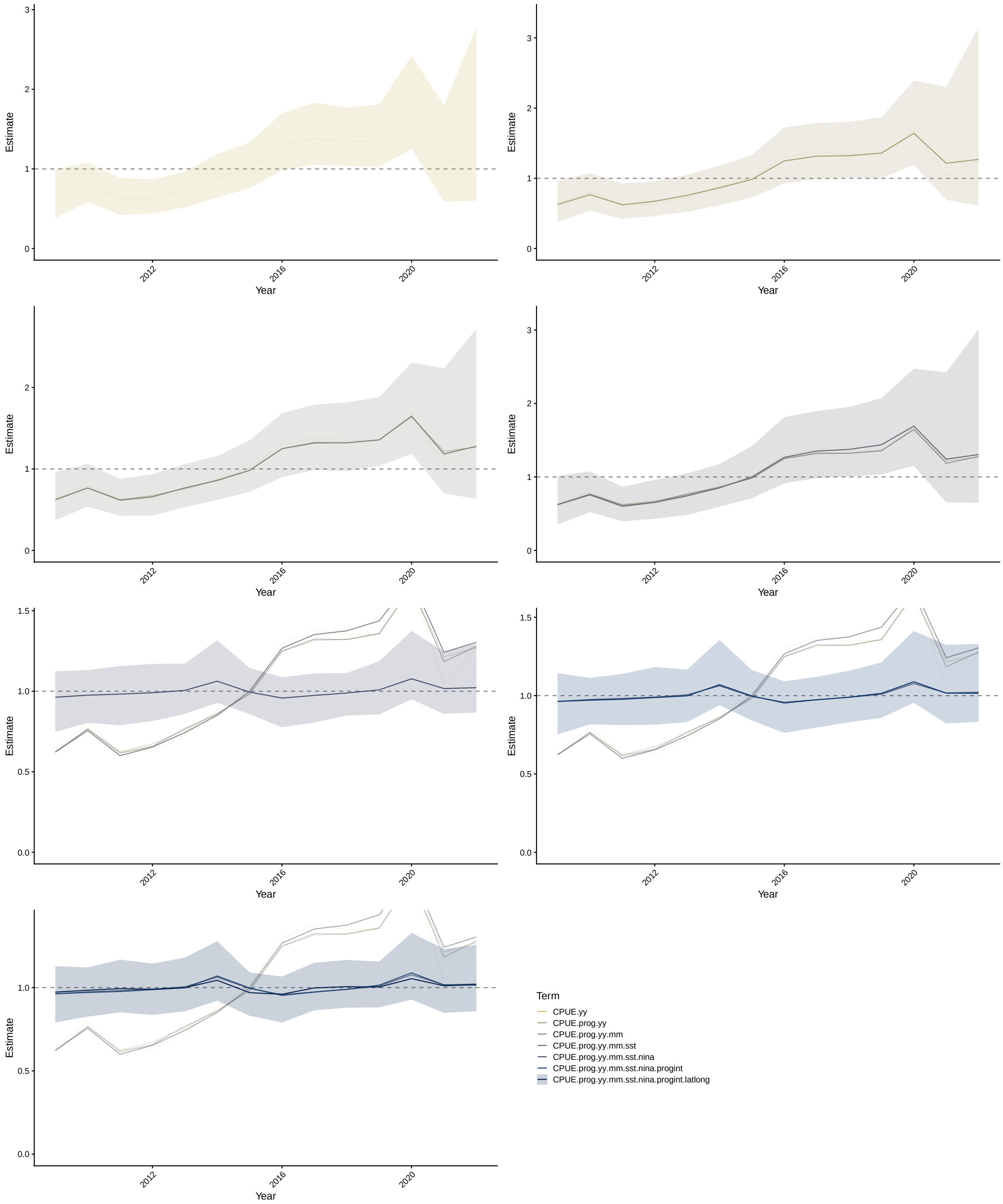


Figure 10: CPUE standardisation effects for free-school purse seine sets. Each row of plots corresponds to the addition of a variable. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

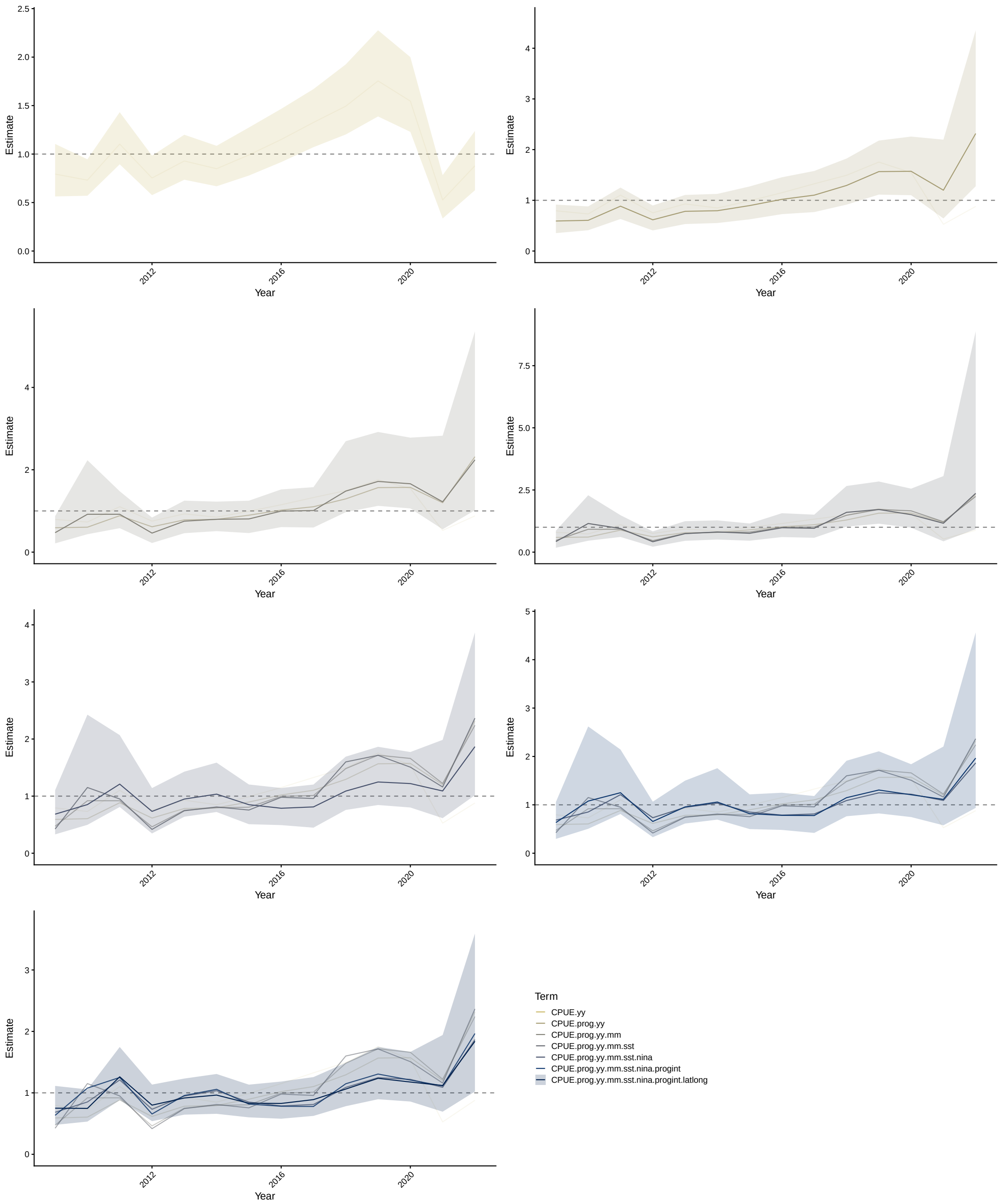


Figure 11: CPUE standardisation effects for object-associated purse seine sets. Each row of plots corresponds to the addition of a variable. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

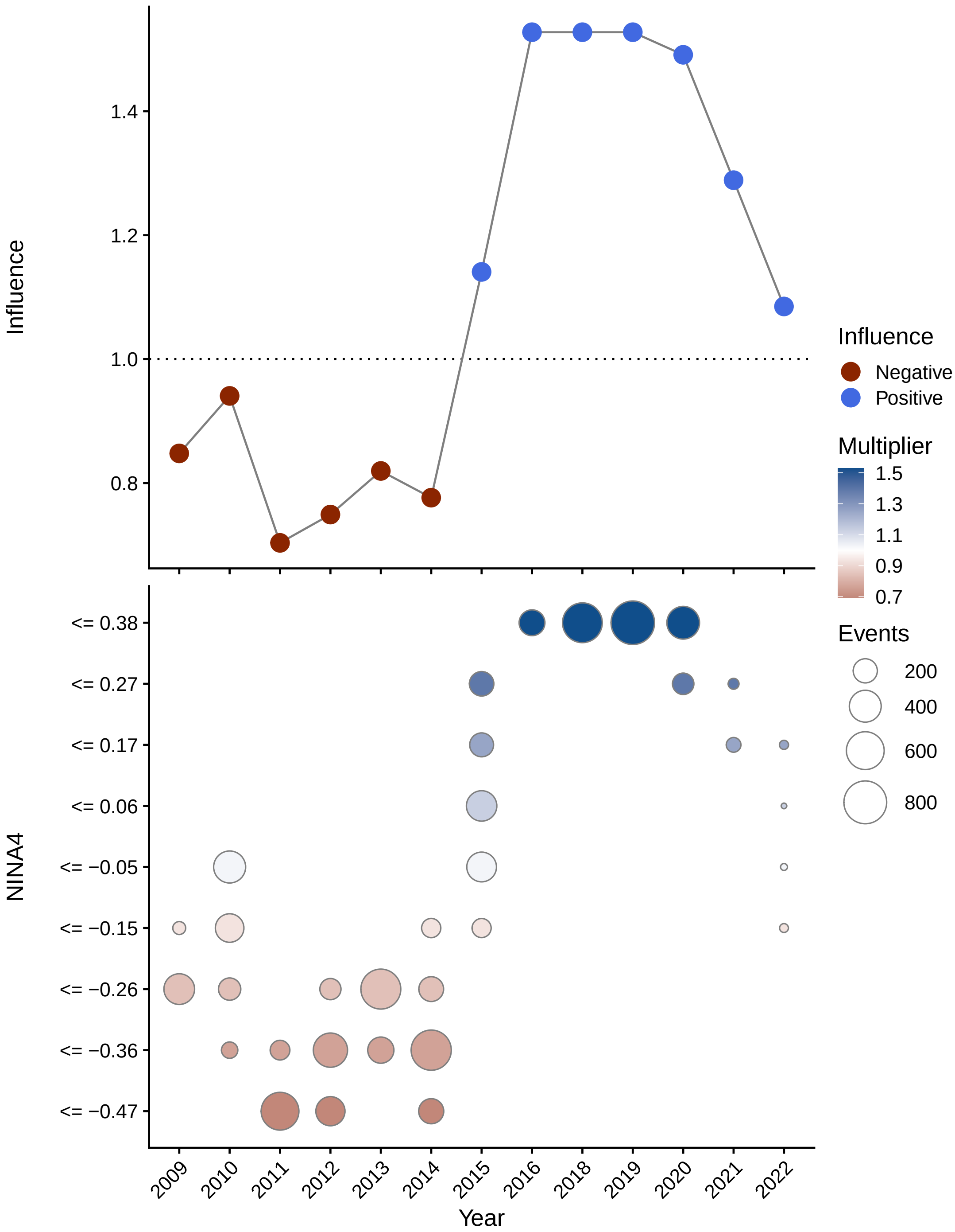


Figure 12: Influence of NINA4 index on catch-rates in observed free-school purse seine sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of environmental conditions. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

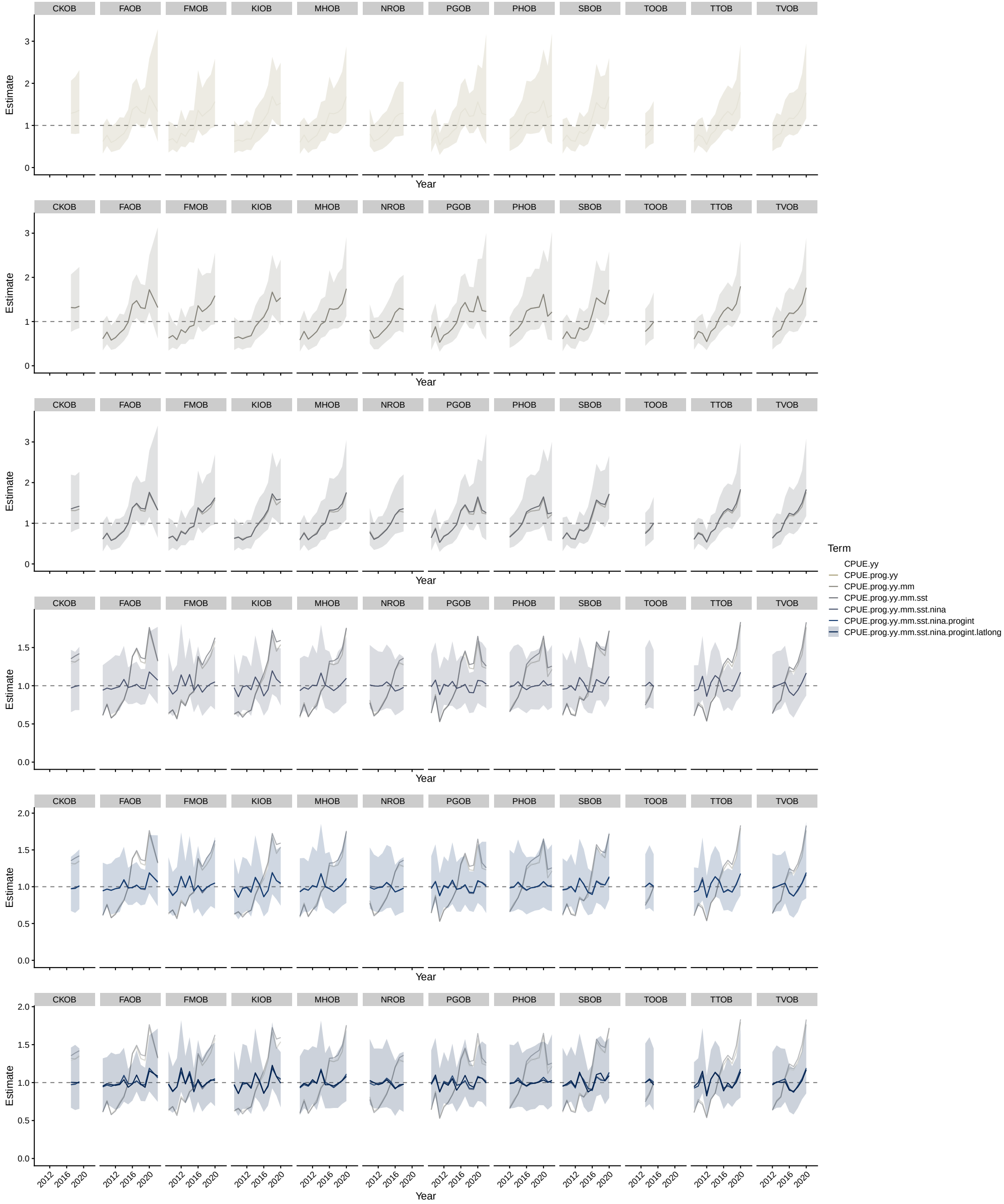


Figure 13: CPUE standardisation effects for free-school purse seine sets by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year catch. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

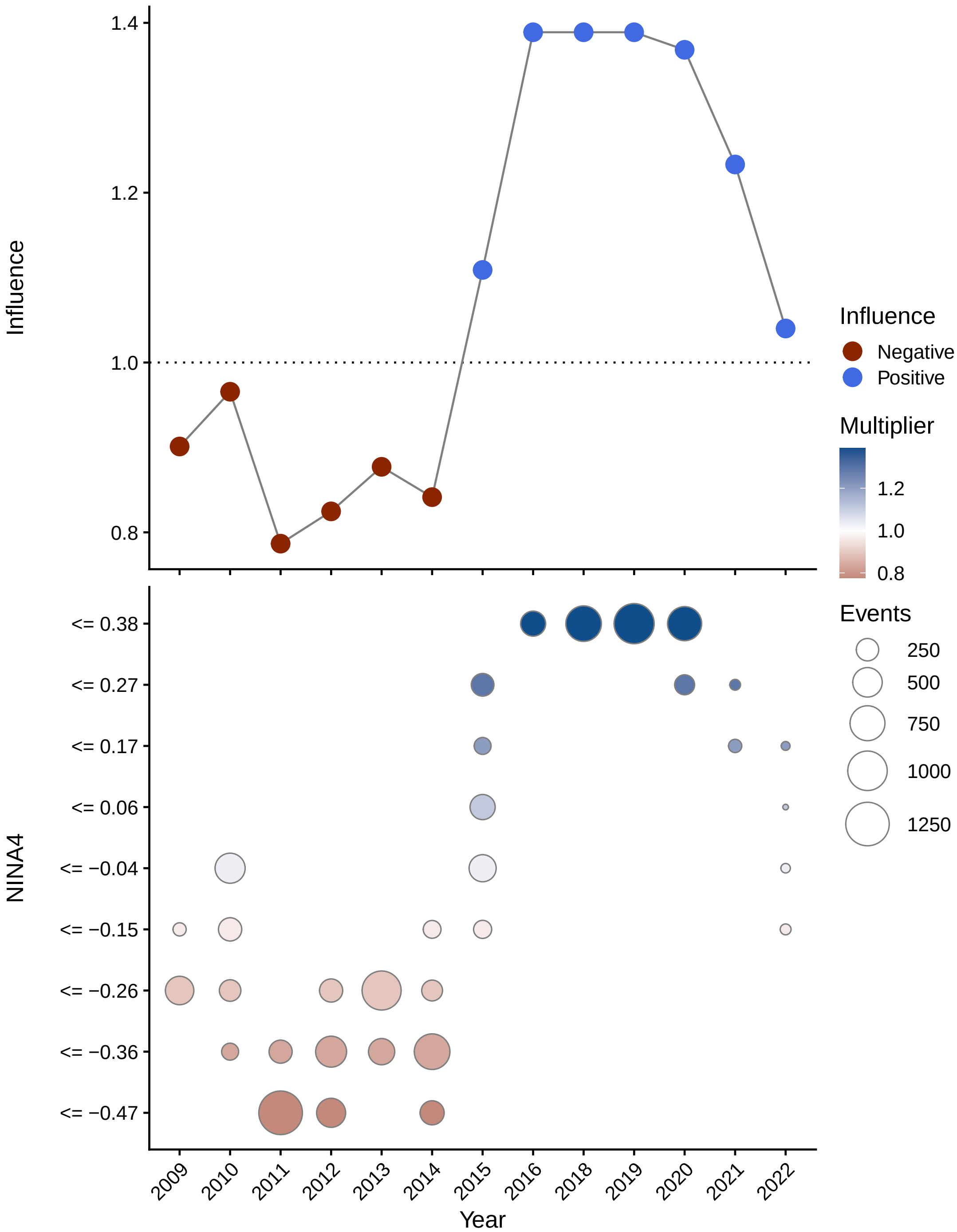


Figure 14: Influence of NINA4 index on catch-rates in observed object-associated purse seine sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of environmental conditions. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

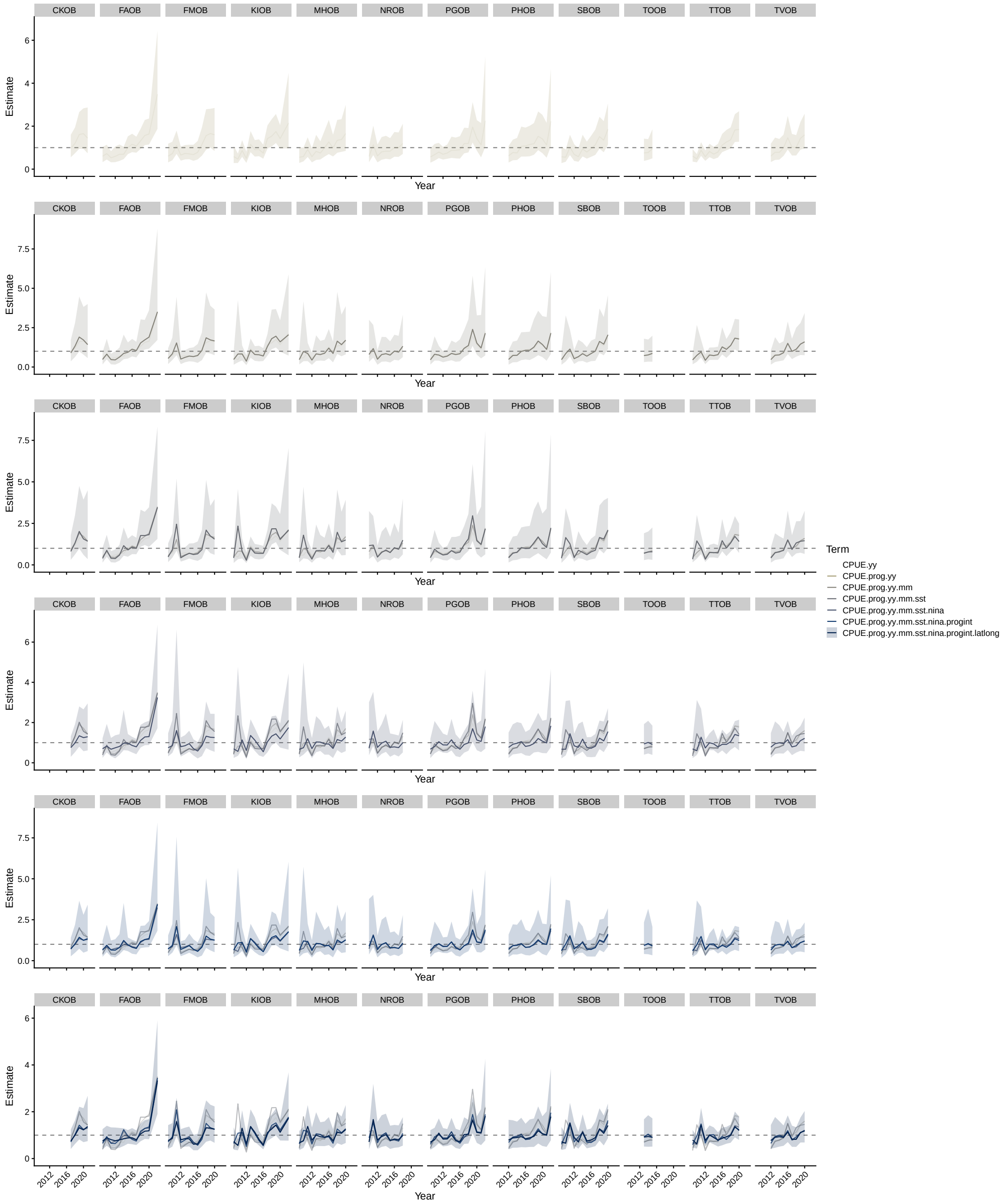


Figure 15: CPUE standardisation effects for object-associated purse seine sets by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year catch. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison. (Note the different scales on the y-axes)

6.6 Predicting catch across the WCPO

6.6.1 Longline catch across the WCPO

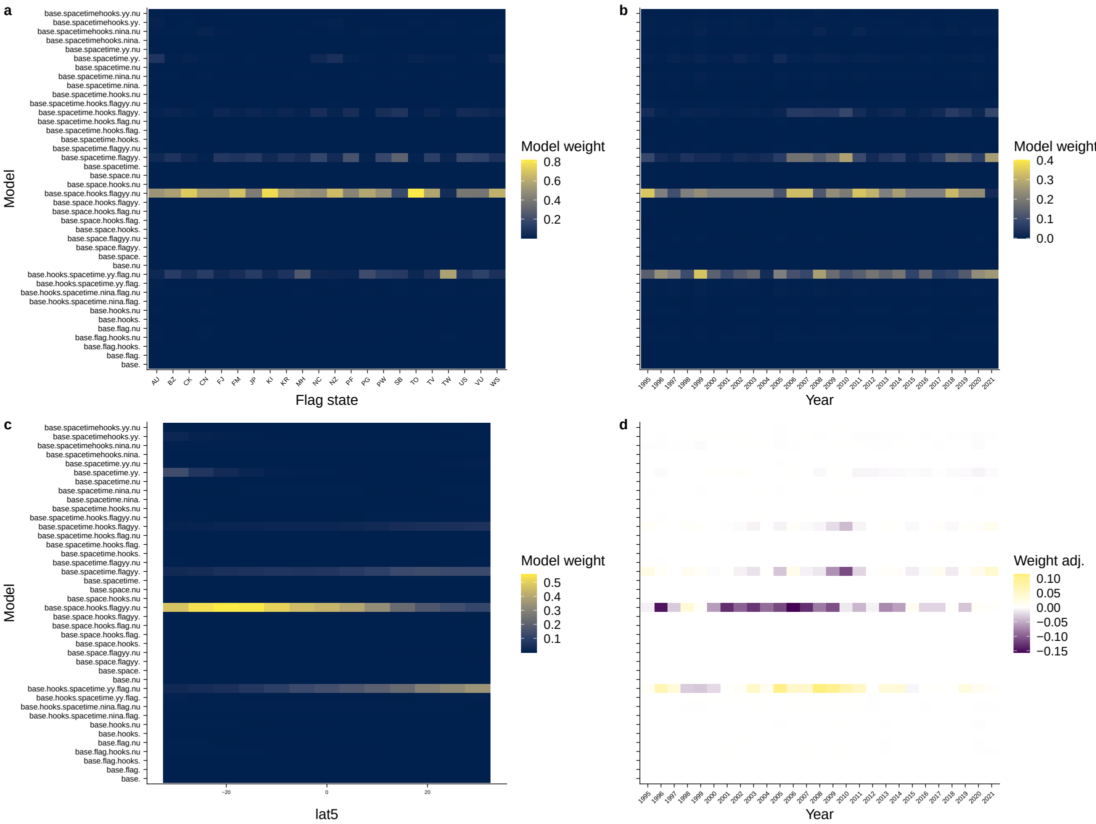


Figure 16: Model weight (geometric mean by stratum) for longline models by (a) vessel flag state, (b) year, and (c) latitude. The stacking-model weight adjustments between the training and prediction datasets by year are shown in (d).

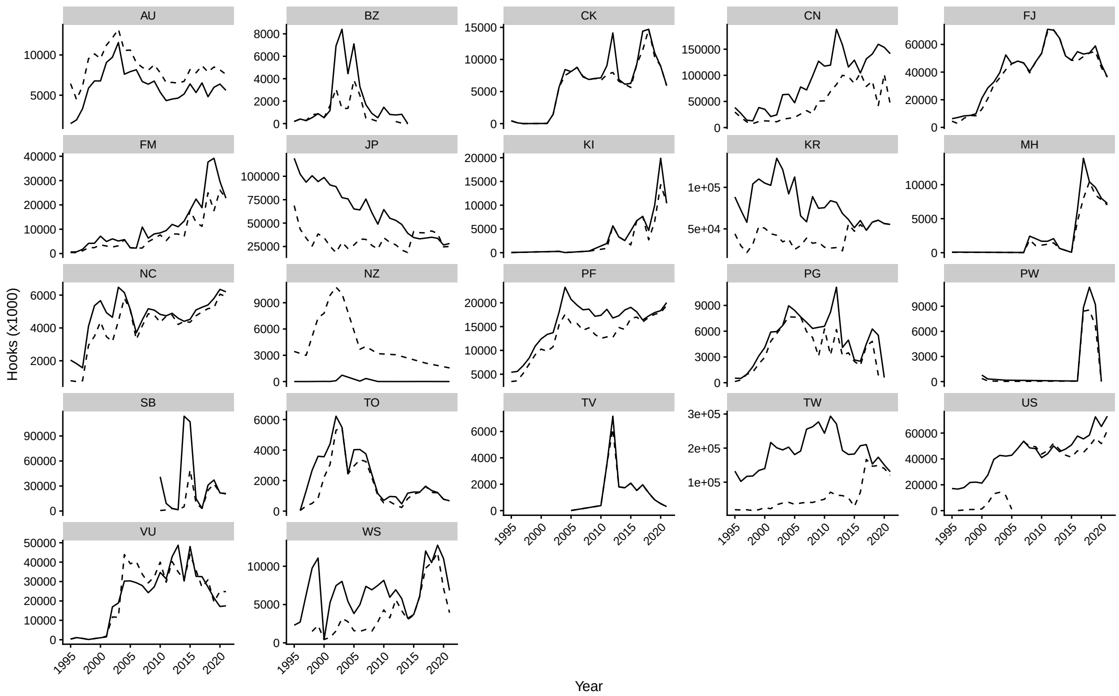


Figure 17: Estimated total hooks by fleet in L-BEST used for predictions of over-all catches of oceanic whitetip shark, with reported hooks in the operational log-sheet data shown for comparison (dashed lines).

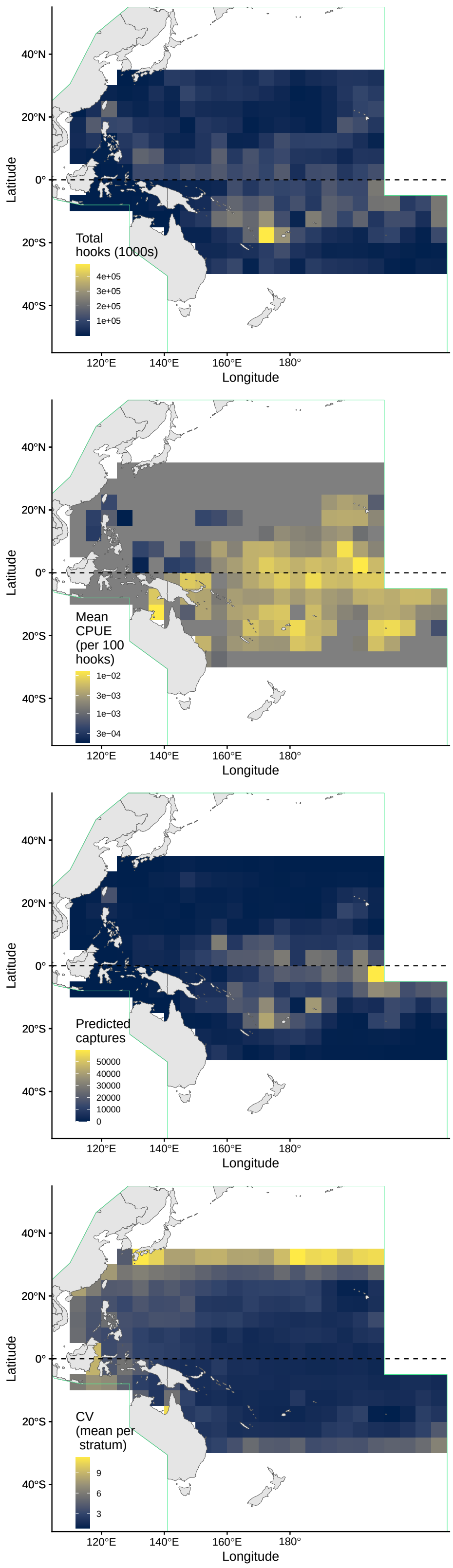


Figure 18: Mean number of hooks per spatial stratum (top), predicted CPUE surface (second from top) total catch of oceanic whitetip shark per year-month-fleet stratum (third plot) from the observer catch rate GLMM, mean CV (bottom) of predicted numbers of oceanic whitetip shark per spatial stratum.

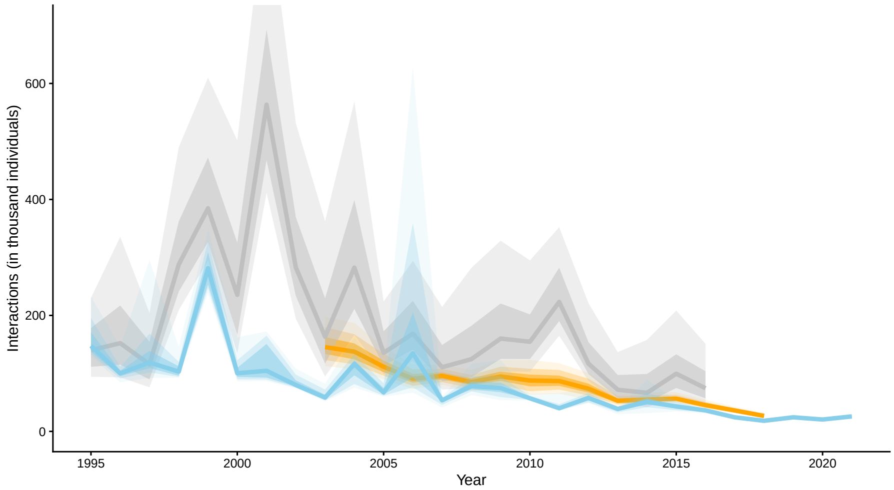


Figure 19: Predicted total oceanic whitetip shark catch from the combined weighted catch reconstruction model; posterior median (blue line); 80% confidence (darkest blue), 90% confidence (mid blue) and 95% confidence (light blue). For comparisons, predictions from Tremblay-Boyer et al. (2019) are shown in grey and predictions from Peatman et al. (2018) are shown in orange.

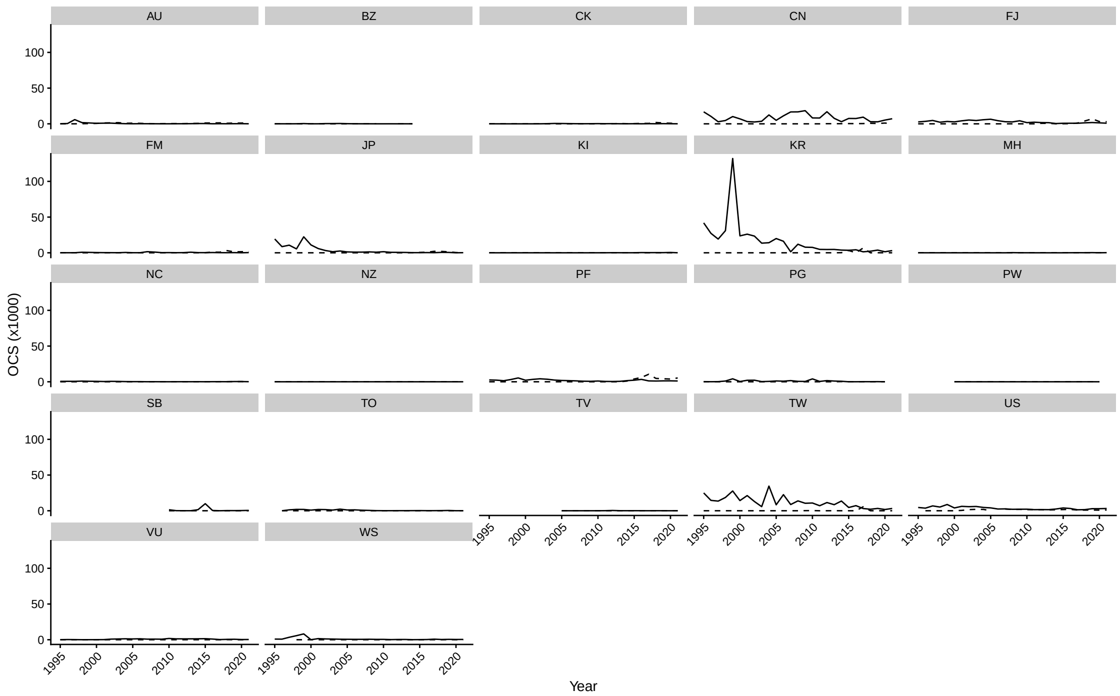


Figure 20: Predicted total oceanic whitetip shark catch by fleet using the observer catch-rate GLMM in conjunction with L-BEST effort. Reported numbers of oceanic whitetip shark from the operational log-sheet data shown for comparison (dashed lines).

6.6.2 purse seine catch across the WCPO

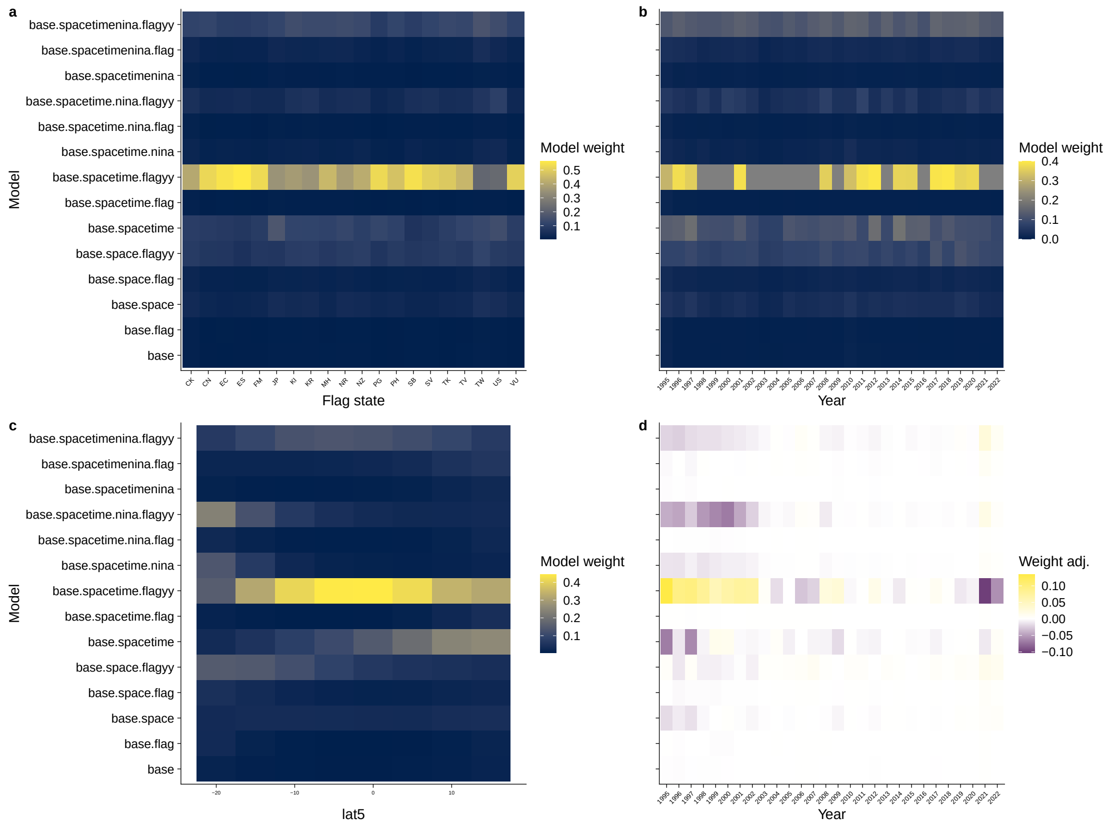


Figure 21: Model weight (geometric mean by stratum) for purse seine by (a) vessel flag state, (b) year, and (c) latitude. The stacking-model weight adjustments between the training and prediction datasets by year are shown in (d).

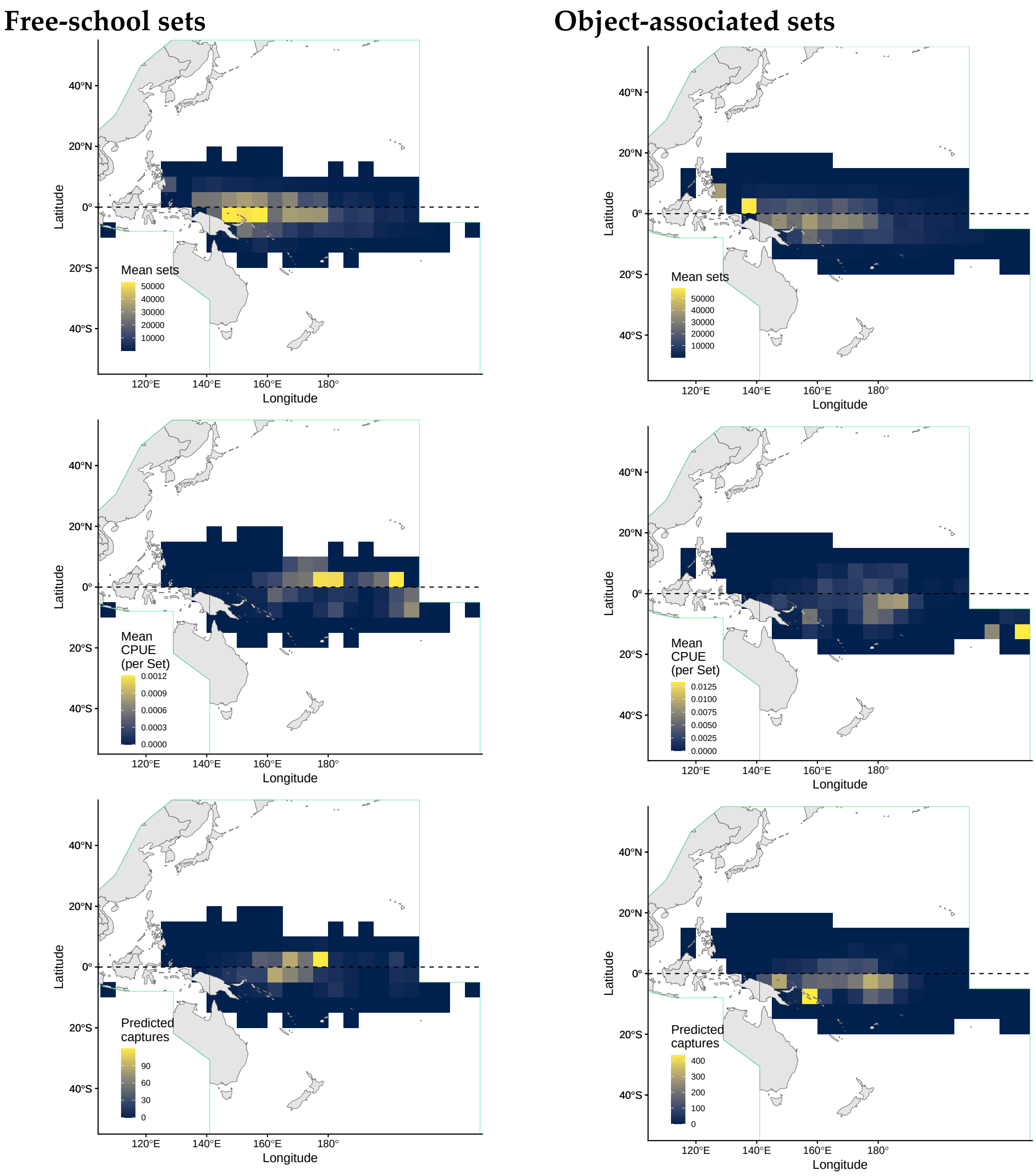
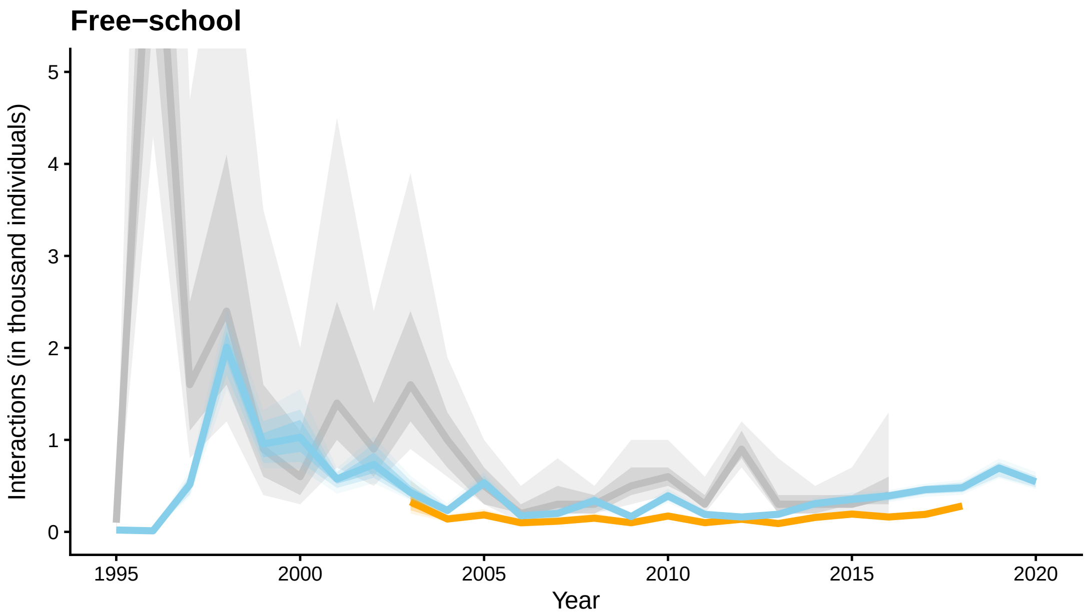


Figure 22: Predicted number of sets (top row), CPUE surface (second row) and predicted numbers of oceanic whitetip shark per spatial stratum (bottom row) given L-BEST effort hook numbers from the observer catch rate GLMM.



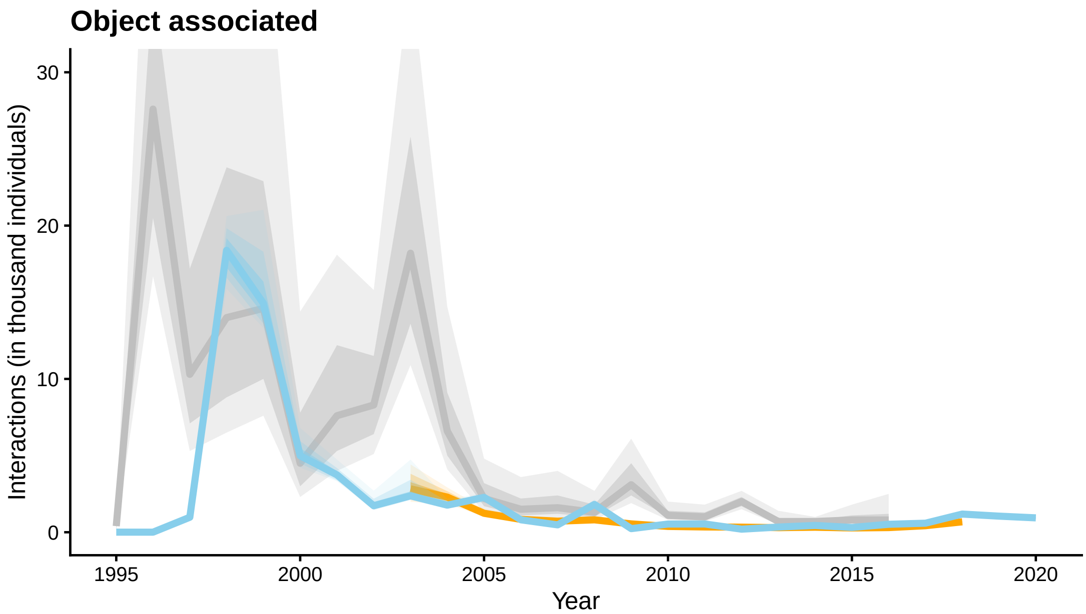


Figure 23: Predicted total oceanic whitetip shark catch from the combined weighted reconstruction model; posterior median (blue line); 80% confidence (dark blue), 90% confidence (mid blue) and 95% confidence (light blue). For comparisons, predictions from Tremblay-Boyer et al. (2019) are shown in grey and predictions from Peatman et al. (2018) are shown in orange.

6.7 Length compositions

6.7.1 Longline length composition

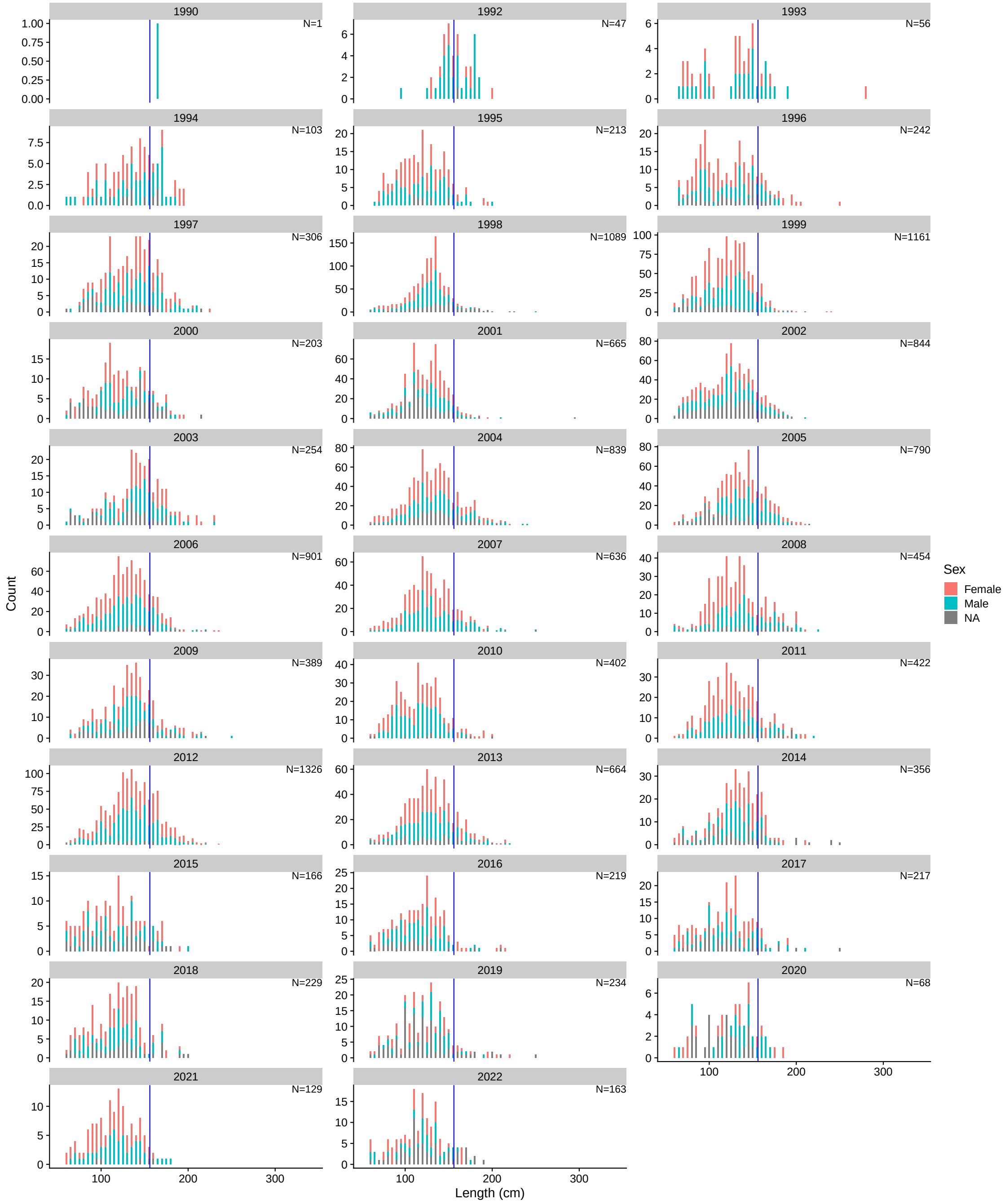


Figure 24: Length frequencies of observer-sampled oceanic whitetip shark by sex and year. The length at maturity for females is indicated with the vertical line.

Figure 25: Length frequencies of observer - sampled oceanic whitetip shark in target fisheries by year. The median length for each year is indicated with the dashed vertical line.

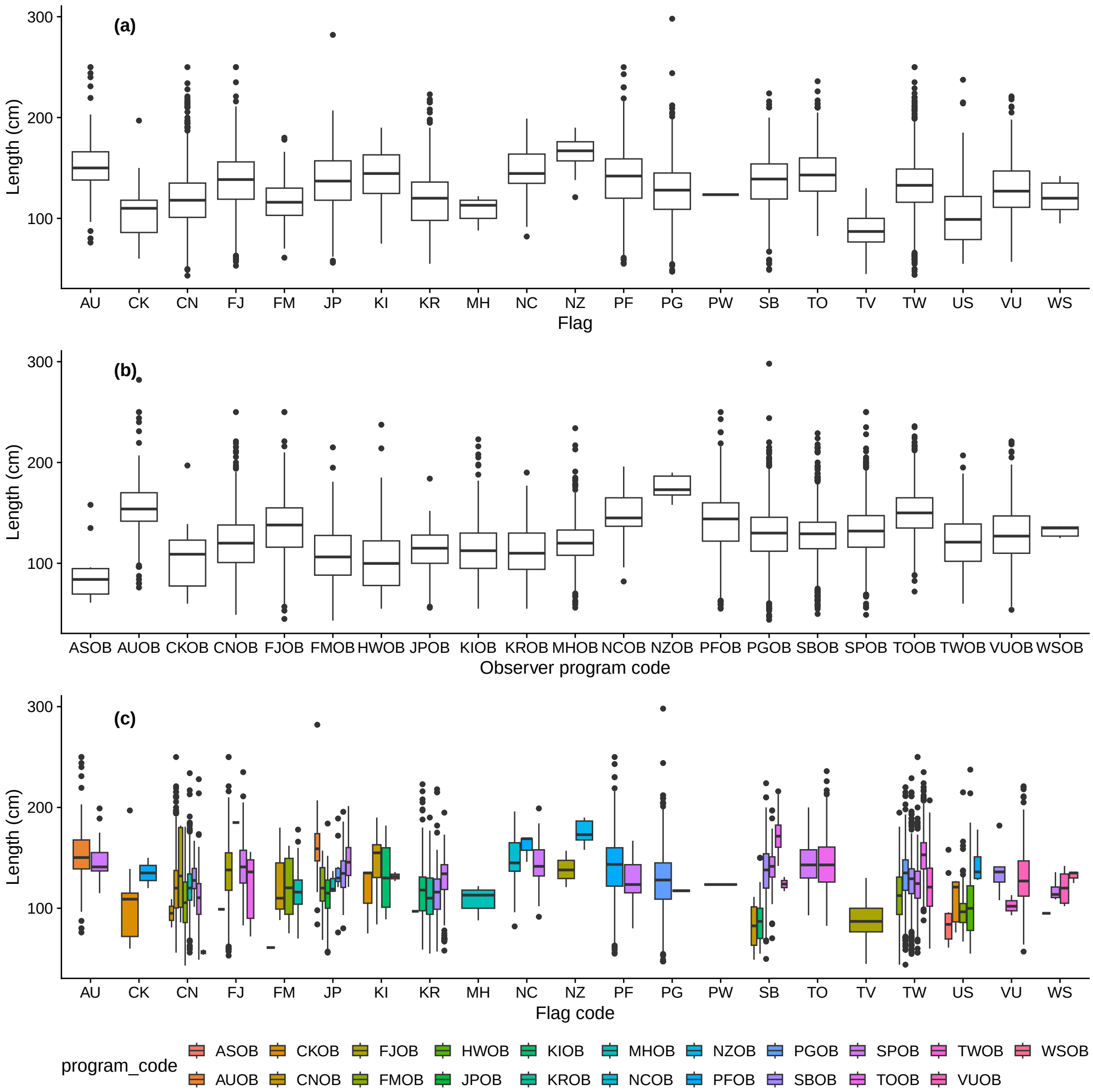


Figure 26: Boxplots showing length distributions of oceanic whitetip shark by vessel flag (a), observer program (b), and both vessel flag and observer program (c).

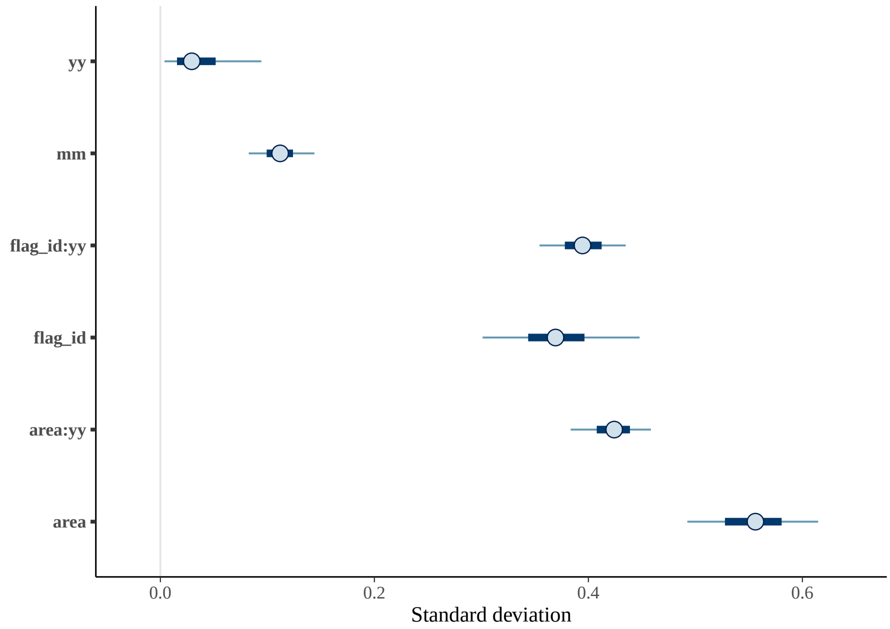


Figure 27: Length-composition standardisation model estimates (posterior median and 95% confidence interval) for standard deviation parameters associated with standardising effects.

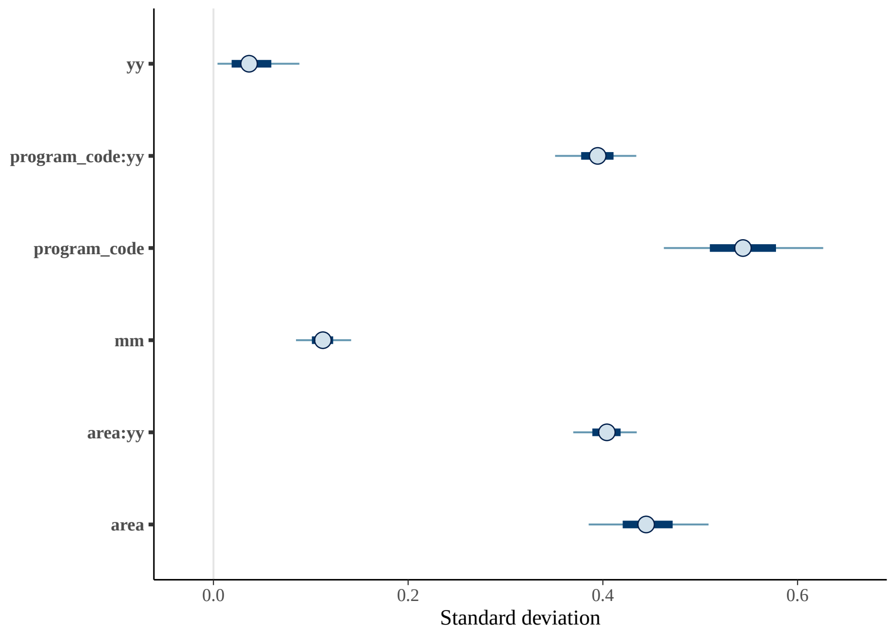


Figure 28: Length-composition standardisation model estimates using CPUE data (posterior median and 95% confidence interval) for standard deviation parameters associated with standardising effects.

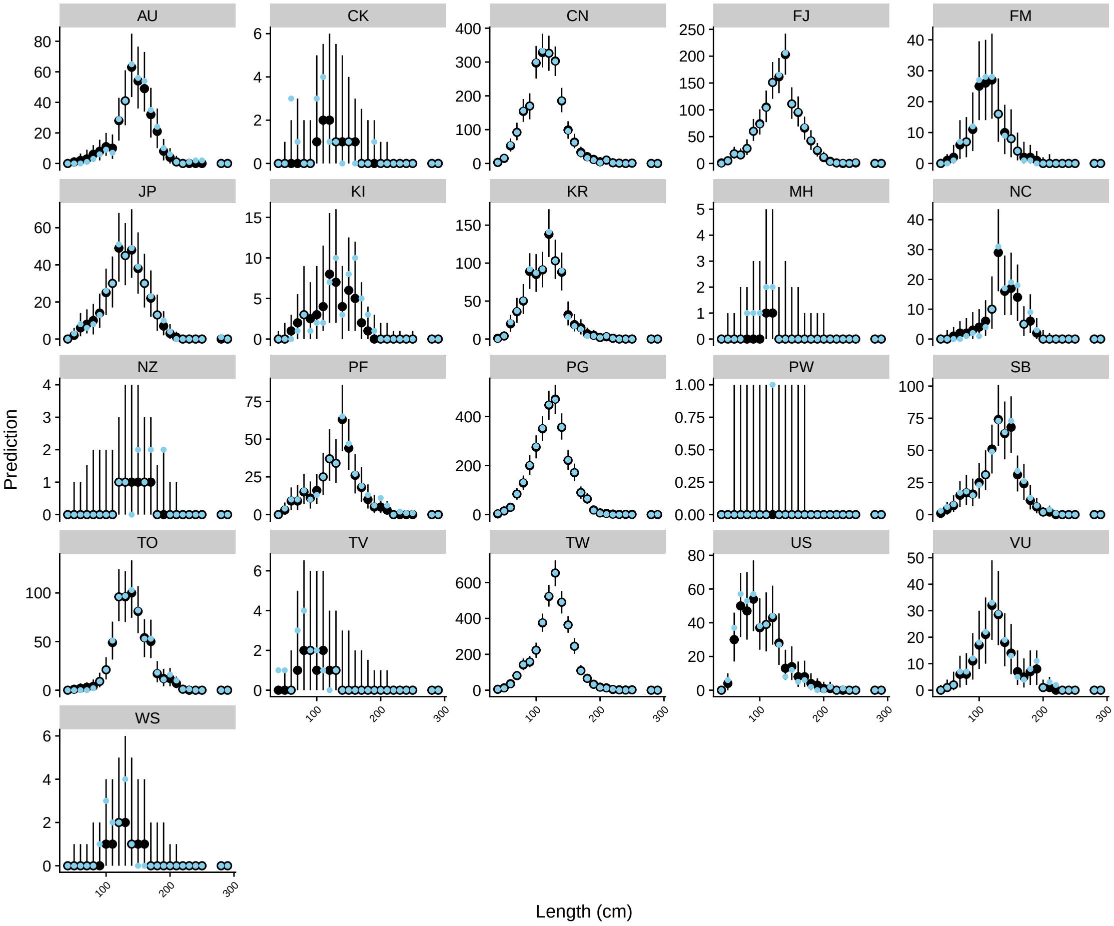


Figure 29: Length - composition standardisation model fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by vessel flag in the WCPO longline fishery catching oceanic whitetip shark.

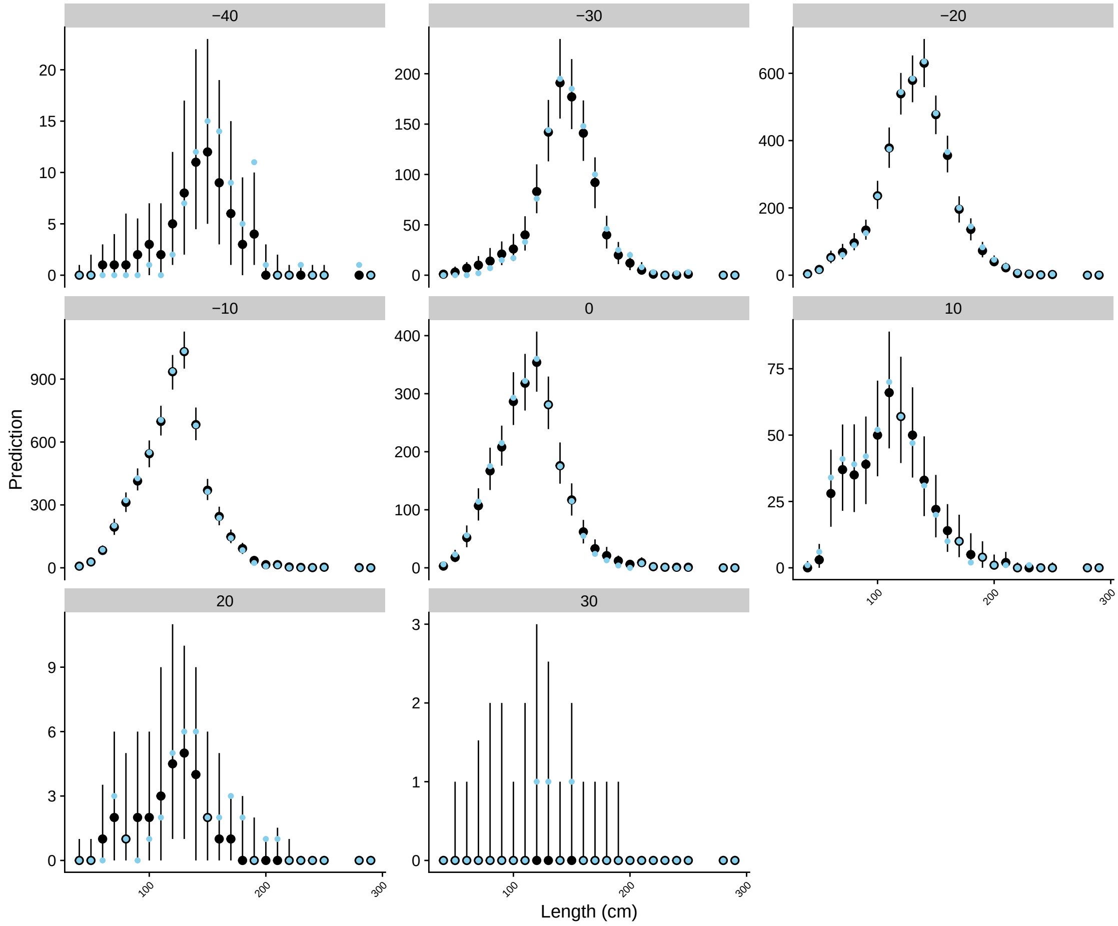


Figure 30: Length-composition standardisation model fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by latitude in the WCPO longline fishery catching oceanic whitetip shark.

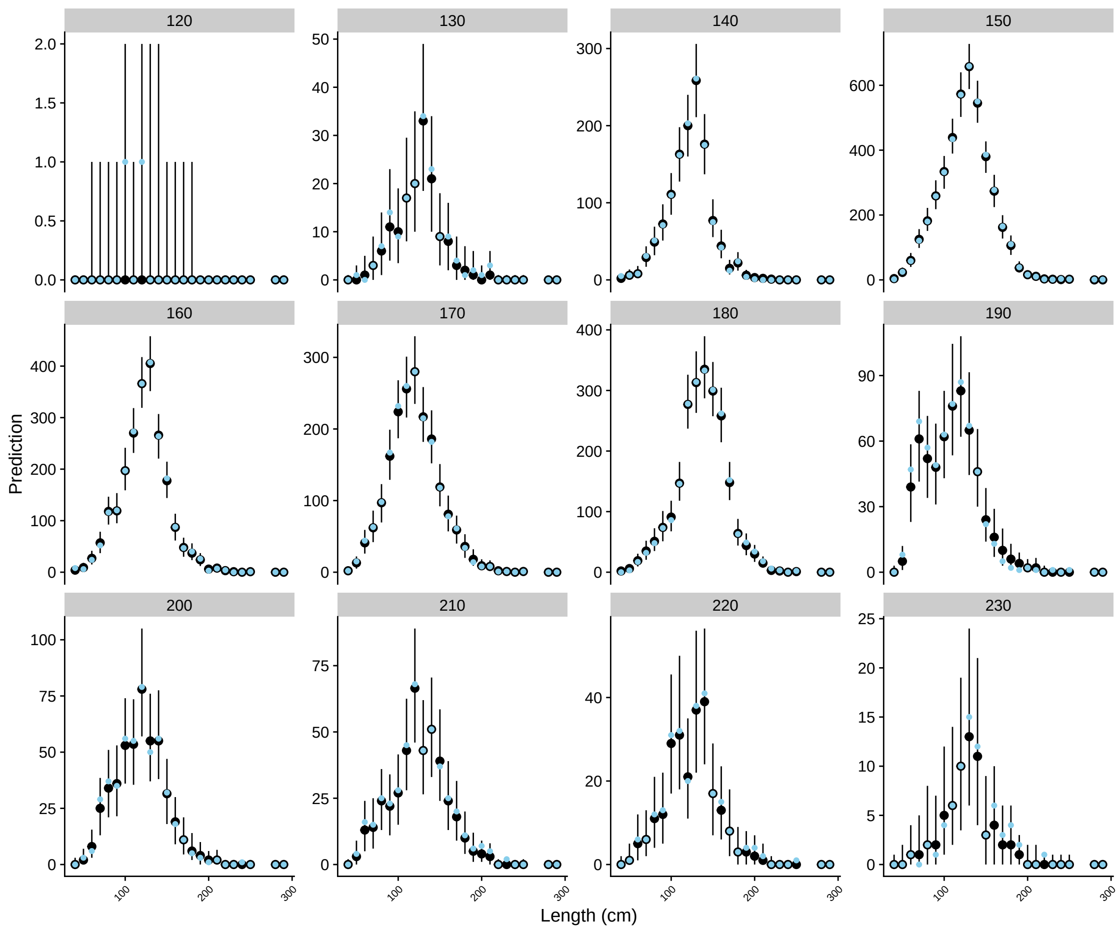


Figure 31: Length - composition standardisation model fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by longitude in the WCPO longline fishery catching oceanic whitetip shark.

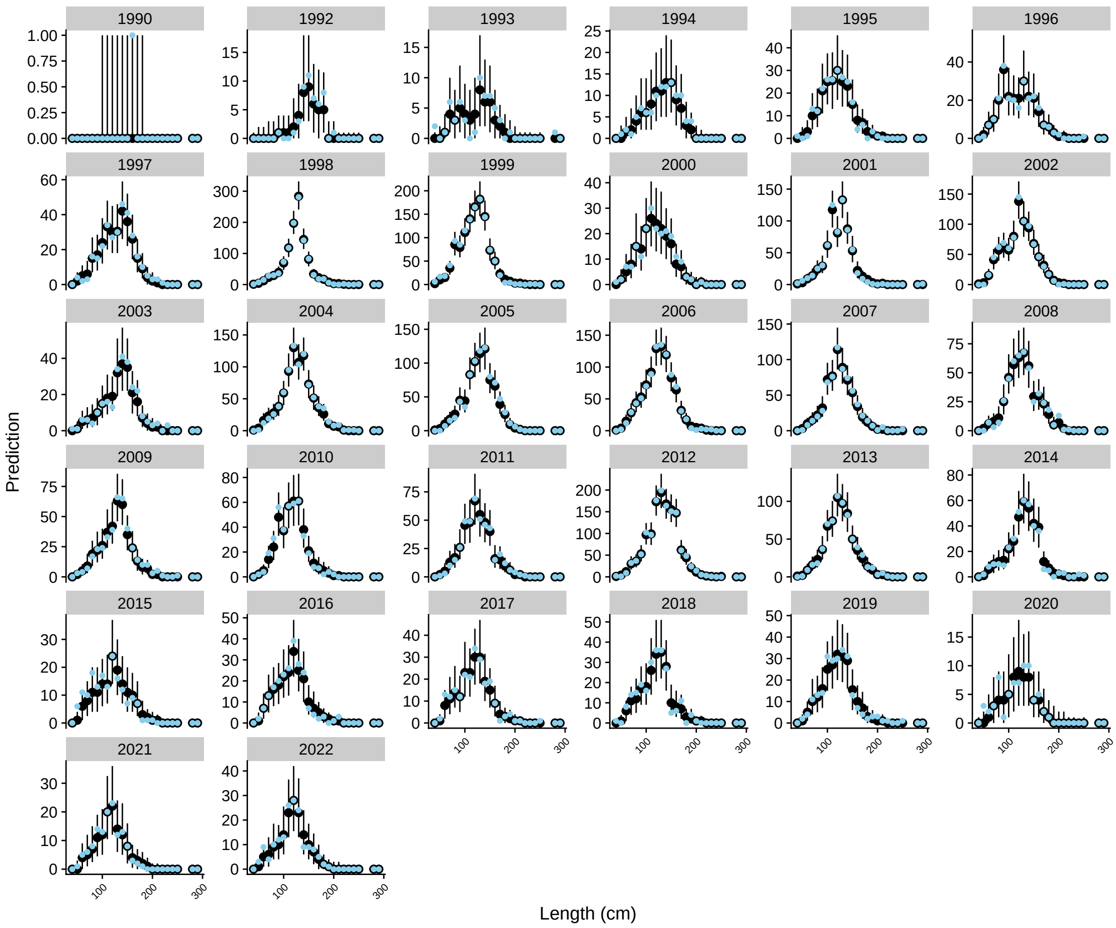


Figure 32: Length-composition standardisation model fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by year in the WCPO longline fishery catching oceanic whitetip shark.

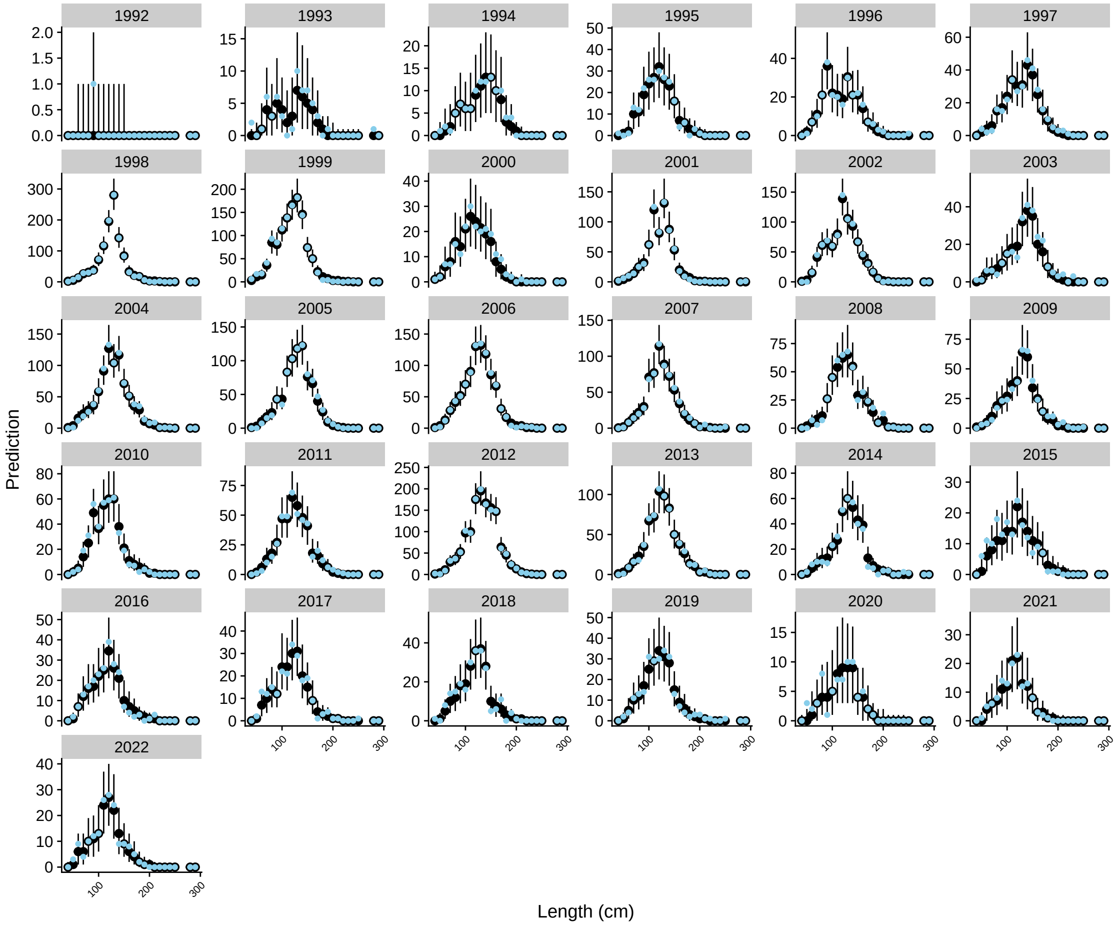


Figure 33: Length-composition standardisation model (using CPUE data) fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by year in the WCPO longline fishery catching oceanic whitetip shark.

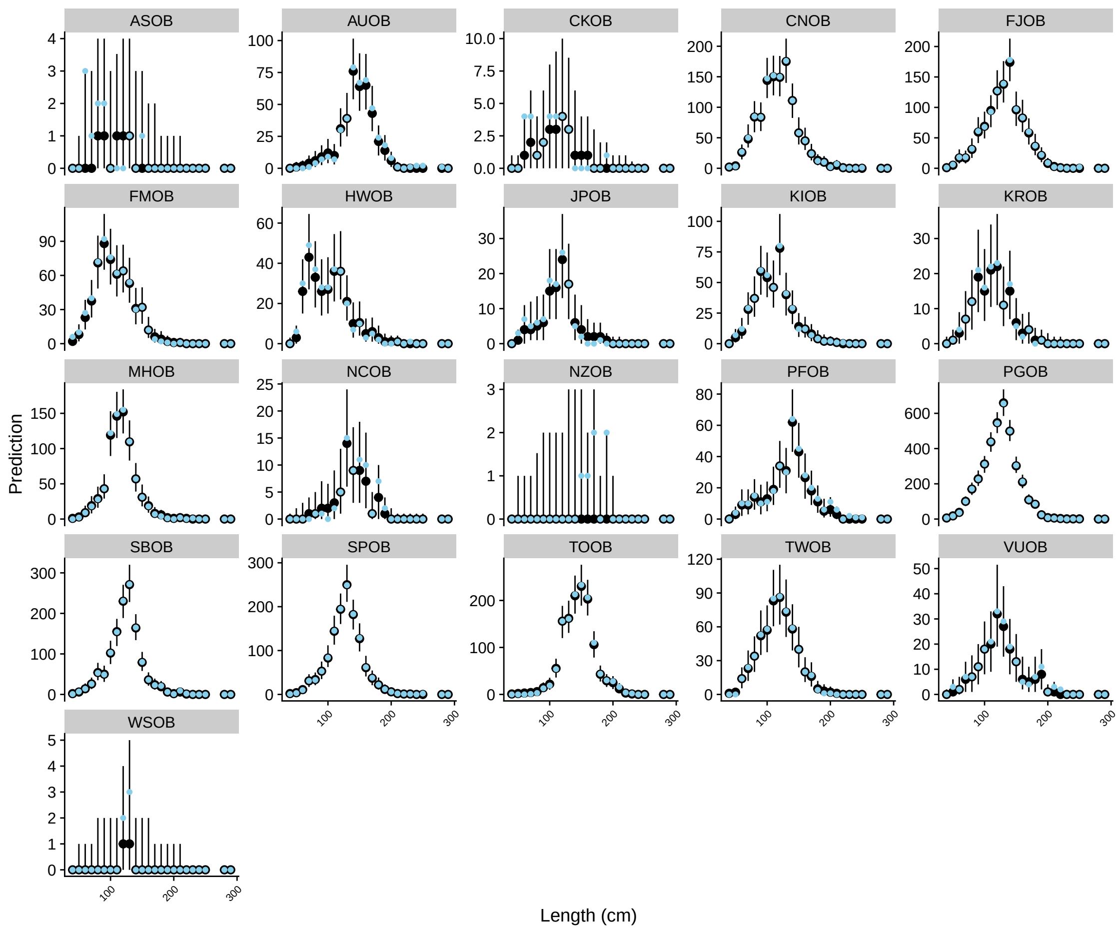


Figure 34: Length-composition standardisation model (using CPUE data) fit (black posterior median and 95% prediction interval) to the observed numbers in each 10 cm length bin (blue) by observer program in the WCPO longline fishery catching oceanic whitetip shark.

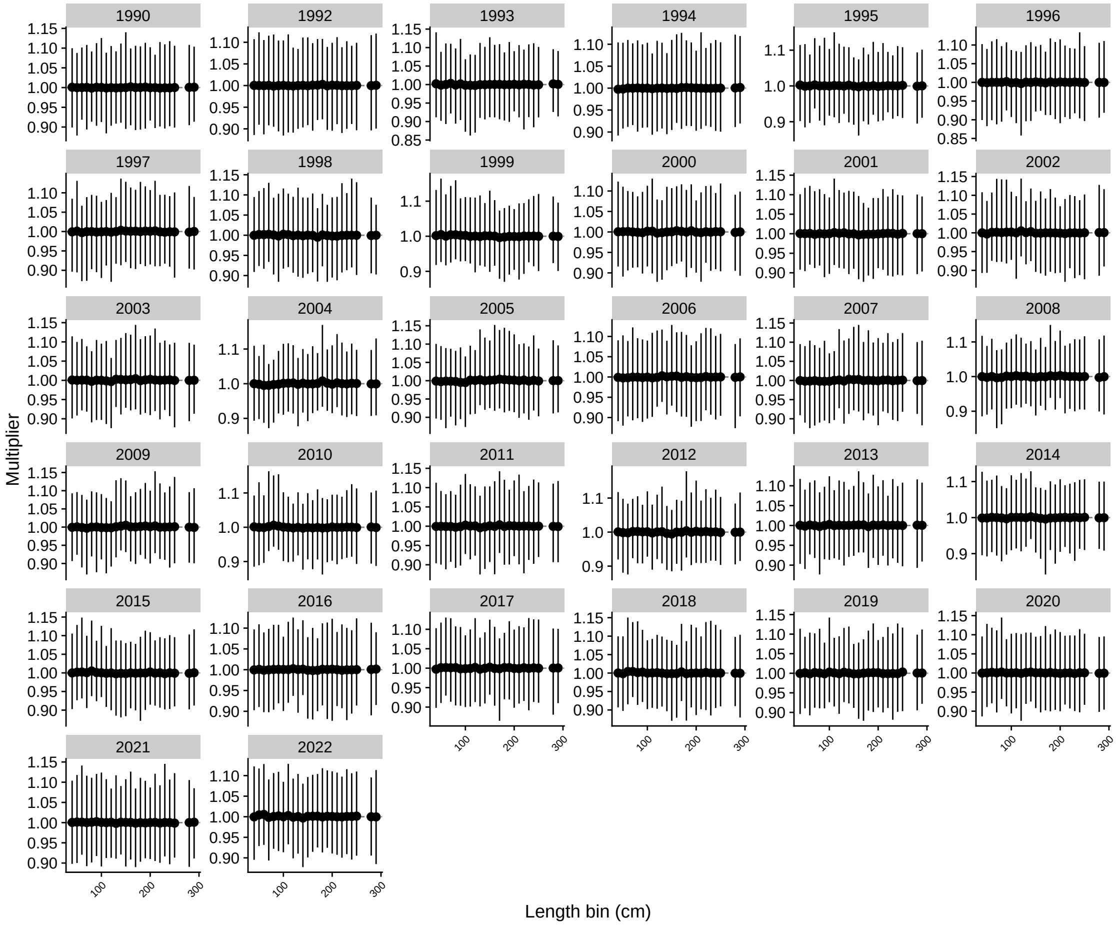


Figure 35: Year effect by 10 cm length bin, relative to the over-all mean length composition in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

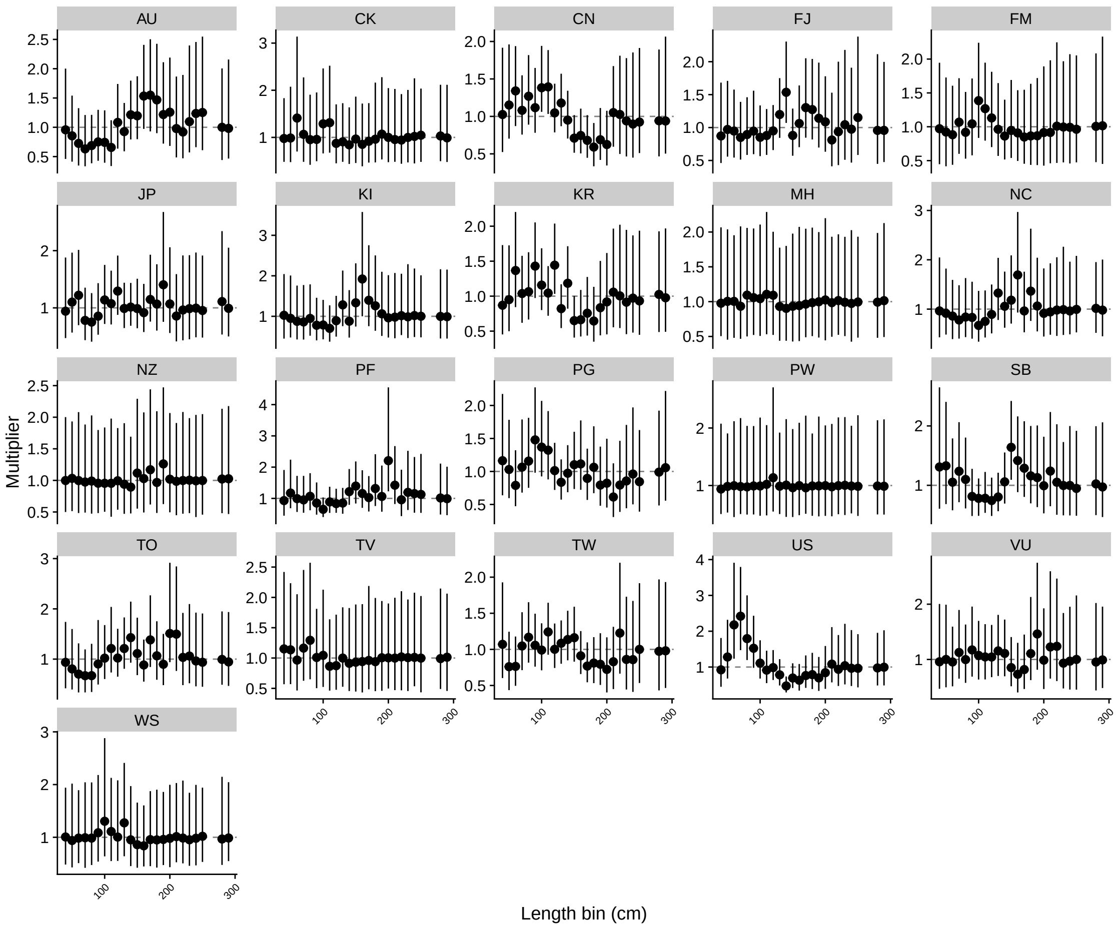


Figure 36: Vessel flag effect by 10 cm length bin, relative to the over-all mean length composition in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

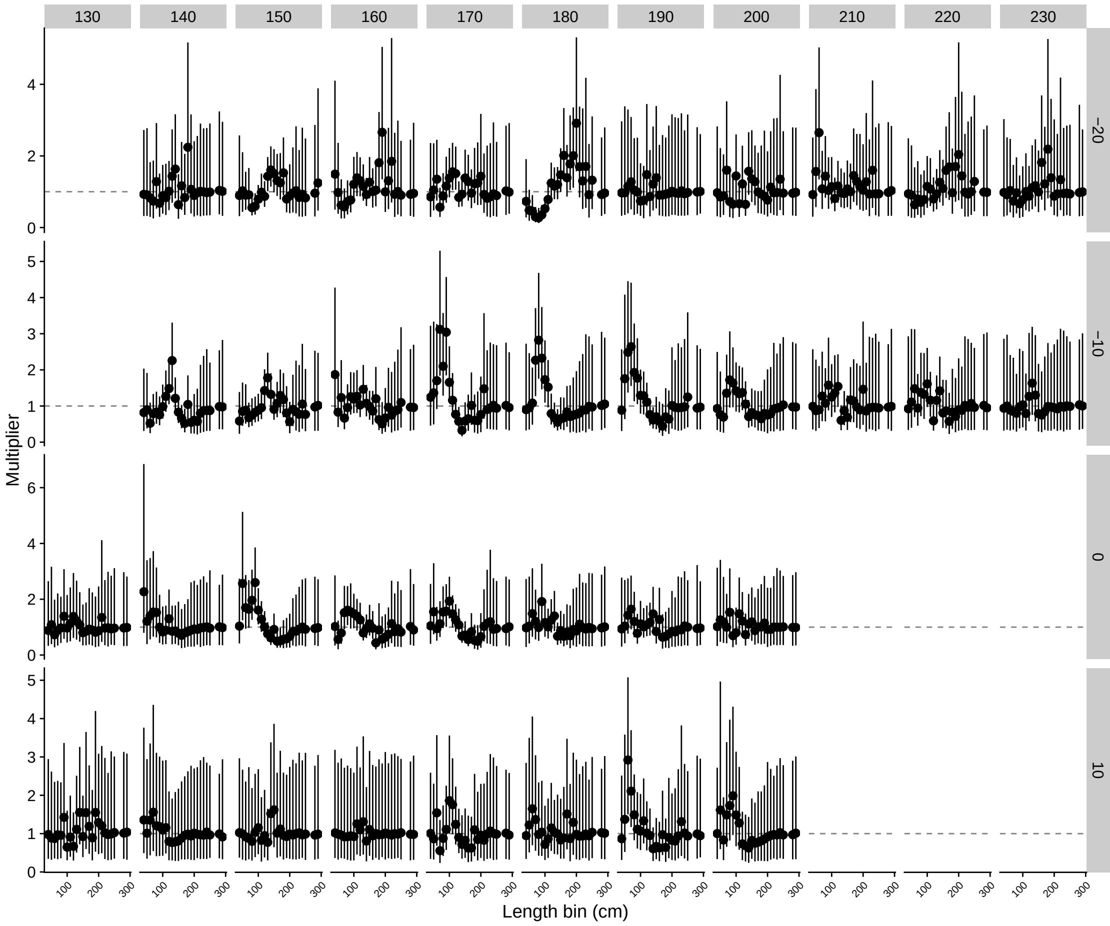


Figure 37: Area (10 degree grid) effect by 10 cm length bin in the WCPO longline fishery catching oceanic whitetip shark, relative to the over-all mean length composition, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

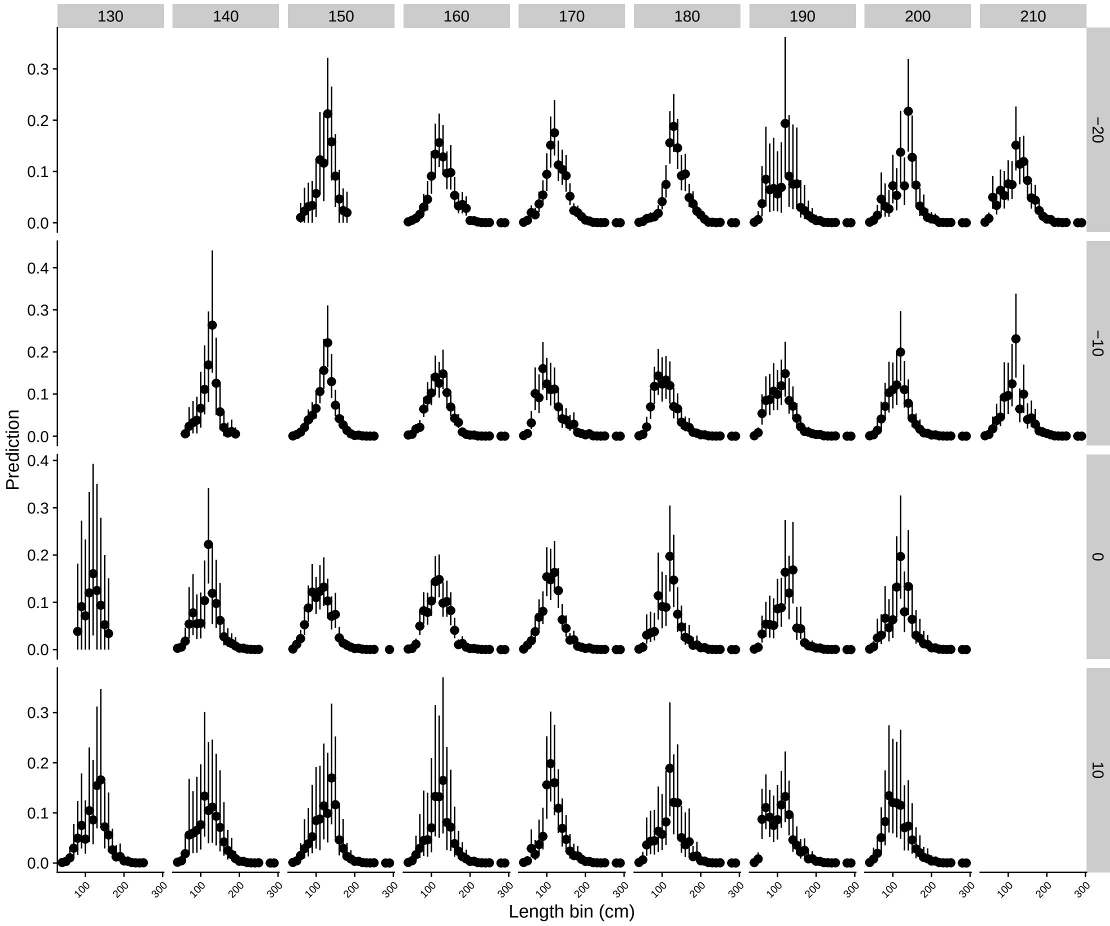


Figure 38: Predicted scaled length frequency by 10 cm length bin and 10 degree latitude - longitude bins, scaled by the predicted number of catch at the level of model strata in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length - composition standardisation model (black posterior median and 95% prediction interval).

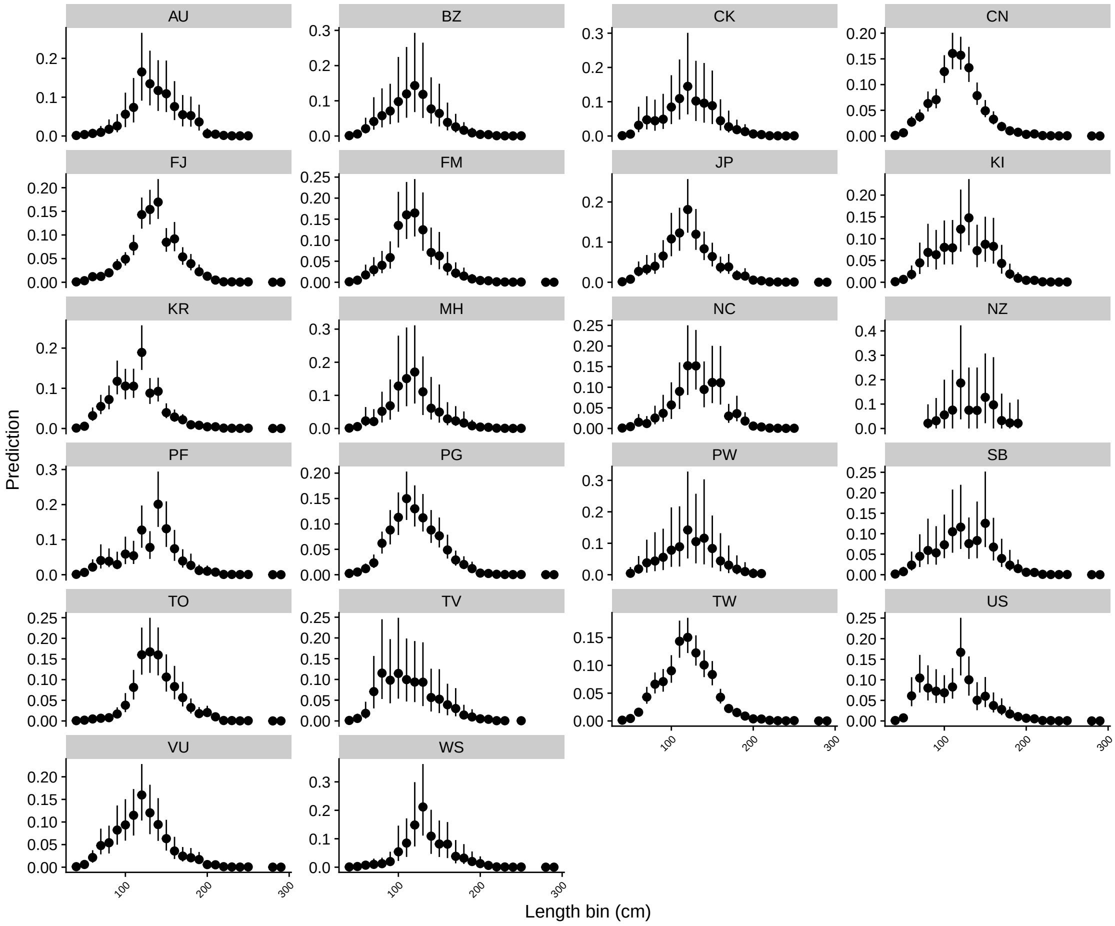


Figure 39: Predicted scaled length frequency by 10 cm length bin and vessel flag, scaled by the predicted number of catch at the level of model strata in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

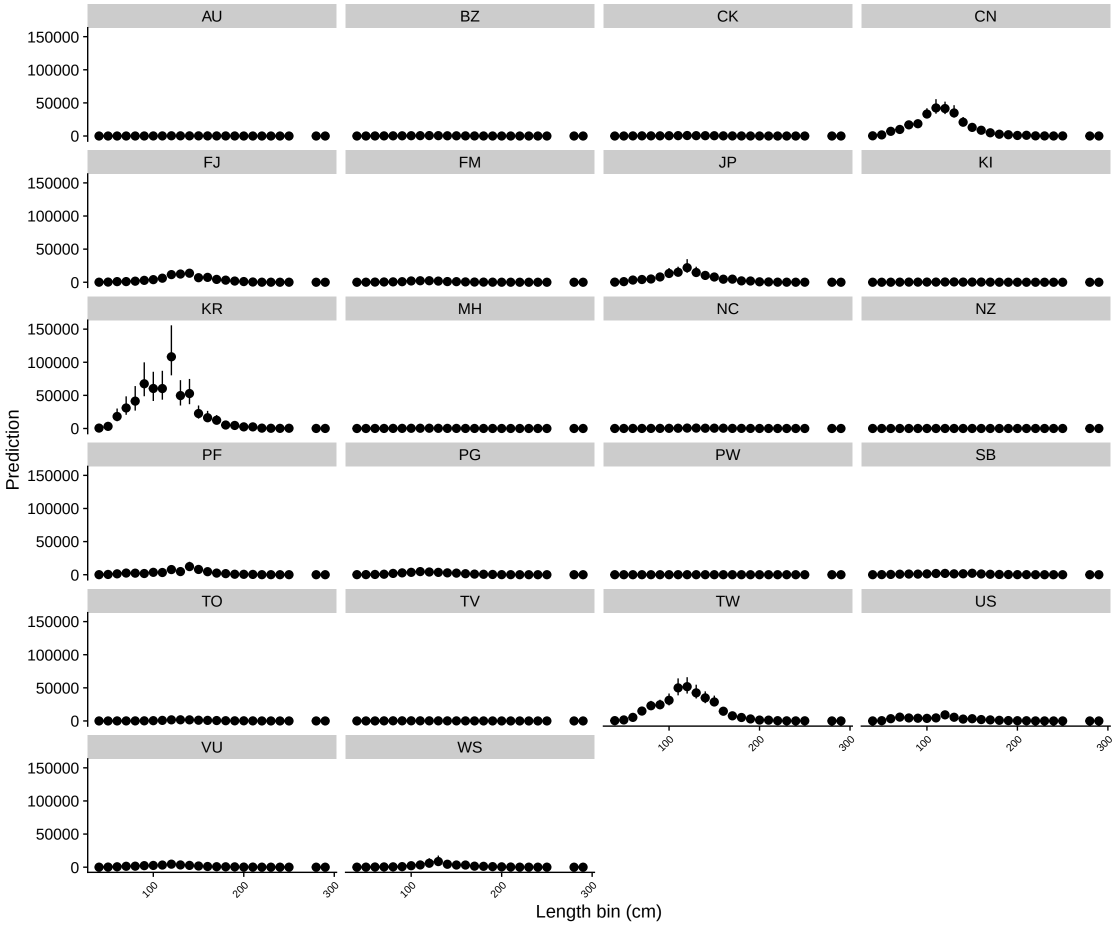


Figure 40: Predicted scaled catch at length by 10 cm length bin and vessel flag, scaled by the predicted number of catch at the level of model strata in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

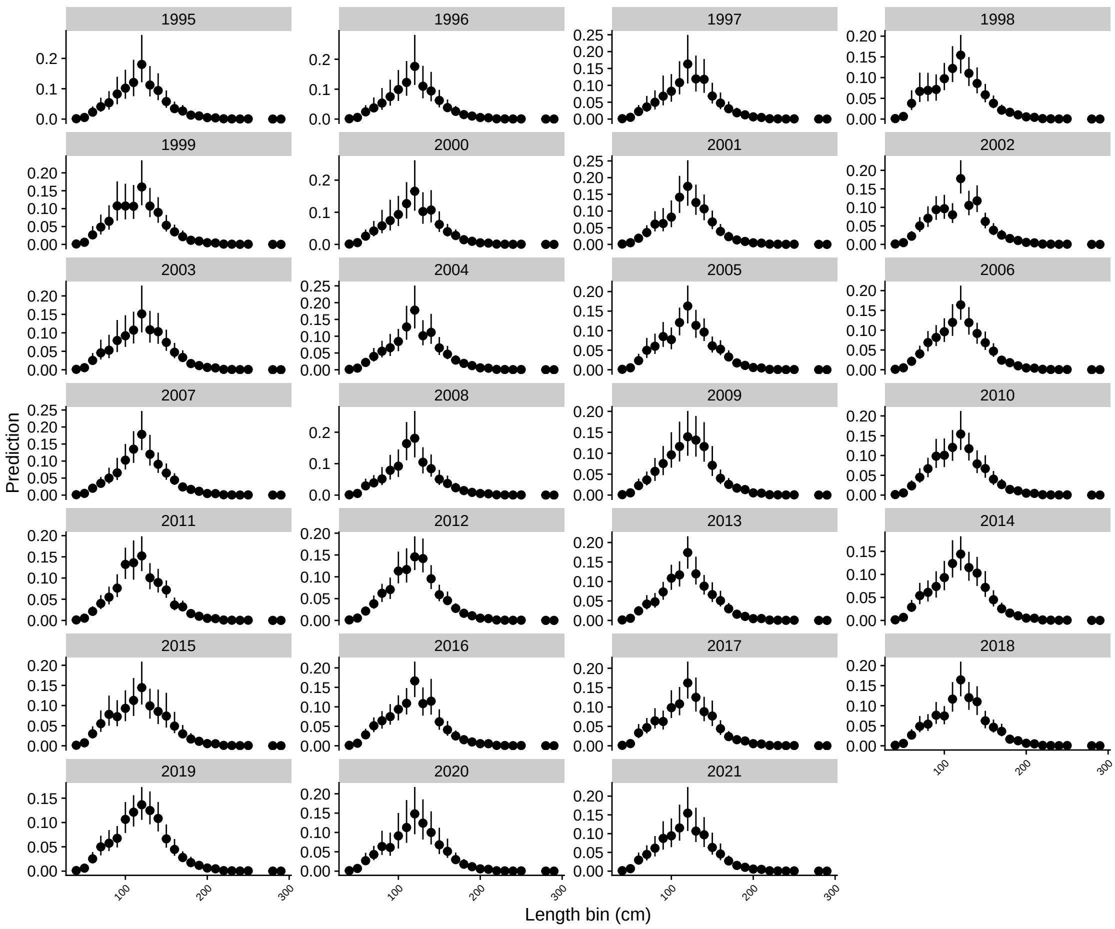


Figure 41: Predicted scaled length frequency by 10 cm length bin and year, scaled by the predicted number of catch at the level of model strata in the WCPO longline fishery catching oceanic whitetip shark, estimated by the length-composition standardisation model (black posterior median and 95% prediction interval).

APPENDIX A HIERARCHICAL STACKING MODEL

The present Stan model is based on formulations developed in Yao et al., (2022) extended to allow for predictions of model weights beyond the training dataset using the "generated quantities" block in Stan. Necessary inputs are described in the data section of the model.

```
data {
int < lower =1 > N; // number of observations
int N_pred; // number of predictions
int < lower =1 > d; // number of input variables
int < lower =1 > d_discrete ; // number of discrete dummy inputs
int < lower =1 > d_pred ; // number of discrete dummy inputs - prediction
int < lower =2 > K; // number of models
// when K =2 , replace softmax by inverse - logit for higher efficiency
matrix [N ,d] X; // predictors
matrix [N_pred ,d_pred+d-d_discrete] X_pred; // predictors for full prediction dataset
// including continuous and discrete in dummy variables , no constant
matrix [N ,K] lpd_point ; // the input pointwise predictive density
real < lower =0 > tau_mu ;
real < lower =0 > tau_discrete ; // global regularization for discrete x
real < lower =0 > tau_con ; // overall regularization for continuous x
}

transformed data {
matrix [N ,K] exp_lpd_point = exp ( lpd_point );
}

parameters {
vector [K -1] mu ;
real mu_0 ;
vector < lower =0 >[K -1] sigma ;
vector < lower =0 >[K -1] sigma_con ;
vector [d - d_discrete ] beta_con [K -1];
vector [ d_discrete ] tau [K -1]; // using non - centered parameterization
}

transformed parameters {
vector [d] beta [K -1];
simplex [K] w[N ];
matrix [N ,K] f;

for (k in 1:( K -1) ) beta [k] = append_row ( mu_0 * tau_mu + mu [k]* tau_mu +
sigma [k ]* tau [k], sigma_con [k ]* beta_con [k ]) ;

for (k in 1:( K -1) ) f[,k] = X * beta [k ];
f[,K] = rep_vector (0 , N);

for (n in 1: N) w[n] = softmax ( to_vector (f[n , 1: K ]) );
```

```
}

model{
for (k in 1:( K -1) ){
tau [k] ~ std_normal () ;
beta_con [k] ~ std_normal () ;
}
mu ~ std_normal () ;
mu_0 ~ std_normal () ;
sigma ~ normal (0 , tau_discrete );
sigma_con ~ normal (0 , tau_con );
for (i in 1: N) target += log ( exp_lpd_point [i ,] * w[i ]) ; // log likelihood
}
generated quantities {
vector [N] log_lik ;
simplex [K] w_pred[N_pred];

for (i in 1: N) log_lik [i] = log ( exp_lpd_point [i ,] * w[i ]);
if(N_pred>0){
matrix [N_pred ,K] f_pred;
vector [d_pred] beta_pred [K -1];
vector [d_pred] tau_pred [K -1]; // using non - centered parameterization


for (k in 1:( K -1) ) {

tau_pred[k,1:d_discrete] = tau[k] ;

if(d_pred>d_discrete) {
for (ds in (d_discrete+1):d_pred) tau_pred [k,ds] = normal_rng(0,1);
}

beta_pred [k] = append_row ( mu_0 * tau_mu + mu [k ]* tau_mu +
sigma [k ]* tau_pred [k], sigma_con [k ]* beta_con [k ]) ;
f_pred[,k] = X_pred * beta_pred[k ];
}
f_pred[,K] = rep_vector (0 , N_pred);

for (n in 1: N_pred) w_pred[n] = softmax ( to_vector (f_pred[n , 1: K ]) );
}
}
```

APPENDIX B CPUE DIAGNOSTICS - SUPPLEMENTARY FIGURES

B.1 CPUE diagnostics for all longline

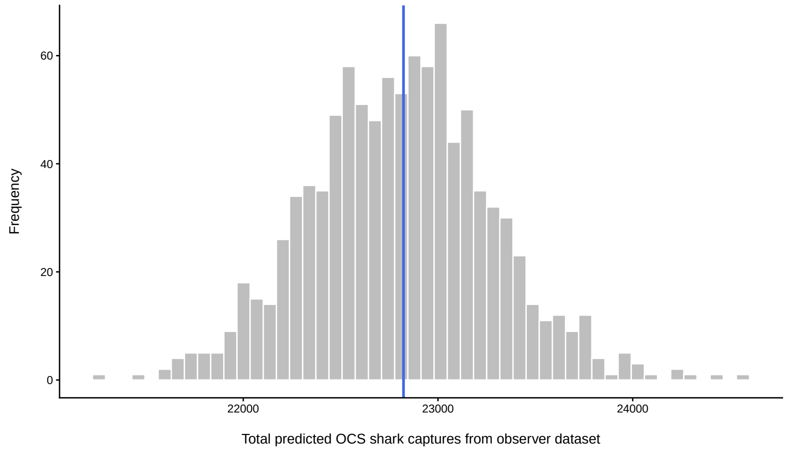


Figure B-1: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

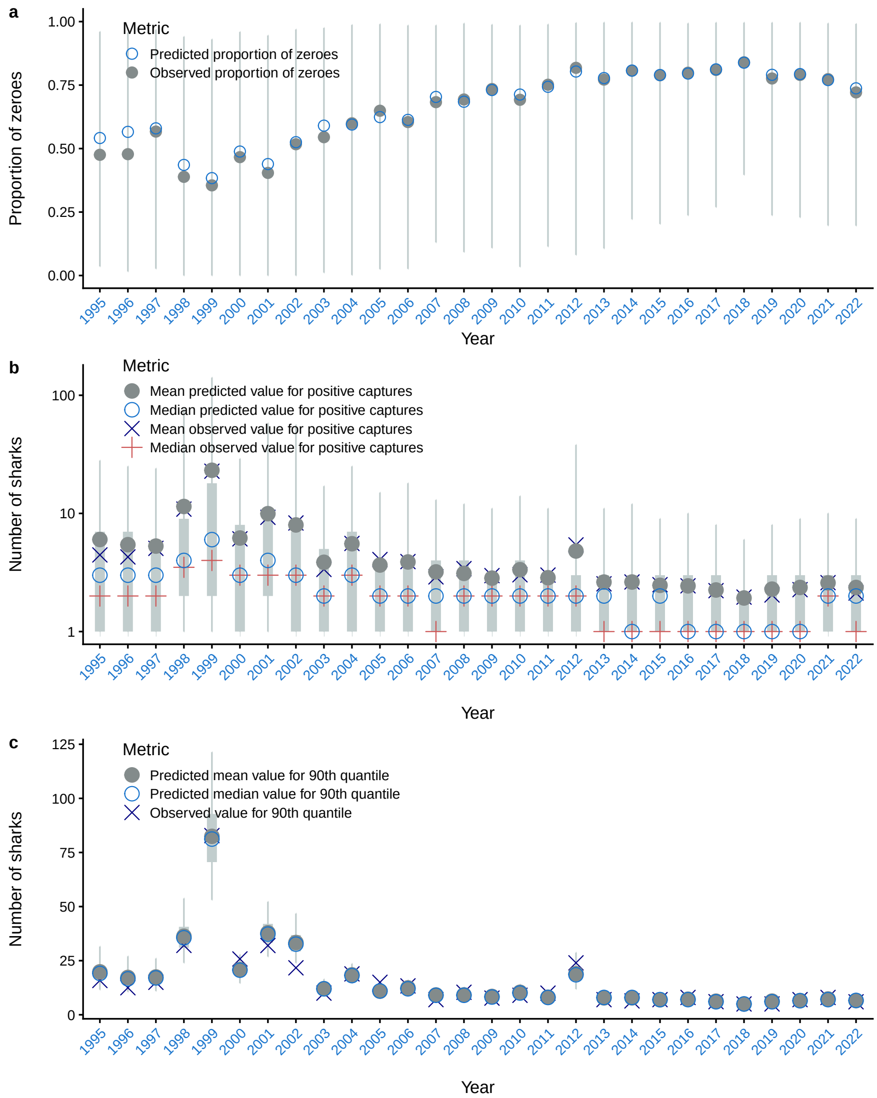


Figure B-2: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

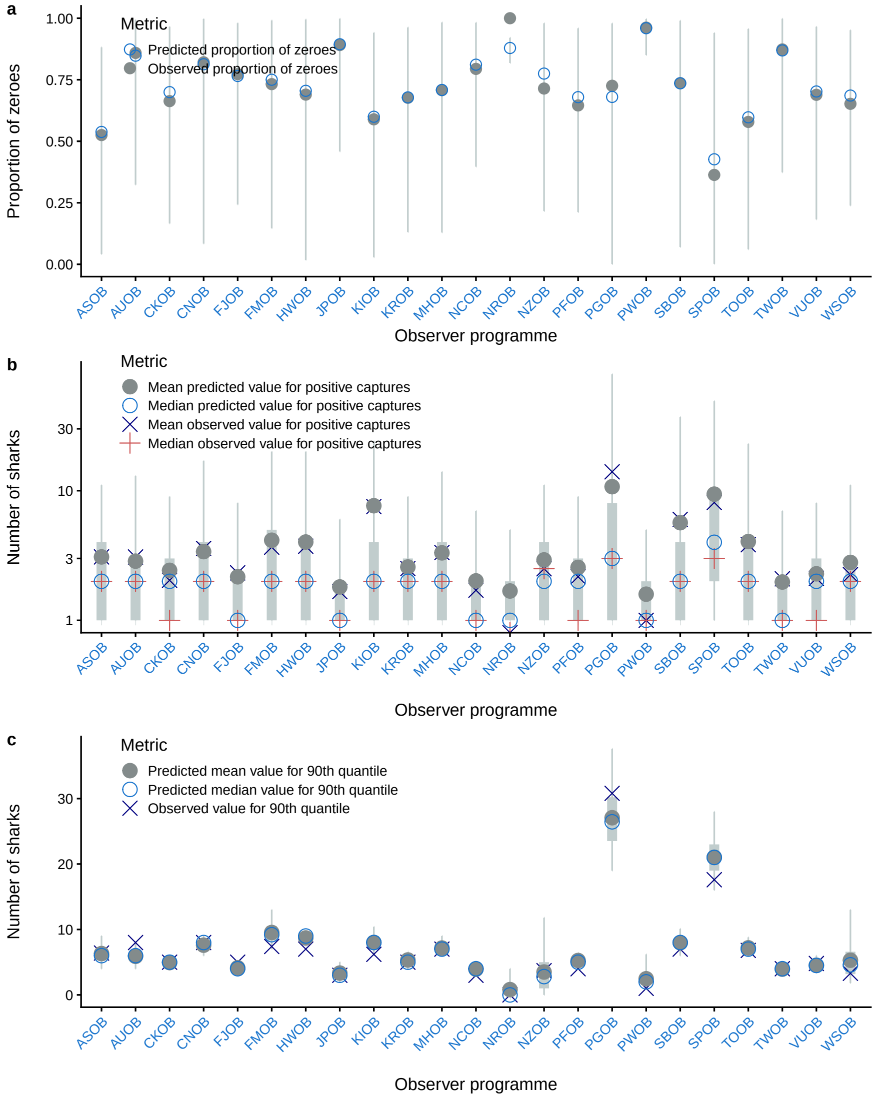


Figure B-3: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

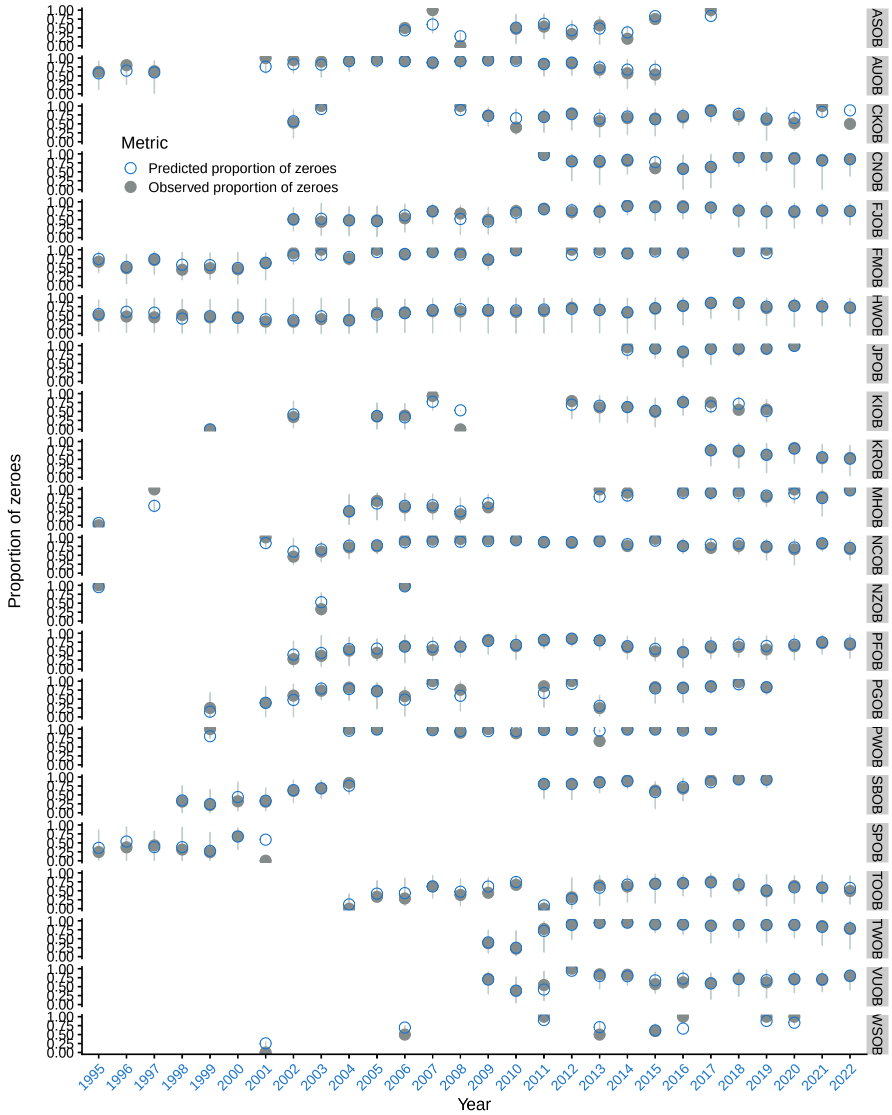


Figure B-4: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

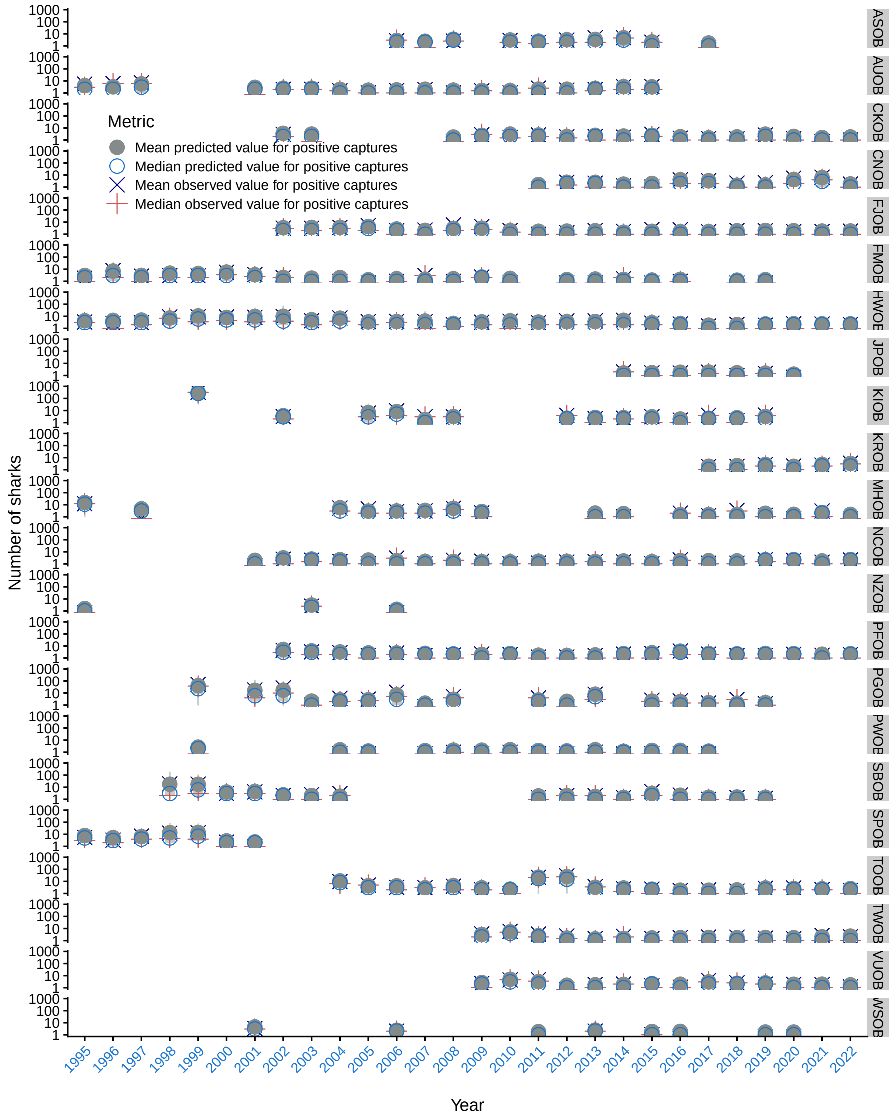


Figure B-5: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

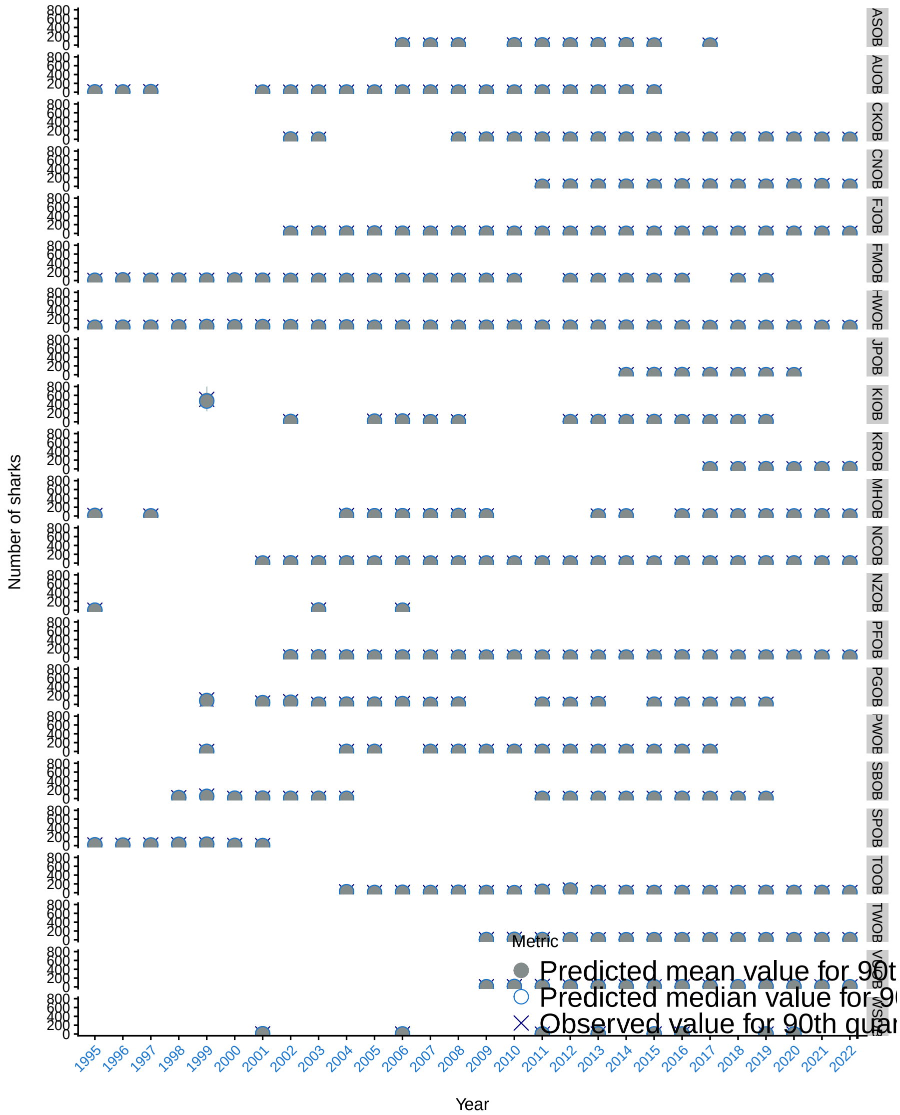


Figure B-6: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

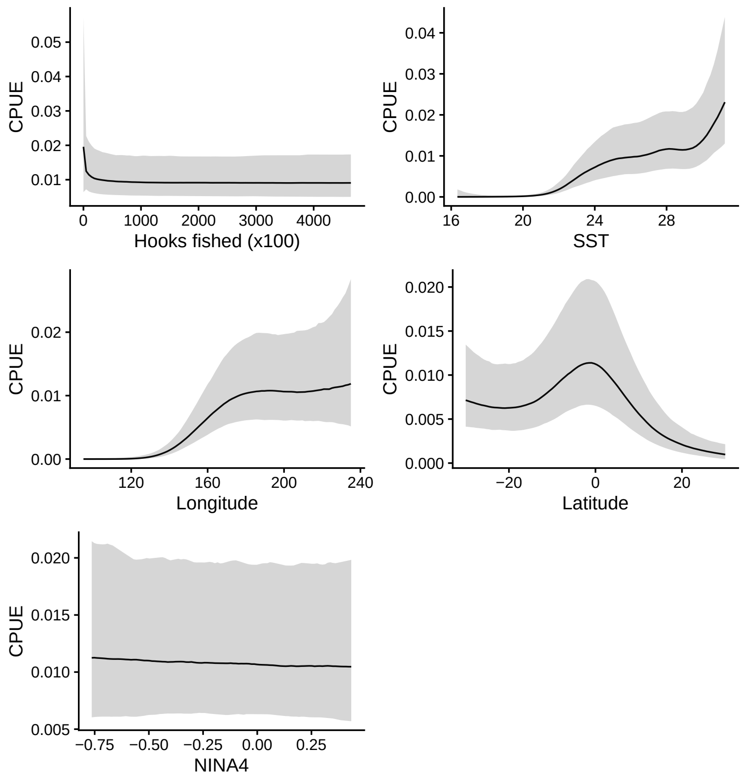


Figure B-7: Conditional effects estimated in the model used to derive CPUE from observed for sets.

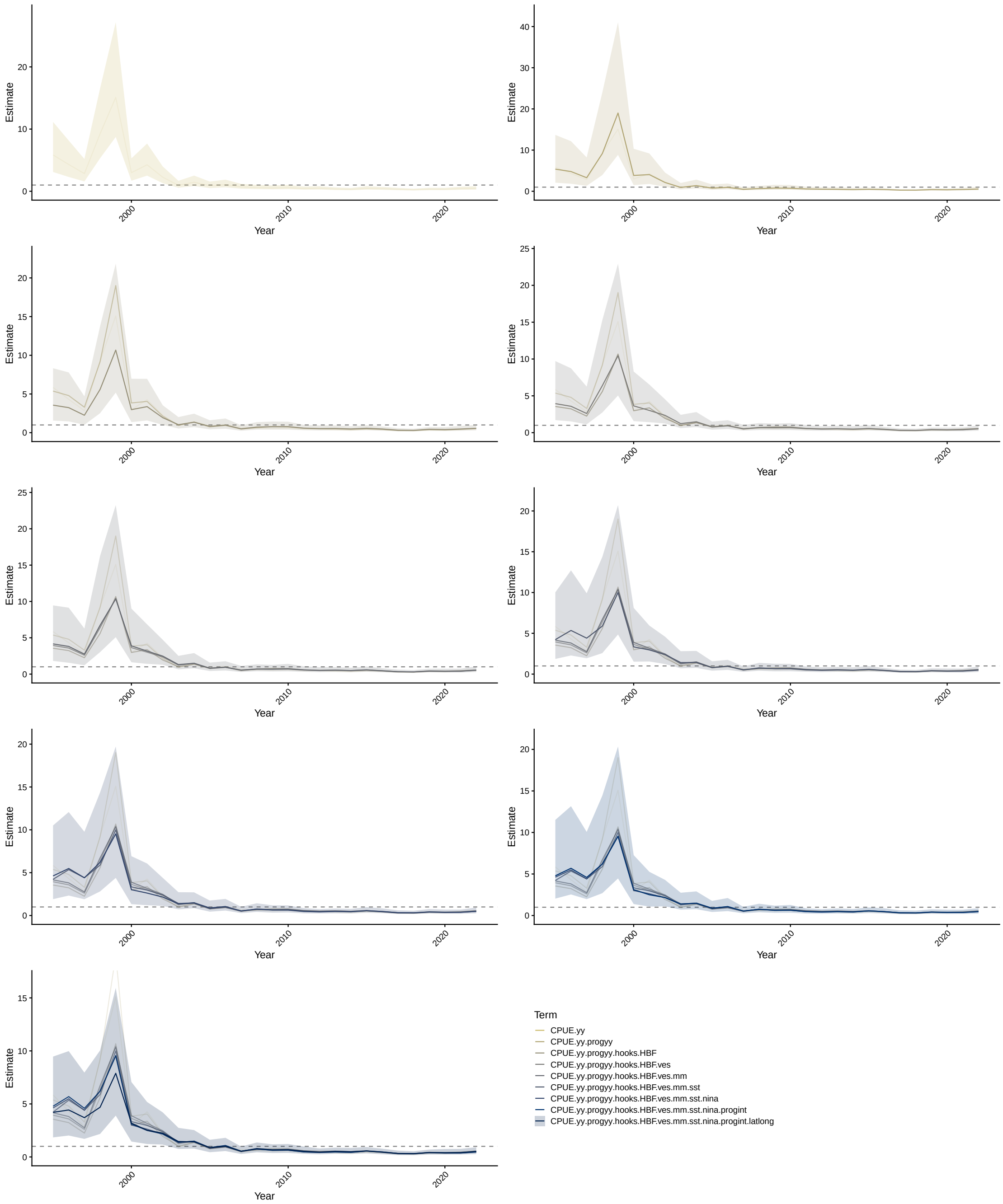


Figure B-8: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

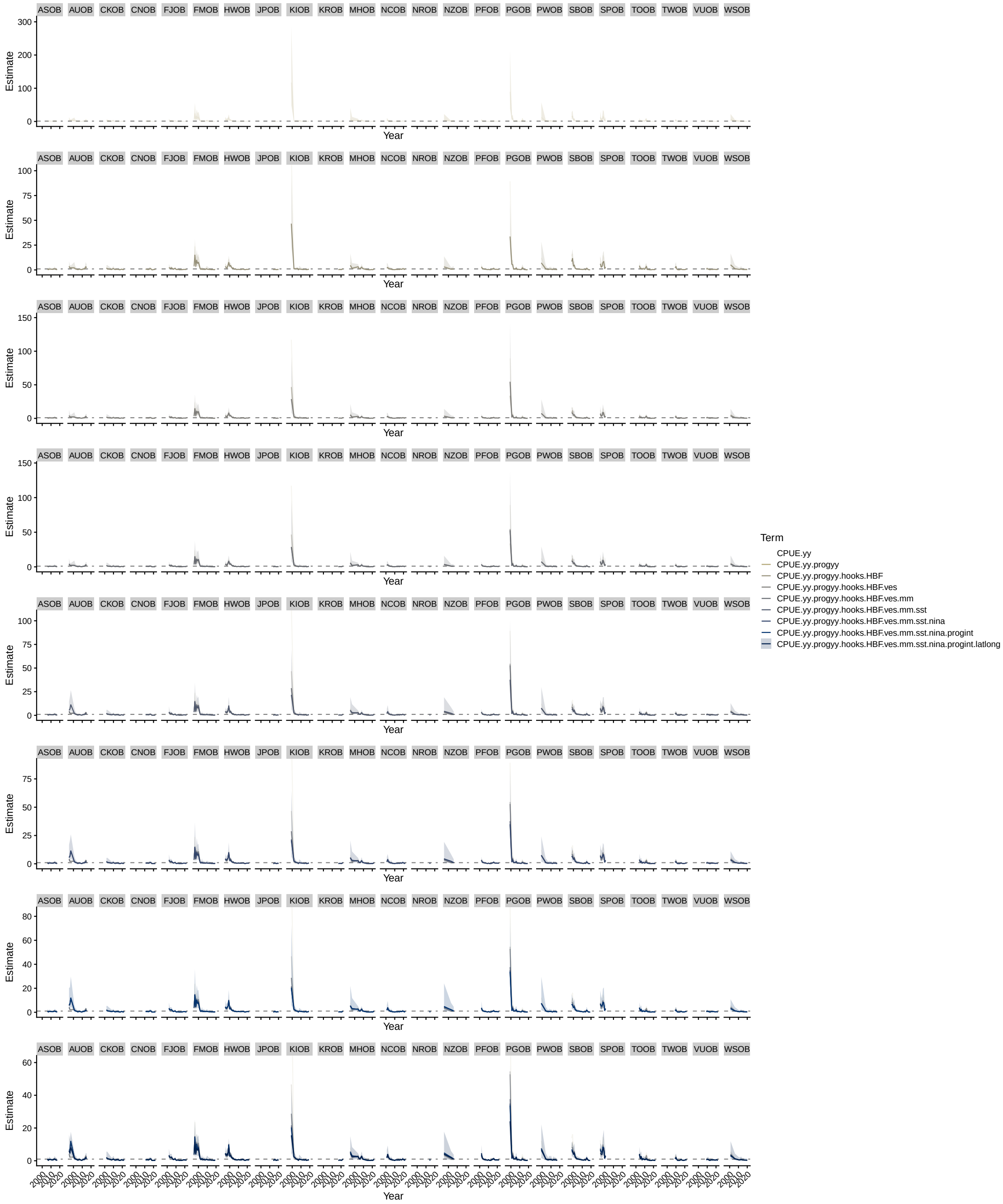


Figure B-9: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

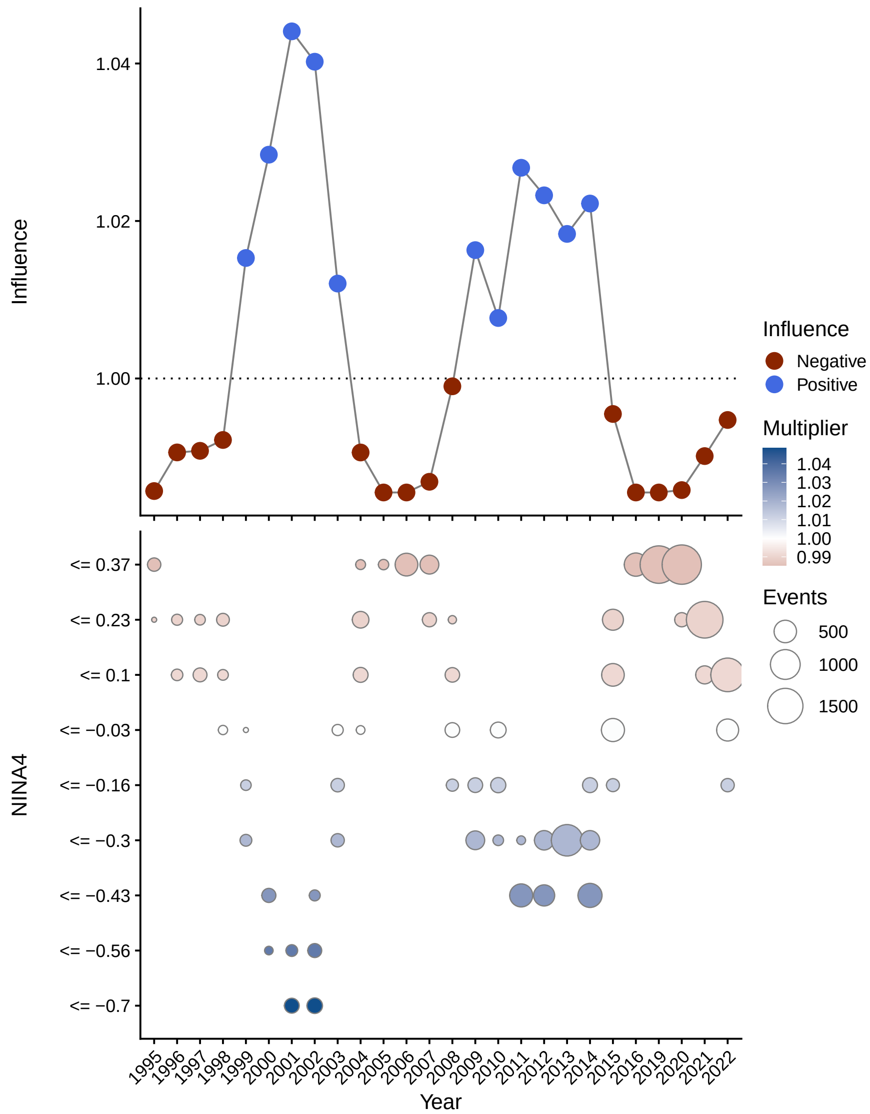


Figure B-10: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

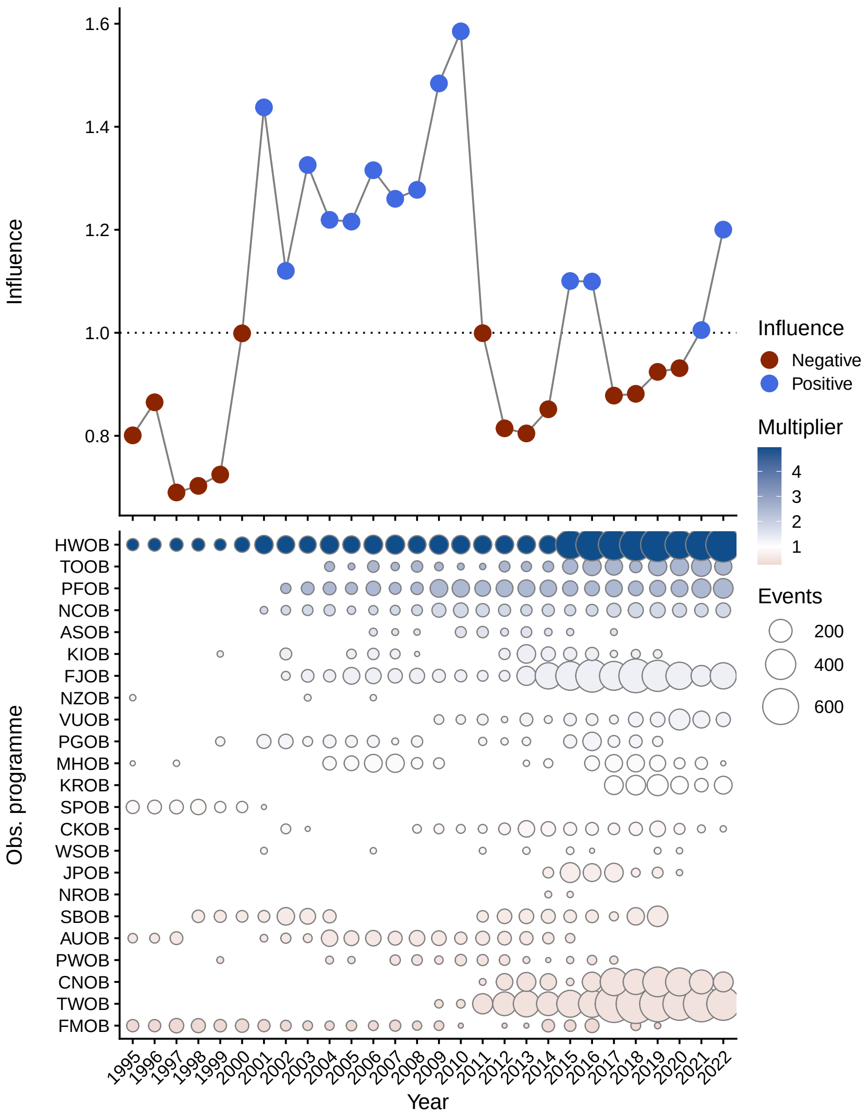


Figure B-11: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

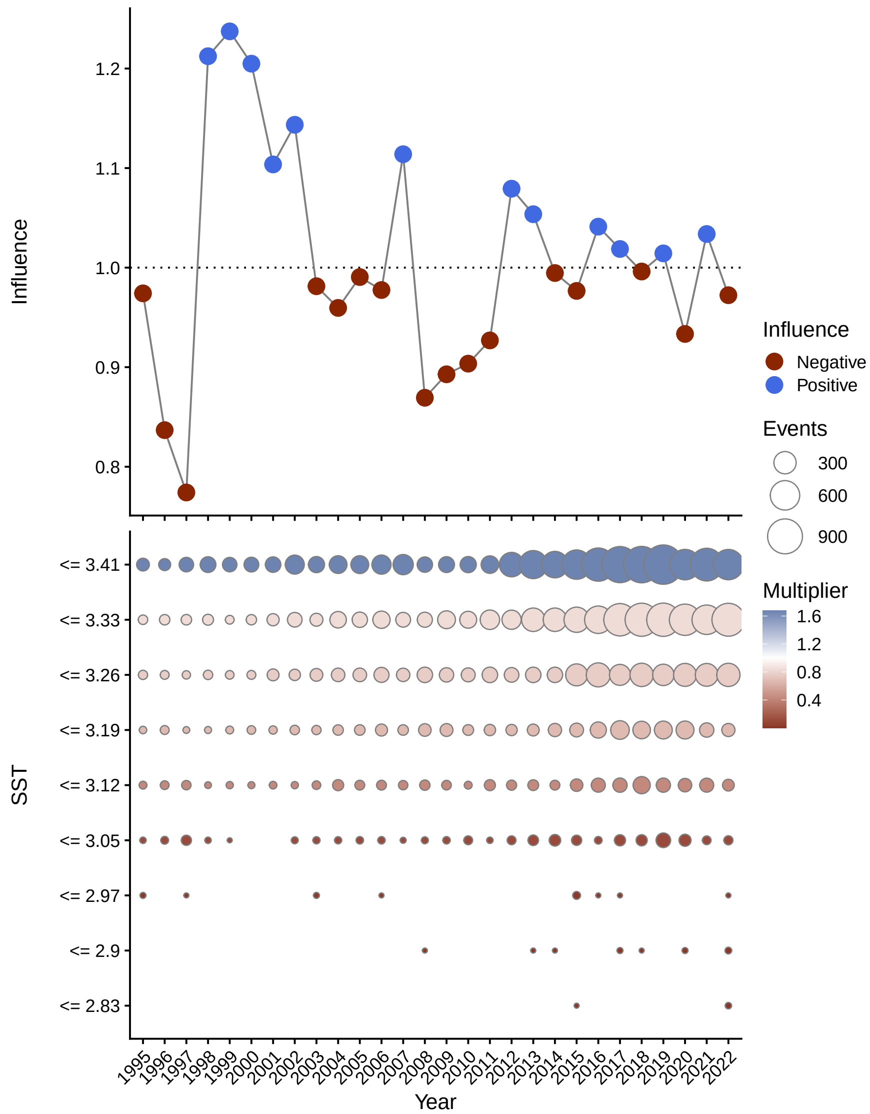


Figure B-12: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

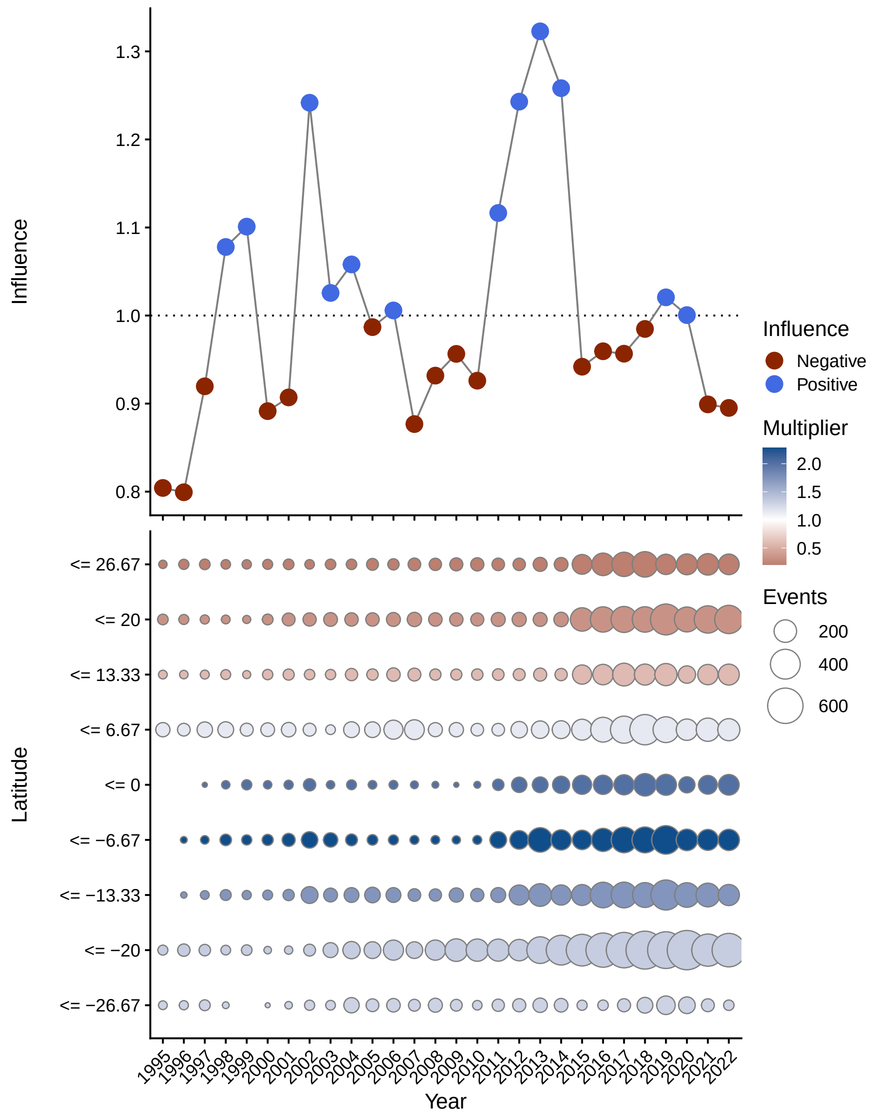


Figure B-13: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

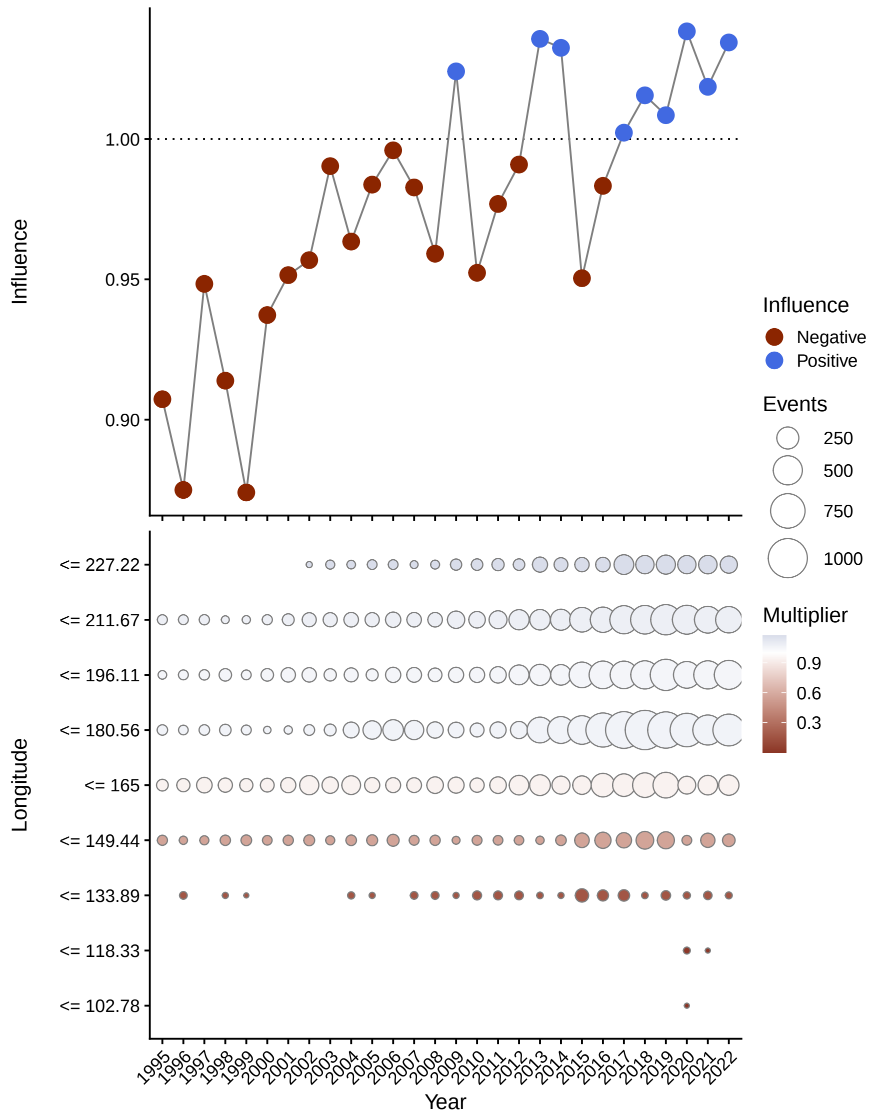


Figure B-14: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

B.2 CPUE diagnostics for observer program longline (Tremblay-Boyer et al. 2019)

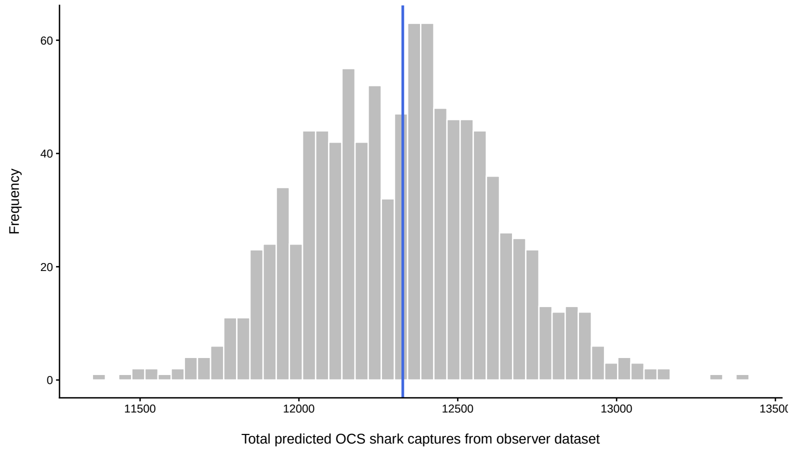


Figure B-15: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

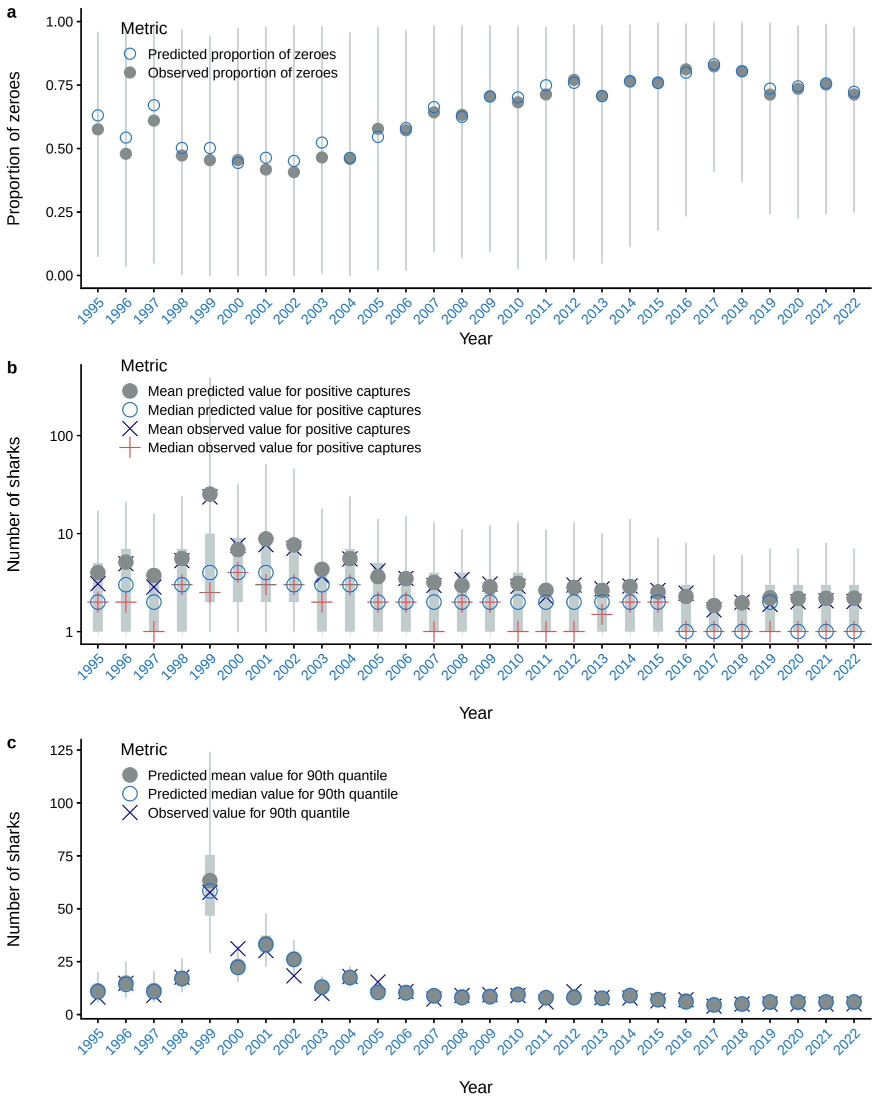


Figure B-16: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

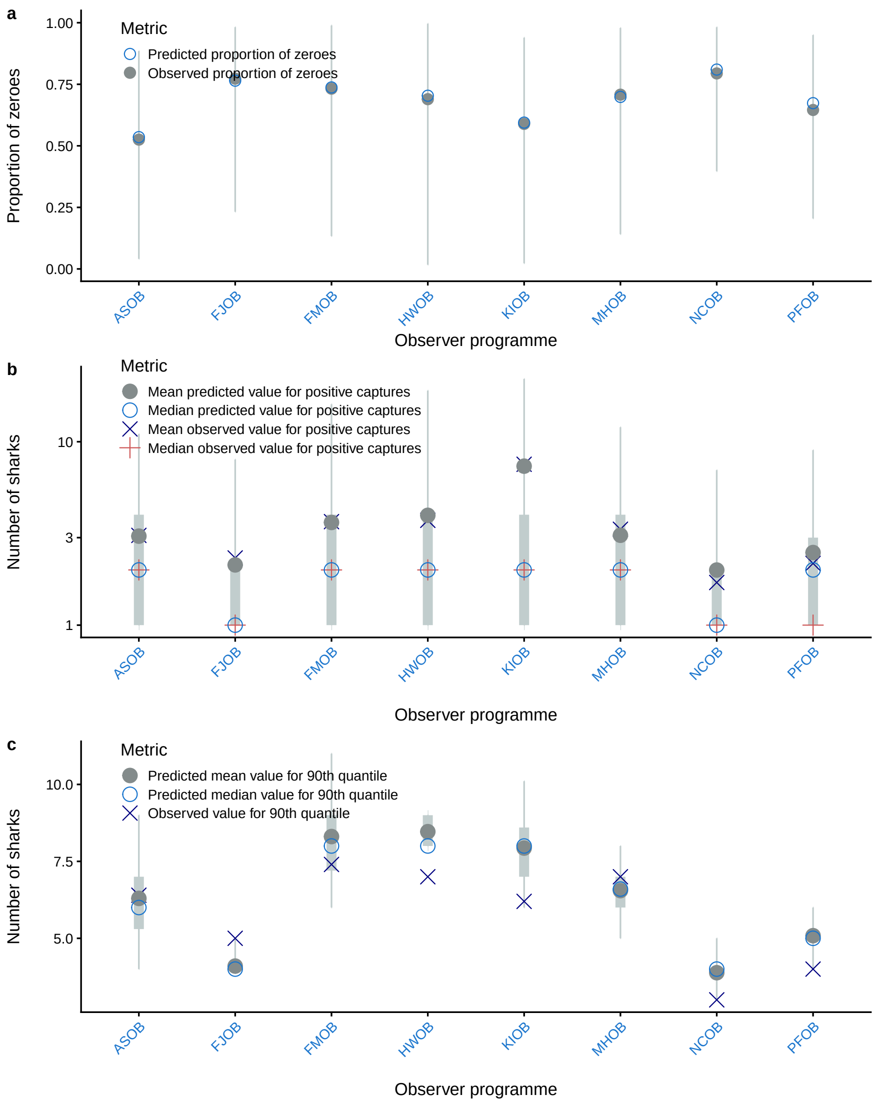


Figure B-17: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

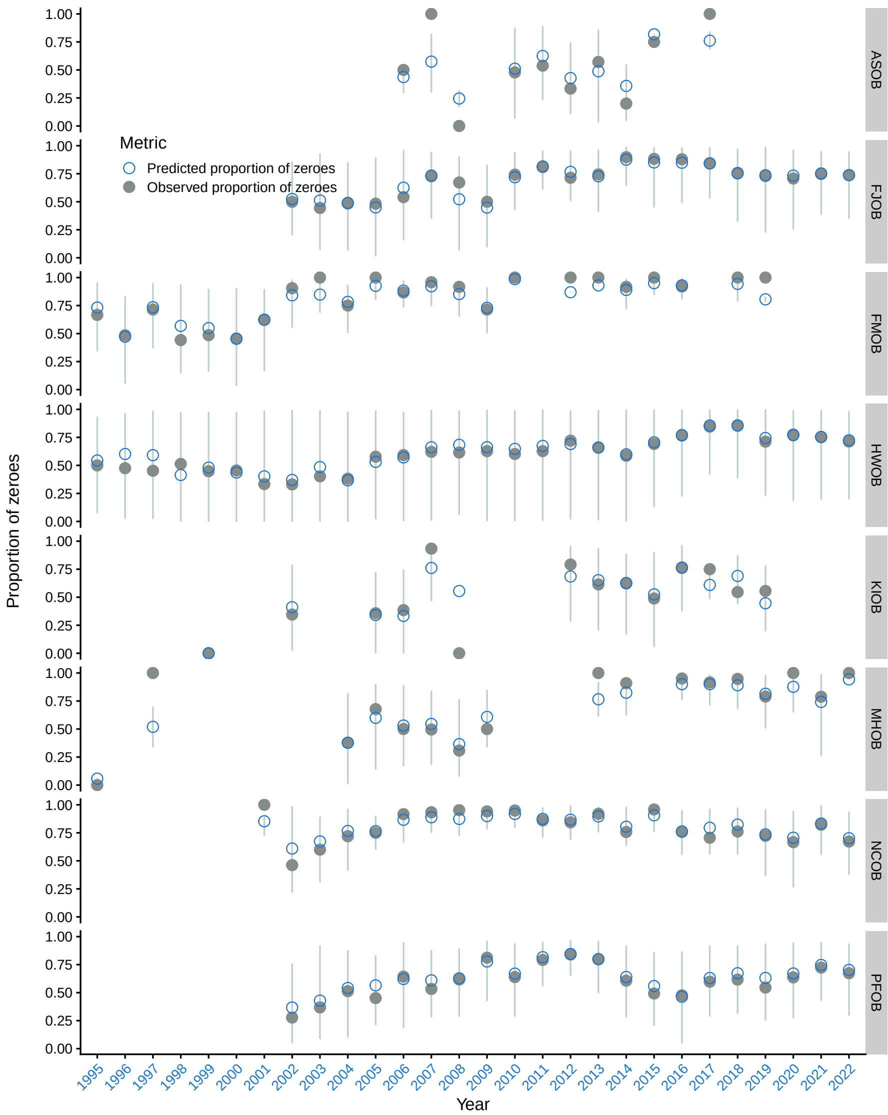


Figure B-18: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

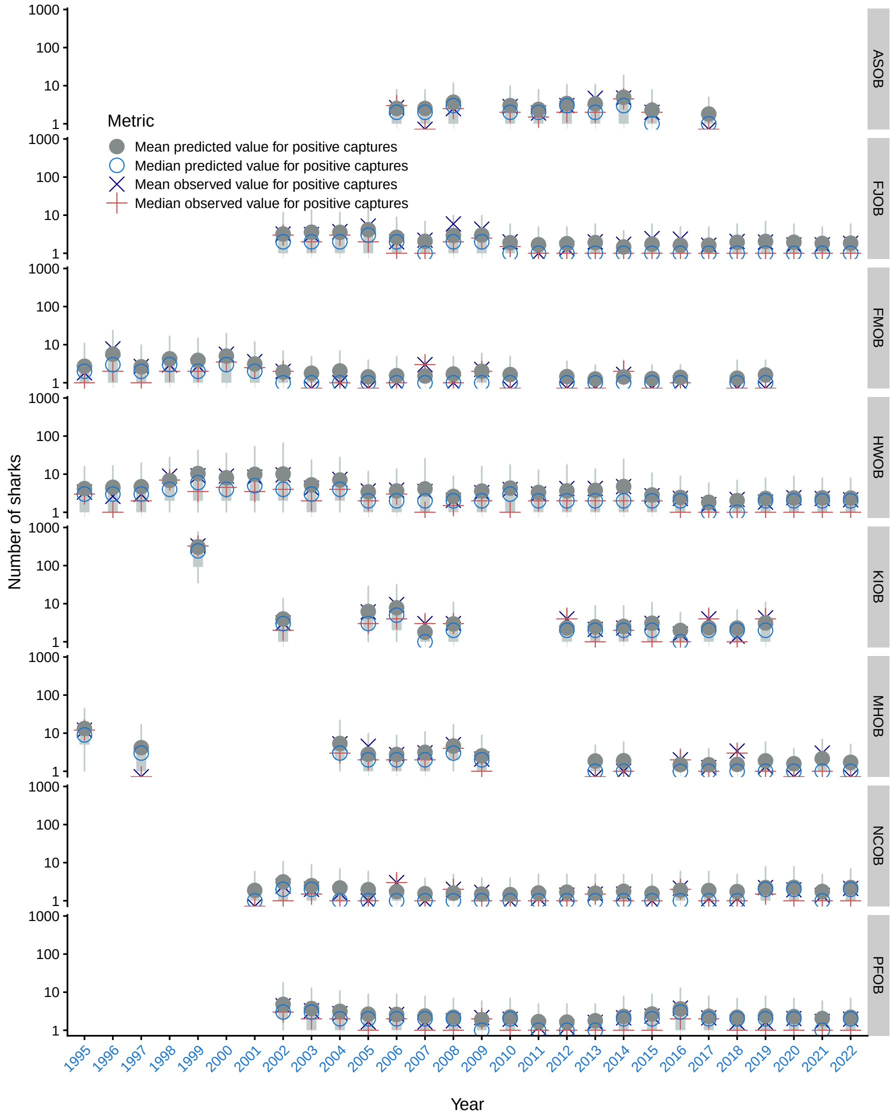


Figure B-19: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

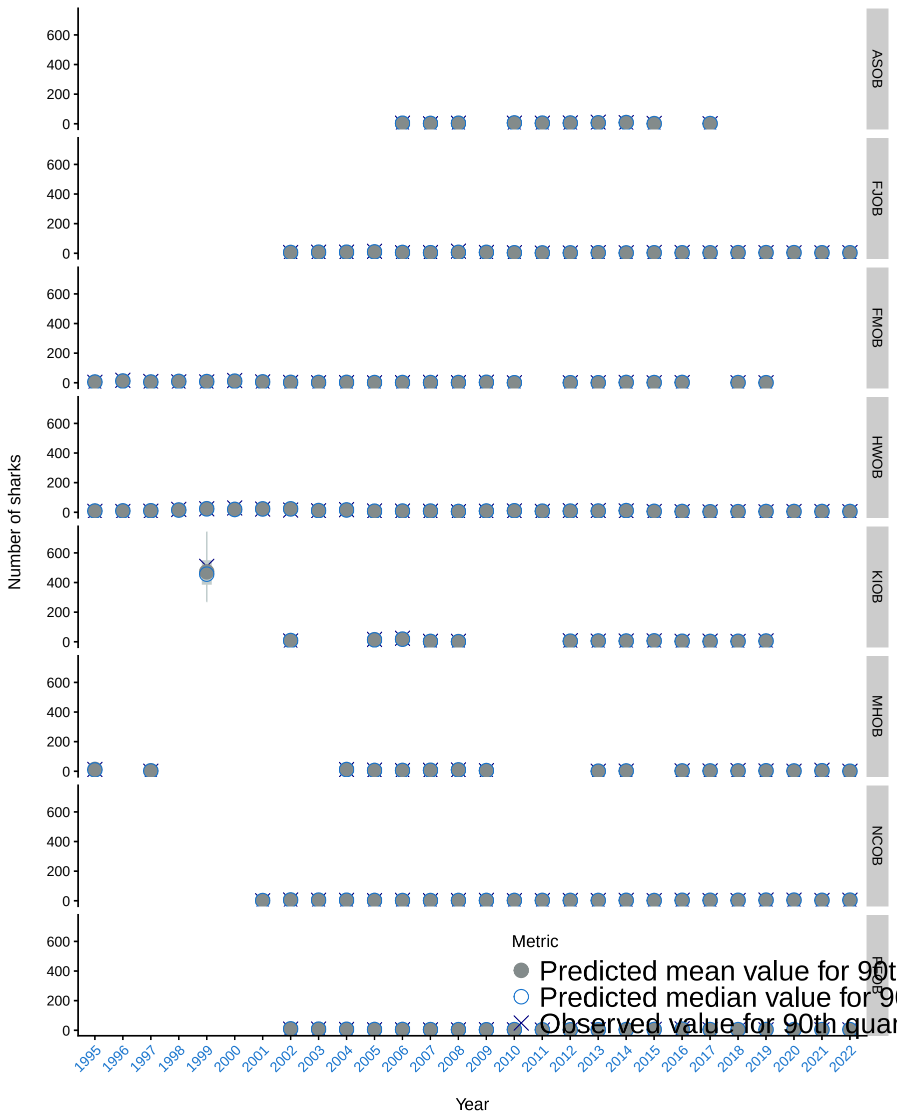


Figure B-20: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

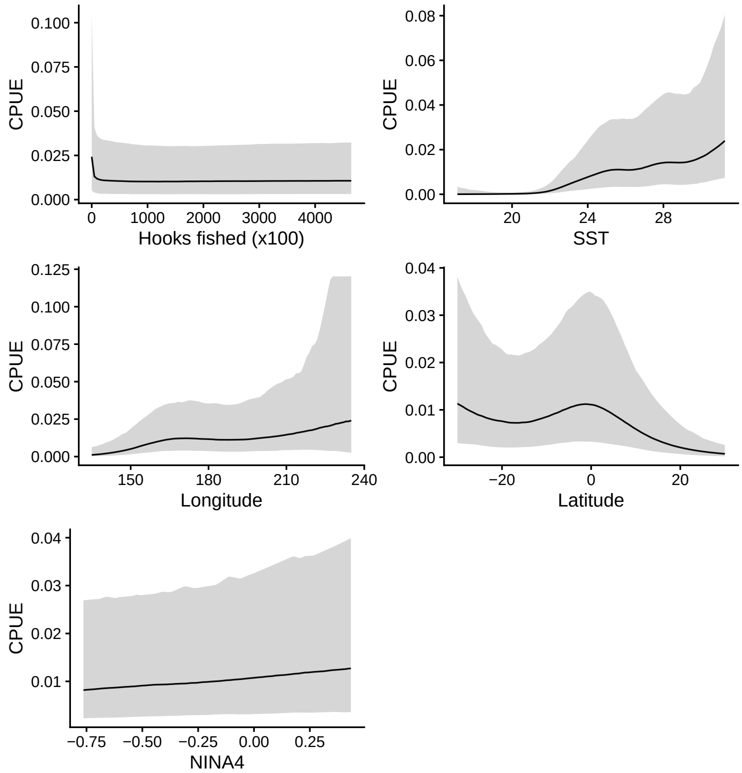


Figure B-21: Conditional effects estimated in the model used to derive CPUE from observed for sets.

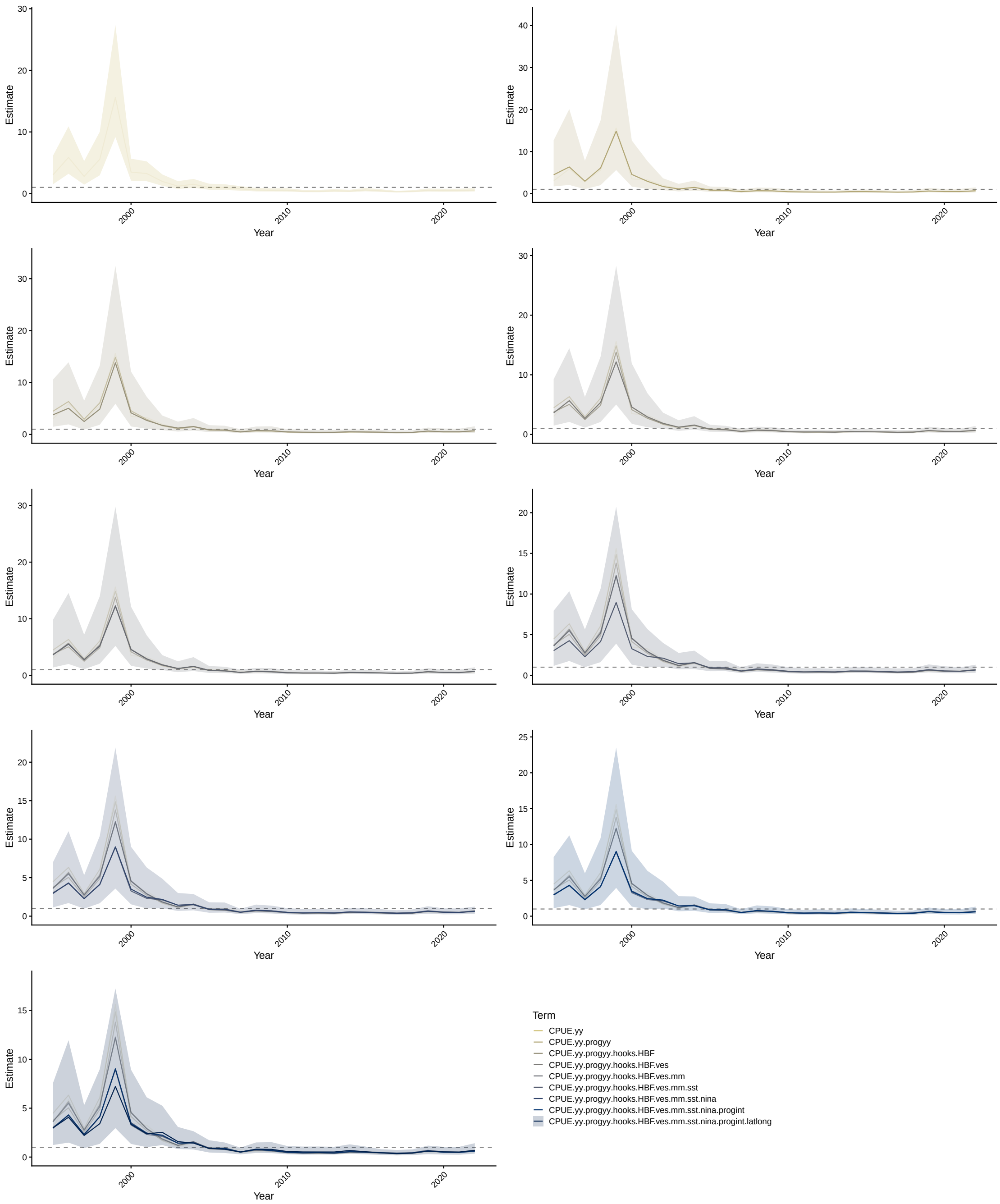


Figure B-22: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

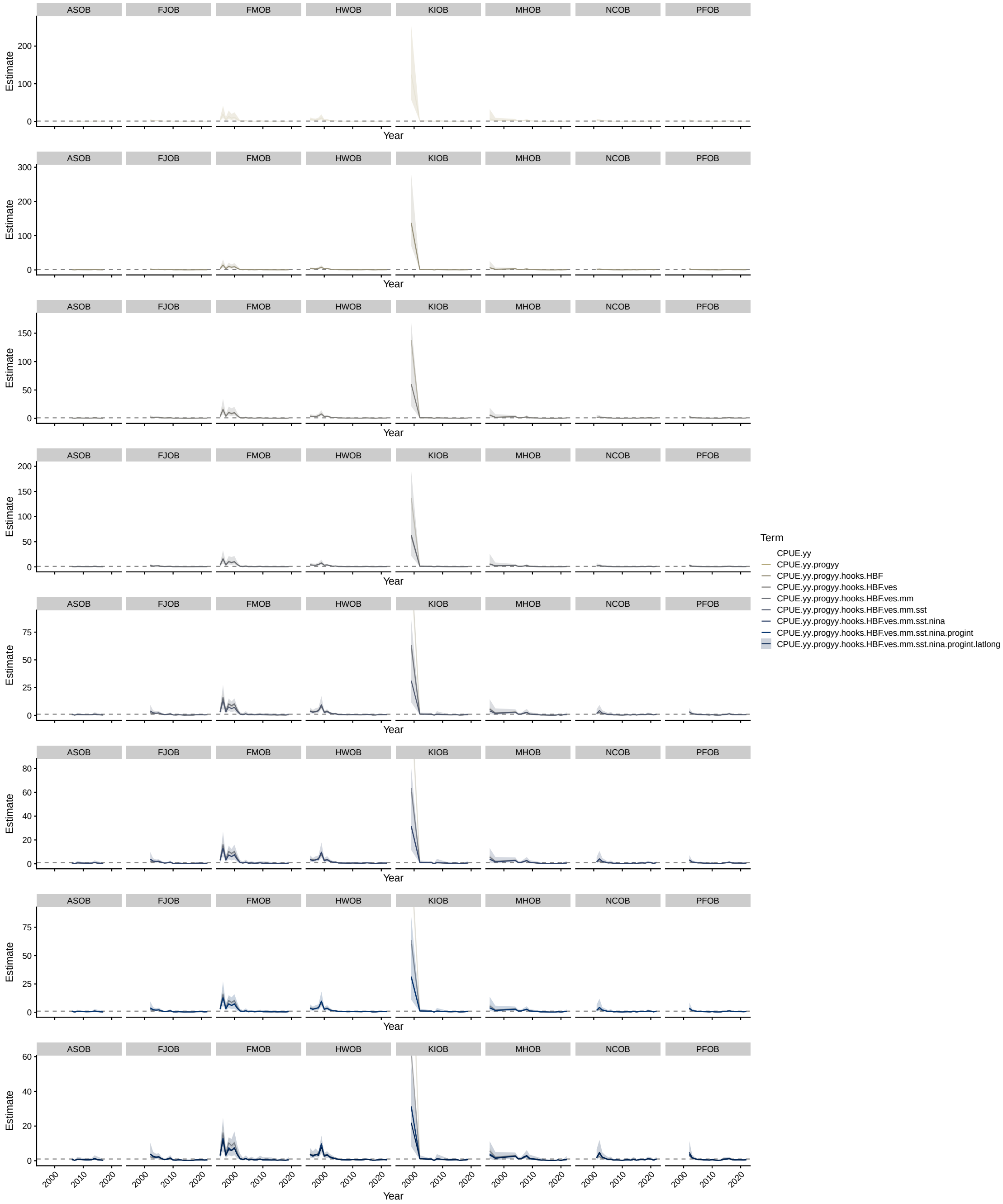


Figure B-23: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

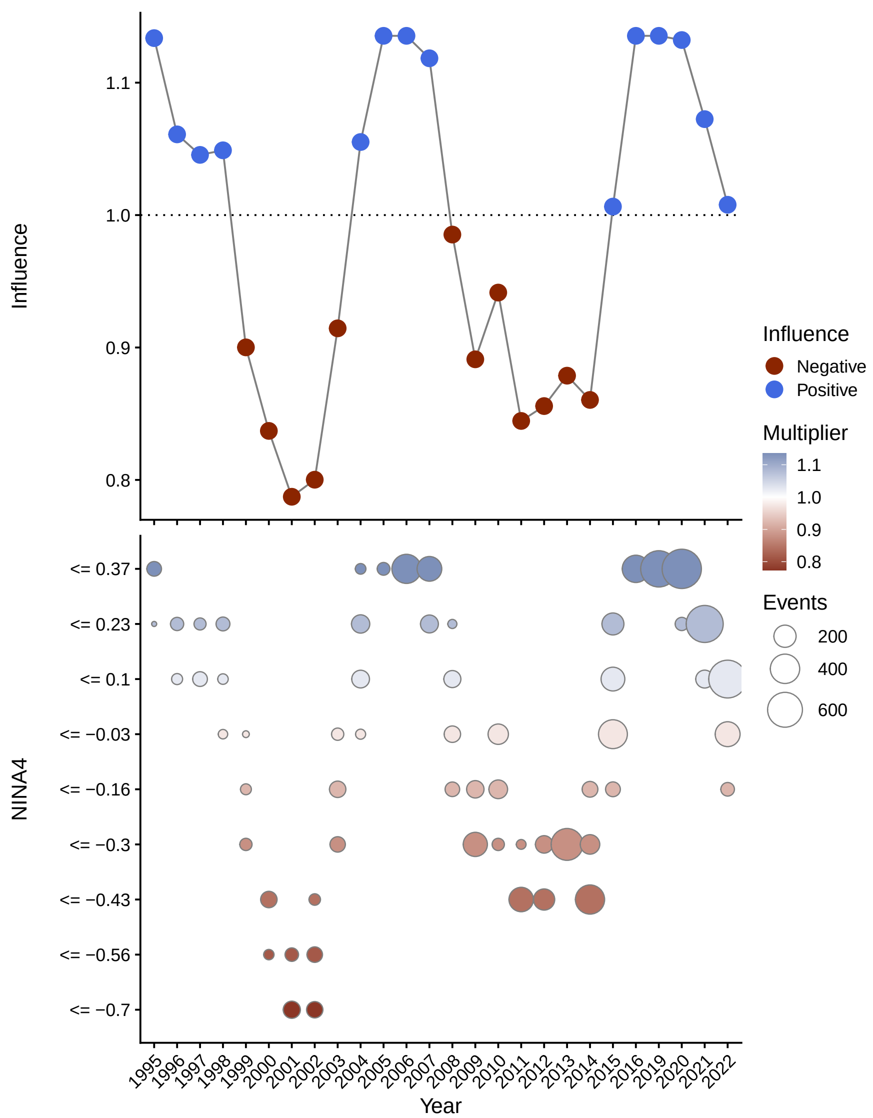


Figure B-24: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

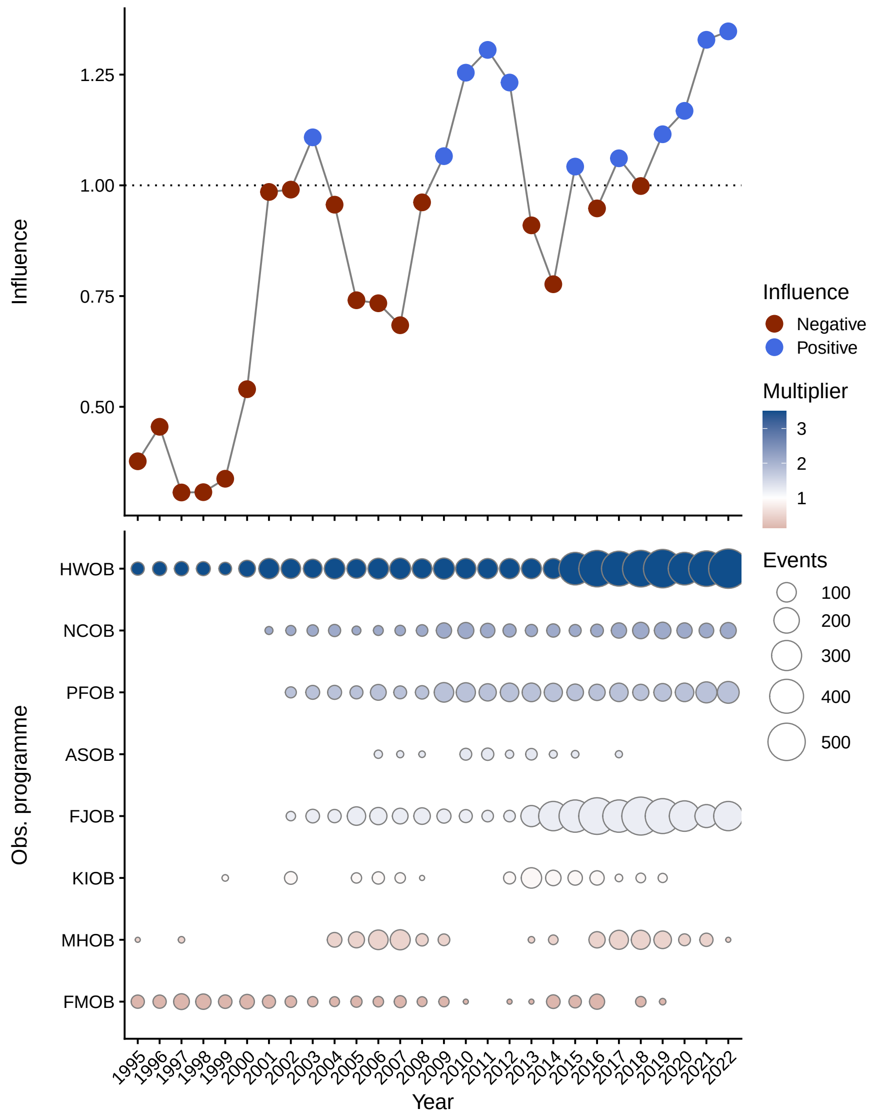


Figure B-25: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

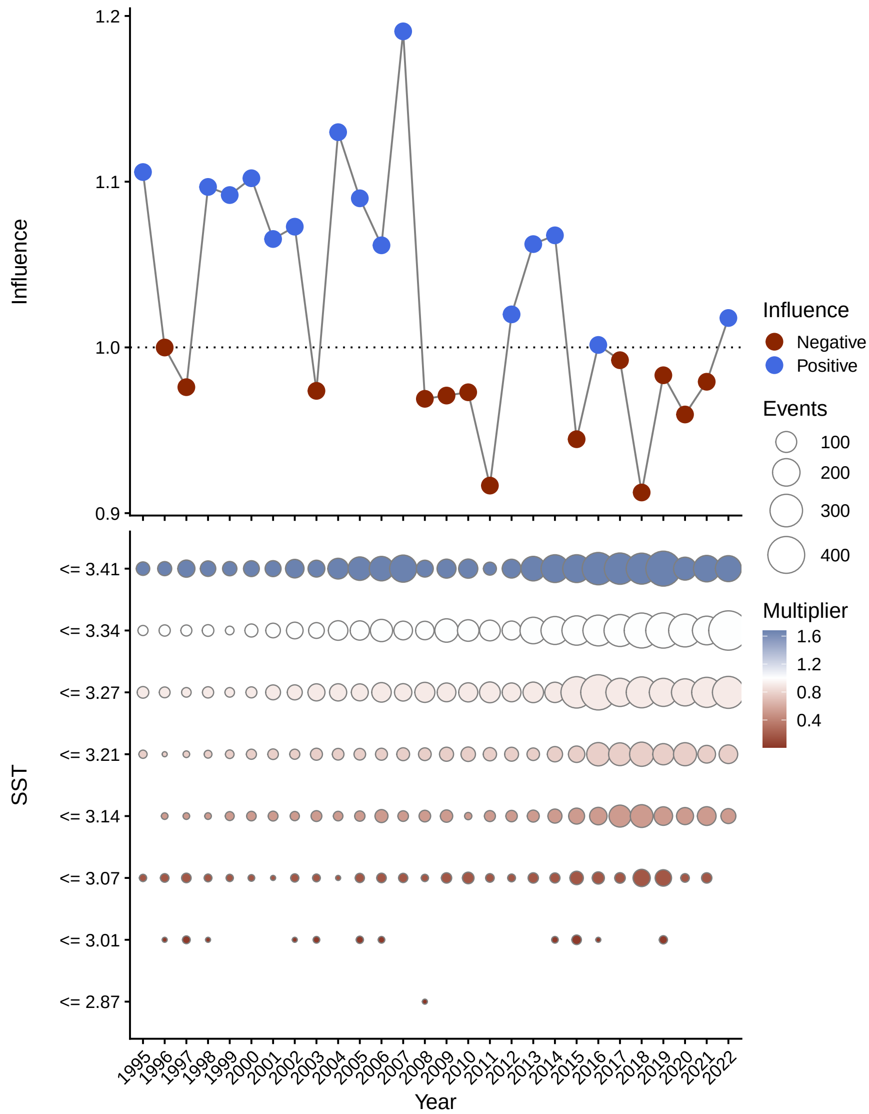


Figure B-26: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

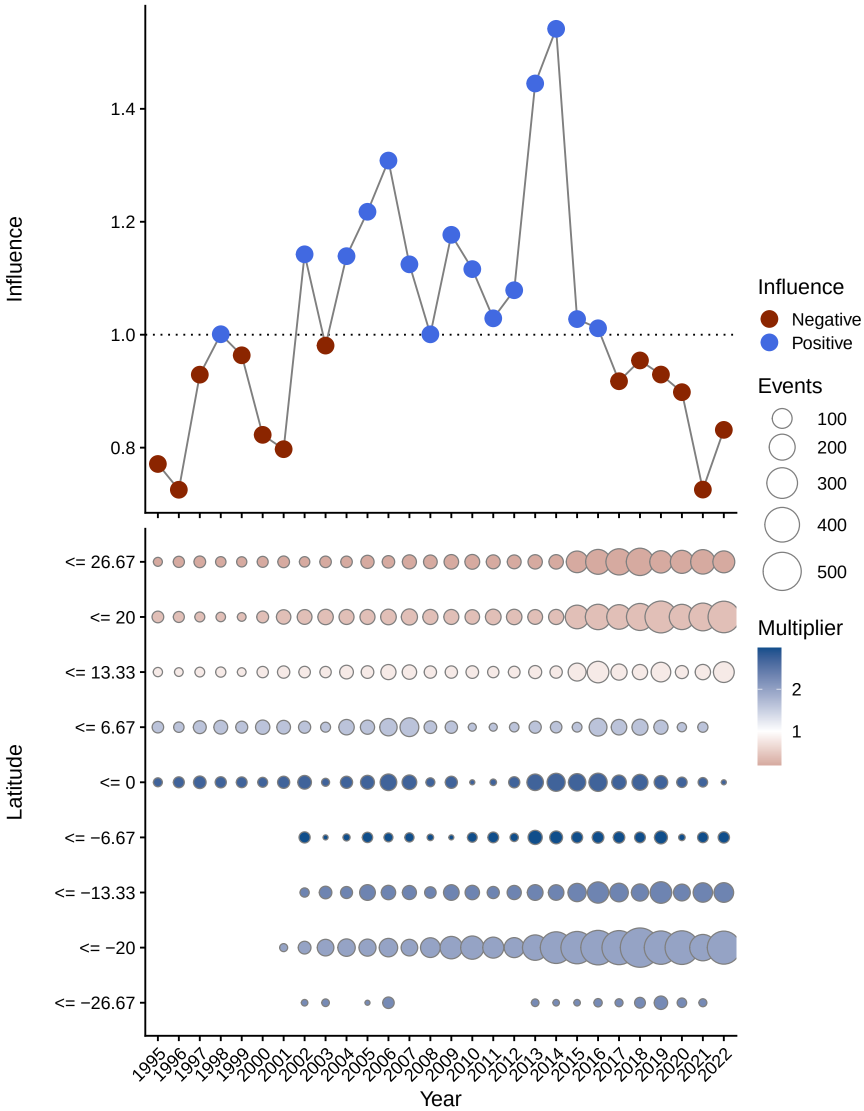


Figure B-27: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

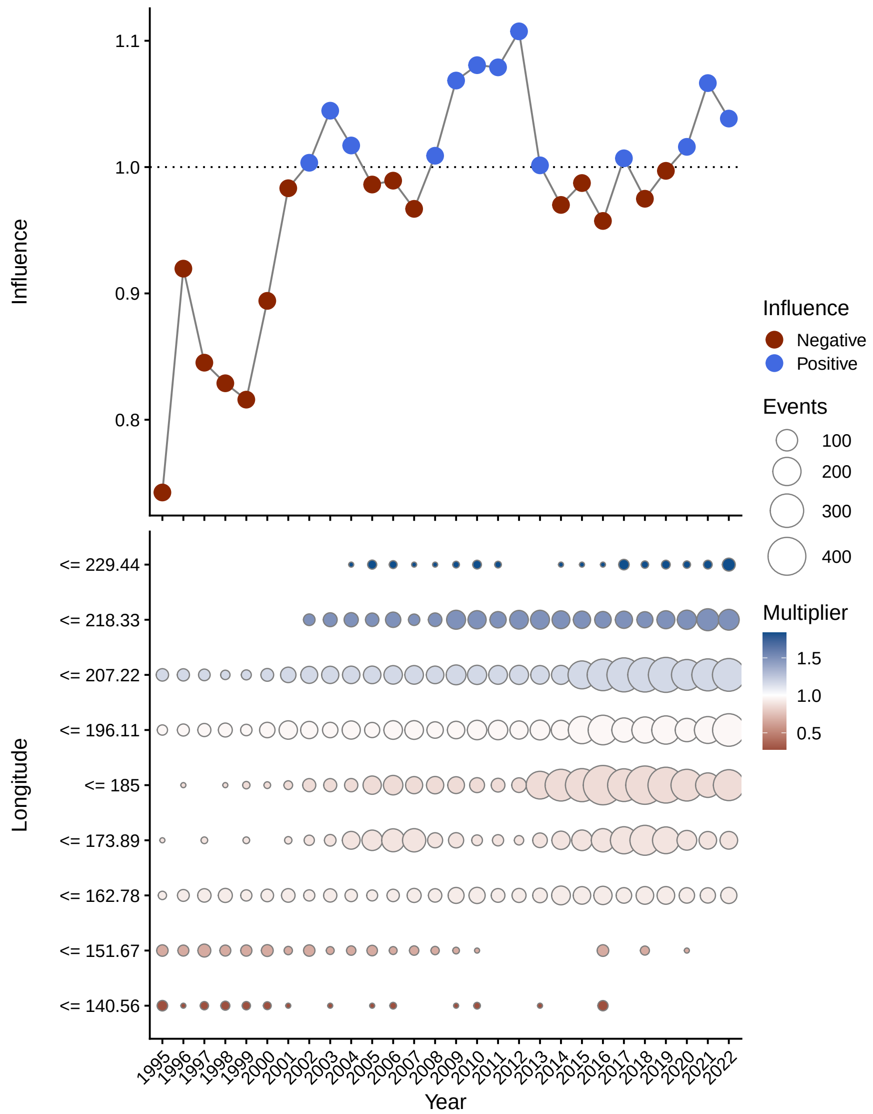


Figure B-28: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

B.3 CPUE diagnostics for additional observer programs longline (based on Tremblay-Boyer et al. 2019)

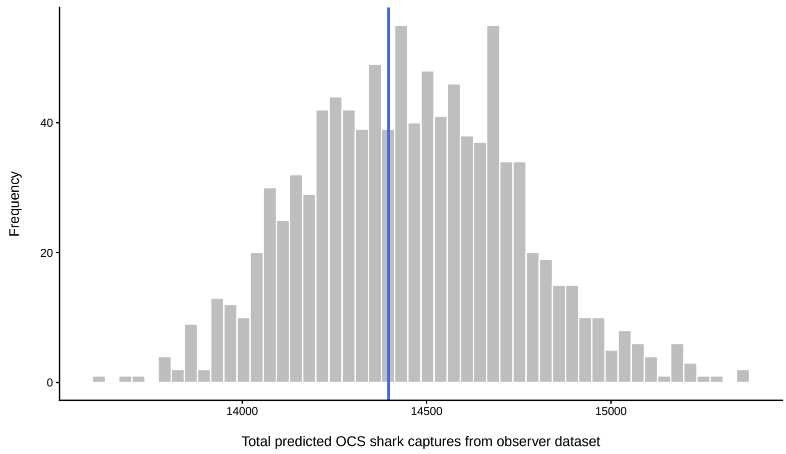


Figure B-29: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

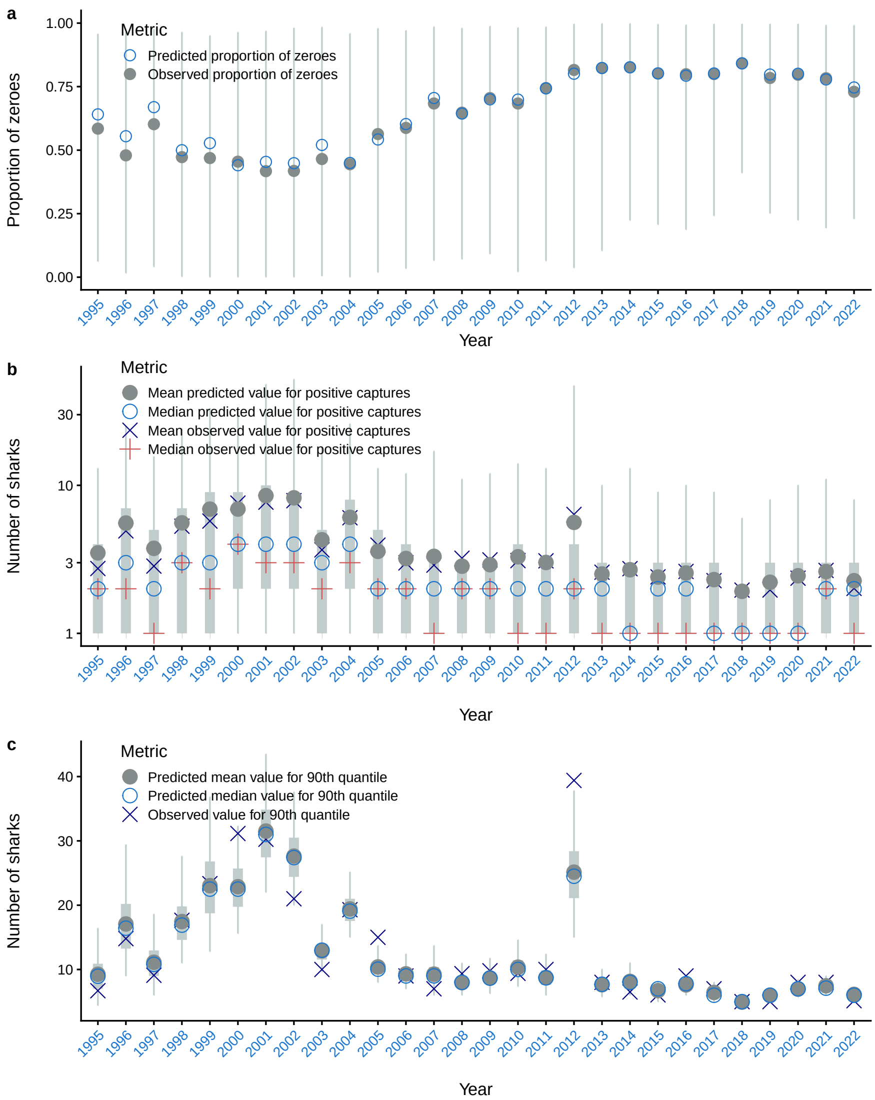


Figure B-30: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

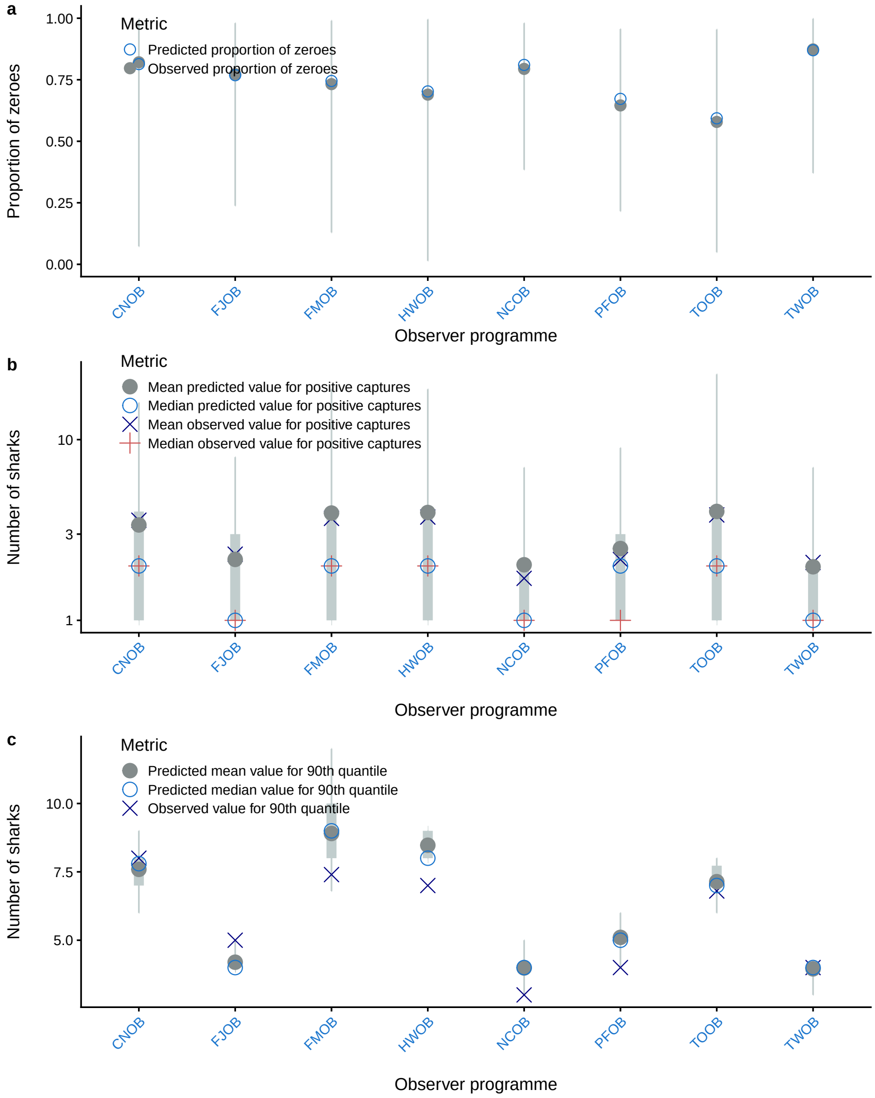


Figure B-31: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

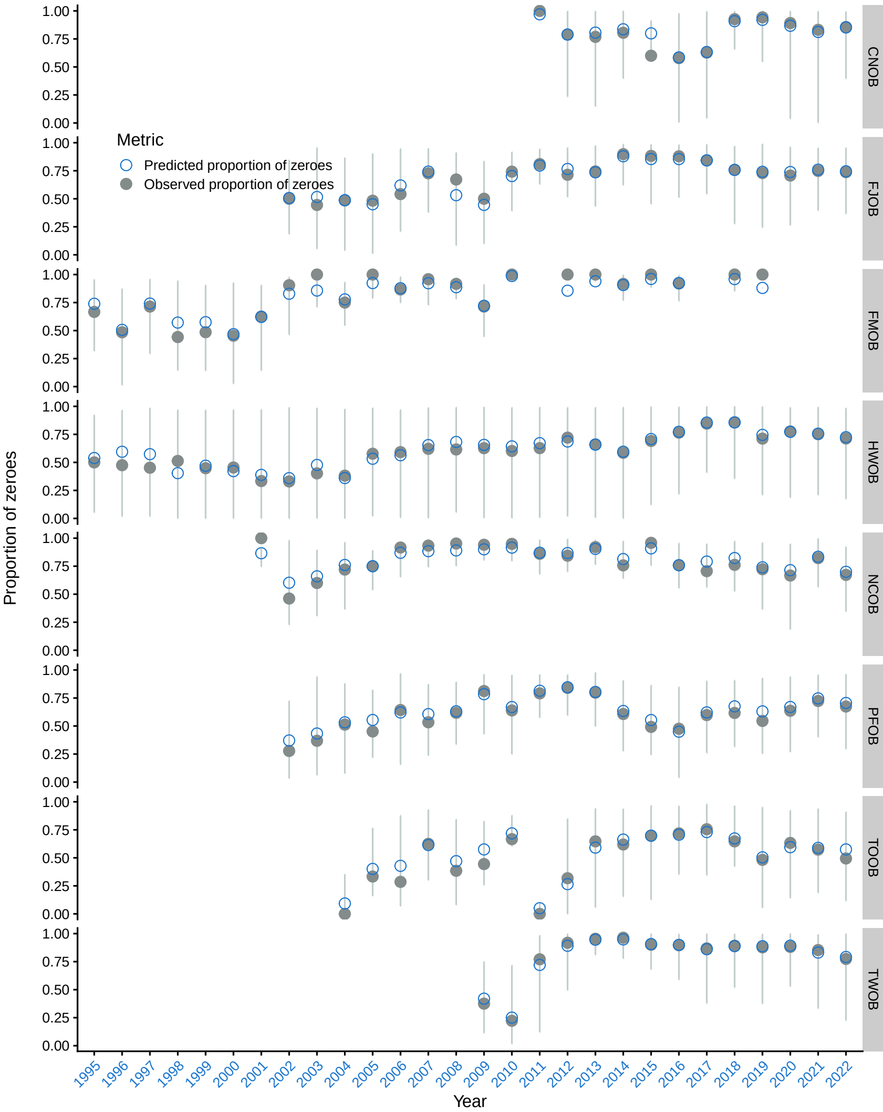


Figure B-32: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

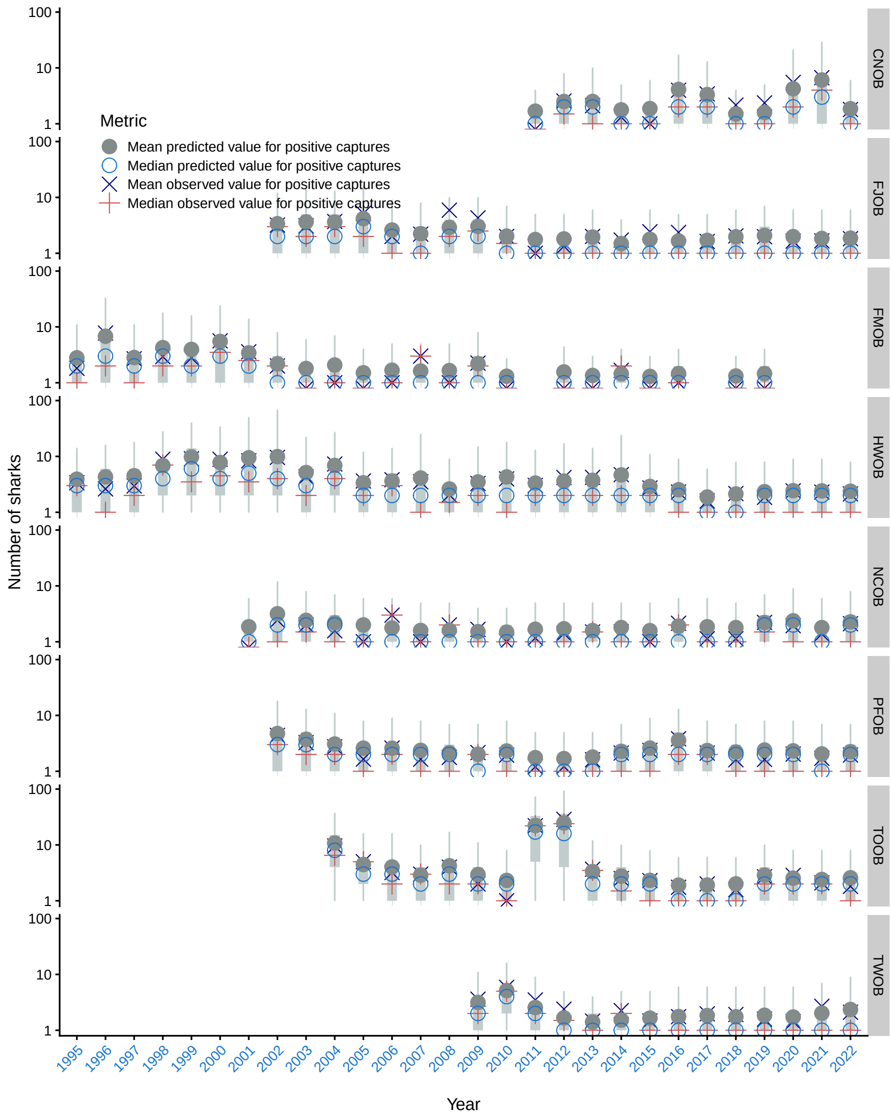


Figure B-33: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

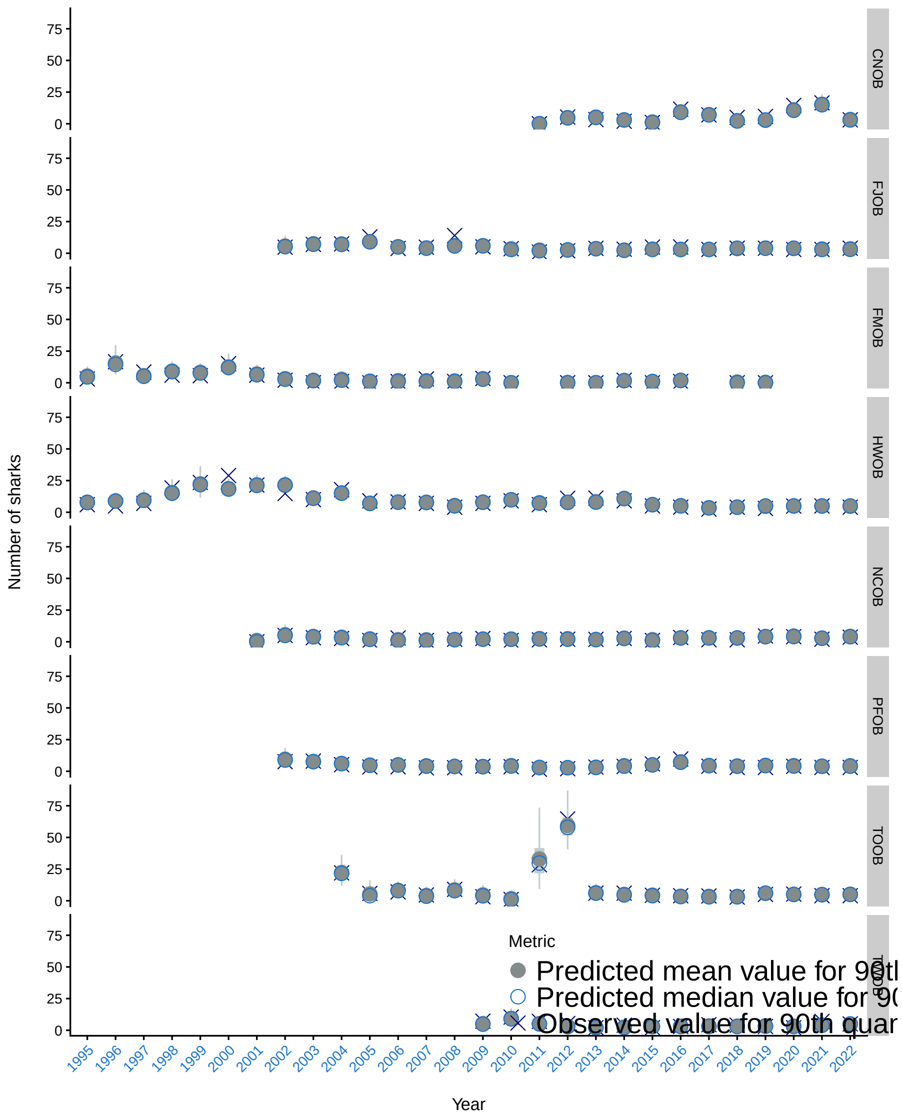


Figure B-34: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

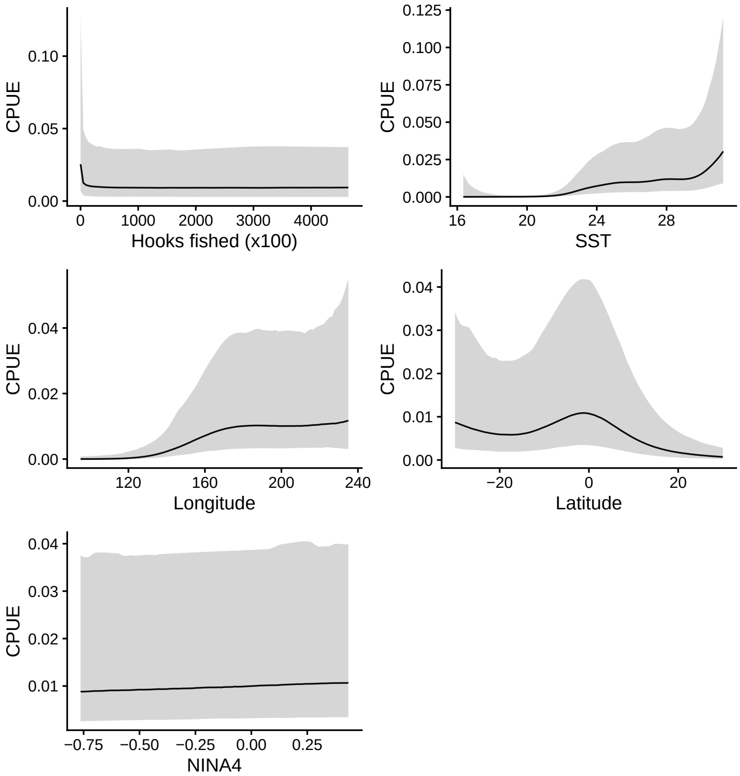


Figure B-35: Conditional effects estimated in the model used to derive CPUE from observed for sets.

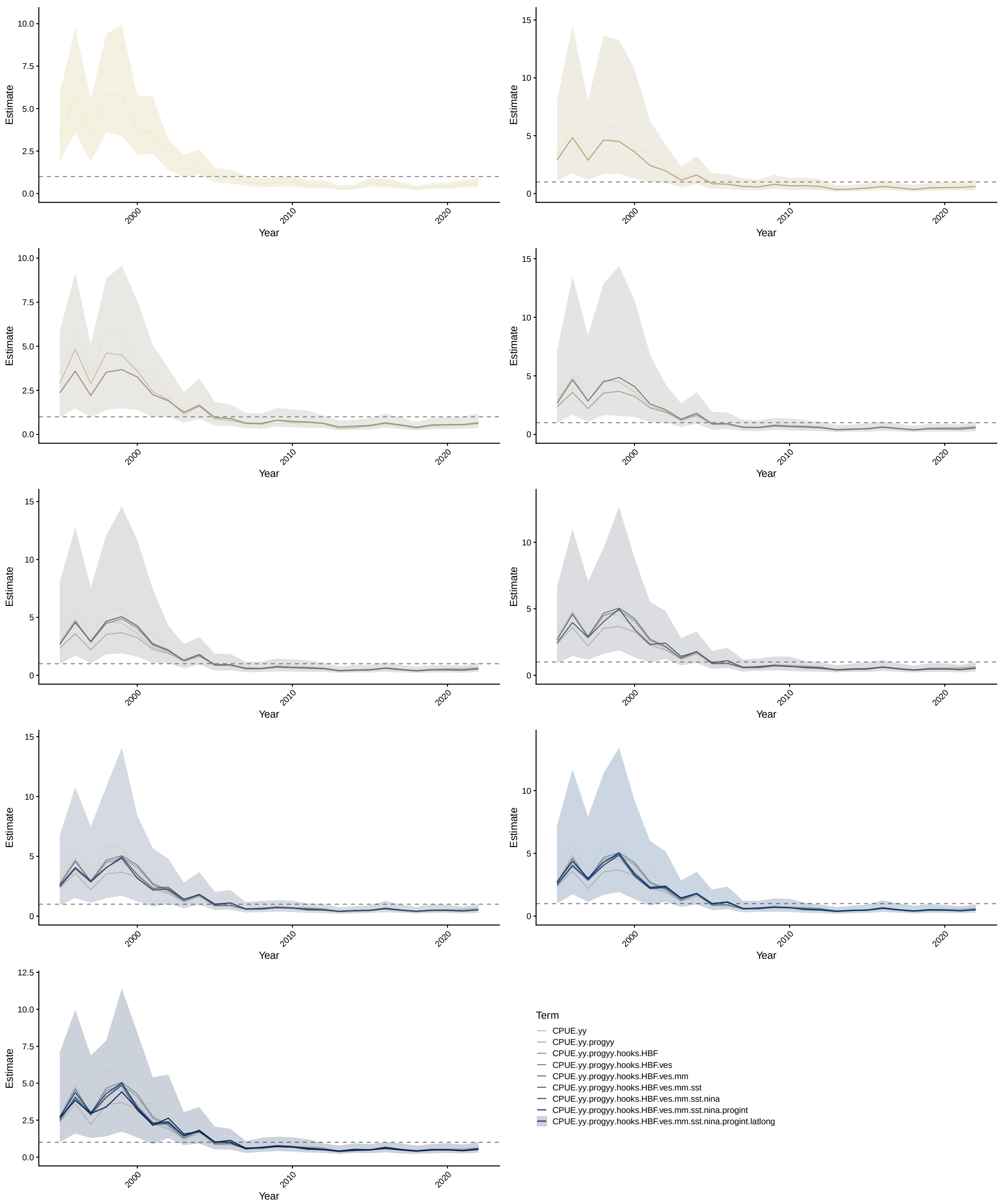


Figure B-36: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

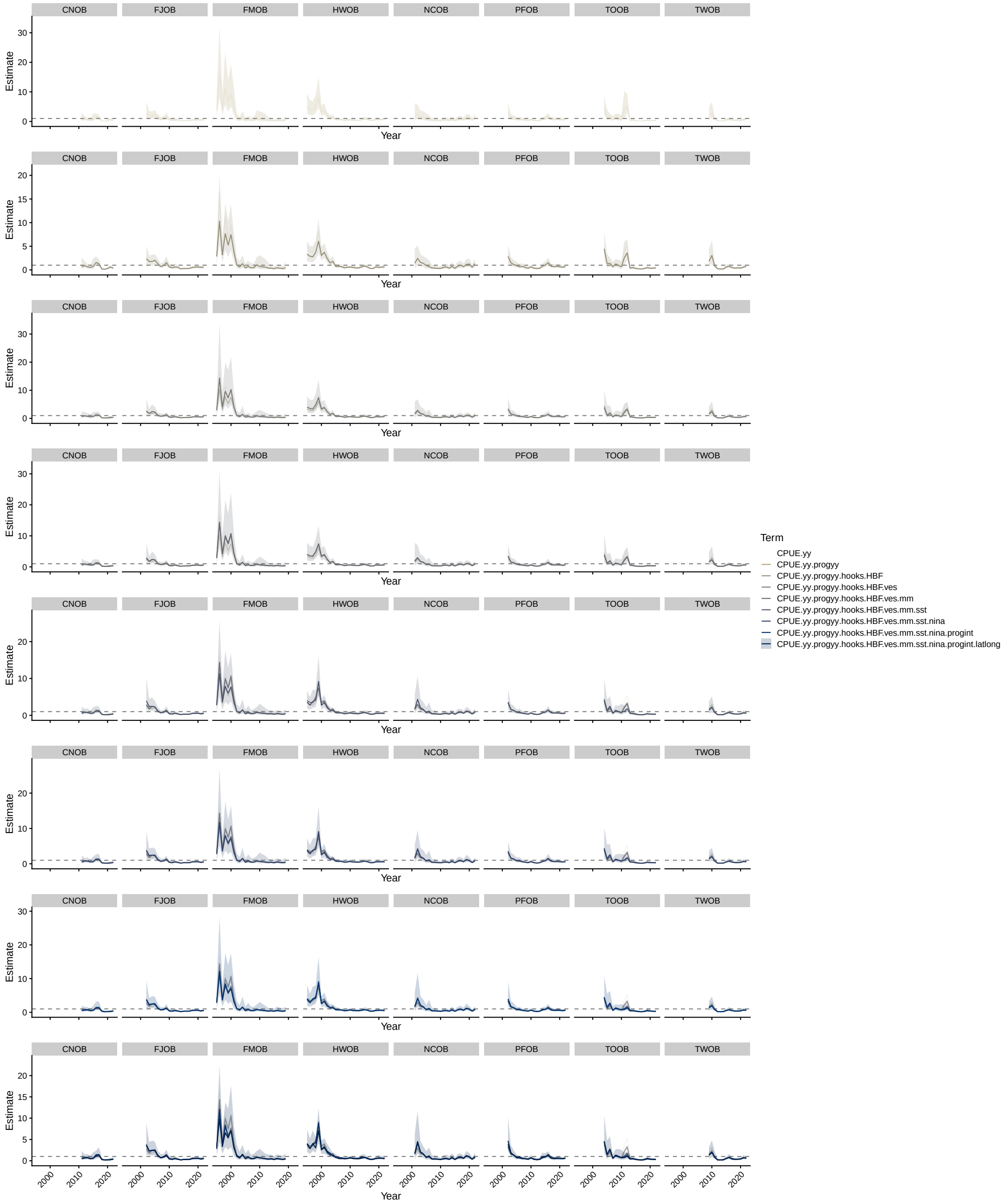


Figure B-37: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

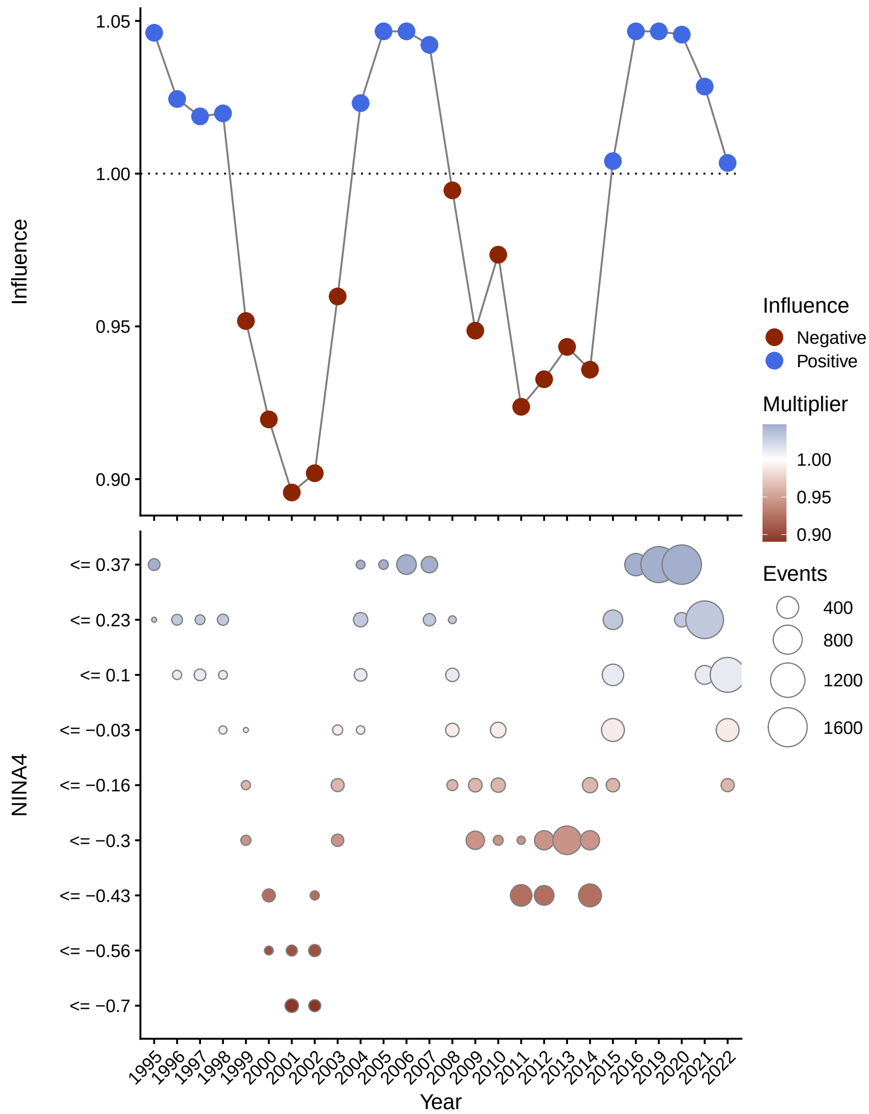


Figure B-38: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

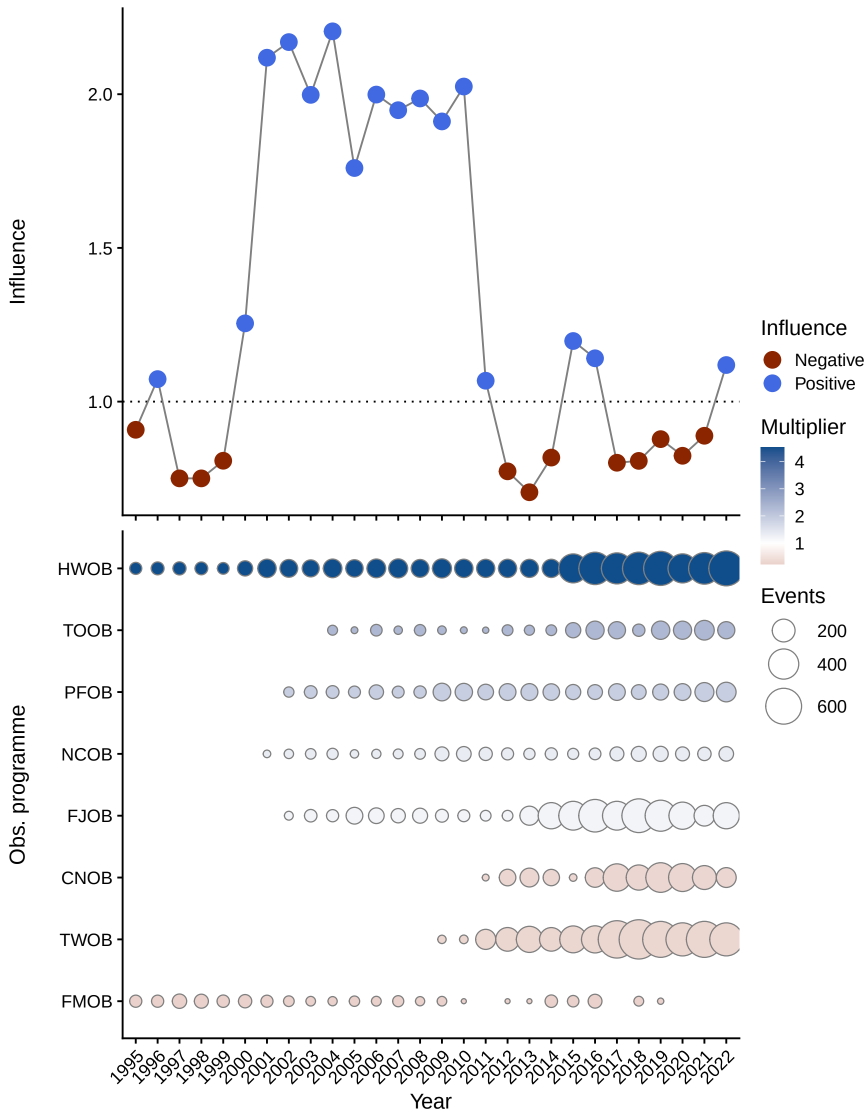


Figure B-39: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

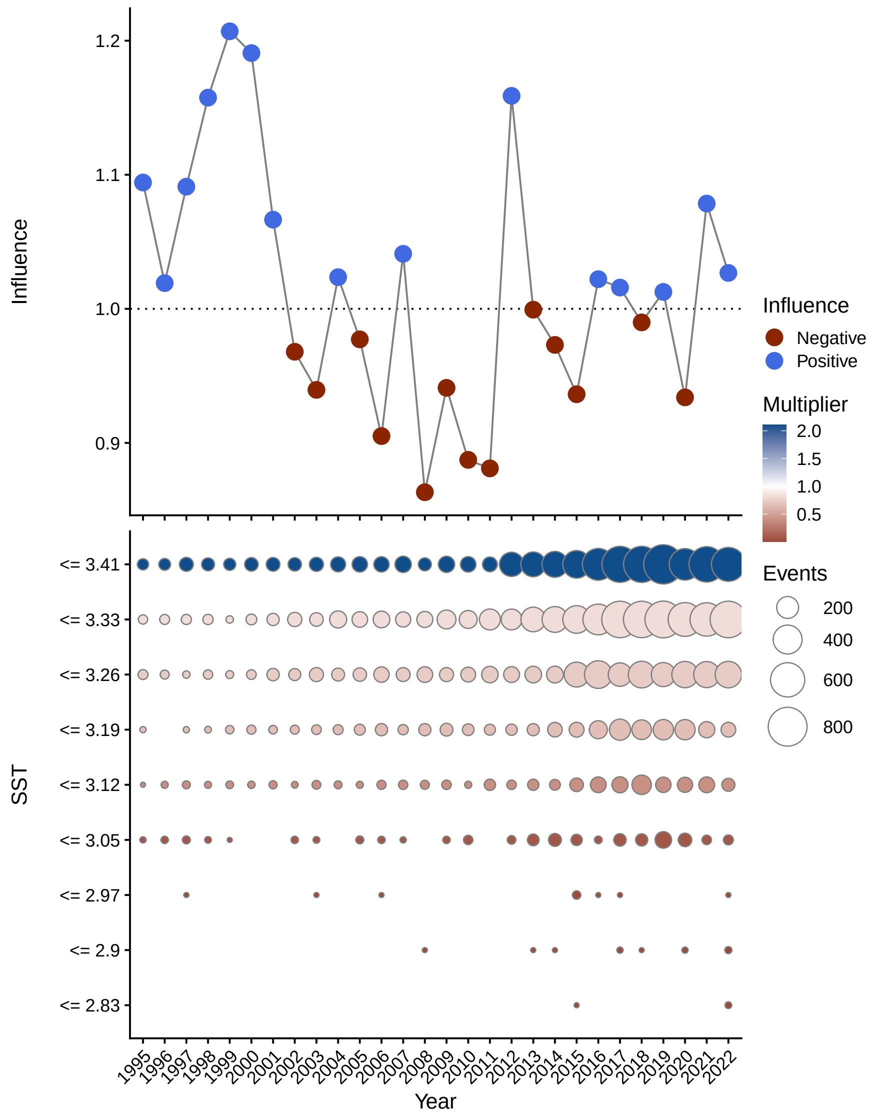


Figure B-40: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

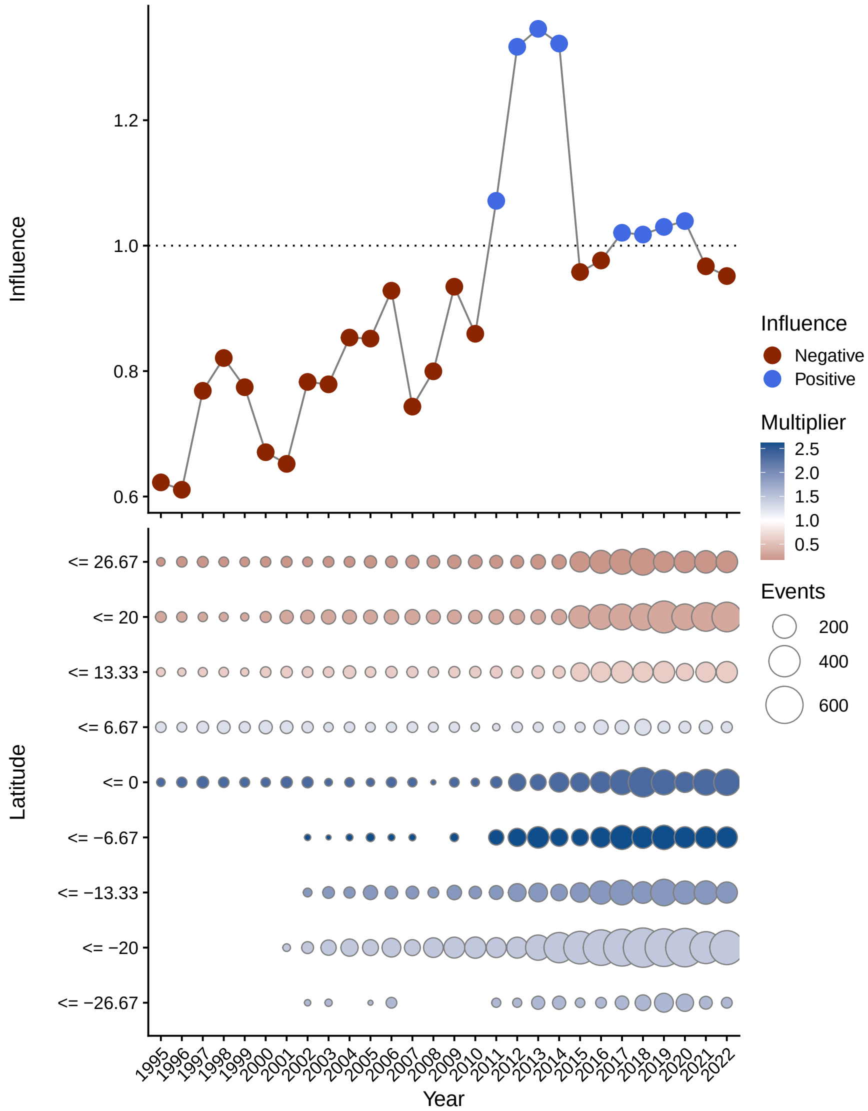


Figure B-41: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

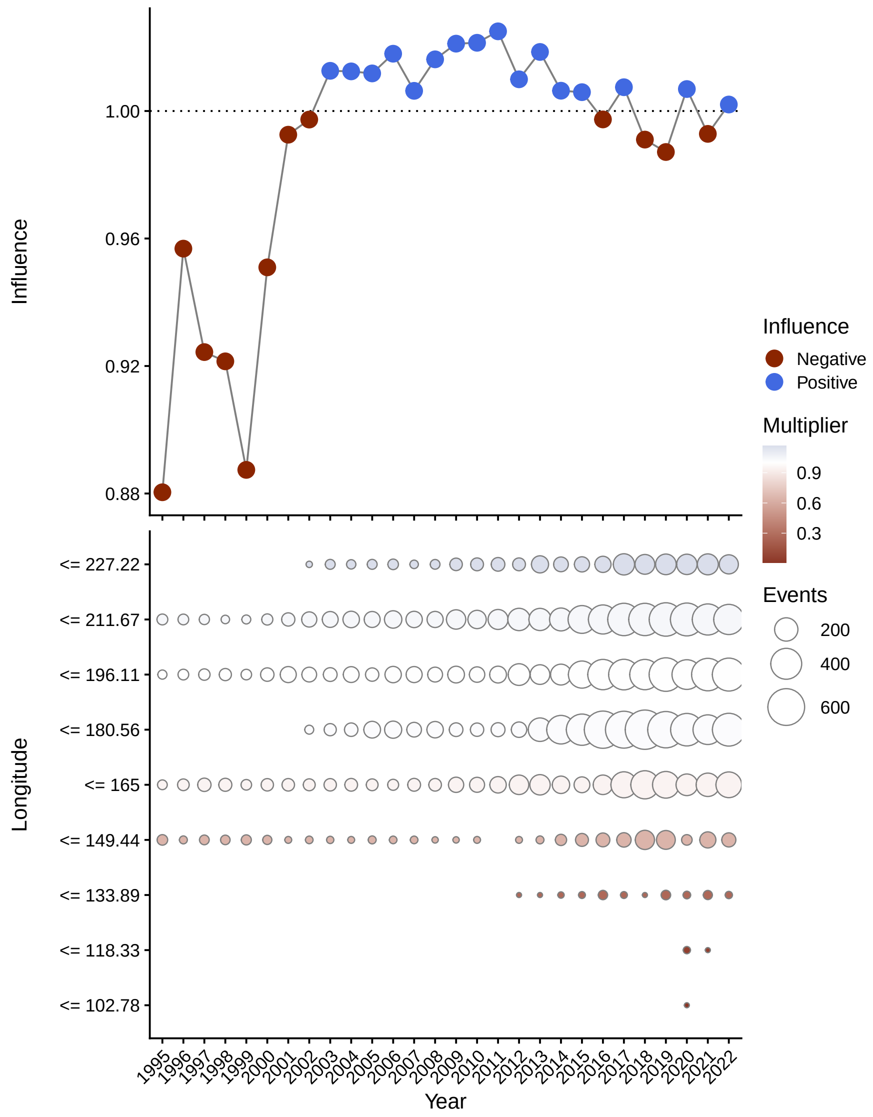


Figure B-42: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

B.4 CPUE diagnostics for distant water fleet longline

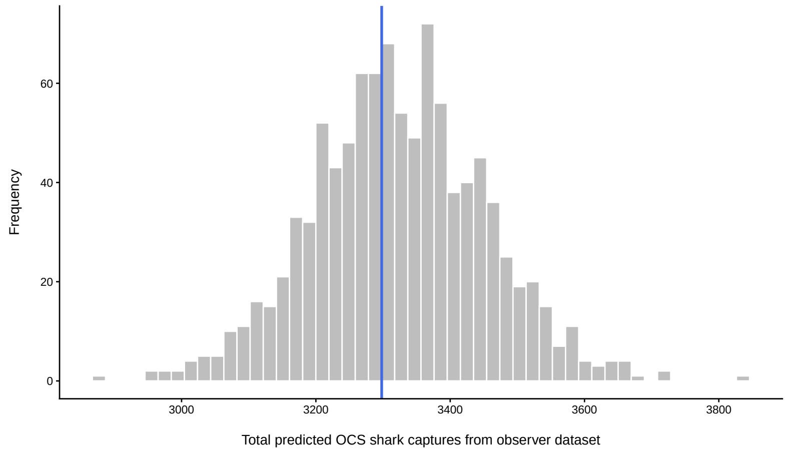


Figure B-43: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

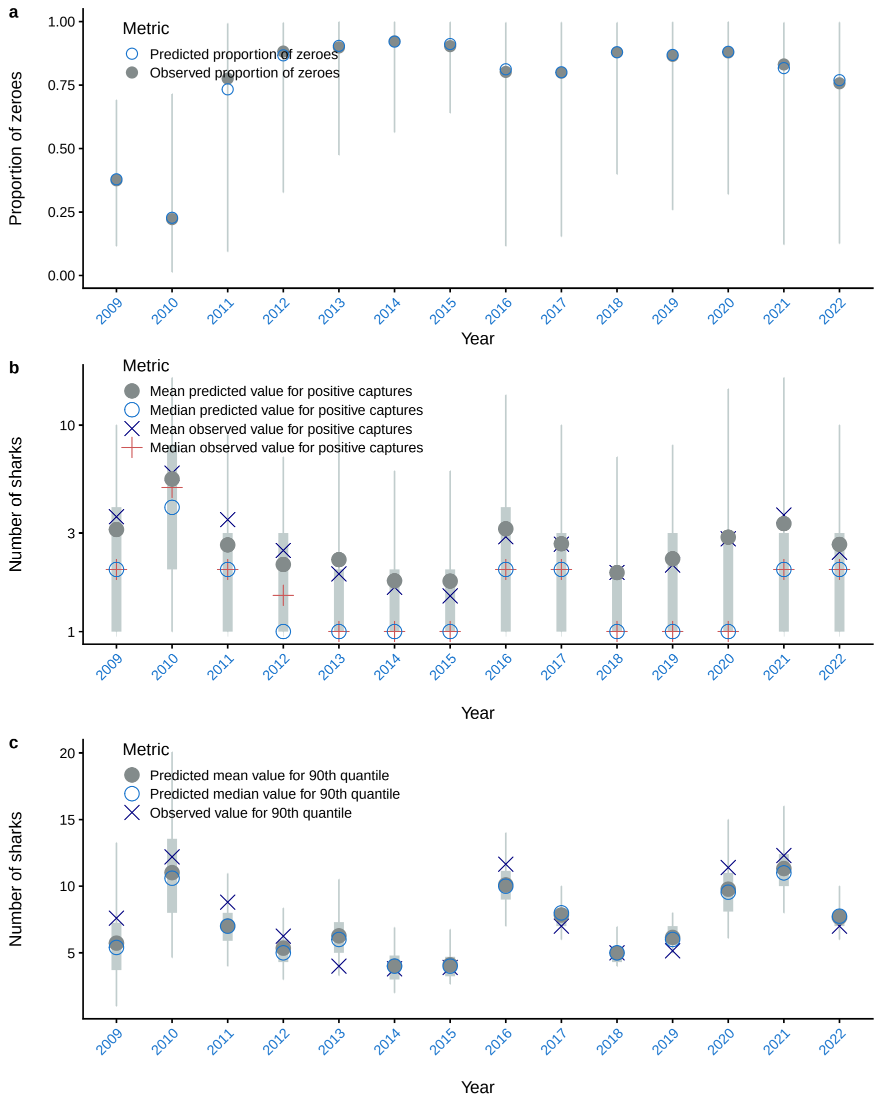


Figure B-44: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

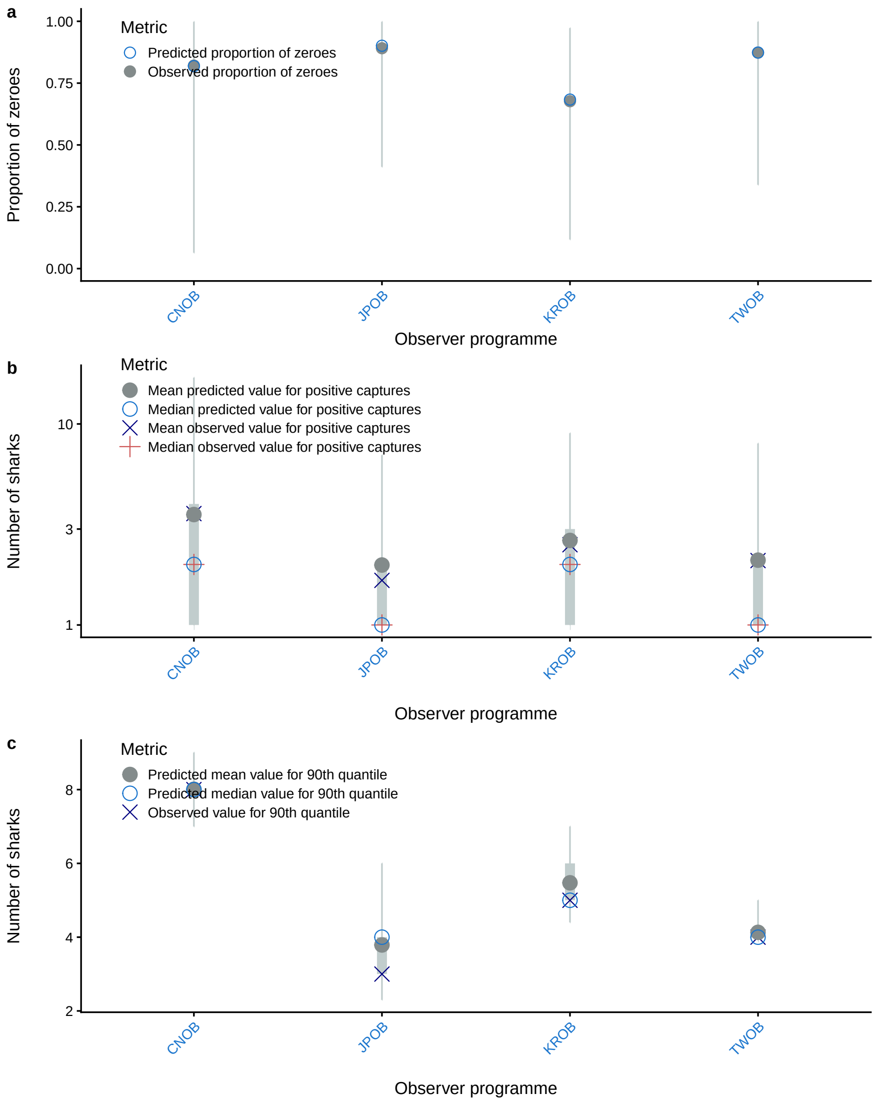


Figure B-45: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

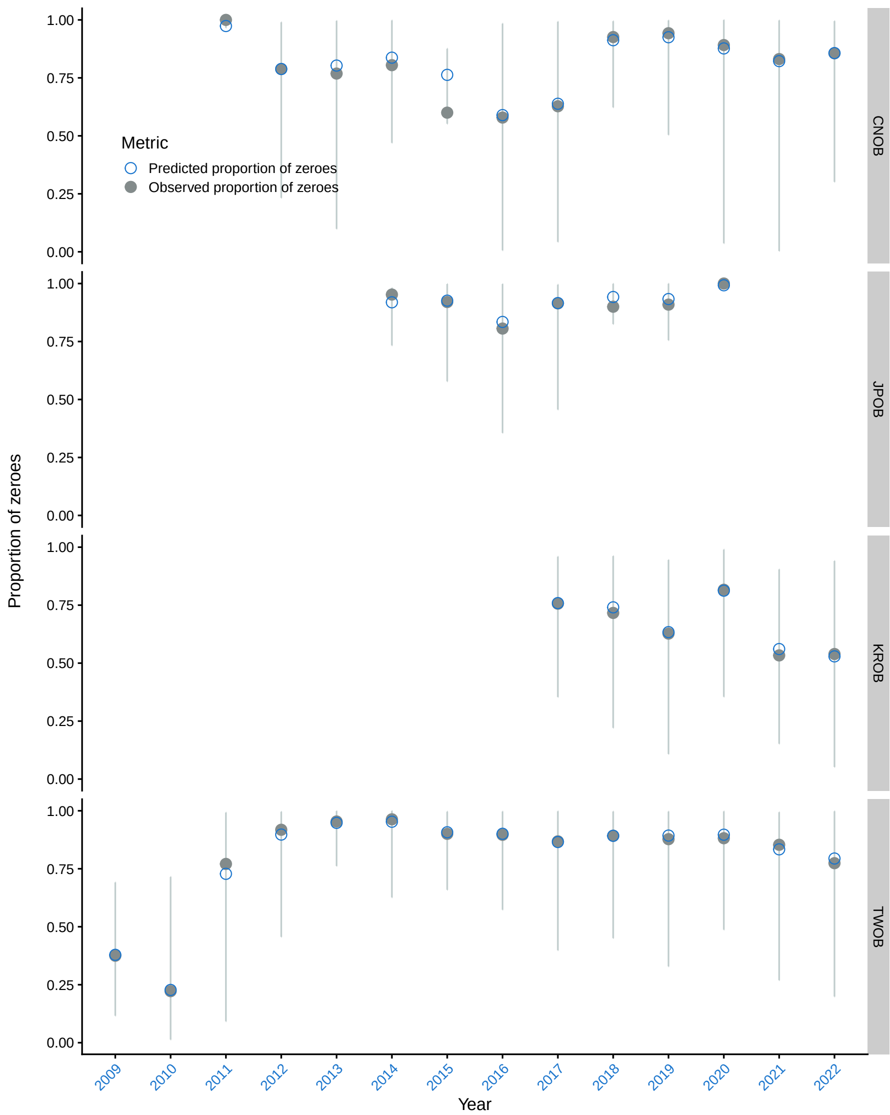


Figure B-46: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

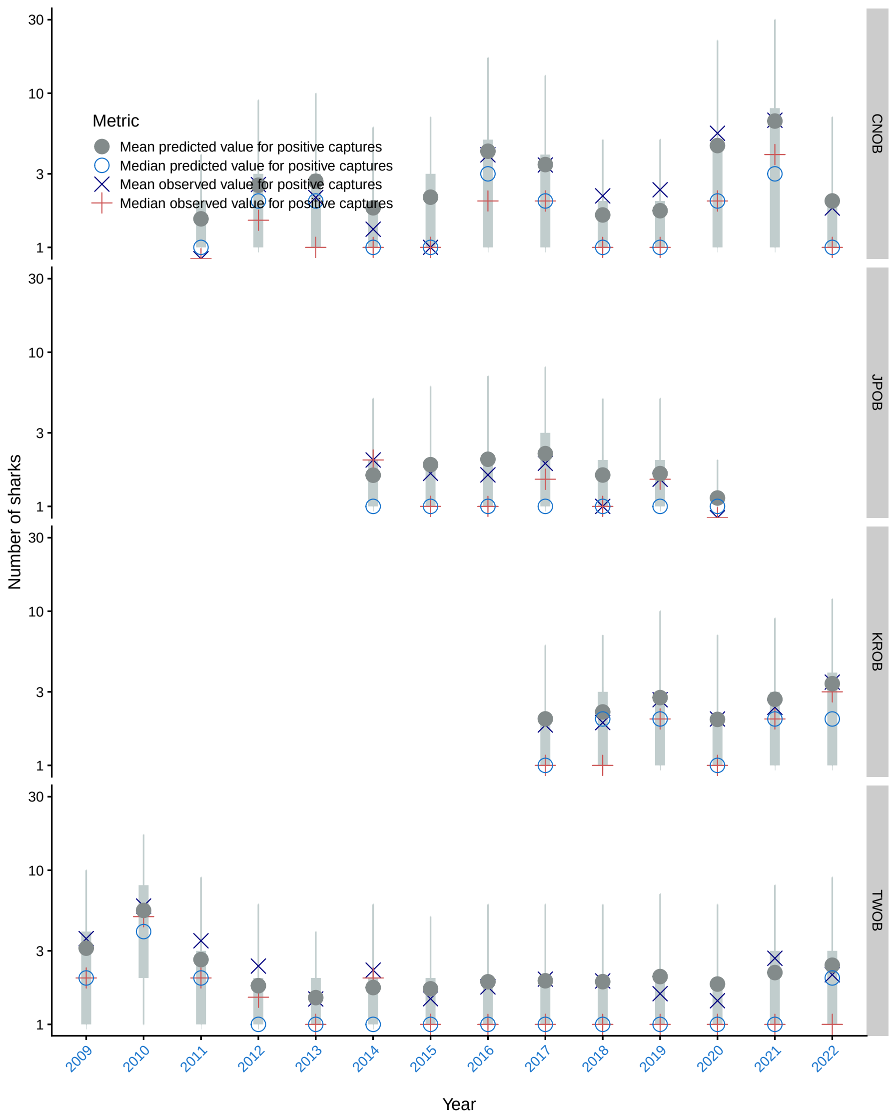


Figure B-47: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

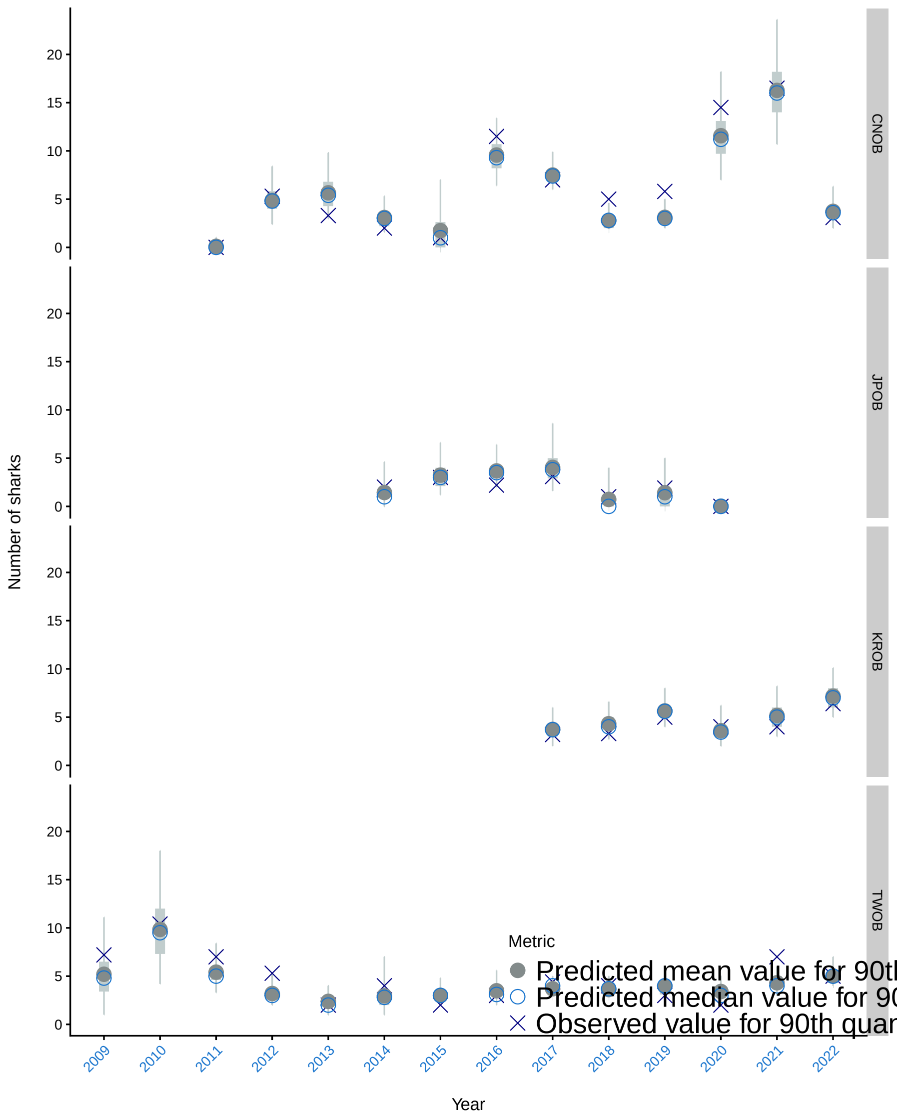


Figure B-48: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

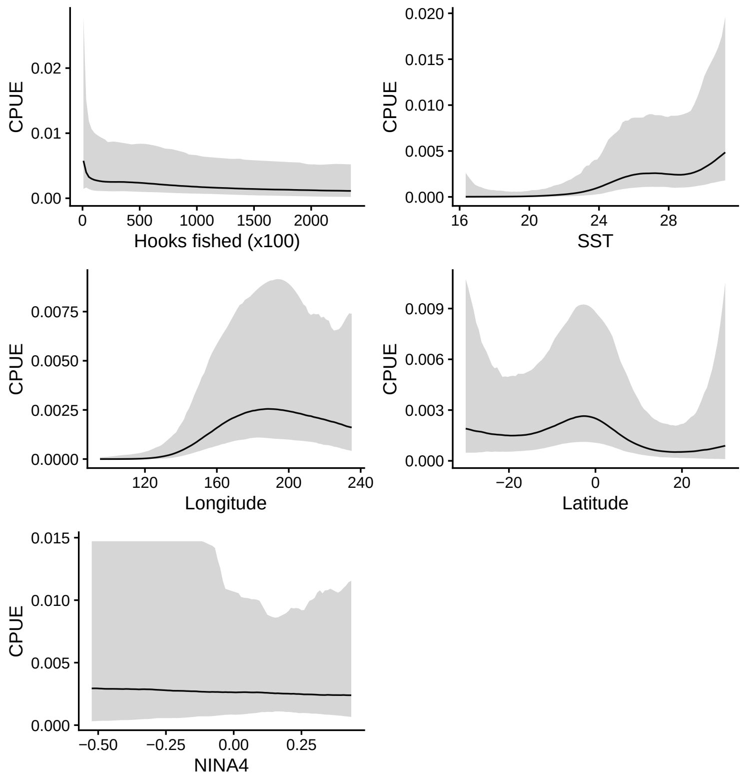


Figure B-49: Conditional effects estimated in the model used to derive CPUE from observed for sets.

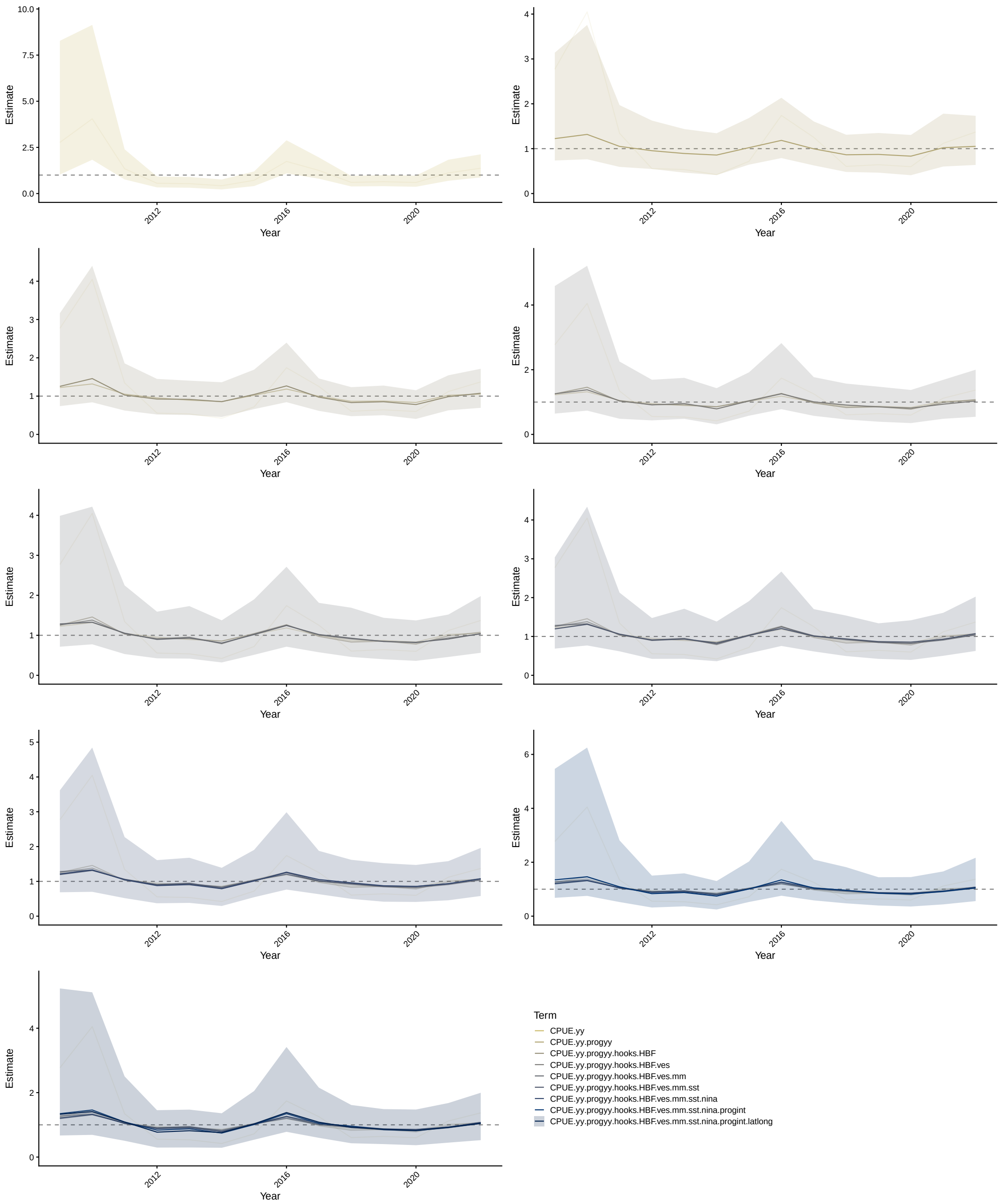


Figure B-50: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

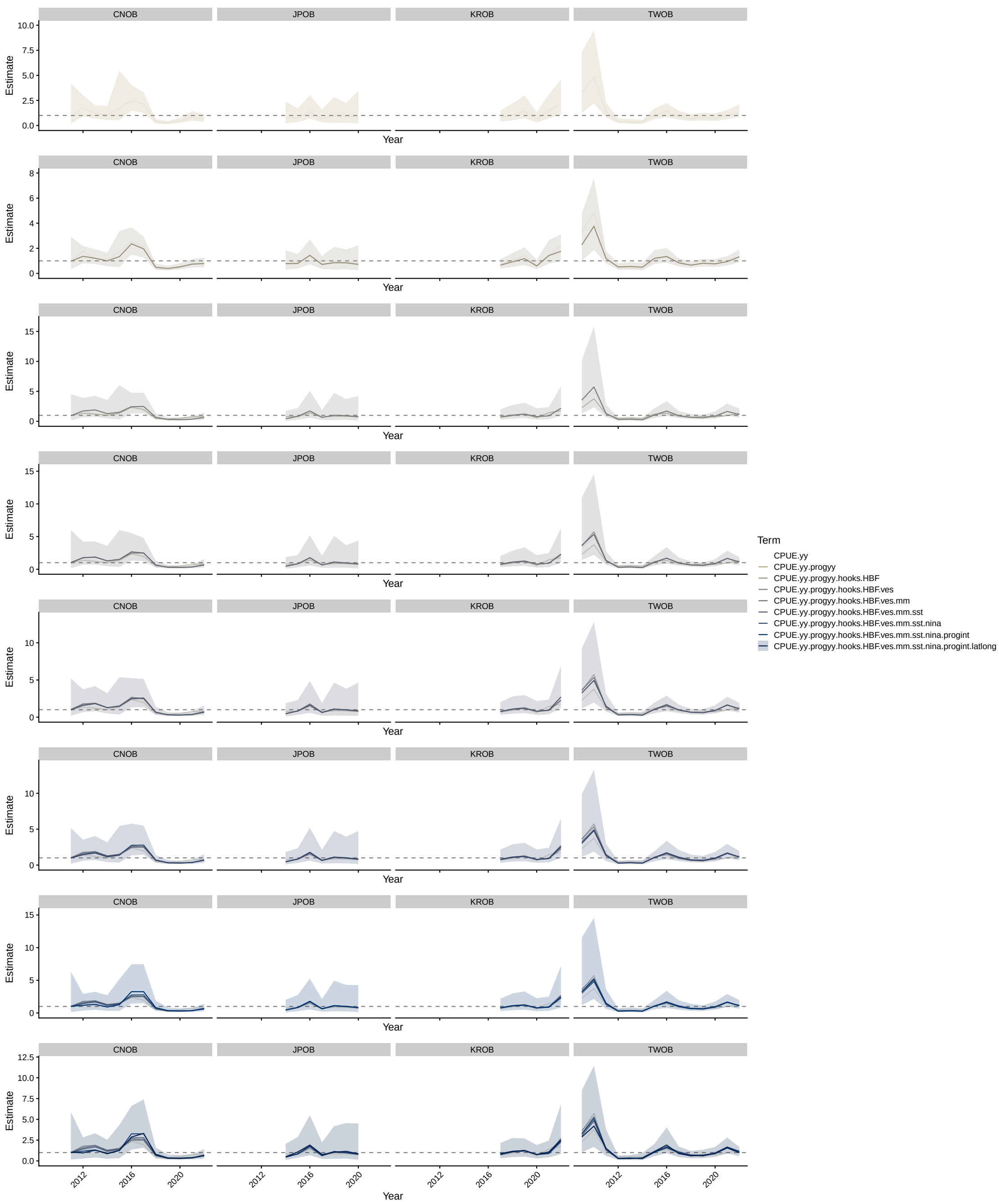


Figure B-51: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

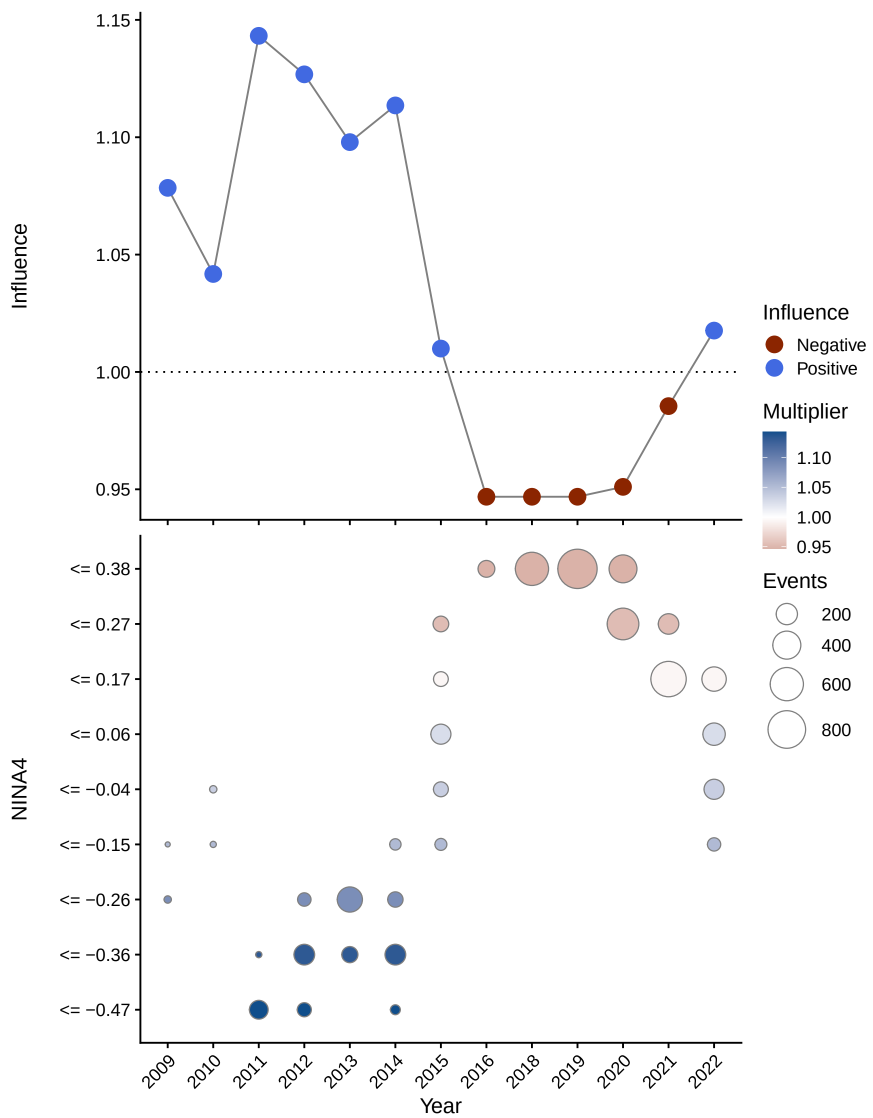


Figure B-52: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

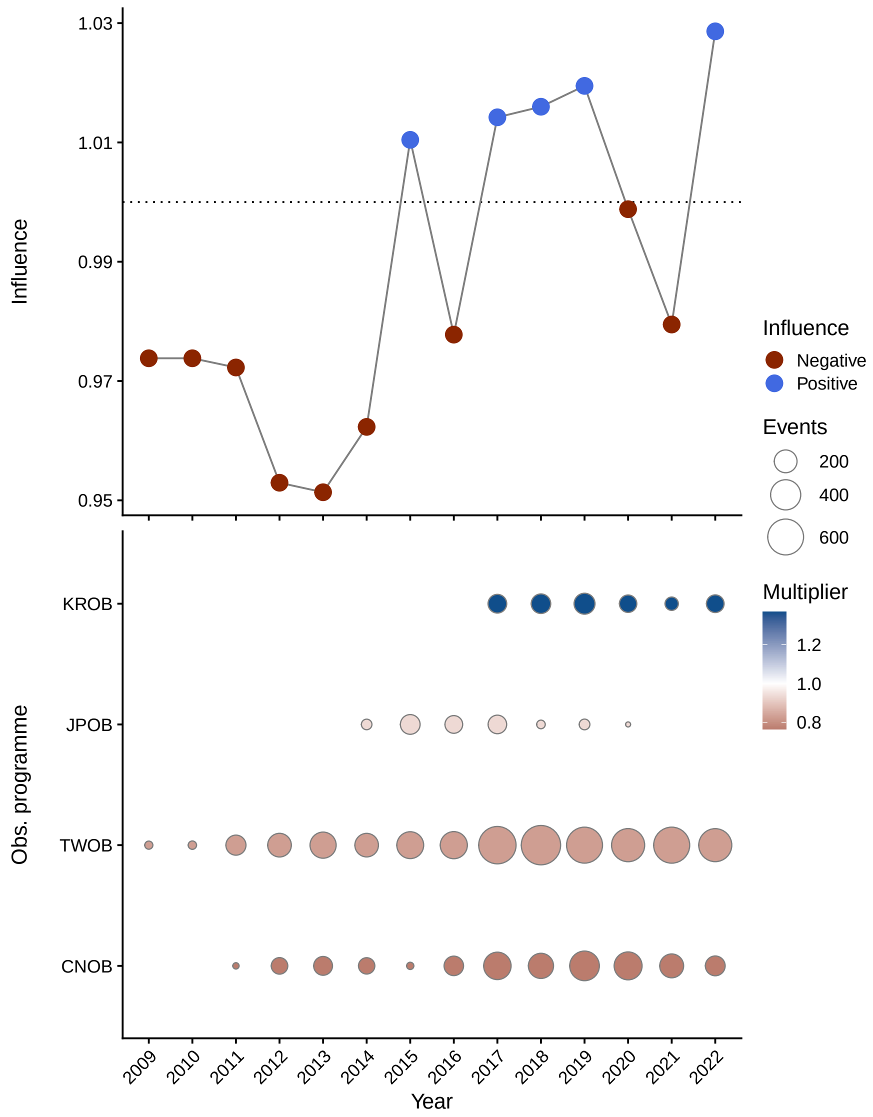


Figure B-53: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

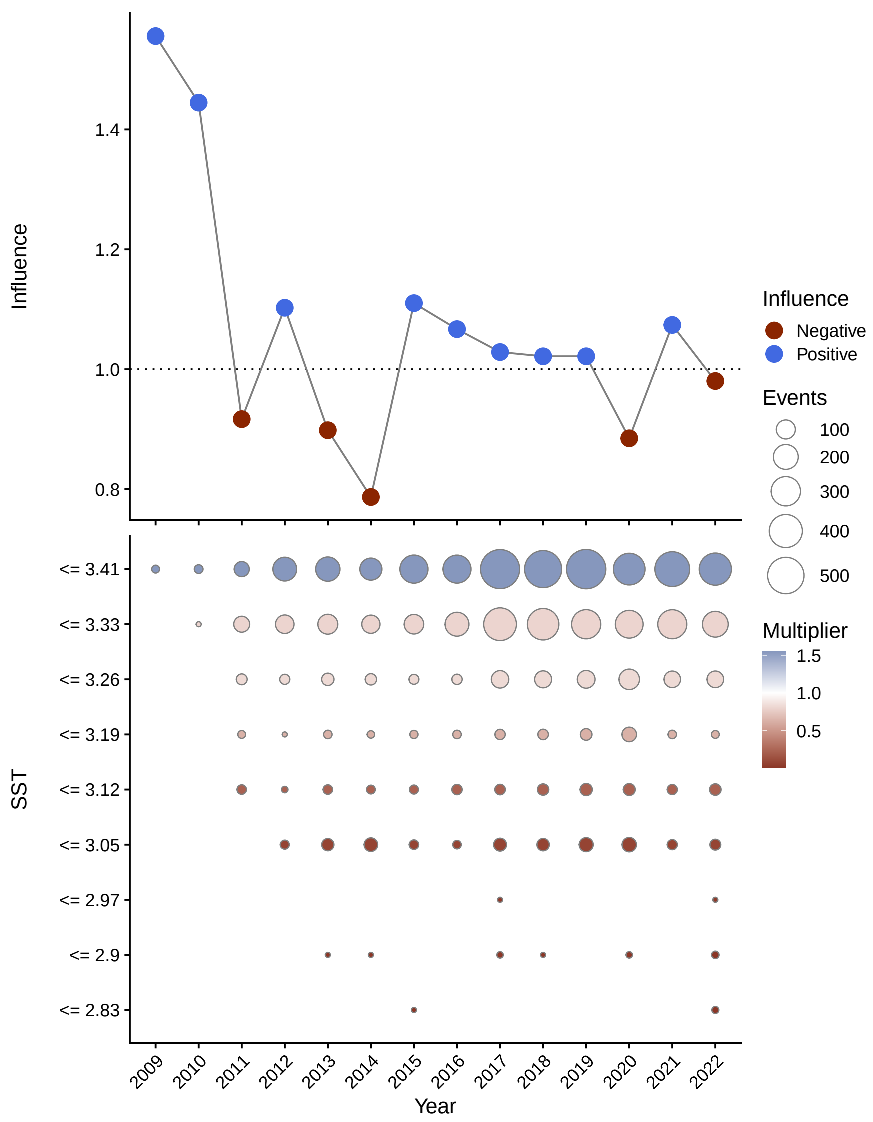


Figure B-54: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

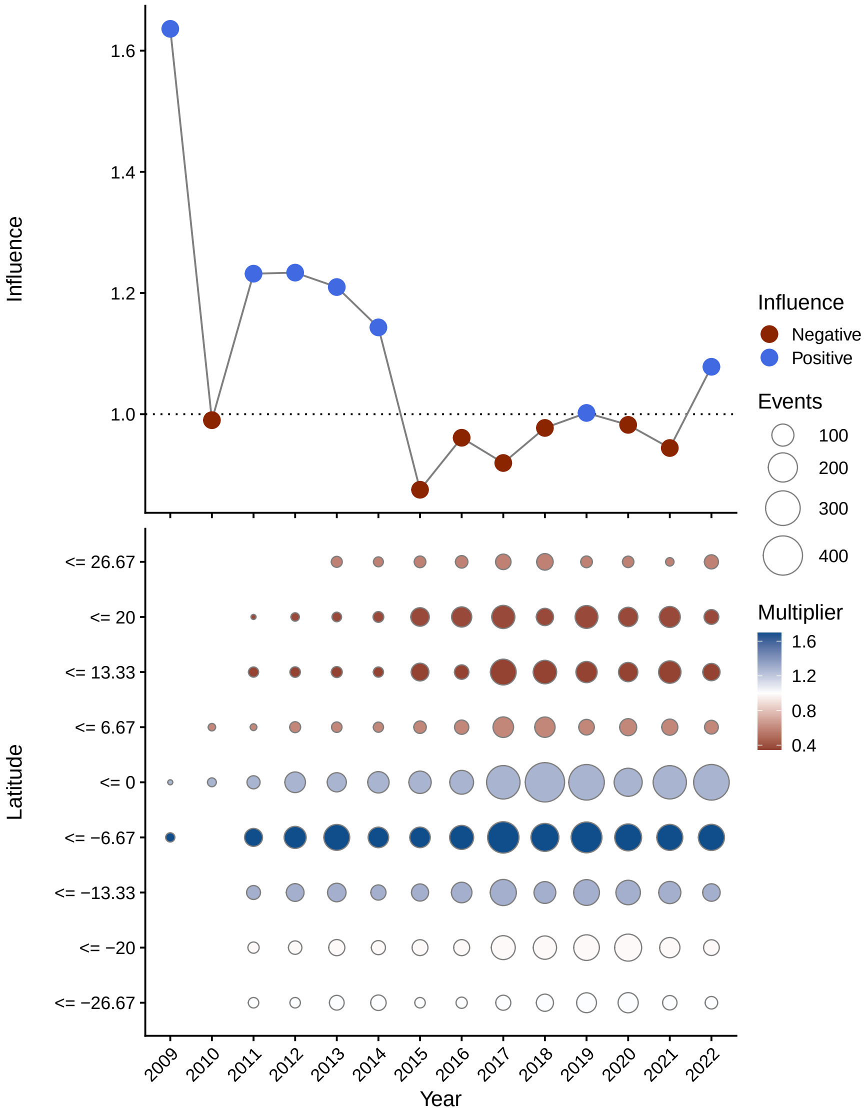


Figure B-55: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

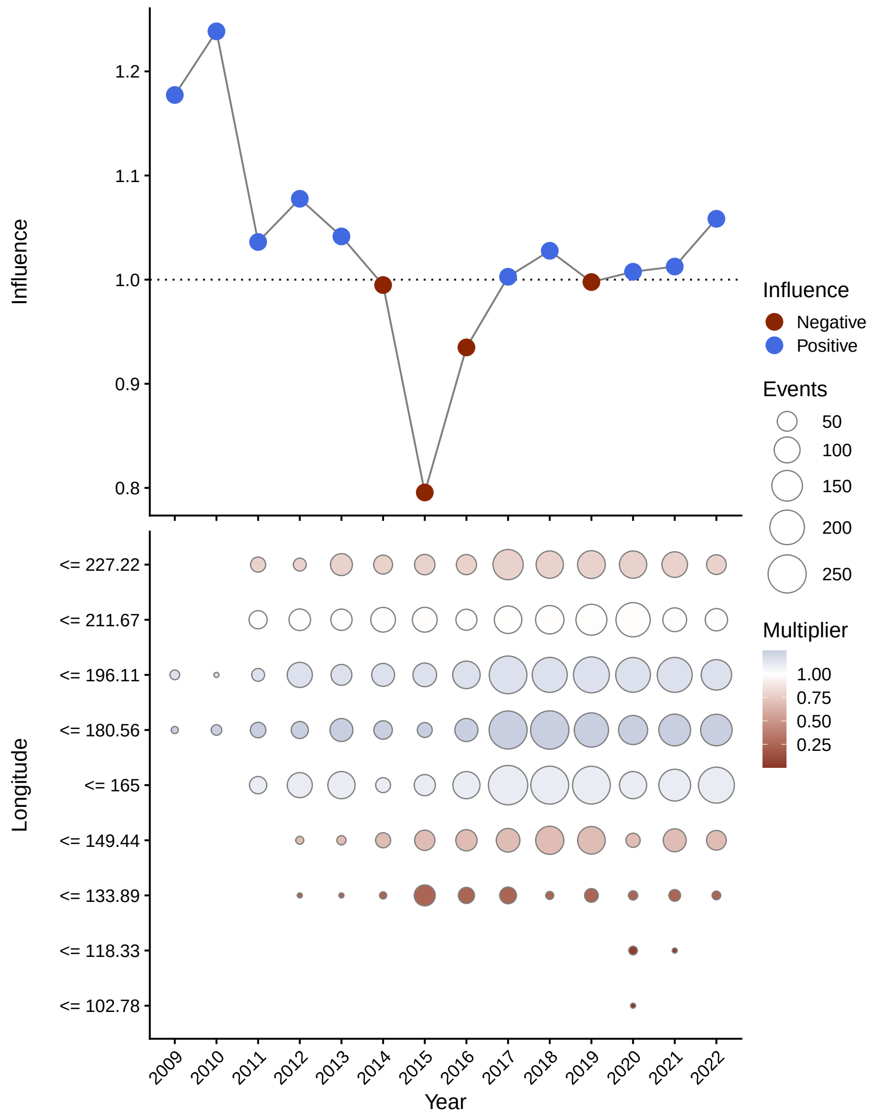


Figure B-56: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

B.5 CPUE diagnostics for free-school purse seine

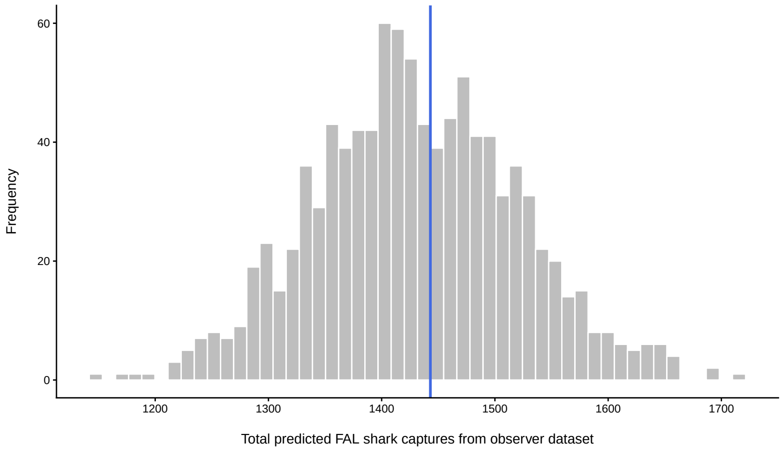


Figure B-57: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

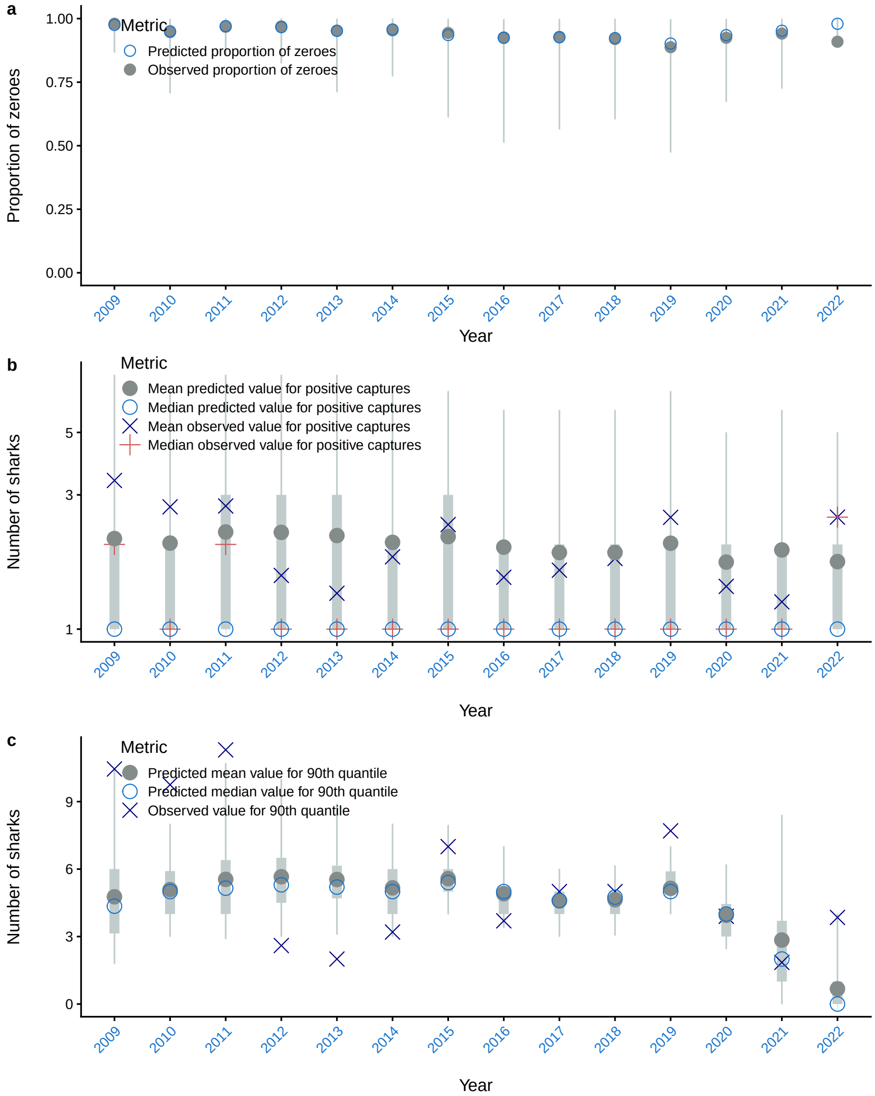


Figure B-58: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

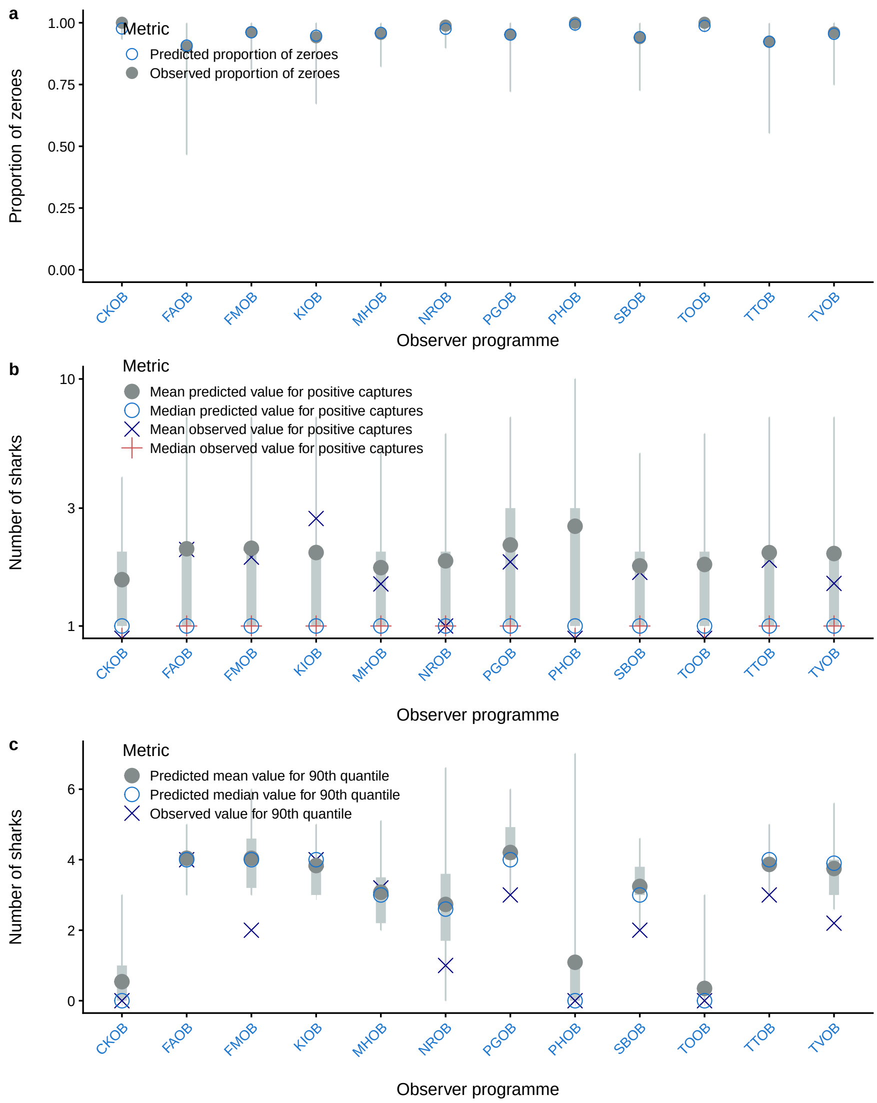


Figure B-59: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

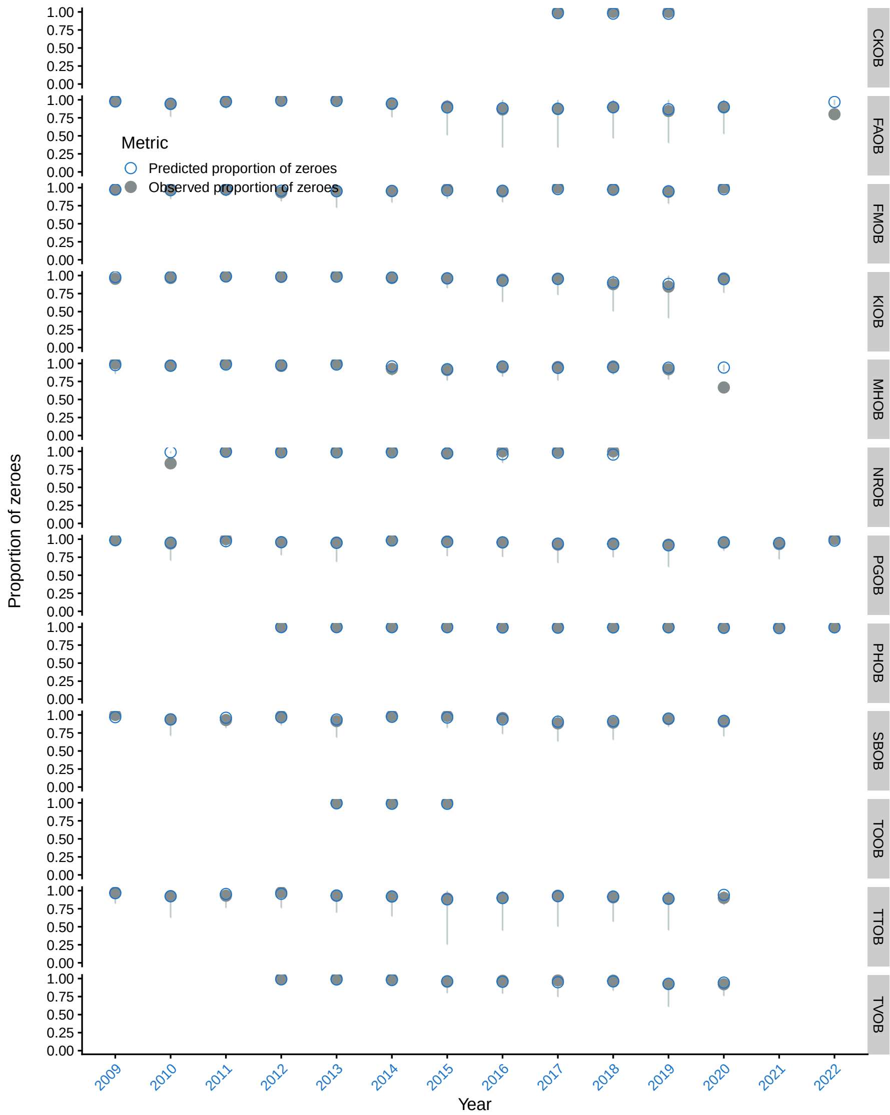


Figure B-60: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

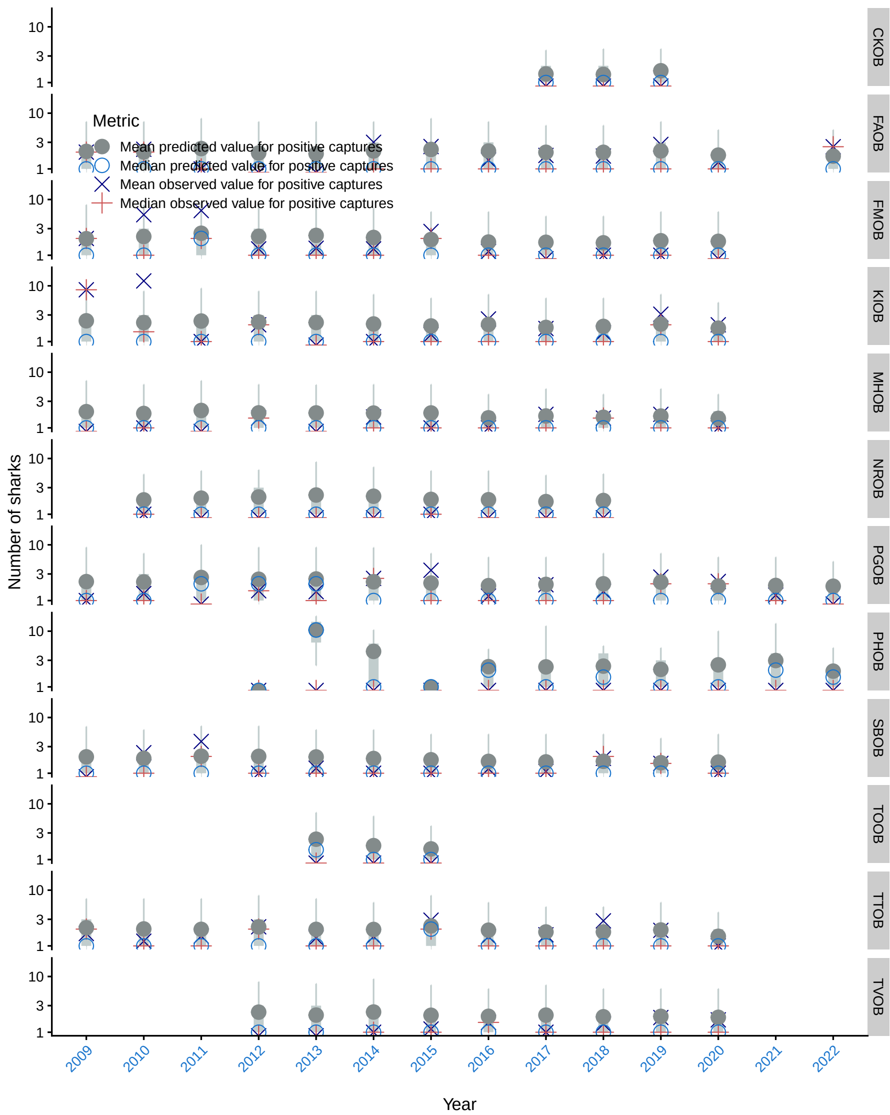


Figure B-61: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

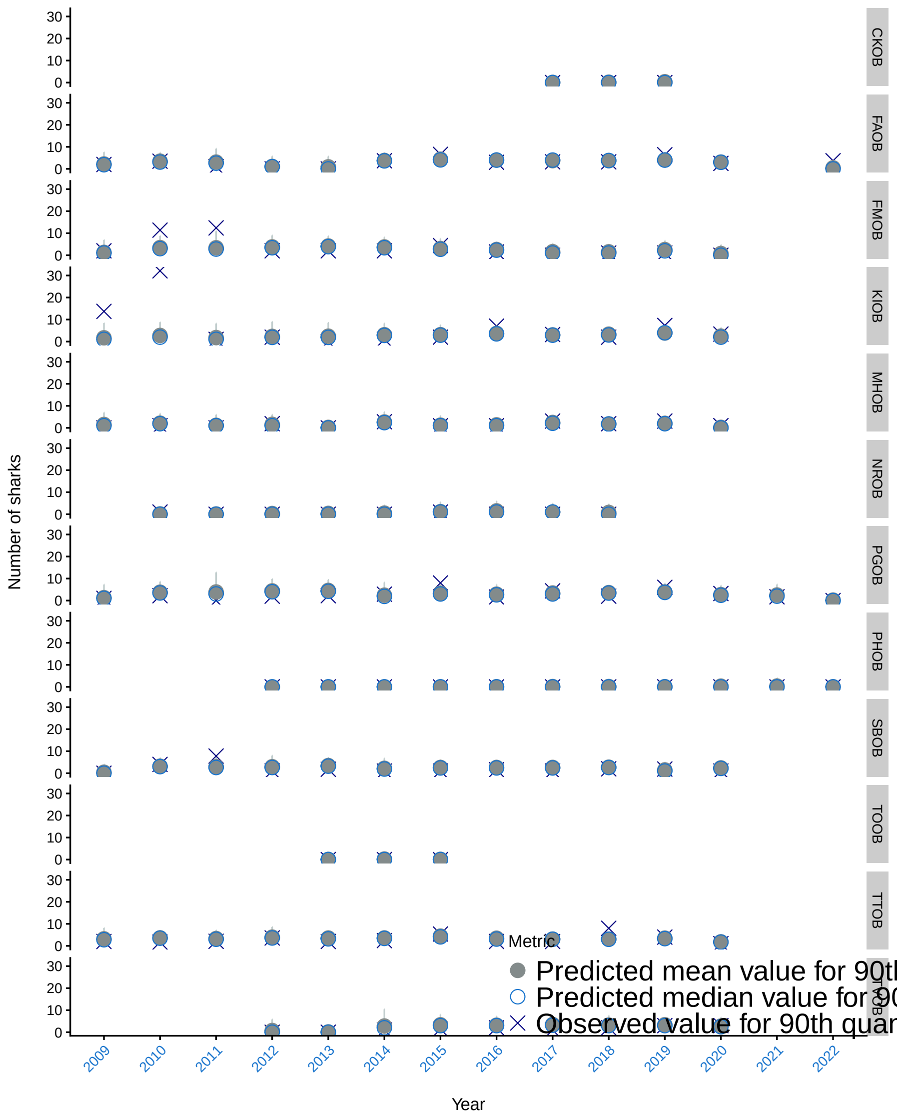


Figure B-62: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

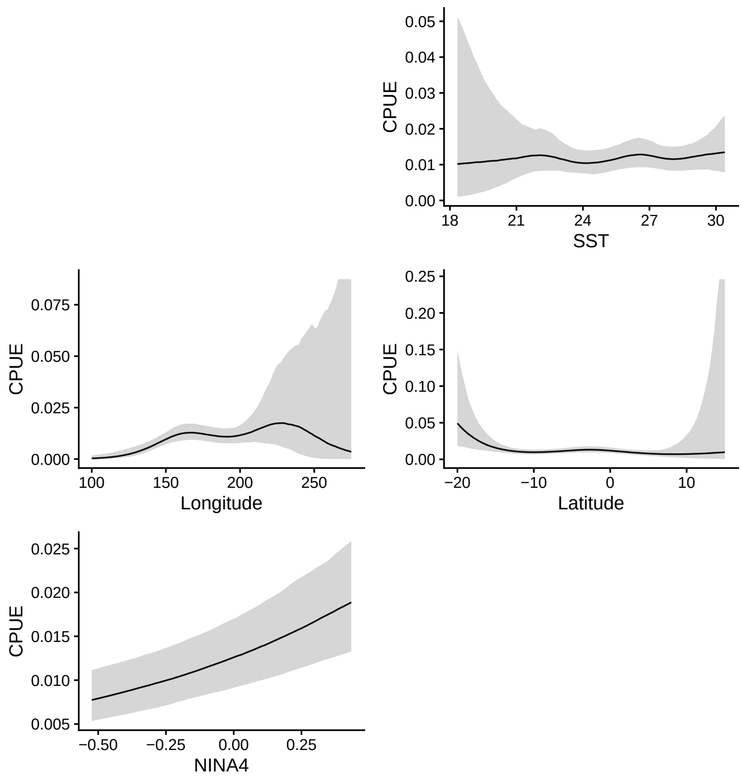


Figure B-63: Conditional effects estimated in the model used to derive CPUE from observed for sets.

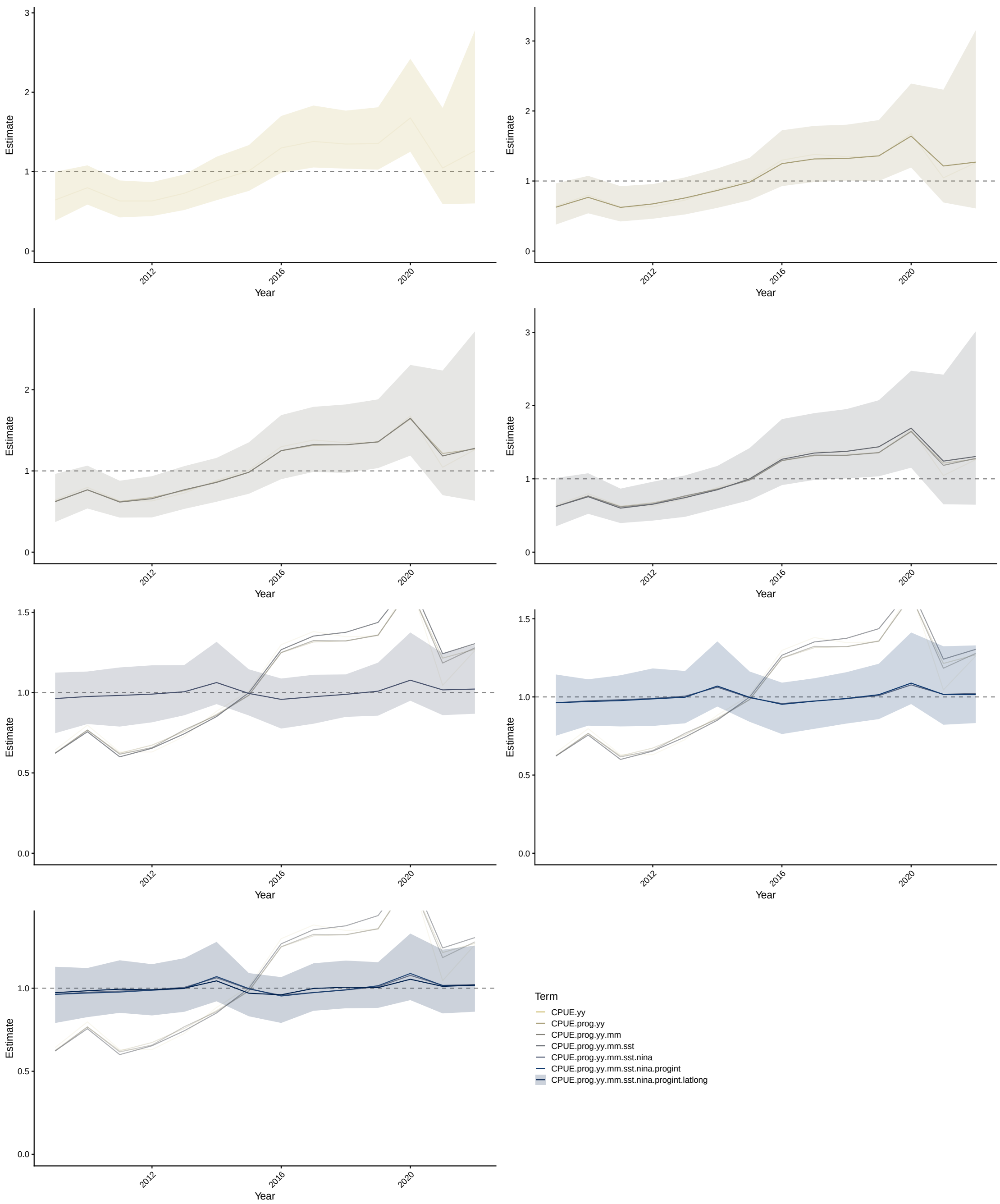


Figure B-64: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

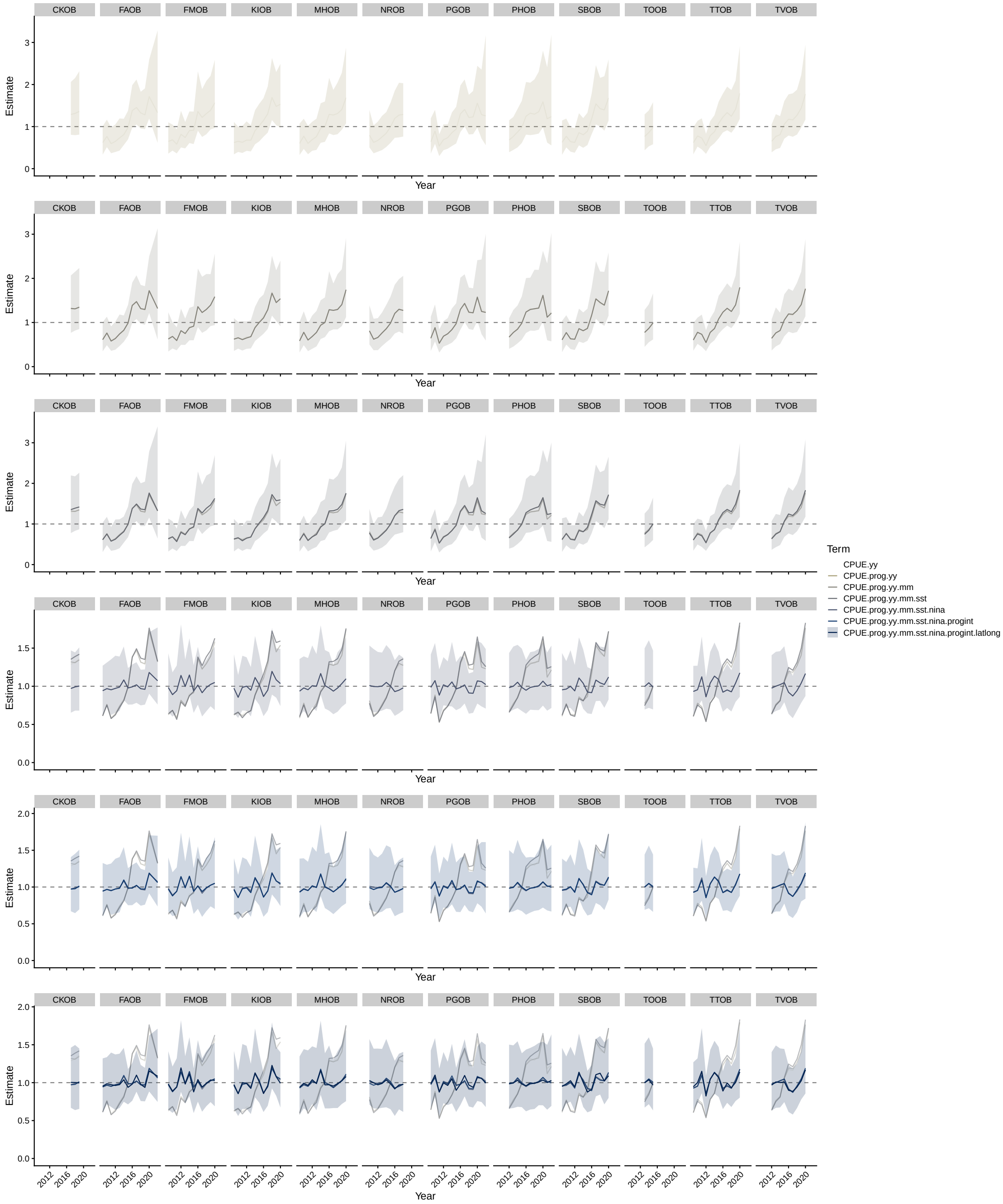


Figure B-65: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

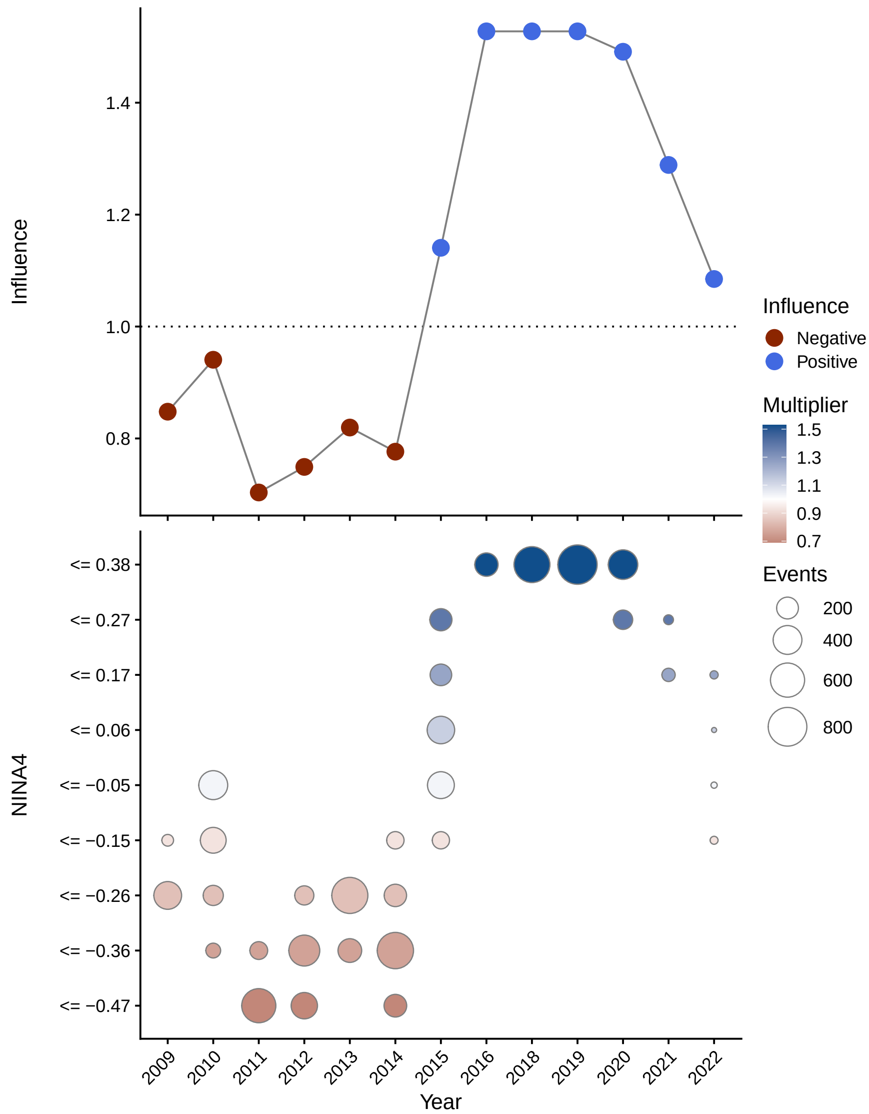


Figure B-66: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

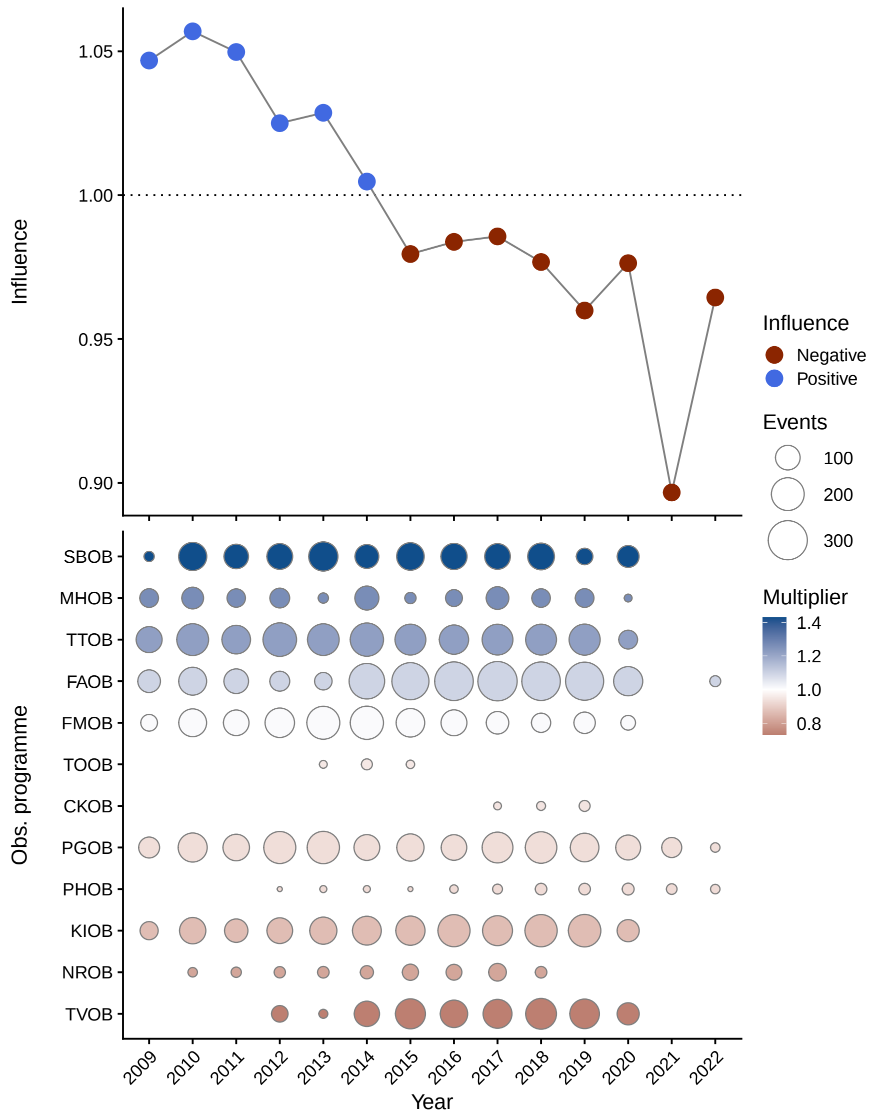


Figure B-67: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

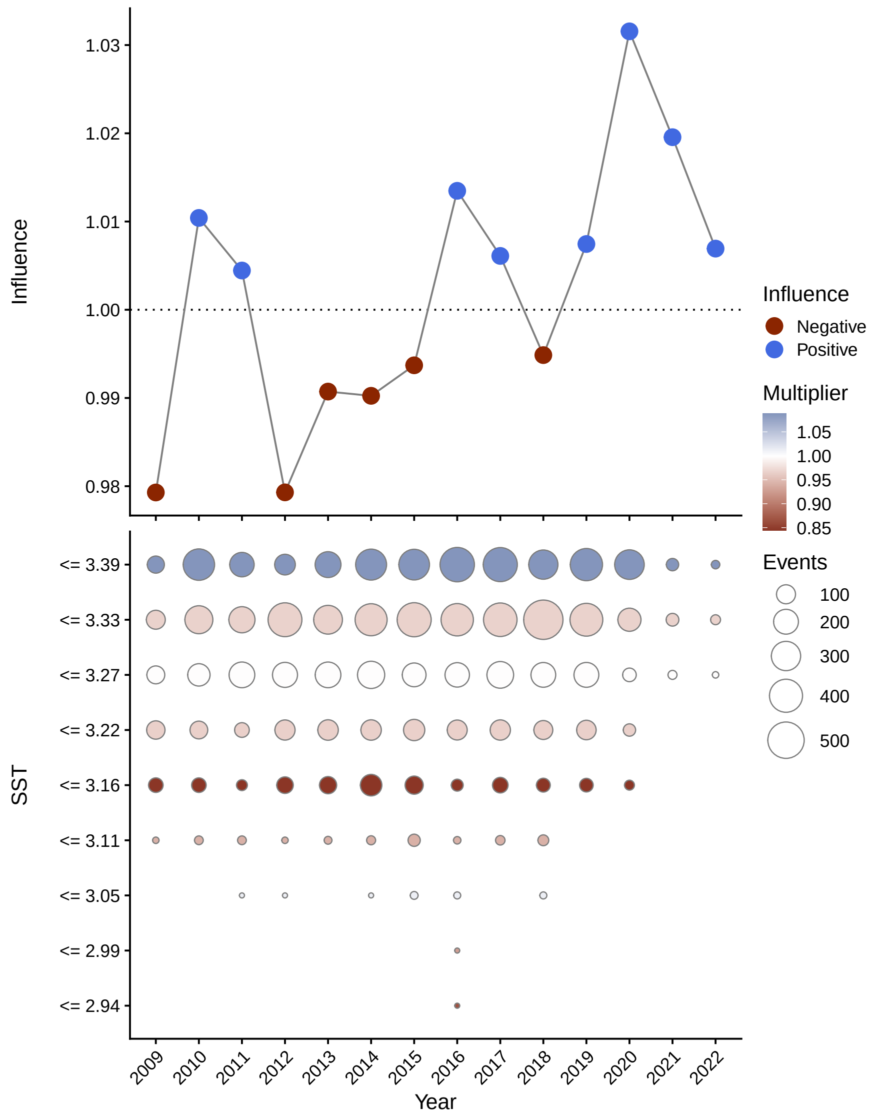


Figure B-68: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

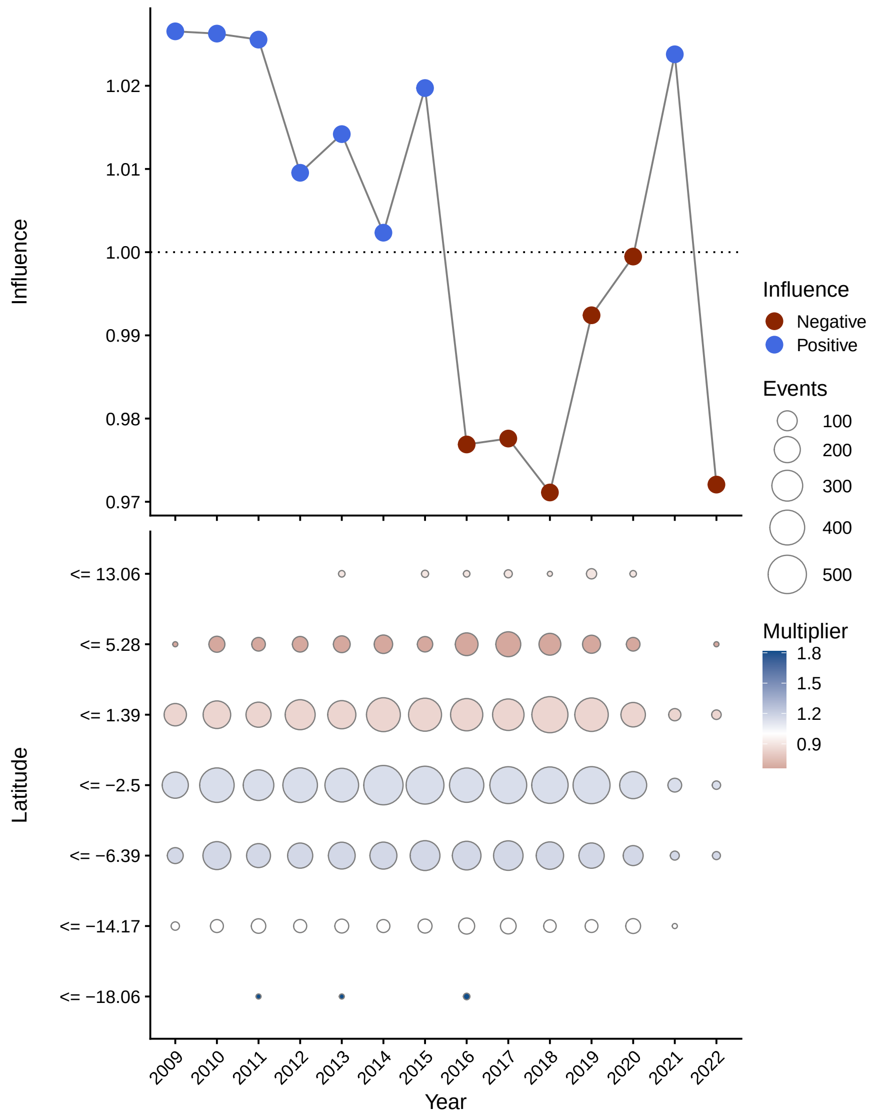


Figure B-69: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

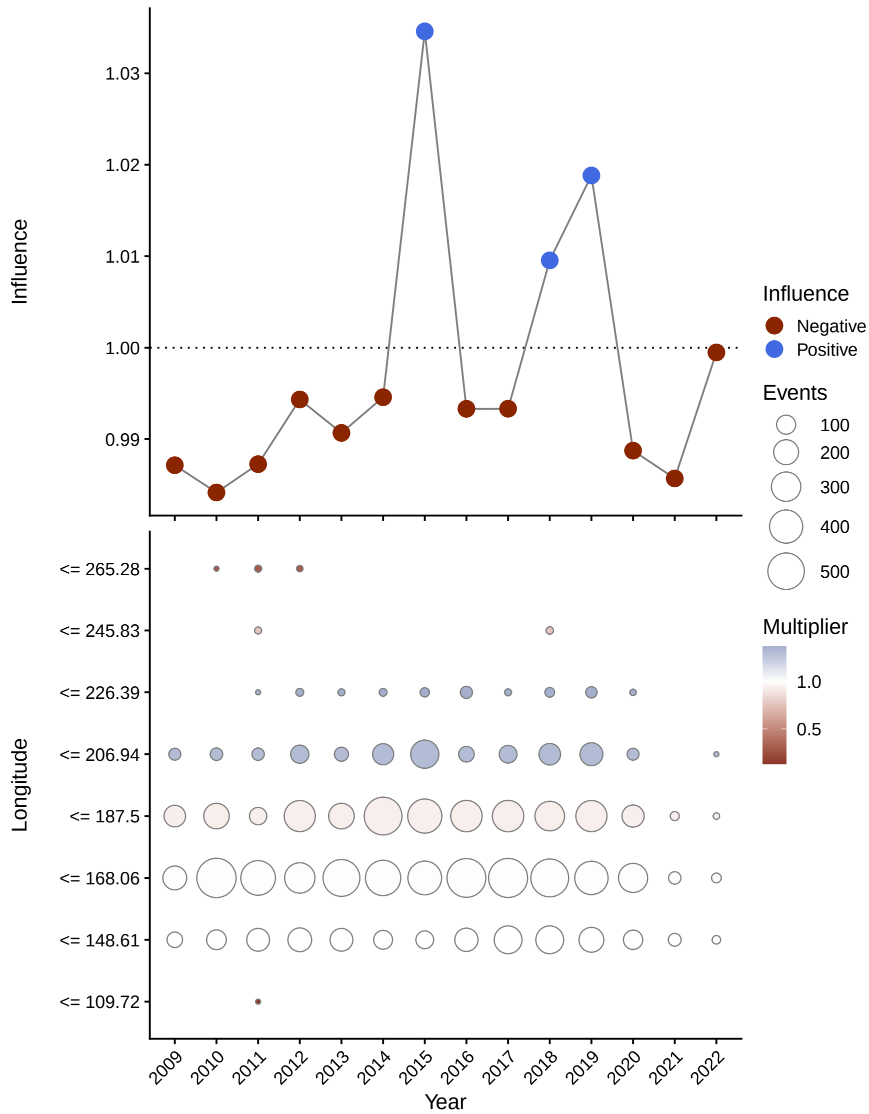


Figure B-70: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

B.6 CPUE diagnostics for object-associated purse seine

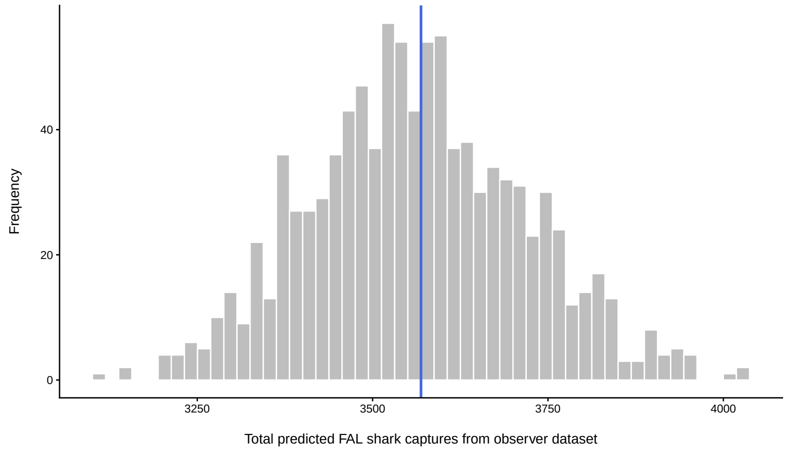


Figure B-71: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for sets.

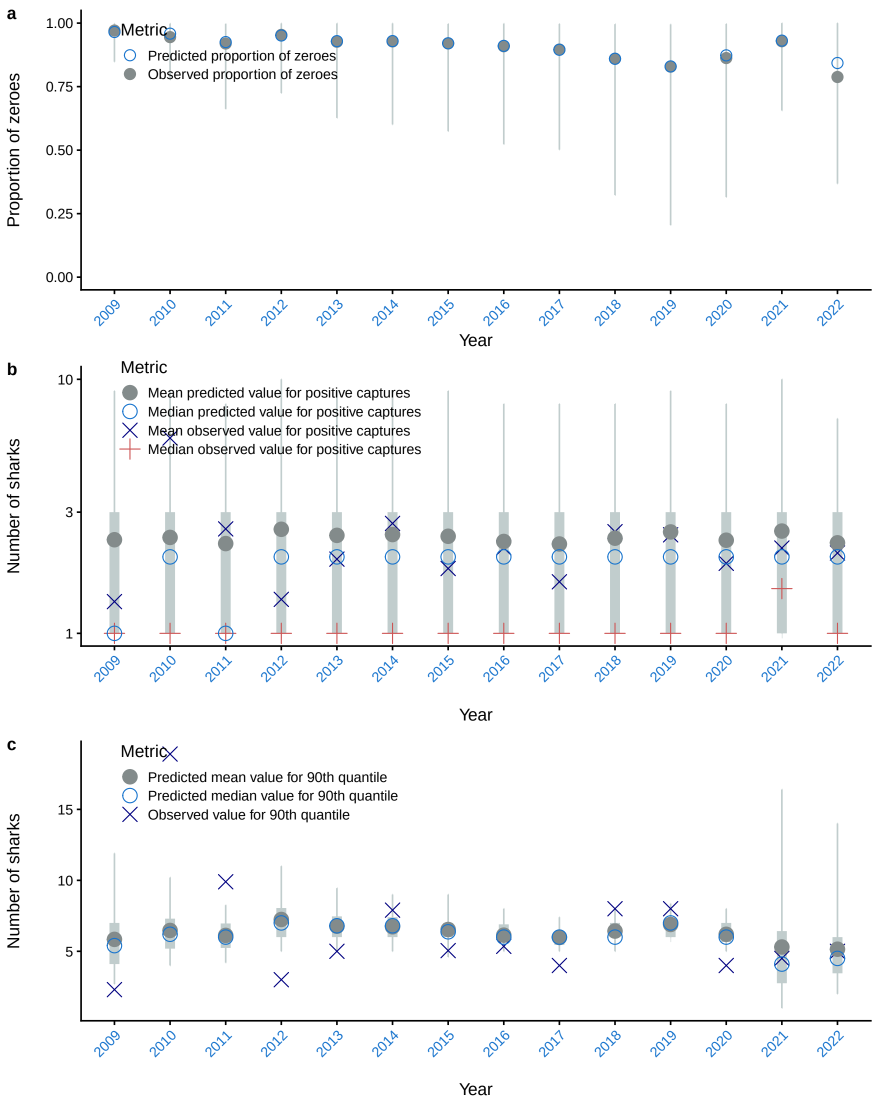


Figure B-72: Posterior predictive model diagnostics by model year for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

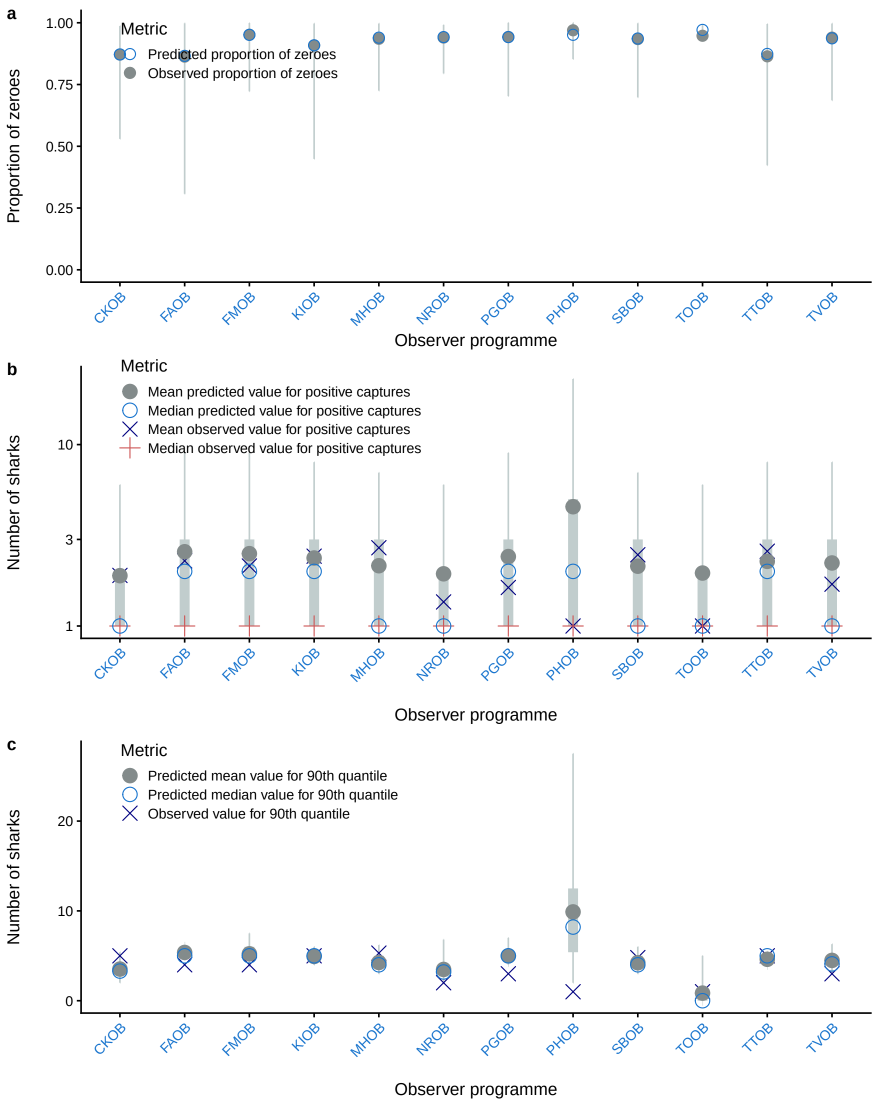


Figure B-73: Posterior predictive model diagnostics by observer program for sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

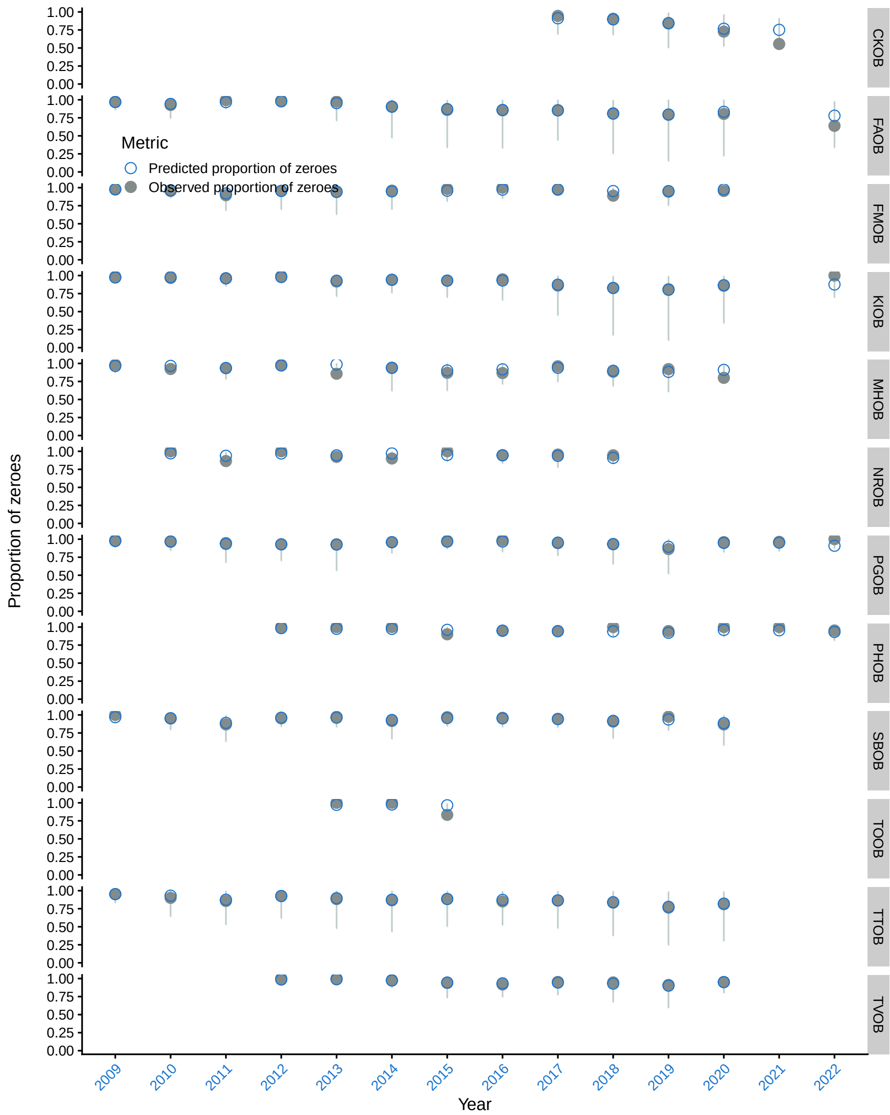


Figure B-74: Posterior predictive model diagnostics for observed and predicted proportion of zero captures by observer program and year for sets.

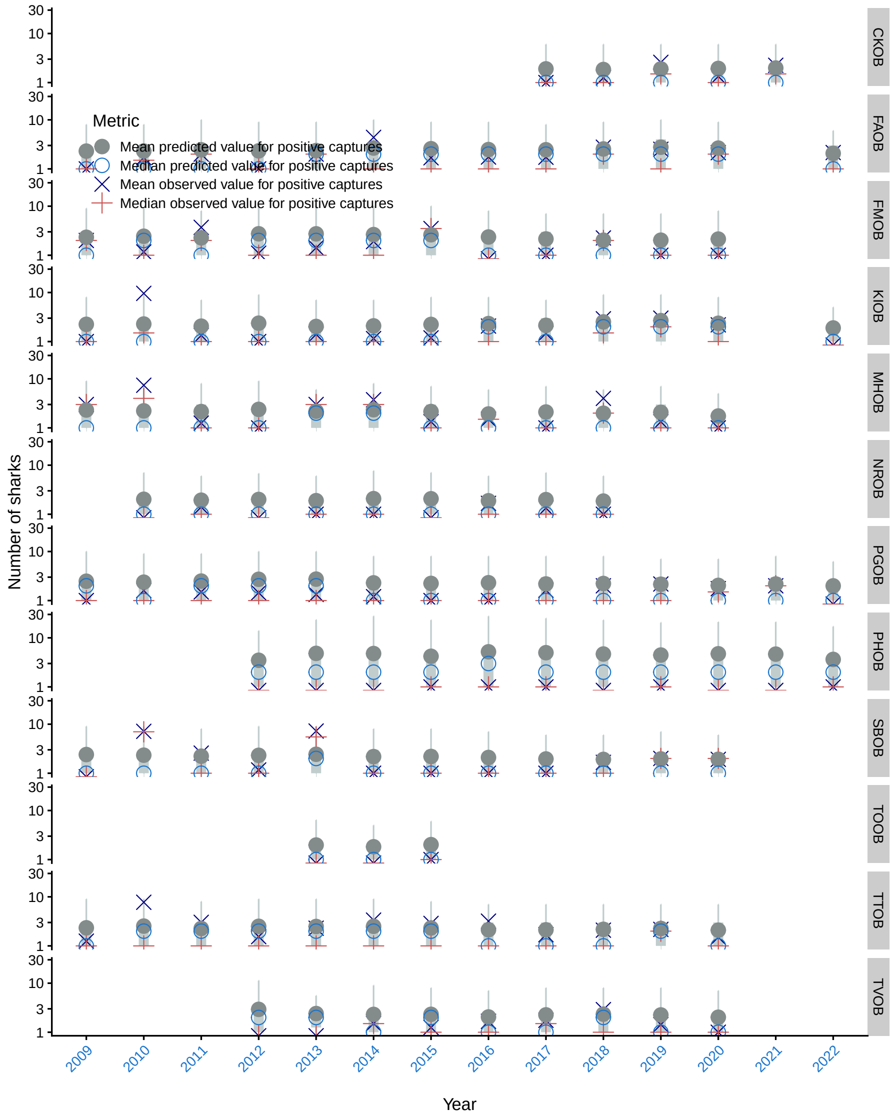


Figure B-75: Posterior predictive model diagnostics for bserved and predicted positive captures by observer program and year for sets.

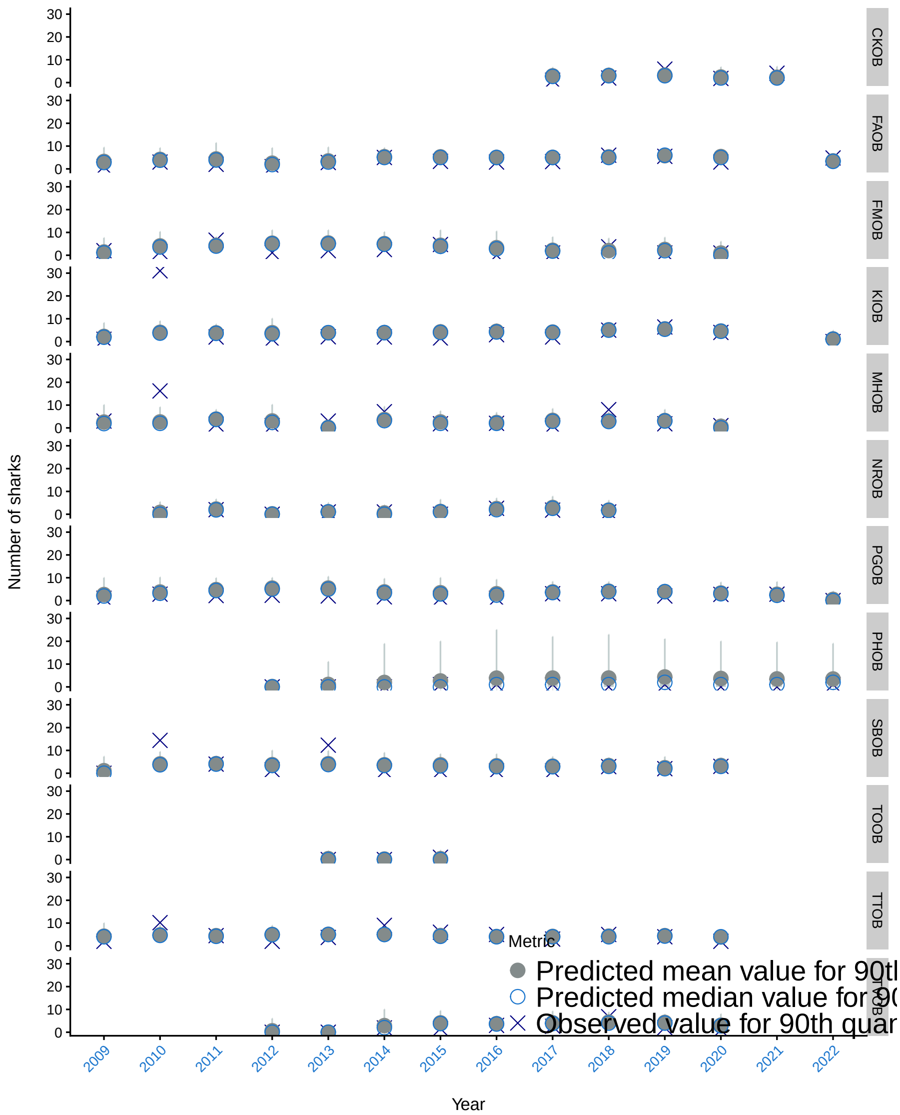


Figure B-76: Posterior predictive model diagnostics for dispersion statistics (90% percentile) of observed data and predictions by observer program and year for sets.

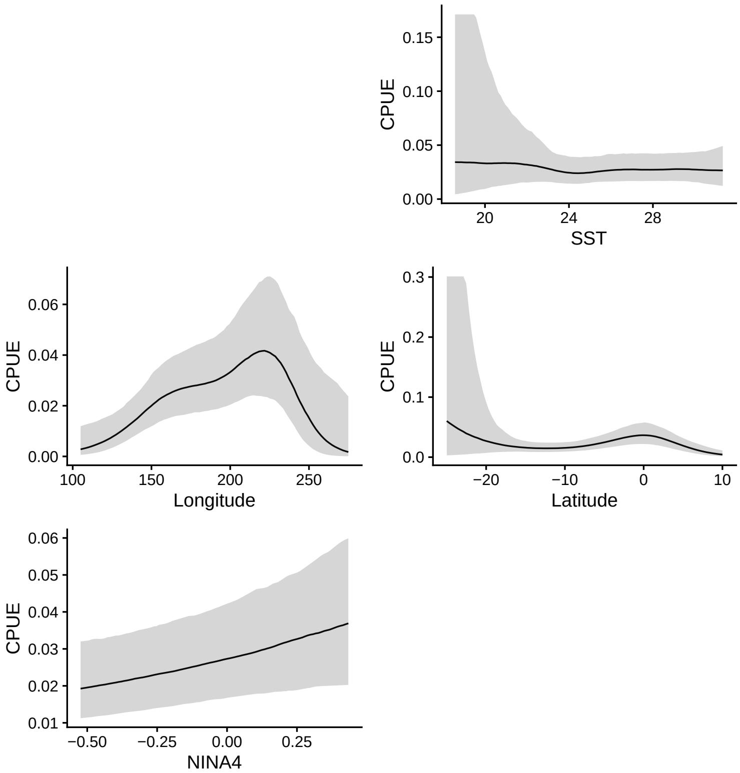


Figure B-77: Conditional effects estimated in the model used to derive CPUE from observed for sets.

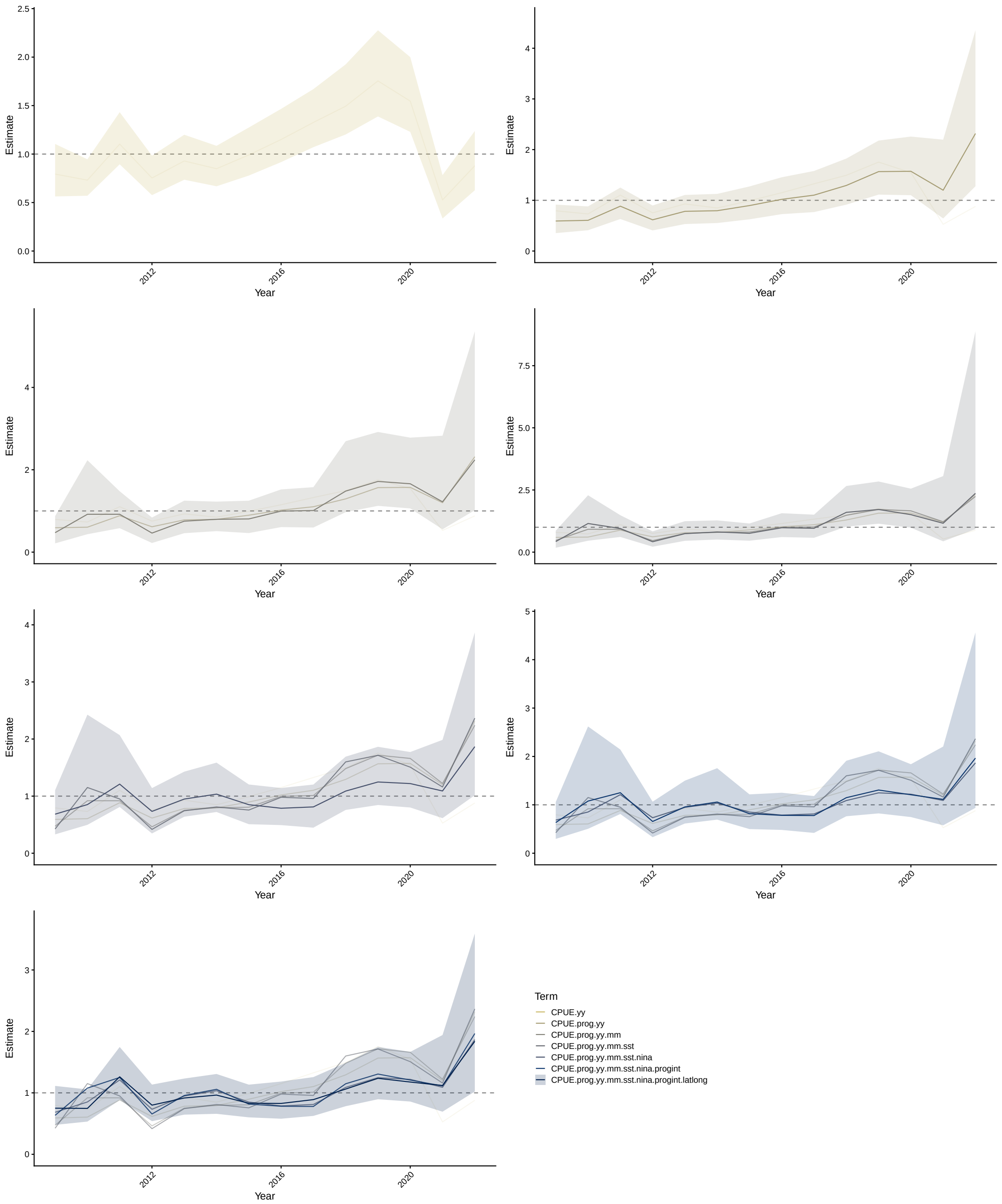


Figure B-78: CPUE standardisation effects for sets. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

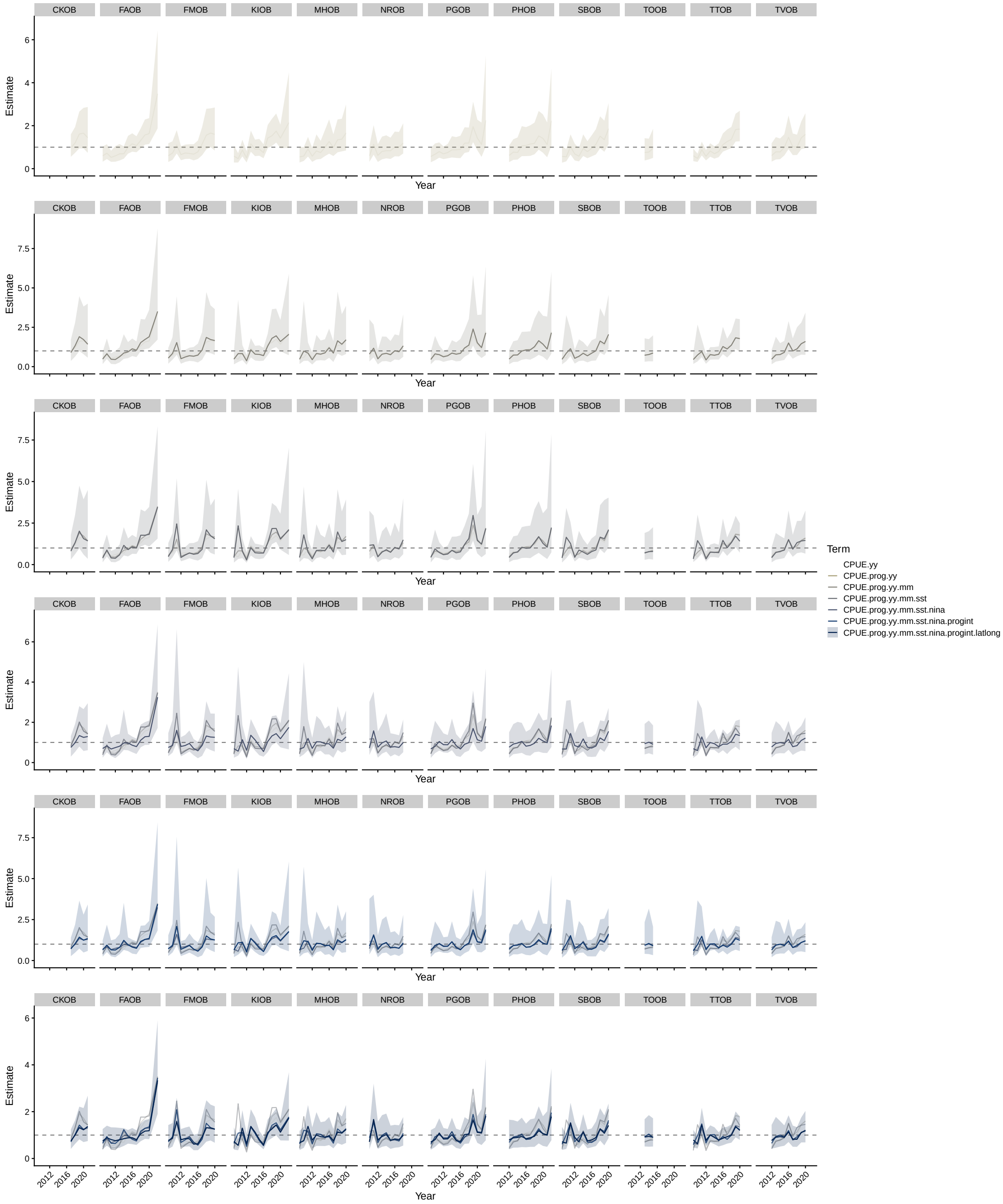


Figure B-79: CPUE standardisation effects for by observer-program. Each row of plots corresponds to the addition of a variable, starting with a model that includes observer-program-year interactions. In each row, the posterior median and credible interval is shown for the updated model, posterior medians for the year effect from sub-models are shown for comparison.

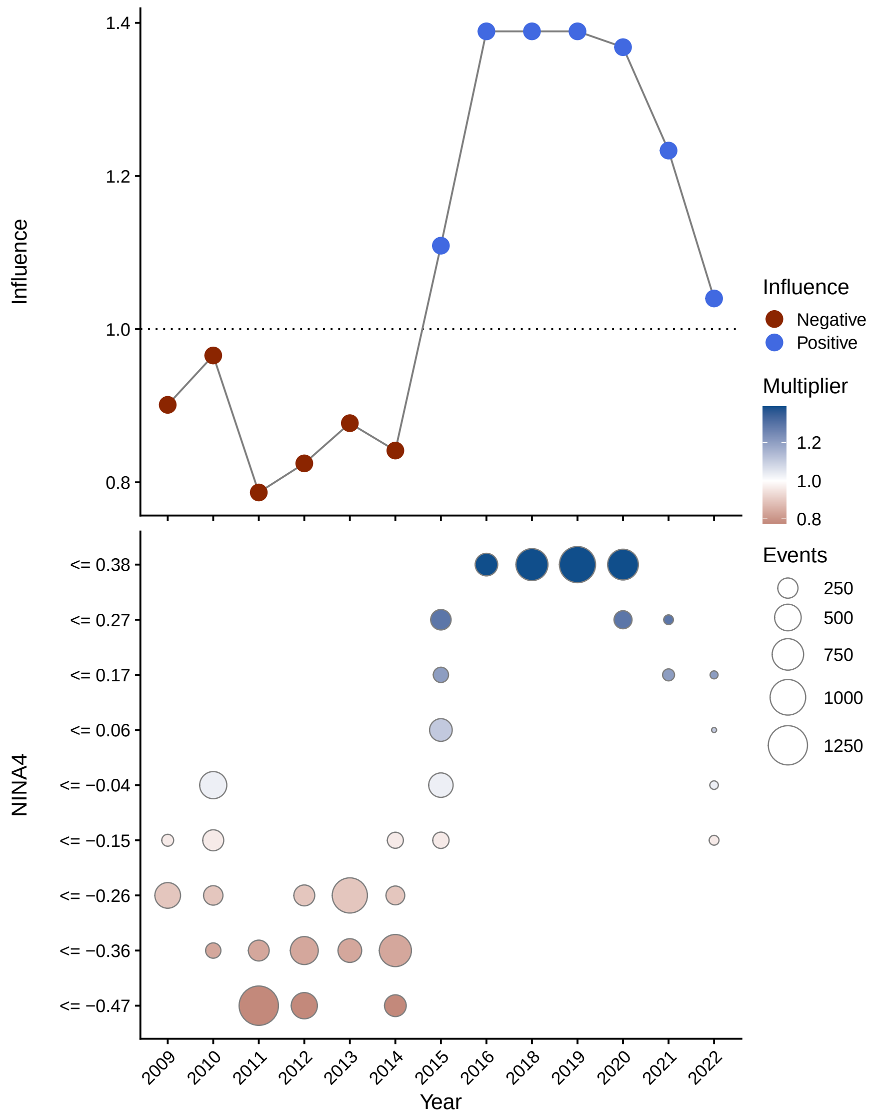


Figure B-80: Influence of the NINA4 index on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences the NINA4 index. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

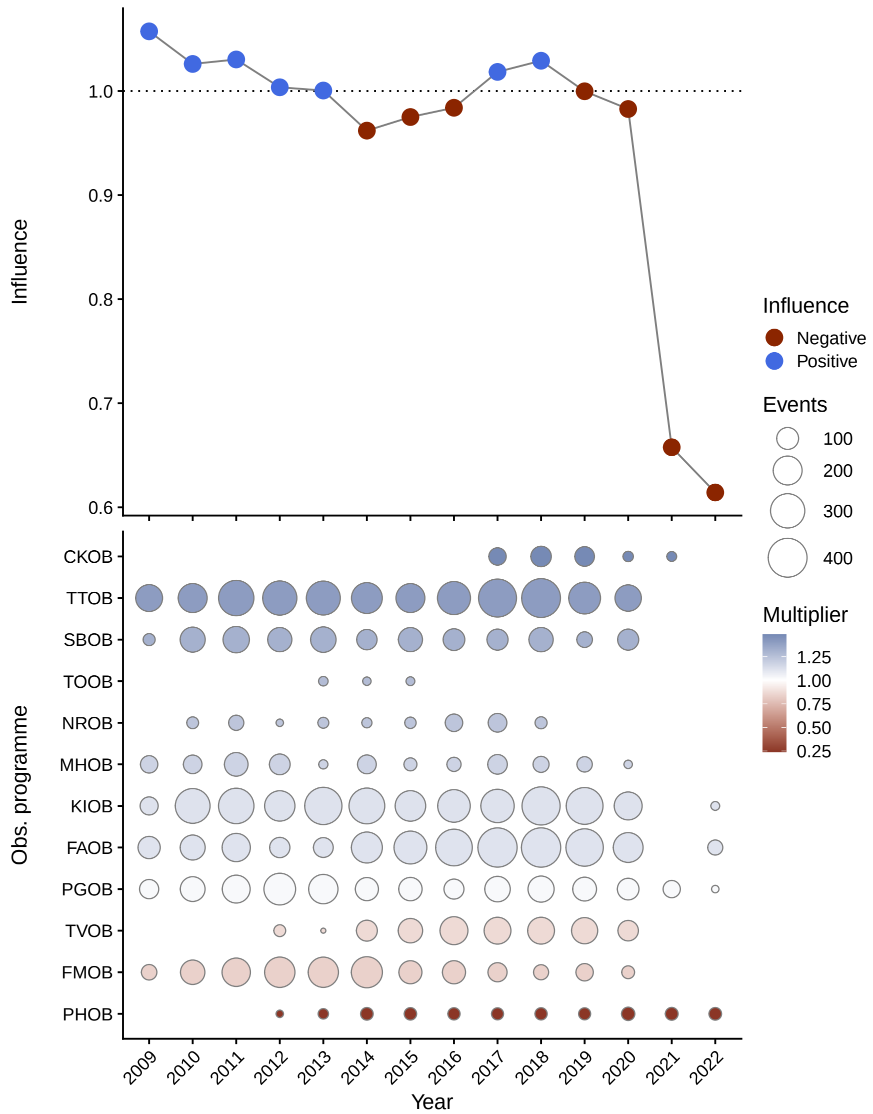


Figure B-81: Influence of observer program on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of observer program. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

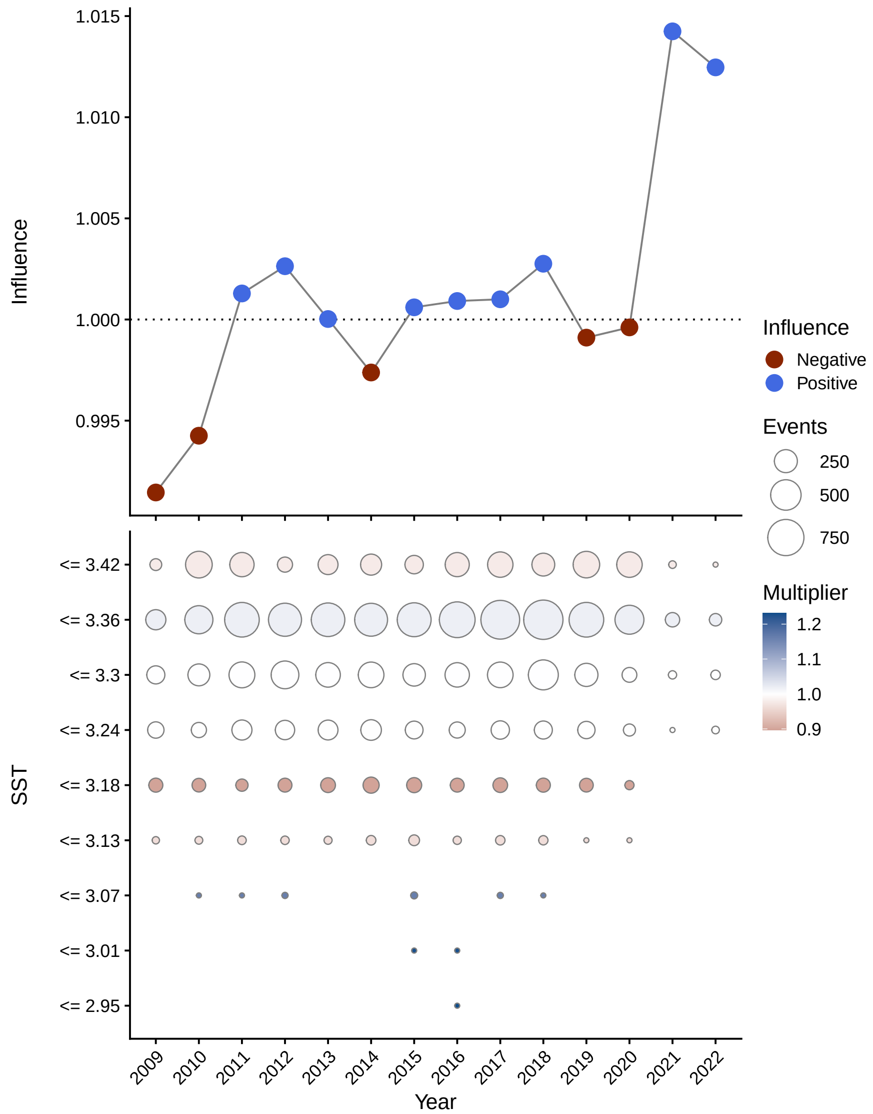


Figure B-82: Influence of sea-surface-temperature (SST) on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of SST. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

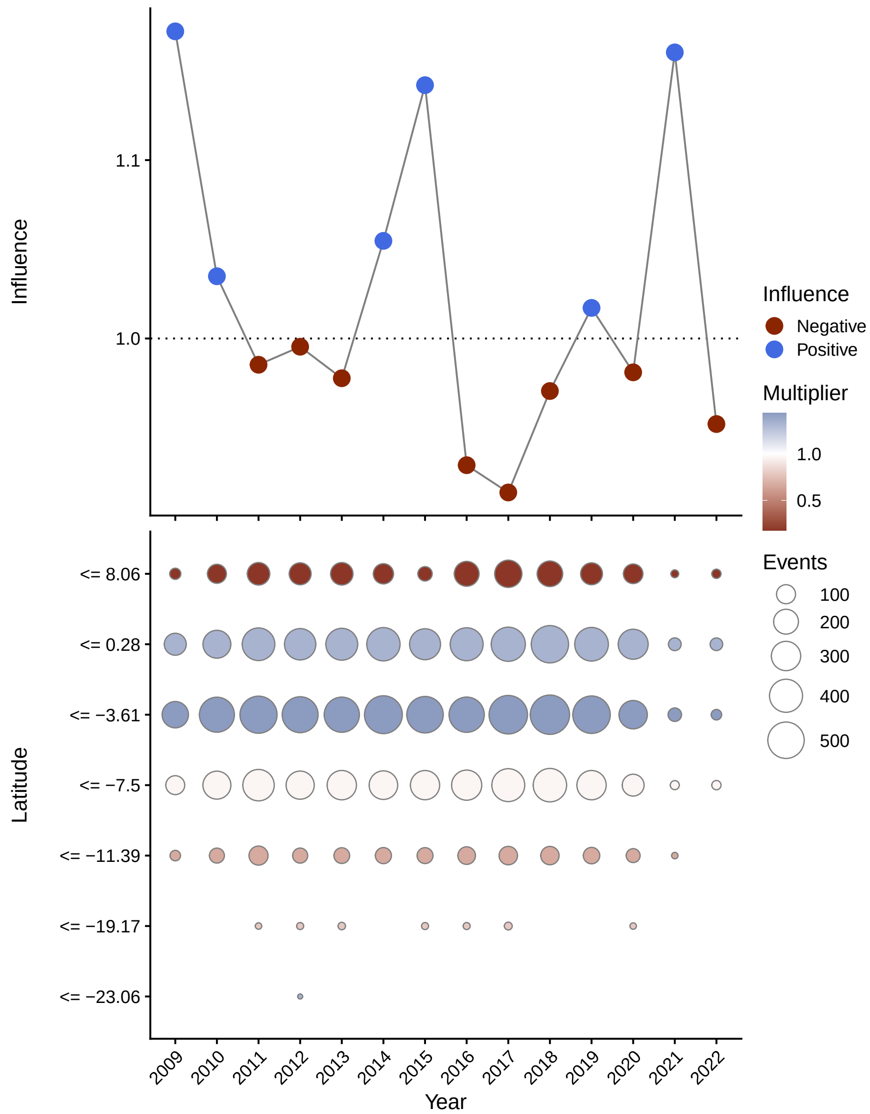


Figure B-83: Influence of latitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of latitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

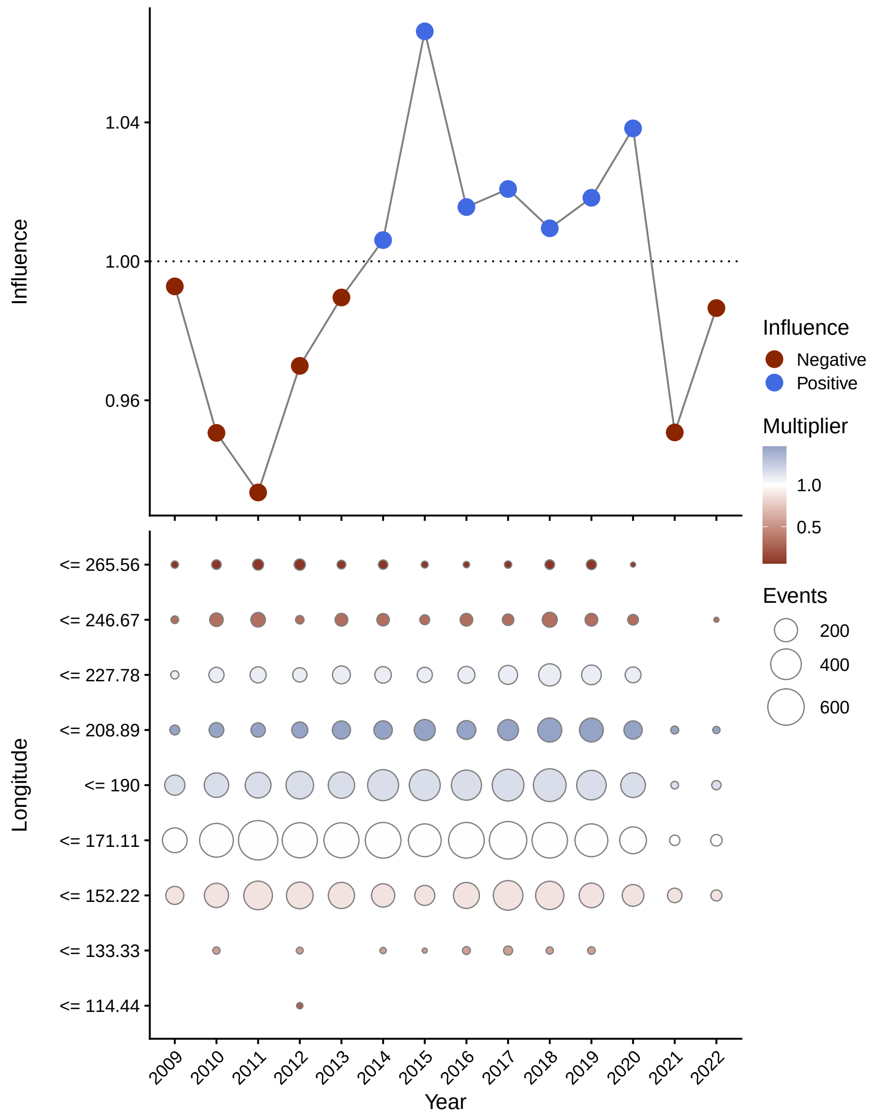


Figure B-84: Influence of longitude on catch-rates for sets, with positive influence showing years where the over-all catch-rate in the model was standardised downward by the corresponding amount to account for influences of longitude. Influence is shown in colour as a multiplier on average catch rates, with circle size corresponding to the amount of effort entering the model. Note that data for the 2022 year is preliminary.

APPENDIX C PREDICTING INTERACTIONS ACROSS THE WCPO - SUPPLEMENTARY FIGURES

C.1 Longline model fits

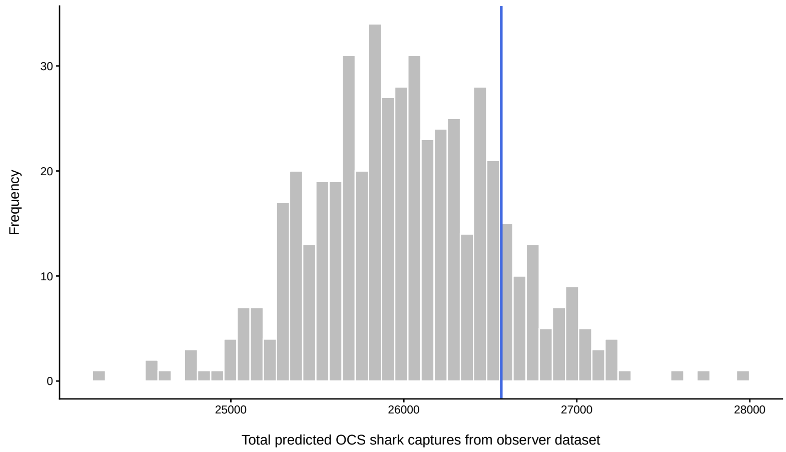


Figure C-85: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for longline sets.

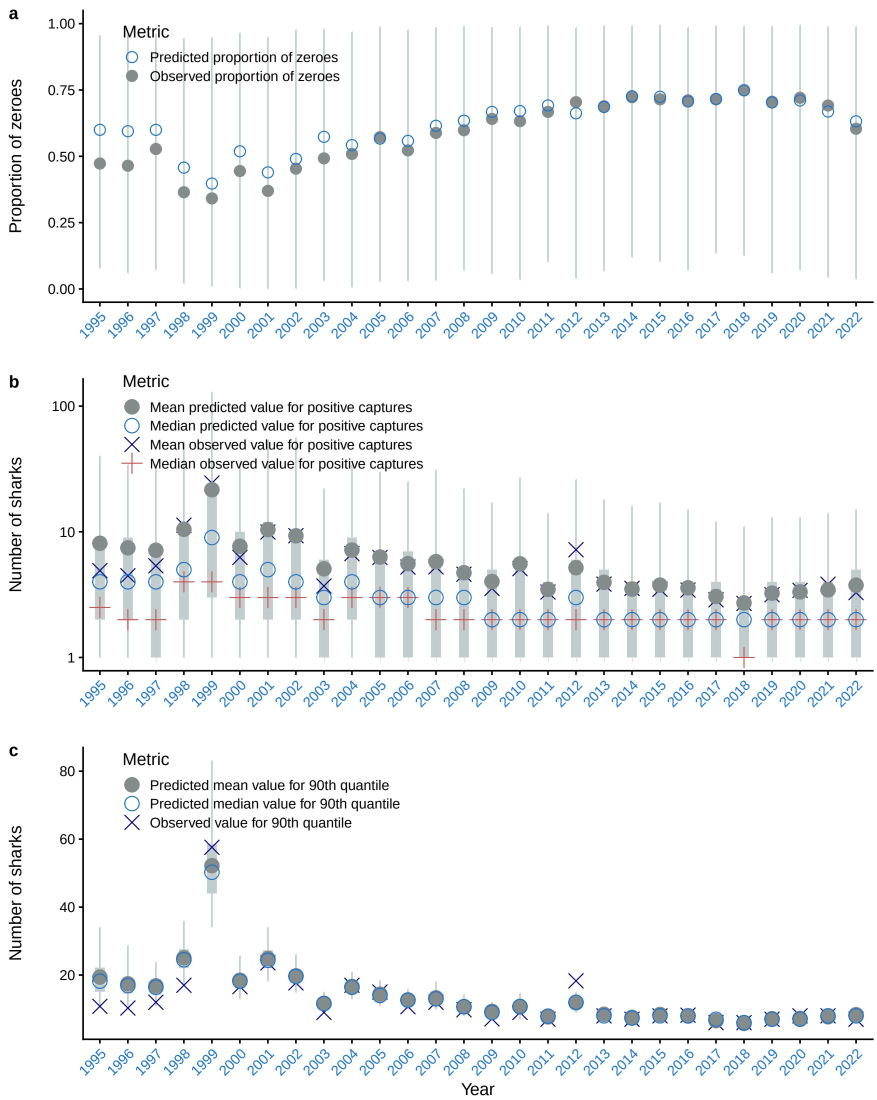


Figure C-86: Posterior predictive model diagnostics by model year for longline sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

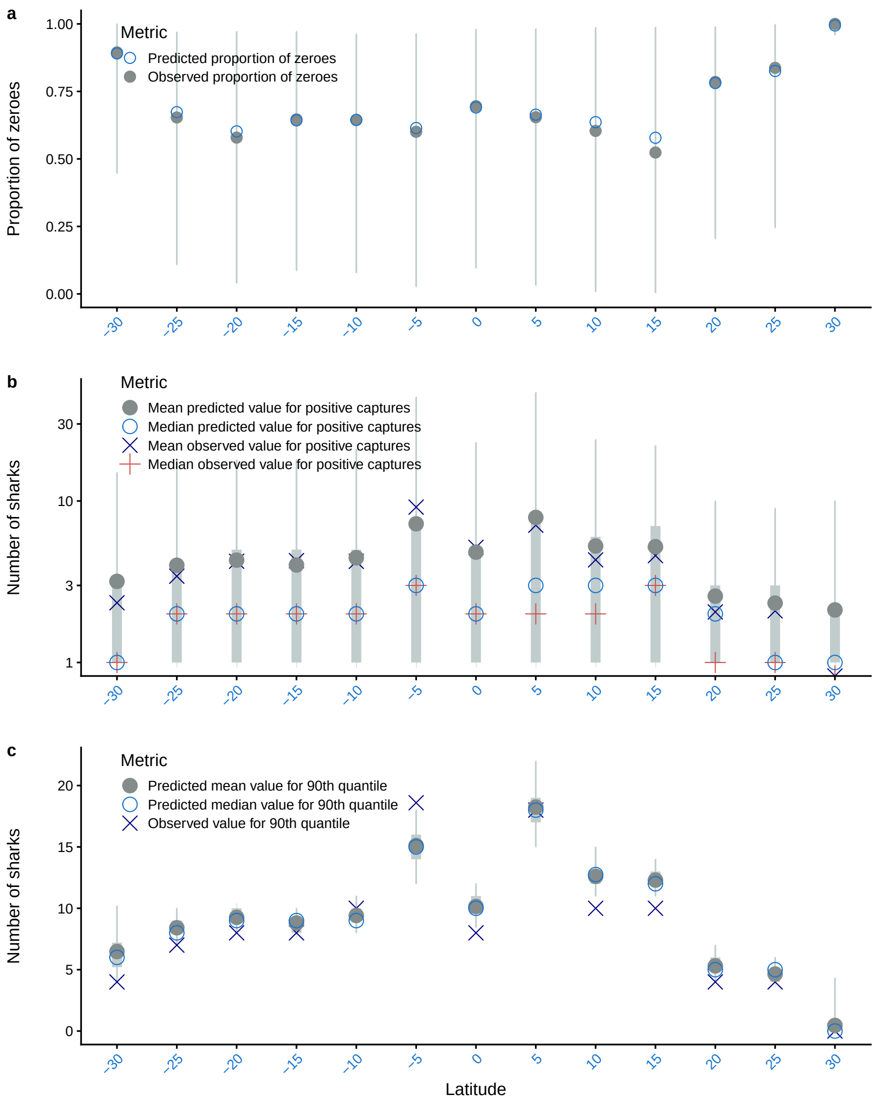


Figure C-87: Posterior predictive model diagnostics by latitude for longline sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

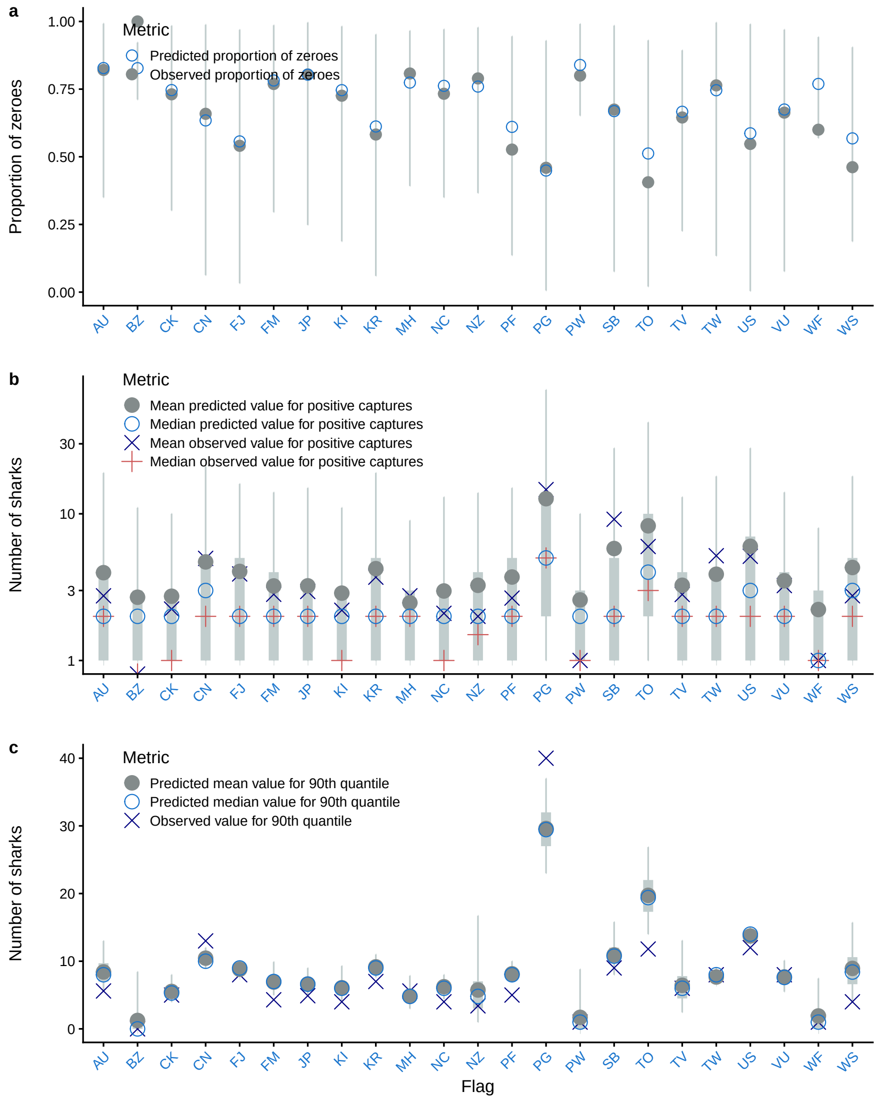


Figure C-88: Posterior predictive model diagnostics by observer program for longline sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

C.2 Purse-seine model fits

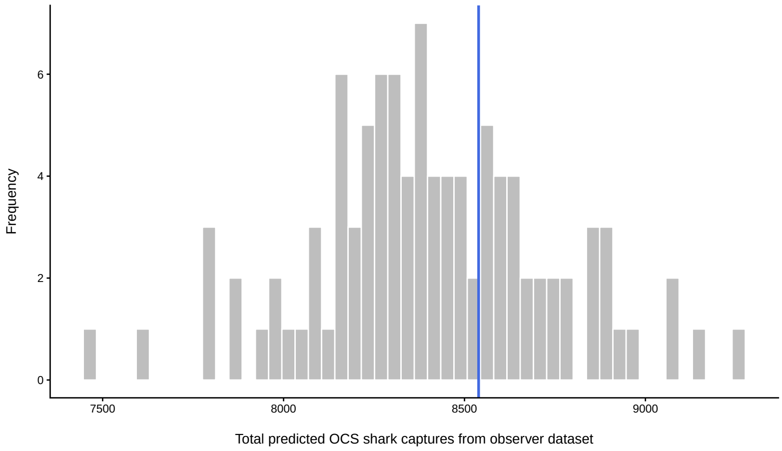


Figure C-89: Observed interactions (vertical line) and model predictions from the model used to derive CPUE from observed for purse-seine sets.

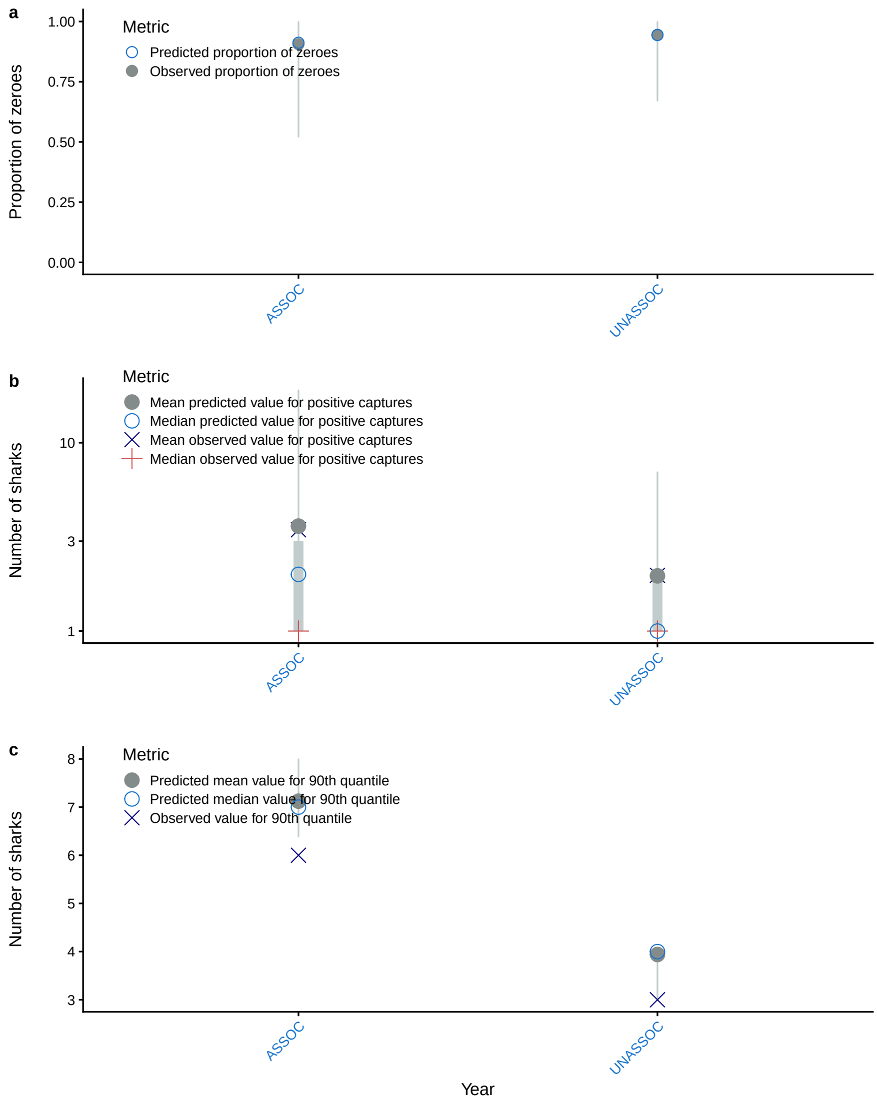


Figure C-90: Posterior predictive model diagnostics by set-type (ASSOC: object-associated sets; UNASSOC: free-school (un-associated) sets) for purse-seine sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

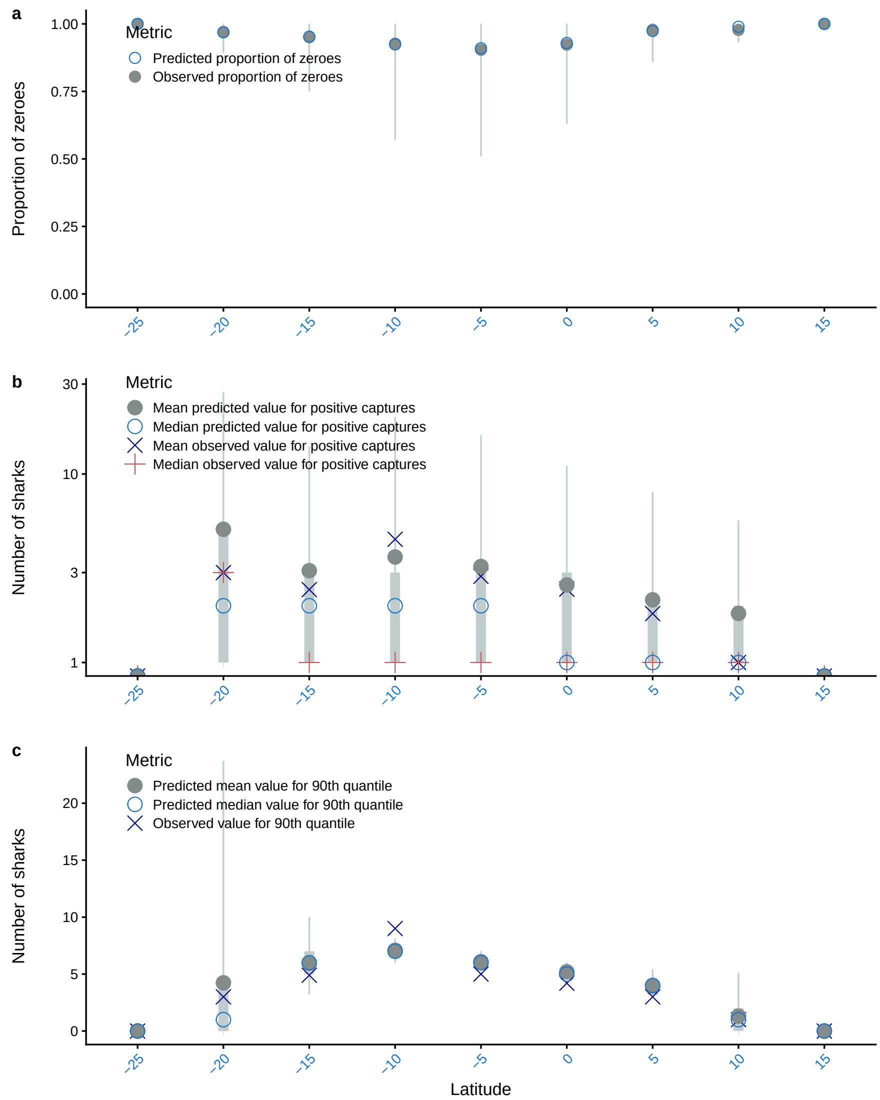


Figure C-91: Posterior predictive model diagnostics by latitude for purse-seine sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

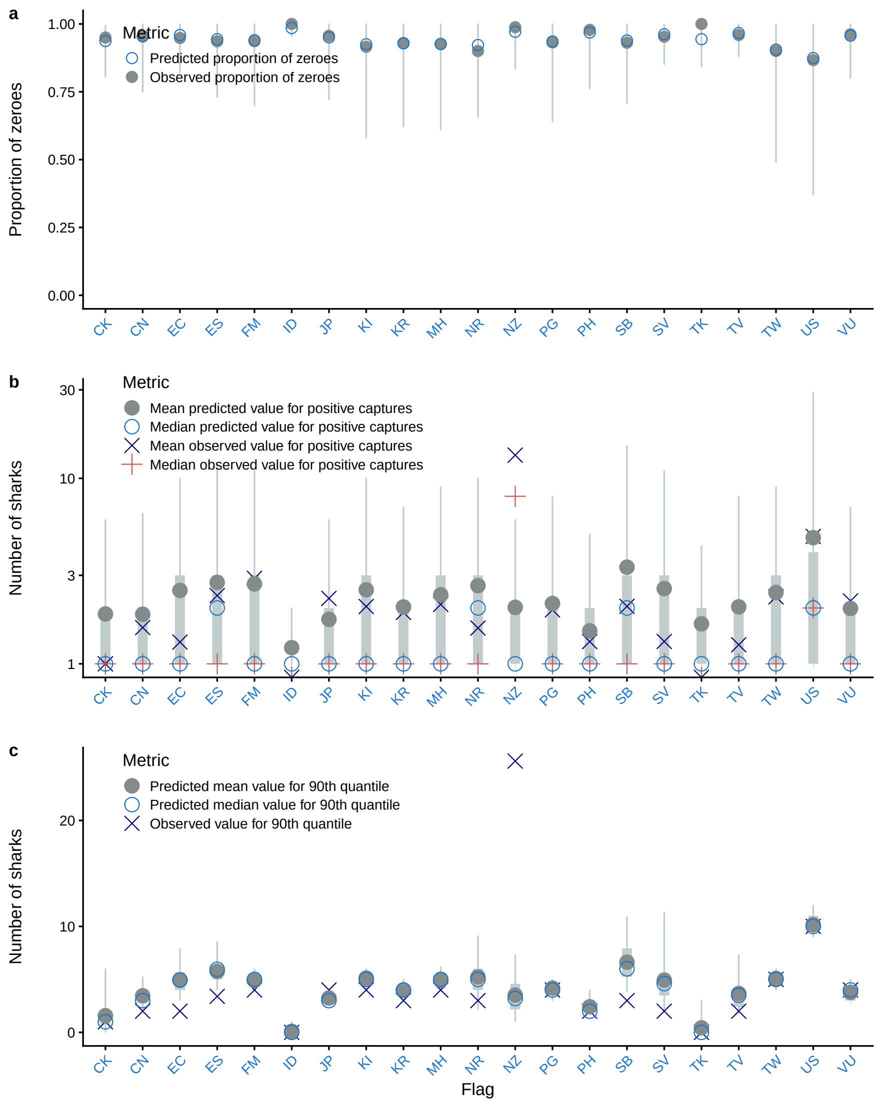


Figure C-92: Posterior predictive model diagnostics by observer program for purse-seine sets, with (a) observed and predicted proportion of zero captures, (b) observed and predicted positive captures and (c) dispersion statistics (90% percentile) of observed data and predictions.

APPENDIX D PURSE-SEINE LENGTH COMPOSITIONS

Figure D-93: Length frequencies of observer-sampled oceanic whitetip shark in target fisheries by year. The median length for each year is indicated with the dashed vertical line.

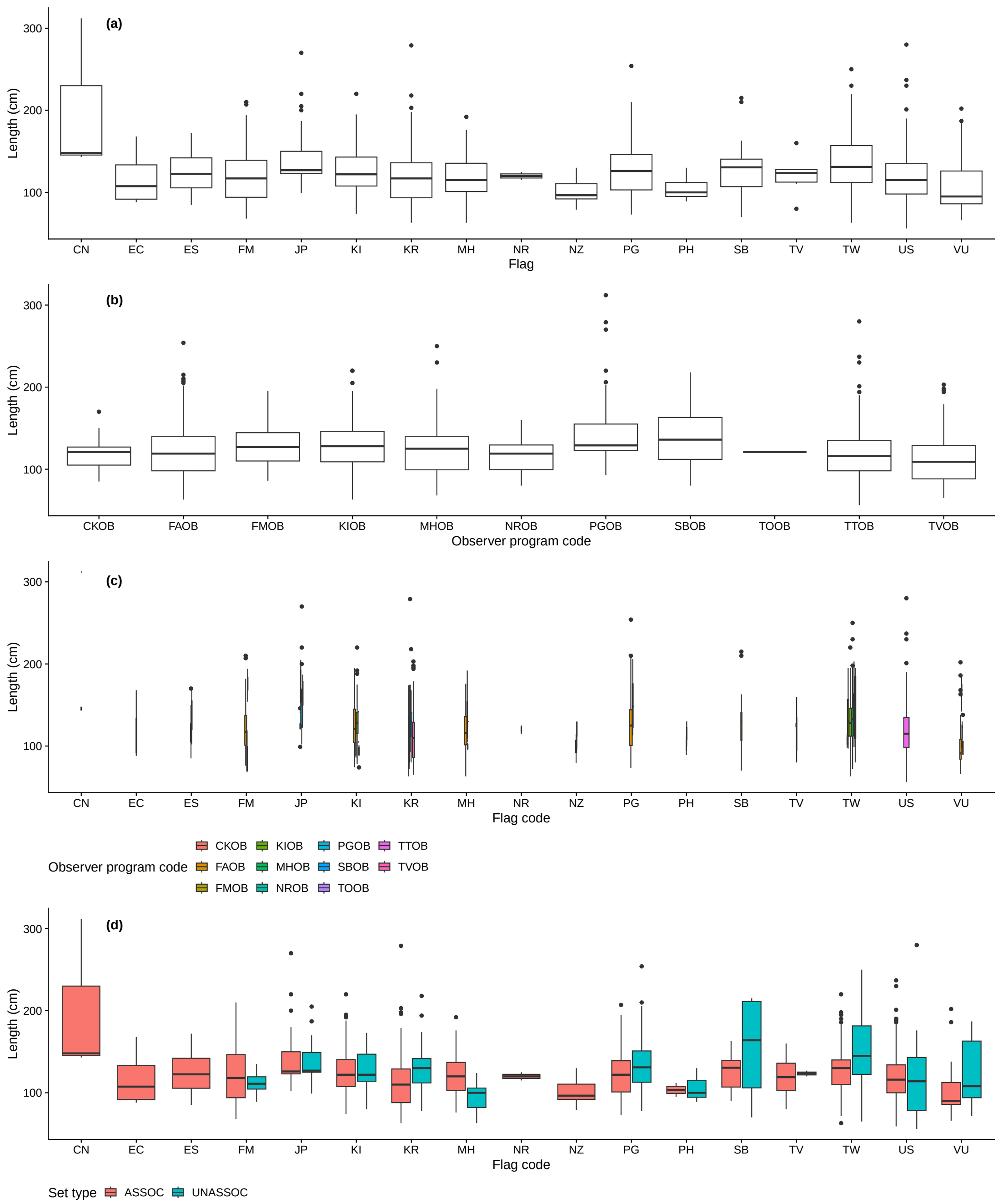


Figure D-94: Boxplots showing length distributions of oceanic whitetip shark by vessel flag (a), observer program (b), vessel flag and observer program (c), and vessel flag and set type (d).

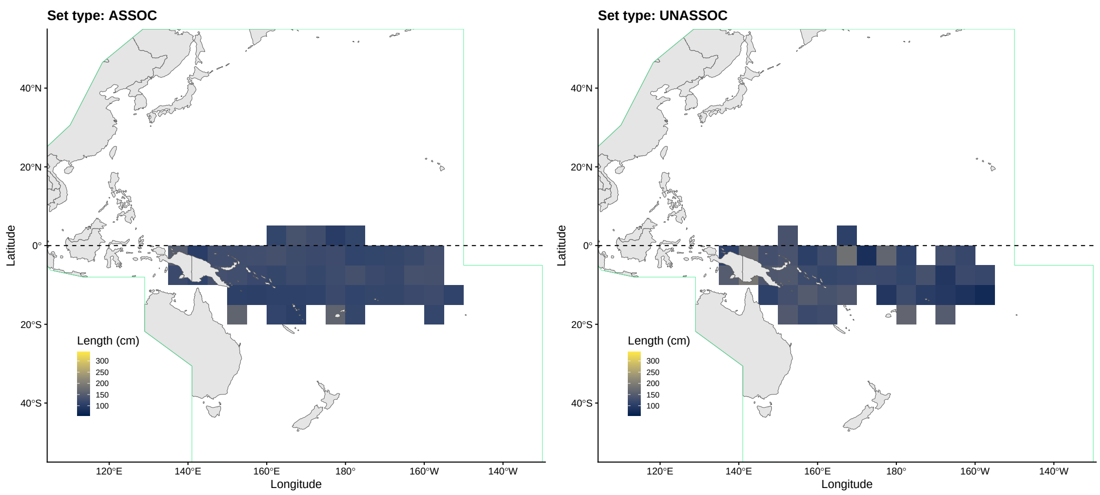


Figure D-95: Maps showing average lengths accross the WCPFC convention area by set type.