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Estimates of SBT catch by CCSBT non-cooperating non-member states between 2007 and 2017

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Executive summary

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This paper responds to a request from the Extended Commission (EC) to the Extended Scientific Committee (ESC) to provide estimates of catch of Southern Bluefin Tuna (SBT) by non-cooperating non-member fleets not reporting catch to the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). We update the results from previous work (CCSBT- ESC/1509/10; CCSBT-ESC/1509/21; CCSBT-ESC/1609/BGD02/Rev.1) that applied different modelling approaches to estimate the potential non-member catch of SBT. Both approaches required estimation of the catch rate from CCSBT data and application of that catch rate to non-member effort in order to predict potential unreported catch.

Information on non-member longline fishing effort in the Indian Ocean, the Western Pacific and the Atlantic was obtained from the Indian Ocean Tuna Commission (IOTC), Western and Central Pacific Fisheries Commission (WCPFC) and the International Commission for the Conservation of Atlantic Tunas (ICCAT), respectively. Catch rates were estimated using two modelling approaches: generalised linear modelling and random forest regression, parameterised with the same data. In order to obtain a sufficiently large dataset of CCSBT catch and effort data with which to fit the models, we converted Japanese catches in number of fish to catches in weight, by modelling fish size patterns in space and time. Effort may be underreported to the CCSBT by some member states, and to mitigate this effect on estimated catch rates, additional effort was included from the WCPFC, IOTC and ICCAT in overlapping spatial and temporal strata. We then modelled catch rates (in kilograms per hook) by year, month, vessel fleet (flag) and 5° grid, using each method. These predicted catch rates were applied to non-member fishing effort by year, month, and 5° square to predict the unreported SBT catches.

When predicting the catches, it was necessary to make assumptions concerning the catchability of the non-member fleets. Two alternative catchabilities were assumed, namely those of the Japanese and Taiwanese fleets, taken to represent alternative fishing behaviours (targeted and non-targeted respectively). These provided upper and lower bounds for the predicted catch. There are some differences between the results of the two modelling approaches, which are discussed, with each method taken to represent an equally valid alternative.

1 Introduction

The Extended Commission of CCSBT in 2013 requested that the Extended Scientific Committee (ESC) provide advice on the potential impact of unaccounted mortality on the stock assessment and rebuild strategy for southern bluefin tuna (SBT). In 2014, the ESC19 noted that the impacts of unaccounted mortality on the stock assessment and rebuilding plan could be substantial, based on a range of projections from different unaccounted mortality scenarios. The ESC19 also noted that such scenarios were plausible given the available data, information and anecdotal market reports. Based on this advice, the EC directed the ESC to undertake specific analyses to provide estimates of non-member catch, referring specifically to non-cooperating non-members of CCSBT, since some non-members do report catches.

There is no reliable information available on SBT catch by non-cooperating non-members. Information from a number of sources has indicated that a market for SBT exists in China. Although a small amount of catch in this market is supplied by catch from members and cooperating non-members, it may also be supplied with SBT that is not reported to CCSBT, since imports into China registered by the CCSBT have been found to be lower than total exports (CCSBT Secretariat, 2014).

Analysis of the effort data reported to other RFMOs, particularly to the IOTC (Indian Ocean Tuna Commission) and WCPFC (Western and Central Pacific Fisheries Commission), shows a large degree of overlap in SBT fishing grounds for these tuna fisheries (Larcombe, 2014). However, SBT catch is generally not reported to the IOTC, WCPFC or ICCAT, even though these tuna fleets likely take quantities of SBT bycatch in the albacore, bigeye and yellowfin target fisheries. Observer reports presented at the 2014 Scientific Committee of the WCPFC, for example, showed SBT catch on some trips in other tuna-targeted fisheries, but only a very small proportion is reported to the CCSBT. There may also be bycatch of SBT in pelagic longline fisheries in the south Atlantic. In general, the extent to which non-member SBT catches are due to targeted or bycatch fishing is unknown.

In 2015, two separate papers were presented to the ESC20 that provided estimates of non-Member catches of SBT (Chambers and Hoyle, 2015, Hoyle and Chambers, 2015). Each paper applied a different modelling approach (General Linear Models and Random Forest) and used a different subset of data. The methods resulted in different estimates, and both approaches estimated catches that were lower than previously expected. Furthermore, these papers did not consider non-member catches of SBT in the Atlantic Ocean. Following their presentation, the EC stressed the importance of obtaining the best possible estimates of non-member catch, and requested the ESC to pursue further improved estimates of non-member catch.

In 2016, Paper CCSBT-ESC/1609/BGD02 (Rev.1) “Updated estimates of Southern Bluefin Tuna catch by CCSBT Non-Member states” was prepared for the ESC meeting. This presented a number of improvements on the previous work. First, it included data from ICCAT, and therefore was able to estimate SBT non-member catches in the Atlantic. Second, it provided estimates of the “adjusted” member effort. Since zero-catch effort may not be reported to the CCSBT, raw catch rates may be overestimated. To account for this, additional effort was obtained for CCSBT member fleets reporting to the ICCAT, IOTC and WCPFC. For overlapping spatial and temporal strata, effort reported to CCSBT and non-CCSBT RFMO's was compared, and maximum effort values were taken as an improved representation of the total SBT fishing effort. However, the effort may still be underestimated, depending on the confidentiality restrictions on the non-CCSBT data, which may mean that a complete set of effort data is not provided. Third, the analysis presented two alternate assumptions for prediction of the non-member catches, assuming that SBT were being caught either by targeted fishing or by-catch. Finally, the two alternative modelling approaches were applied to the same data, with the same covariates assumed, and presented alongside.

In considering the information presented in CCSBT-ESC/1609/BGD02 (Rev.1), the ESC noted:

- The analyses provided an improved basis on which to assess the potential for additional catches of SBT to be taken by non-member longline effort.
- The ESC agreed the "adjusted effort" method provided the most appropriate basis available for constructing plausible scenarios of the potential scale of SBT catches taken by non-member longline effort. It was noted that these analyses are based on effort reported to the tuna RFMOs. Any effort not reported to these RFMOs is not included and, therefore, there is the potential for these to be under-estimates.
- The estimates of potential catches from the two analysis methods (GLM and Random Forest Regression) are similar and the overall trends are the same, even though the analyses use different assumptions.
- One of the most influential factors in the analysis was whether the effort was assumed to be by-catch or targeted. Hence, the ESC agreed to present scenarios for both forms of assumed effort.

The ESC agreed that the scale of the potential catches from non-member effort, particularly for the targeted effort scenario (Average for 2011-14 = 306t), was sufficient to require further attention by the EC.

The objective of the current work is to repeat the analysis presented in CCSBT-ESC/1609/BGD02 (Rev.1), with data updated through to 2017 inclusive. Following advice of the ESC, only results for the adjusted effort scenario are presented. During the analysis, marked changes to the data were noted for the CCSBT, IOTC and WCPFC, which had a noticeable impact on the results compared to previous analyses. In particular, the estimated non-member catch for the Indian and Atlantic Ocean region has increased.

2 Overview of methodology

The data preparation and analyses can be summarized in the following steps:

a) Obtain catch, effort and size data from member and cooperating non-member states reporting to CCSBT by 5° square, year and month, for the Pacific, Indian and Atlantic oceans.

b) Model length data in order to estimate catch weight in tonnes for CCSBT member fleets that report catches in numbers only (i.e. Japanese fleet).

c) Create adjusted CCSBT effort data for Japan (JP), Korea (KR) and Taiwan (TW) that includes unreported, zero-catch effort recorded in the WCPFC, IOTC and ICCAT data bases.

d) Fit statistical models to catch and adjusted effort data for all CCSBT fleets and estimate spatial and temporal covariates contributing to the catch per unit effort.

e) For each ocean, use the model results to predict the non-Member SBT catch per unit effort for spatial (5° square) and temporal (year and month) strata, and based on two alternate assumptions: all non-Member effort has the same catchability as estimated for Japan, and; all non-Member effort has the same catchability as estimated for Taiwan. These fleets represent fisheries in which SBT is largely a target (Japan) or a bycatch species (Taiwan).

f) Obtain longline fishing effort reported to the WCPFC, IOTC and ICCAT by non-Member, non-cooperating states, by 5° grid, year and month.

g) Estimate catch for non-Member states by multiplying inferred catch rates by the effort per strata and summing across strata.

3 Spatial definitions

The CCSBT spatial strata are shown in Figure 1. The spatial definitions for each ocean, used throughout this analysis, are as follows:

	Latitude	Longitude	CCSBT area
Pacific Ocean	20°S to 55°S	150°E to 290°E	4, 5, 6, 7, 12
Indian Ocean	20°S to 55°S	20°E to 150°E	2, 3, 4, 7, 8, 9, 14
Atlantic Ocean	20°S to 55°S	290°E to 20°E	9, 10, 11, 15

These areas are non-overlapping, meaning that each unit of fishing effort can be assigned to only one of the three oceans. The areas of competence for the WCPFC, IOTC and ICCAT largely fit within the Pacific, Indian and Atlantic Ocean definitions given above. However, there is a small area of overlap between the south-eastern edge of the IOTC area, which ends at 150°E, and the south-western edge of the WCPFC area, which ends at 141°E. This area of overlap forms part of CCSBT areas 4 and 7. There is no non-member fishing effort reported to either the WCPFC or the IOTC in this region of overlap. However, the two member states responsible for the majority of effort report differently to the two RFMOs: Australia reports more effort to the WCPFC, whereas Japan reports more to the IOTC. Given the importance of Japanese data in the current analysis we chose to use the IOTC data for this region. Future analyses may benefit from analysing both IOTC and WCPFC combined, which is now possible given the higher WCPFC data resolution (see below).

The latitudinal boundaries were set following inspection of the CCSBT catch data. SBT catches are bounded by latitude from approximately 20°S to 55°S, which was used as a consistent latitudinal boundary across oceans for the analyses. This excludes CCSBT areas 1, 13 and most of area 11. This is particularly important for the Atlantic (area 11) due to overlap with Atlantic Bluefin Tuna at lower latitudes. The spatial distributions of CCSBT catch, effort and catch rate are shown in Figure 3 and Figure 4.

4 Data acquisition and preparation

4.1 Effort data for the Pacific Ocean

Effort data collected by the WCPFC are now submitted directly to CCSBT and were obtained from the CCSBT secretariat for the current analysis. Similar to the member data from CCSBT, data were aggregated by flag, year, month and 5° x 5° grid. The latitude and longitude referenced the mid-point of a 5° x 5° grid square. All records with zero effort or outside of the 5° x 5° grid spatial strata occupied by the CCSBT data were removed. Some effort is reported in days fished, rather than number of hooks. Using estimates of the median hooks per day per state from the CCSBT data, it was possible to impute the effort in hooks for WCPFC data recorded in days. However for the non-member states this difference was negligible and the imputed values were not used further.

In previous analyses, only partial public domain data were available from the WCPFC at a 5° x 5° grid resolution, which was scaled to match the total public domain data available per latitudinal band. Public domain data omit effort from strata fished by fewer than 3 vessels, which affected the former extract more than the latter. Comparison of the current extract with the data used by Edwards et al. (2016a, 2016b) indicated negligible difference in the total effort per latitudinal band. However, differences are apparent when the data are partitioned into the spatial strata used for the current analysis (Figure 20; Appendix A). This indicates that the spatial distribution of data in the public domain data extracted for the previous analysis differs from the more complete data supplied to CCSBT. Overall, this has led to an increase in WCPFC effort within the spatial strata that overlap with effort reported to the CCSBT. The WCPFC effort data are plotted by year and statistical area in Figure 2.

4.2 Effort data for the Indian and Atlantic Oceans

Indian Ocean effort data were obtained from the IOTC website (IOTC, 2019). In cases when an individual vessel can be identified, the data are aggregated prior to release by year, month, grid or flag to preclude such identification. Therefore, no catch and effort data were missing from this dataset.

Atlantic Ocean effort data were obtained from the Task II catch and effort database on the ICCAT website (ICCAT, 2019). For longline, these data are aggregated by flag, year, month and grids (usually 5° x 5°). However, in order to avoid identification of vessel, data aggregations are only reported for a particular stratum if they contain observations from a minimum of three vessels. Unfortunately for this dataset, no information on the total effort was available for scaling, which meant that total reported effort is likely underestimated.

For IOTC and ICCAT data, 5° x 5° grid coordinates indicate the corner closest to 0 latitude and 0 longitude. In this paper, all spatial data are managed at the 5° x 5° grid square level, and all latitudes and longitudes have been converted to indicate the centre of the grid square. Some ICCAT and IOTC data were recorded at higher levels of aggregation. In these few instances, all data were assigned to the 5° x 5° grid square closest to the 0 latitude and 0 longitude.

The IOTC and ICCAT effort data are plotted per year and statistical area in Figure 2. Comparison of the spatial distribution of IOTC effort with that from the previous analysis indicated that more effort was now allocated to higher (more southerly) latitudes, probably due to fixing a coding error. This has led to an increase in the IOTC effort in statistical areas 8 and 9 (Figure 23; Appendix A).

4.3 CCSBT catch, effort and size data

Longline catch and effort data for parties reporting to the CCSBT were obtained directly from the secretariat. Data were aggregated by flag, year, month and 5° x 5° grid, with the exception of data from South Africa which was reported at a higher spatial resolution. The following changes to the data should be noted:

- In 2017 South Africa revised its catch and effort data back to 2005 which resulted in a small increase in weight for most years. In addition, it provided all of its effort data, not just where SBT was targeted or caught, which means it now provides substantially more effort data than before. This has resulted in a marked drop in the raw catch rate from South Africa.
- Two Japanese data sets were provided, from the real time monitoring program (JP_RTMP) and adjusted (JP_ADJ) to reflect the total SBT catch for Japan. Total catches were similar, but effort coverage for this latter data set was noticeably higher and this is the one used for downstream analyses. This may be because zero catches are not reported to the JP_RTMP database. Previous analyses (Edwards et al., 2016a, 2016b) used both data sets combined. Restriction to only JP_ADJ led to a drop in the raw Japanese catch rates.
- No Taiwanese effort records were recorded east of 150 degrees in 2017 (i.e. in the Pacific region).
- Unusually high catch rates were occasionally reported to the CCSBT by AU and ZA, ranging from 3 to 12 kilograms per hook. These outliers were removed from the current analysis, amounting to five records from AU between 2015 and 2017, in statistical areas 6 and 7, and two records from ZA in 2010 and 2017 in areas 9 and 7. This greatly improved model fits to the data without impacting catch rates estimates for JP and TW.

Data were prepared by removing those with missing values for year, effort or location. Missing catch data were assumed to be zeros. Values for the retained and discarded catch (in either numbers or weight) were summed to calculate the catch per record. For CCSBT data, the latitude and longitude numbers indicate the north-western corner of a 5° x 5° grid square and were translated to represent the mid-point of each grid. The spatial distribution of the CCSBT catch and effort is shown in Figure 3 and Figure 4.

The overall objective was to predict non-member catches in weight by multiplying non-member effort (in hooks) by predicted catch rates (in weight per hook). These predicted catch rates were estimated using statistical models parameterised with the CCSBT catch and effort data. Catches reported to CCSBT prior to 2007 are known to be unreliable (Polacheck, 2012). Therefore, we used data from 2007 onwards to parameterise the models and to predict non-member catches.

Following the argument given by Hoyle and Chambers (2015), we considered Japanese catch and effort data to be essential for estimating predicted catch rates, because of the spatial and temporal coverage of the Japanese fleet, and their relatively consistent fishing methods. However, all of the Japanese data in the JP_ADJ data set are reported in catch numbers, not weight, which made it necessary to convert the catches in number to catches in weight.

4.3.1 Conversion from catch numbers to weight

To estimate catch weights for the Japanese longline fishery, we needed to estimate the average weight per fish per strata. This was achieved by fitting a statistical model to the Japanese length frequency sampling data held by CCSBT. What follows is a summary of a more detailed methodological description given by Edwards et al. (2016b).

The longline length sampling data held by CCSBT were obtained directly from the CCSBT secretariat for all available years (1965 - 2017). When preparing the data for analysis, length records were replicated according to the ‘adjusted frequency’. This involved randomly sampling the length records with replacement, with a probability proportional to the frequency and with the number of samples thinned due to computational memory constraints. These length data were then converted to weight using the agreed length to processed weight conversion factors (see Table 1; Edwards et al., 2016b). Processed weights were converted to whole weight by adding 15% (Edwards et al., 2016b)

To allow prediction of the average weight per fish per strata, we fitted to the reconstructed weight data using a General Linear Model (GLM), with a Gaussian error distribution and a square root transform to normalise the errors. Predictor variables were the year, month and statistical area:

$$\mathrm{E}\left[\sqrt{w_i}\right] = \beta_0 + \beta_{year} + \beta_{month} + \beta_{area} + \beta_{month,area}$$

where $\mathrm{E}\left[\sqrt{w_i}\right]$ refers to the expected square root transform of the weight per fish, w_i. An interaction term was included between month and area effects.

The above model was fitted using maximum likelihood to two subsets of the CCSBT size sampling data, corresponding to the Pacific Ocean and the Indian and Atlantic Oceans combined. Fits were performed within the R statistical package (v. 3.5.1, R core team, 2018). Residuals were close to normally distributed, and there were no trends in the residual distribution with year, month or area (Appendix C). The model allowed mean weights per fish to be predicted for year, month and statistical area strata. However, there were insufficient data to estimate the interaction term for all month-area combinations. In these instances, the weight was predicted using the orthogonal month and area effects β_{month} and β_{area}. Visual inspection was used to check the realism of the model predictions. In the few instances where they were considered unrealistic, a result of the imbalanced and sometimes sparse nature of the sampling, estimates were copied from adjacent values.

To remove predictive bias introduced by the square root transform, model prediction was performed by sampling the residuals for each strata and adding them to the mean to create a bootstrapped distribution of expected values on the transformed scale. Applying the inverse transform and taking the mean and 90th percentile intervals from this distribution generated the predicted values (Duan, 1983). Predicted weights per month and statistical area are shown in Figure 5.

The model was then used to predict the mean weight for strata containing relatively few empirically measured fish. Specifically, strata with total adjusted size sampling frequencies of at least 100 fish were assigned the empirical mean weight, whilst strata with adjusted frequencies of fewer than 100 fish were assigned a predicted mean weight based on the fitted model.

Predictive ability of the above procedure was checked for flag states that reported catch in both numbers and weight, by multiplying the numbers caught by the modelled or empirically predicted average weight per fish (Figure 6). The relationship between predicted and observed retained weight varied between flags. In the Indian and Atlantic Oceans, the predicted weights were similar to reported weights for Australia and Korea, higher than reported for Taiwan and lower for South Africa. For the Pacific Ocean, the predicted weights were a close match to reported weights for Australia and New Zealand, but underestimated the weights reported by Taiwan. This may be due to the low spatial resolution of the model, since finer scale movement within each statistical area will likely also influence the average weight of the fish caught. The assumed processed weight conversion factor will also differ between flag states. Finally, predicted weights per year, month and strata were plotted over time with the empirical values used to fit the model, and shown to be a reasonable representation (Figure 7).

4.3.2 Adjustment for unreported effort

The reporting of effort by Japan, Taiwan and Korea depends on the spatio-temporal strata in which fishing takes place. If fishing occurs in areas 4 to 9, during months 4 to 9, then all effort and catch is reported to CCSBT. These “core” strata typically account for the majority of the catch. However, if fishing occurs outside of these core strata, then effort is only reported when there is a positive catch of SBT. This means that in the more lightly fished areas and outside of the normal SBT season, catch rates for Japan, Taiwan and Korea may be overestimated because of unreported zero-catch effort.

To adjust the CCSBT effort to account for unreported effort we used the effort reported to the WCPFC, IOTC and ICCAT. For each year, month and grid cell combination outside of the core strata, and for Japan, Korea and Taiwan only, we compared the effort reported to the CCSBT with the effort reported to either the WCPFC, IOTC or ICCAT as appropriate. For each comparison, the maximum effort value was selected. Catches were not adjusted since CCSBT data were assumed to include all SBT catch. Since several countries report SBT catches to the IOTC (including, for example, JP and AU), this assumption could be investigated in future iterations of the work.

Following application of this adjusted effort to estimation of the CCSBT catch rates (Edwards et al., 2016), it was agreed at ESC21 that this is the more realistic approach for estimating non-member catches. Therefore, only estimates produced using the adjusted catch rates are presented in the current study.

4.4 Summary of changes to data since the last assessment

For CCSBT, the primary data changes have been for JP and ZA. For JP, data from the JP_RTMP were included in the previous assessment but have been removed for this assessment following closer examination of the content. The JP_ADJ database has been retained. Overall, since this contains more effort records, the raw JP catch rate has declined. However, it is apparent that the distribution of catch rates in the JP_RTMP database may have skewed summary estimates of the catch rate towards lower values. The implications are that the mean catch rate (measured as a mean of the catch to effort ratio) has increased, despite underlying changes to the raw data (Appendix B). For ZA, more effort data have been reported, and this has also led to a noticeable decline in the empirical catch rates.

More data are available from the WCPFC, which has led to an increase in non-member effort in all areas (Figure 20; Appendix A). For JP and TW, the effort recorded by the WCPFC has increased (Figure 21). This has implications for use of WCPFC data to adjust the effort reported to the CCSBT by JP and TW. Outside of the core strata, an increase in the WCPFC effort for JP and TW has led to an upwards revision in the adjusted fishing effort (Figure 22), and an associated reduction in the adjusted catch rate recorded by the CCSBT.

Overall, IOTC and ICCAT effort is largely unchanged since the last assessment. However, an error in the spatial allocation of IOTC effort has been corrected, resulting in a southward shift of 5° into statistical areas 8 and 9 (Figure 23). There has therefore been an increase in the proportion of effort allocated to the core fishing strata (Figure 24). This means that less non-core effort is available to adjust the effort reported to the CCSBT by JP, TW and KR. Compared to the previous assessment, there has been a reduction in the adjusted effort (Figure 25). Therefore, despite a reduction in the raw empirical catch rates for JP due to changes in the CCSBT data, the adjusted catch rate has not changed compared to the previous assessment. For KR however, the adjusted catch rate has increased compared to the previous assessment. These differences are examined in more detail in Figure 26 and Figure 27 (Appendix B).

5 Analysis and results

Non-member catches were obtained by first estimating catch rates per stratum from the CCSBT member data, and then multiplying these predicted catch rates by the non-member effort in the same strata. The spatial distribution of the non-member effort obtained from the WCPFC, IOTC and ICCAT has been mapped in Figure 8. This distribution overlaps substantially with the effort reported to the CCSBT (Figure 3 and Figure 4). Any non-member effort that did not overlap spatially with the CCSBT data was discarded, under the assumption that SBT catch in these regions was negligible (since no SBT targeted catch or effort had been recorded).

Since catch and effort data from CCSBT are provided in aggregated form, the observed index for model fitting is a summation of individual catch records within each stratum. For example, for strata *k*, which may represent a unique combination of spatial and temporal covariates, the catch rate index is:

$$y_k = \frac{\sum_i w_{i,k}}{\sum_i n_{i,k}}$$

where $w_{i,k}$ now represents the weight hooked in kilograms, $n_{i,k}$ is the fishing effort in hooks, and the *i* subscript represents the individual fishing events.

Two modelling approaches were applied to predict non-member catches: Generalised Linear Models (GLM) and Random Forest (RF) regression. These models were applied to the same data sets and included the same response and predictor variables to enable a valid comparison of the results from the two modelling approaches. Analyses were conducted separately for Pacific Ocean data and the Indian and Atlantic Oceans combined, using all data between 2007 and 2017 inclusive.

During prediction it was necessary to assume a surrogate flag for non-member fishing fleets. Two alternatives are presented, assuming that non-members fish in a manner similar to either JP or TW.

5.1 Generalised Linear Model

5.1.1 Catch rate estimation

Catch rates in kilograms per hook were estimated using a two-part GLM with covariates that included temporal and spatial changes, plus flag state (Hoyle and Chamber, 2015). As in previous analyses, the probability of zero catch was modelled using a binomial model, whereas the conditional positive catch assumed a Gaussian error distribution. A power transformation of $y_k^{1/5}$ was used to normalize the residuals (Edwards et al., 2016b).

For the binomial model, it is important to represent the seasonal nature of fishing, and therefore a combined year:quarter factor was included. Spatial variation was represented per 5° grid square, defined by the combined lat:lon coordinates of the centre point. Use of combined factor levels rather than an interaction term restricts estimation to factor combinations with data present and therefore increases stability of the model for prediction. A cubic spline *ns()* with 4 degrees of freedom was used to describe the influence of month, treated as a continuous variable. Similarly for hooks with 10 degrees of freedom. The inclusion of effort as a covariate was because records with more effort were expected to be more likely to include a positive catch. We also included a core covariate, to identify whether the effort took place within or outside of the core spatio-temporal strata, and the flag. The binomial model can therefore be written as:

$$\mathrm{E}[\mathrm{logit}(\theta_k)] = \beta_0 + \beta_{year:quarter} + \beta_{core} + \beta_{flag} + \beta_{lat:lon} + ns(month) + ns(hooks)$$

where $\theta_k = P[y_k > 0]$ is the probability of a positive catch.

For the conditional, Gaussian model part:

$$\mathrm{E}\left[y_k^{1/5} | y_k > 0\right] = \beta_0 + \beta_{year:flag} + \beta_{core} + \beta_{lat:lon} + ns(month)$$

In this case, model selection using the AIC showed improved fits to the data from inclusion of a combined year:flag covariate, at the expense of finer temporal resolution. This represents a proxy for a year-space interaction and was necessary to fit recent changes in the catch rates for AU and JP.

All fits were performed using maximum likelihood within the R statistical programming language (v. 3.5.1, R core team 2018).

To estimate non-member catches it is necessary to predict the weight per hook from estimated model coefficients and the associated covariate data. If we write:

$$\mu_k = \mathrm{E}\left[y_k^{1/5} | y_k > 0\right]$$

then using a non-parametric smearing approach to back-transform the model prediction (Duan, 1983), the predicted catch rate per unit of effort is:

$$\mathrm{E}[y_k] = \frac{\sum_{i=1}^{N} \theta_k . (\mu + e_i)^5}{N}$$

where e_i is an error sampled from the residual distribution of the Gaussian model fit, and *N* is a large number, 2000 in this case. Values of μ_k and θ_k for each record where obtained from maximum likelihood fits to the effort adjusted CCSBT data. Because the number of data records used to parameterise the Gaussian model is smaller than the number of data records used for the binomial model, in some cases a particular stratum returned an estimated coefficient for the latter model but not the former. In these cases it was assumed that $E[y_k]$ = 0.

Following model fits to the adjusted catch rates from the Pacific and combined Indian and Atlantic oceans, performance was evaluated from the residual distributions plotted against factor levels (Appendix D), and fits to the empirical data. Standardizations for both Pacific and Indian/Atlantic Ocean CCSBT catch rates fitted the data reasonably well (Figure 9 and Figure 10), but with positively biased residuals for small numbers of hooks in the Indian Ocean (Figure 30; Appendix D).

5.1.2 Catch prediction

Catches were predicted by aggregating the non-member effort data by stratum, predicting the catch rate using the model-based procedure above, and multiplying this expectation by the effort. We checked the estimates by predicting catches for member fleets using the CCSBT input data, and comparing them with reported catches. These are shown in Figure 11. Catch predictions with CCSBT data gave total catch estimates for JP and TW that were close to the observed estimates and without significant bias. Although catches for AU and NZ in recent years are underestimated, this result suggests that the model is acceptable for predicting non-member catch.

Finally, non-member catch was estimated for the Pacific, Indian and Atlantic Oceans, by year and by statistical area, and for each catchability assumption (JP or TW), by multiplying non-member effort by the predicted catch rate per stratum, and summing across strata to produce estimates per year and statistical area (Figure 12 and Figure 13; Table 1 and Table 2). The average spatial distribution of catches is shown in Figure 14.

5.2 Random forest analysis

5.2.1 Catch rate estimation

Catch rates were predicted using the random forest machine learning algorithm, similar to Chambers and Hoyle (2015) and Edwards et al. (2016). Random forest analysis involves fitting an ensemble of regression trees, then averaging the predictions across all trees. The standard random forest algorithm first selects many (e.g. >1000) bootstrap samples from the data, each of which may contain ~60-80% of the original observations depending on different tunings of algorithm (Strobl et al., 2009). Observations that are not selected in each bootstrap sample are referred to as “out-of-bag” observations. A regression tree is then fitted to each bootstrap sample, but only a subset of randomly selected predictor variables are used at each node. The trees are fully grown with no pruning, then each tree is used to predict the out-of-bag observations. The predicted value of an observation is calculated by averaging the out-of-bag predictions for that observation across all trees. The out-of-bag estimates are considered a cross-validation of the accuracy of estimates because they are not used in the fitting of trees. The relative importance of each predictor variable is then determined from the misclassification rate for the out-of-bag observations.

Random forest analysis is a non-parametric modelling approach that has considerable flexibility for handling correlated variables and complex non-linear interactions (Strobl et al., 2009). Therefore, it was not necessary to create single categorical variables for year and quarter (year:qtr), and 5° squares (lat:lon) as was done for the GLM approach. We used the *randomForest* R-package (Liaw and Wiener, 2002) to predict catch rates of SBT. Similar to the random forest model used by Edwards et al. (2016b), we fitted the random forest model to the same predictor variables that were used in the GLM: year, quarter, month, flag, latitude, and longitude, to enable a valid comparison of results between the two modelling approaches. The random forest model can be written as:

$$y_k \sim year + quarter + month + flag + lat + lon$$

We also fitted random forest models with an extra predictor variable specifying whether the catch was inside the core strata, but these models underperform models without this variable.

All of the predictor variables were treated as continuous variables except flag, which was a categorical variable. A sufficiently large number of trees (500) were used to achieve a stable error rate, and different tunings of random forest hyper parameters were tested to find the best fit with minimum out-of-bag error (see tuning tables; Appendix F). We found only marginal differences in results when using different configurations of the hyper parameters. In our analyses, we used the values of the best configuration to tune the random forest models for each effort data and ocean group.

The relative importance of variables varied between oceans, but latitude was most important for all oceans (Figure 33 and Figure 35; Appendix E). Flag and year were important for the Indian and Atlantic Oceans, while flag and month were important for the Pacific Ocean. Fitted random forests models are difficult to interpret comprehensively (Prasad et al., 2006). The partial effects plots (Figure 36 and Figure 37) provide some indication of the effects of individual predictor variables of the model on SBT catch rates in the Pacific and Indian and Atlantic Oceans. The partial effects of year, latitude, month, and flag were similar among oceans. The partial effect of year increased markedly since 2007, which is consistent with various monitoring series for SBT CPUE (Chambers, 2014, Itoh and Takahashi, 2014). Similarly, the partial effect of latitude increased with latitude which is consistent with higher catch rates south of 35°S. The partial effect of month was generally greater during the austral winter and spring, consistent with the period of greater SBT catches. The partial effect of flag indicated that catch rates of SBT by the Taiwanese and EU fleets were different to other fleets.

5.2.2 Catch prediction

Catch predictions derived from the random forest model followed a similar procedure as the GLM approach described above. That is, catches were predicted by multiplying the aggregated non-member effort data by stratum by the predicted catch rates from the random forest model generated by using the randomForest 'predict' function. Predictions were made for the years 2007 to 2017 inclusive, and areas without reported effort by Members were assigned an SBT catch rate of zero. We checked the estimates by predicting catches for member fleets using the adjusted CCSBT effort data, and comparing these predictions with reported catches (Figure 15).

We also used P–P plots (Figure 36 and Figure 37) to assess the fit of the estimated predictive distribution model to the empirical data. For the Indian and Atlantic Oceans model, there is a good fit at both extremes as well as in the centre of the distribution, although there are values below the 45° reference line in the upper right hand tail indicating that the model is more conservative than the data in this region. Similarly for the Pacific Ocean, there is also a good fit in both extremes as well as in the centre of the distribution, however there are values both below and above the 45° reference line in the upper right hand.

Catch predictions with CCSBT data produced total catch estimates that were close to the reported estimates and without significant bias, indicating that the model is acceptable for predicting non-Member catch (Figure 15). Finally, non-member catch was predicted for the Pacific, and Indian and Atlantic Oceans, by year and by statistical area, for each catchability assumption (JP or TW), by multiplying non-member effort by the predicted catch rate per stratum, and summing across strata to produce estimates per year and statistical area (Figure 16 and Figure 17; Table 3 and Table 4). The average spatial distribution of catches is shown in Figure 18.

6 Discussion and Conclusions

The estimation approaches applied here generate catch predictions based on the assumption that non-member catch rates match those of members, but targeted effort will catch more SBT than non-targeted effort. The higher Japanese catch rates represent targeted effort, while the lower Taiwanese catch rates represent non-targeted effort. This partitioning of effort types is an approximation, because a number of different fishing and targeting practices occur in the areas of interest. However, the main aim of this study was to identify the approximate plausible range of catches. A more comprehensive exploration of the possible fishing methods and catch rates was beyond the scope of this study.

A key source of uncertainty included in the results concerns unreported effort by some of the CCSBT member vessels, which may have introduced an upward bias in the raw catch rates. A correction, by adjusting the raw effort using effort reported to other RFMOs, was introduced in the previous analysis (Edwards et al., 2016b) and considered by the ESC to provide more realistic estimation of the catch rate. This method has been adopted in the current study. This adjustment may be incomplete, because it does not account for zero-catch effort that may be missing from the effort data reported to CCSBT by Australia and New-Zealand. Furthermore, we are unable to verify whether the unreported effort by Japan, Korea and Taiwan is comparable to the reported effort in terms of the fishing practices employed.

Compared to previous analyses, there have been a number of changes to the raw data. These changes have affected data from the IOTC, WCPFC and CCSBT, which have in turn led to changes in the raw CCSBT catch rates, different levels of effort adjustment using data from the IOTC and WCPFC, and different non-member fishing patterns. Overall, these have combined to produce substantial changes to the estimated catches, particularly in the Indian and Atlantic Oceans, which are higher than previously predicted. Estimates for the Pacific are less noticeably changed, appearing slightly lower than previous analysis. For both the Pacific, and Indian and Atlantic Oceans, catches for the recent period 2015 -2017 have increased substantially, now being almost double that of the earlier 2007-2014 time period (Figure 12, Figure 13, Figure 16 and Figure 17). This is primarily a result of the upwards trends in member catch rates observed for JP, AU and NZ (Figure 9 and Figure 10; catch rates for KR and TW have remained stable).

A comparative summary of the results from the GLM and random forest approach is given in Figure 19. These results were generated independently but used the same data and with the same covariates available for model fitting (although model development in each case led to some small difference in how these covariates were used). Estimates are similar but some differences remain, depending on the catchability assumption and the ocean being considered. Identifying the precise cause of these discrepancies is beyond the scope of this study, and the results are presented here as equally valid alternatives.

There are a number of differences between the random forest and GLM methodologies. The random forest approach is able to better model interactions between effects such as time, area and flag, which can be seen from closer fits to the data (Figure 15). This comes at the cost of less flexible main effects, since the random forest model uses continuous time and spatial terms, while the GLM is fitted with categorical effects that can have a finer resolution. Although fits of the random forest estimates are better, the model is highly parameterised and so we cannot assume better catch estimates for the non-member data. A useful evolution from the GLM approach would be to include a geostatistical model to better represent the spatial effects, and in so doing improve predictive performance (Zhou et al., 2019). This may have the additional benefit of narrowing the difference between the random forest regression and more traditional modelling approaches.

Acknowledgments

The analyses described in this report are based on publicly available data from the Indian Ocean Tuna Commission (IOTC) and the International Commission for the Conservation of Atlantic Tunas (ICCAT). The analyses also use the CCSBT data provided by members and cooperating non-Members, as well as Western and Central Pacific Fisheries Commission (WCPFC) effort data submitted to CCSBT. Thanks to Colin Millar of the CCSBT Secretariat for providing and helping to interpret the CCSBT and WCPFC data.

This work was funded by the Fisheries New Zealand (Project code SEA2018-35), and the Australian Bureau of Agricultural and Resource Economics and Sciences' Fisheries Resources Research Fund.

Figures

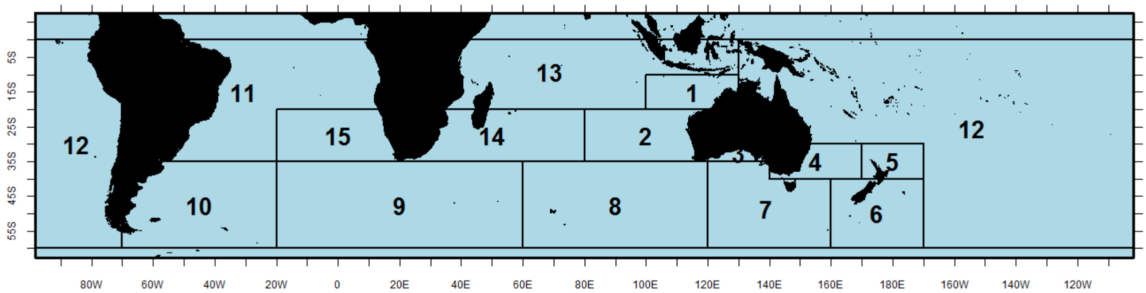


Figure 1. Map showing CCSBT statistical areas. Only areas between 20°S and 55°S are included in the current analysis.

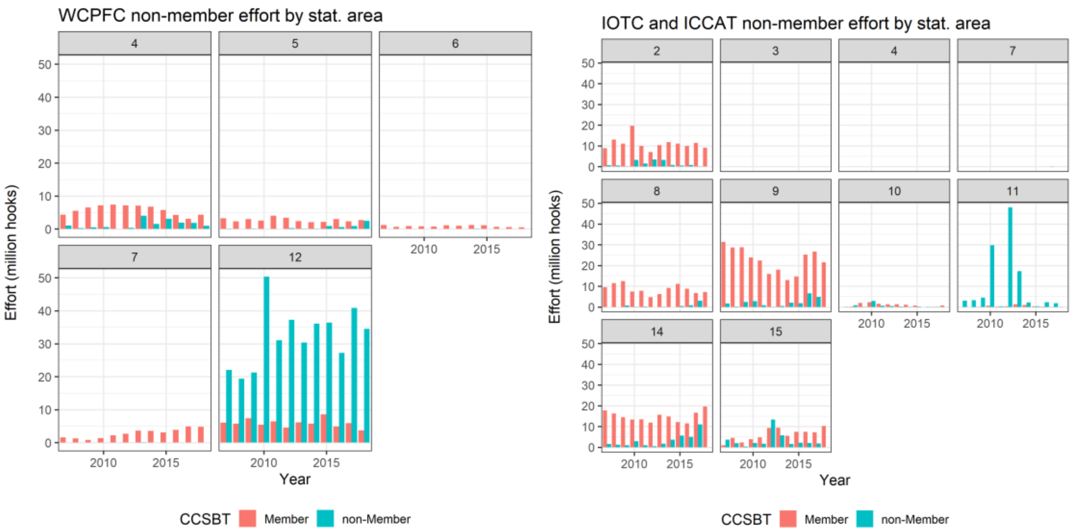
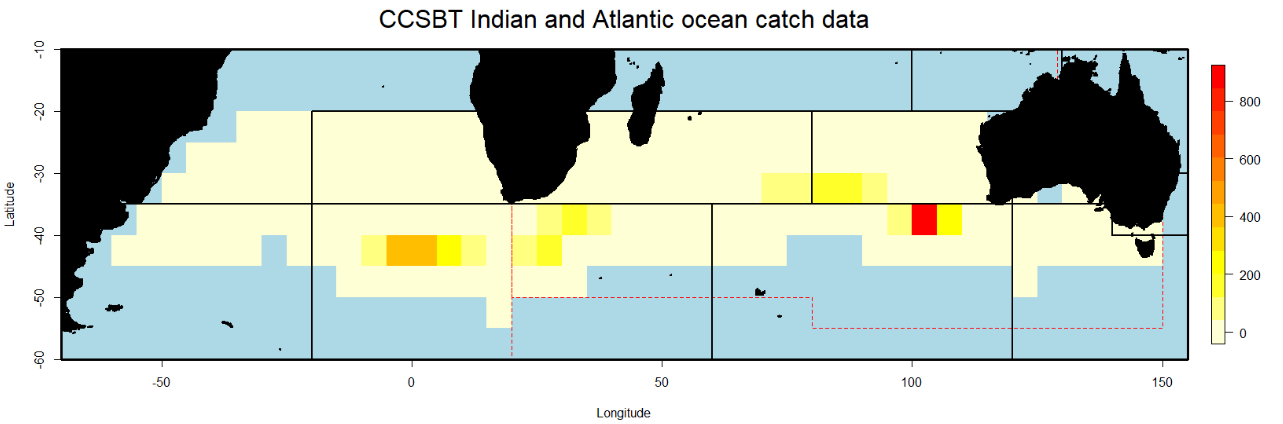


Figure 2. Raw member and non-member effort reported to the IOTC, ICCAT and WCPFC. No non-member effort is reported to the IOTC in statistical areas 3, 4, and 7.



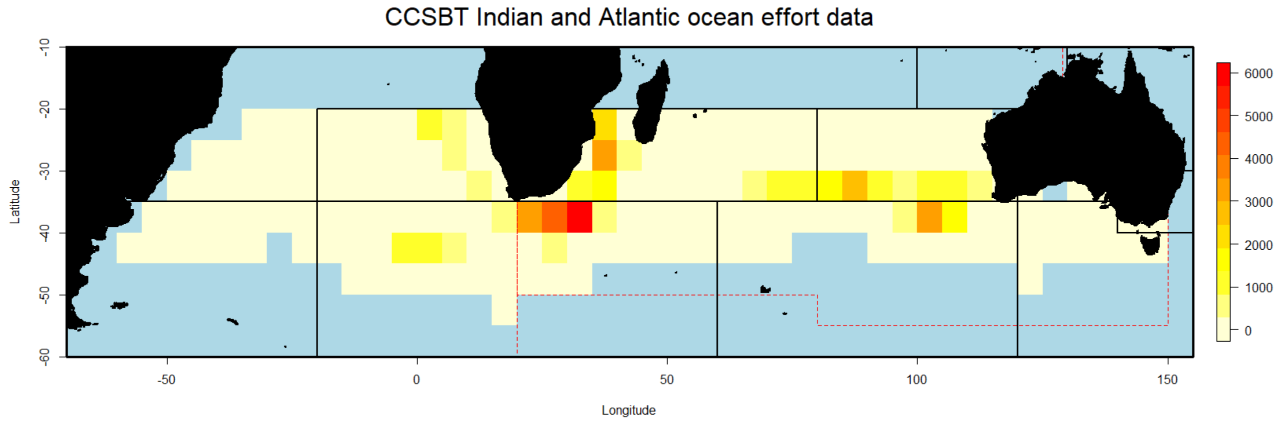


Figure 3. Spatial distributions of the average annual catch (tonnes) and effort (thousands of hooks) in the Atlantic and Indian Oceans reported to CCSBT from 2007 to 2017

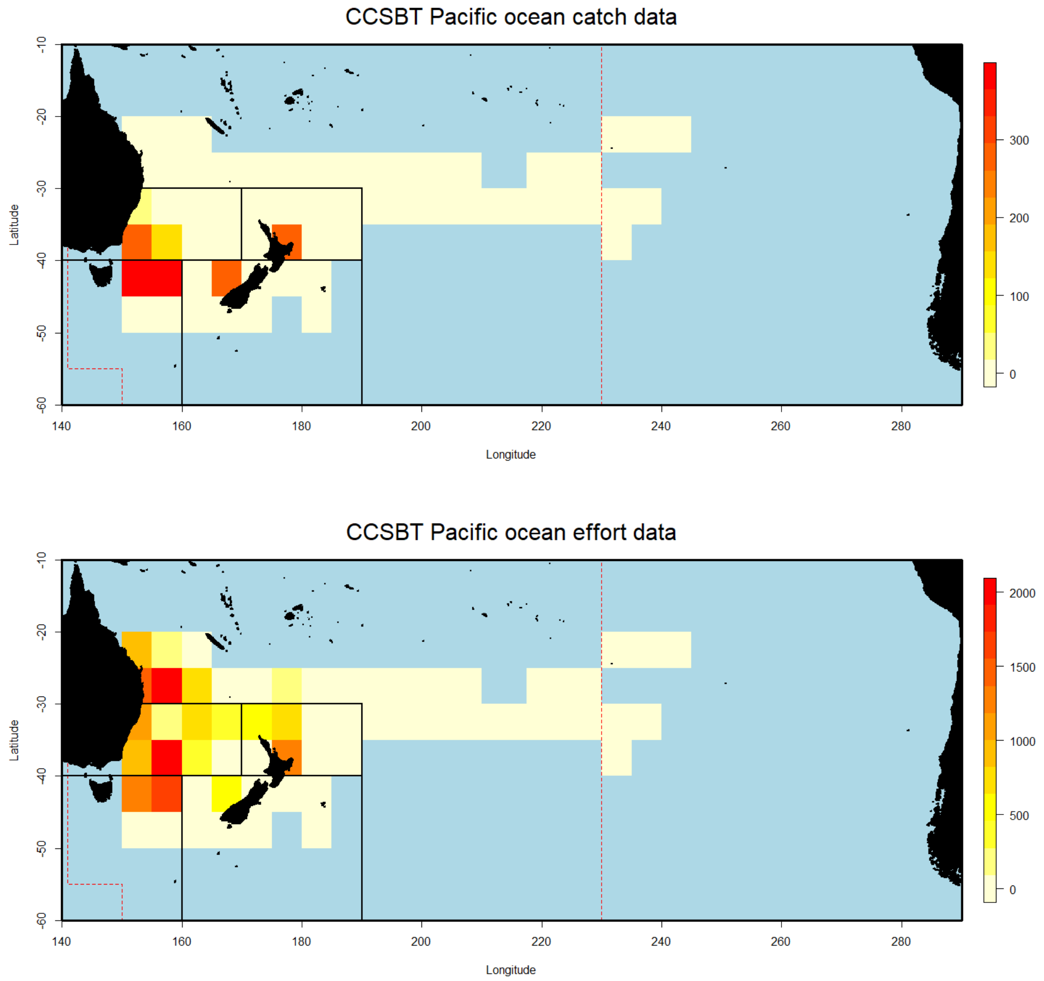
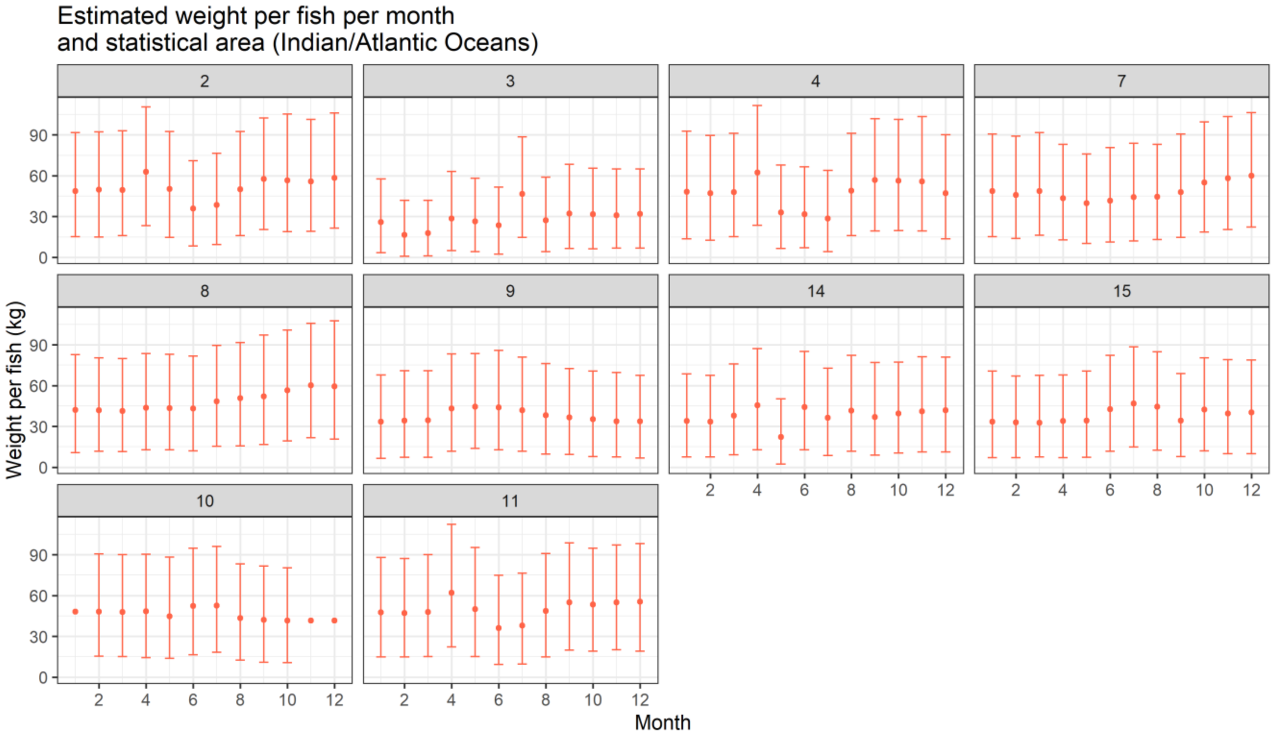


Figure 4. Spatial distributions of the average annual catch (tonnes) and effort (thousands of hooks) in the Pacific Ocean reported to CCSBT from 2007 to 2017



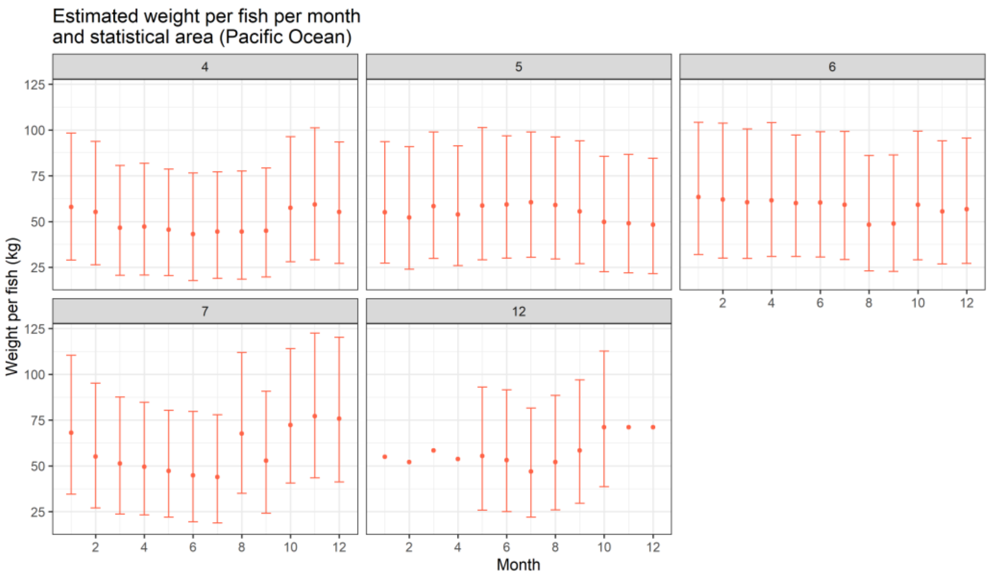


Figure 5. Estimated weight per fish from data reported to the CCSBT. Only a single reference year (1990) is included for clarity of presentation. Mean values with 90th percentile error bars are shown. Error bars are missing for values imputed from adjacent months or areas.

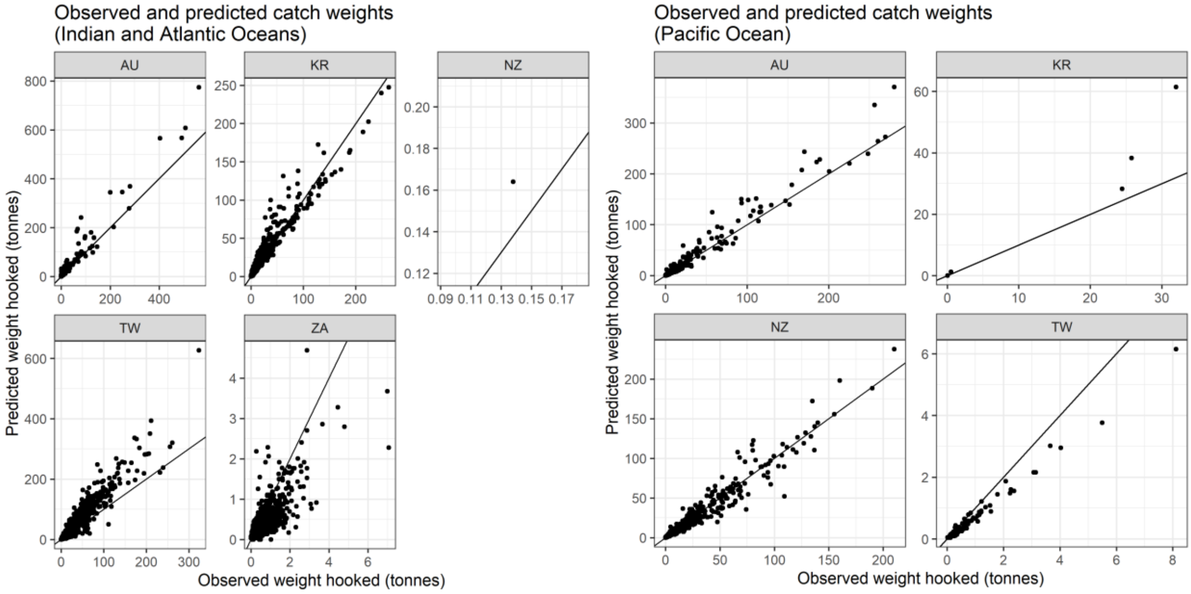


Figure 6. Observed and predicted catch weights for validation of the predictive mode. The line of equivalence is shown to illustrate performance of the model fit.

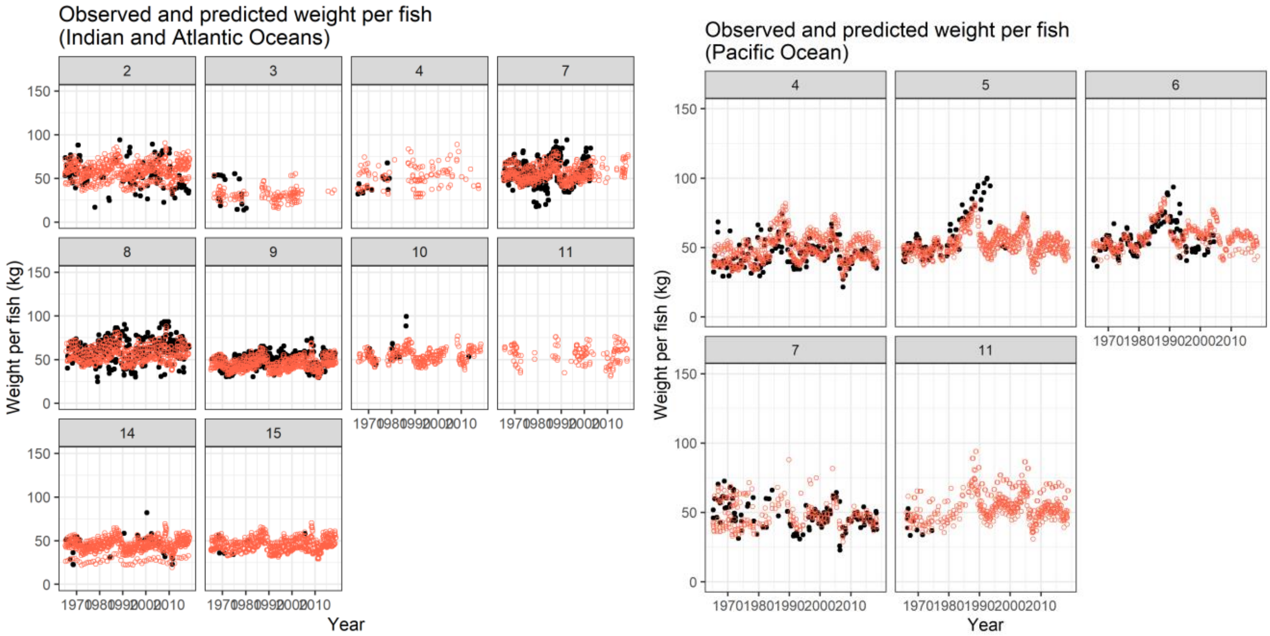
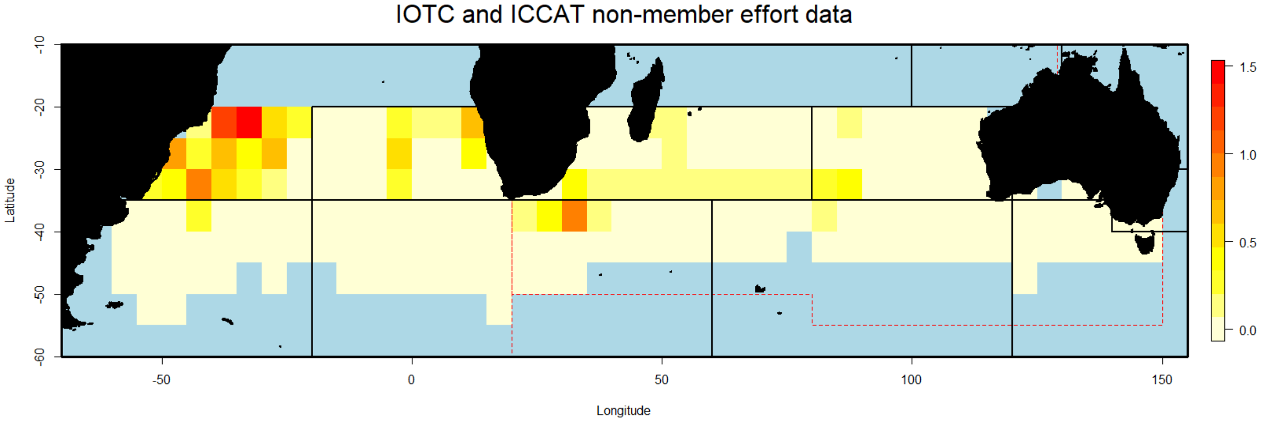


Figure 7. Observed and predicted catch weight per fish over time. Observations are given as black dots; predicted values in red. Only predicted results for fished strata are shown.



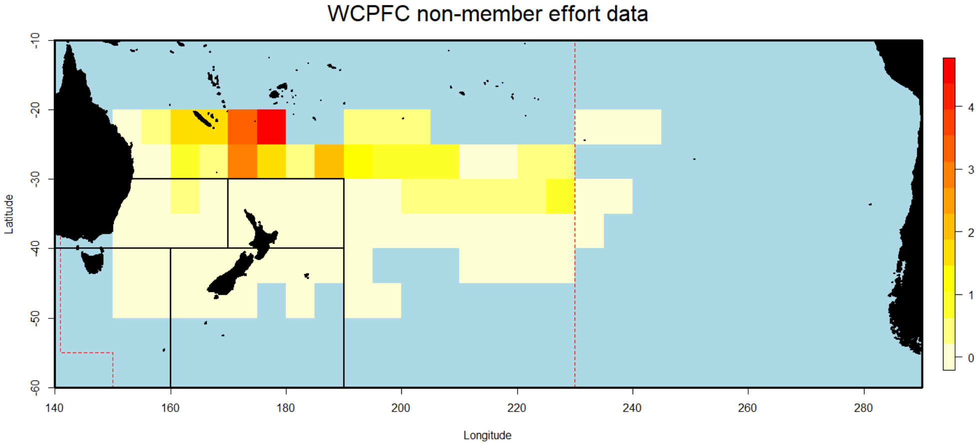


Figure 8. Spatial distributions of average annual non-member effort (in millions of hooks) reported to the IOTC, ICCAT and WCPFC.

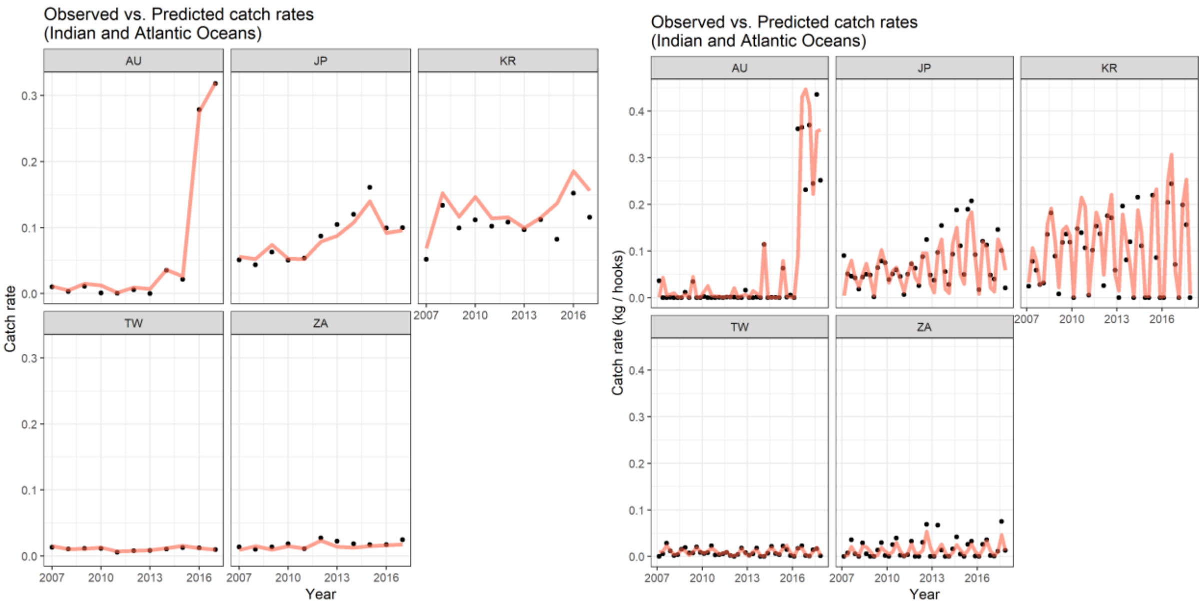


Figure 9. Catch rate GLM fits for the Indian and Atlantic oceans aggregated by year (left) and quarter (right)

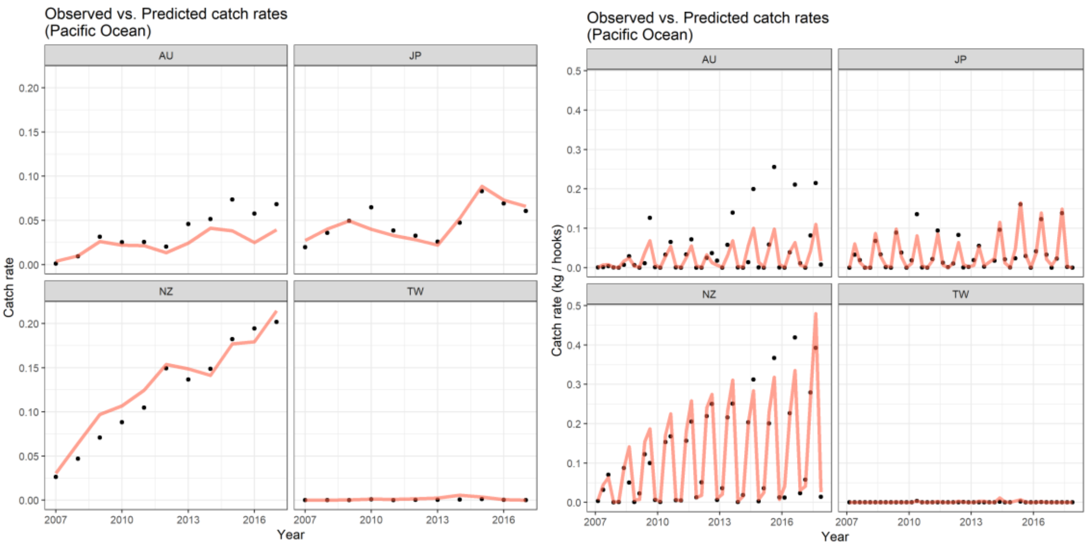


Figure 10. Catch rate GLM fits for the Pacific Ocean aggregated by year (left) and quarter (right)

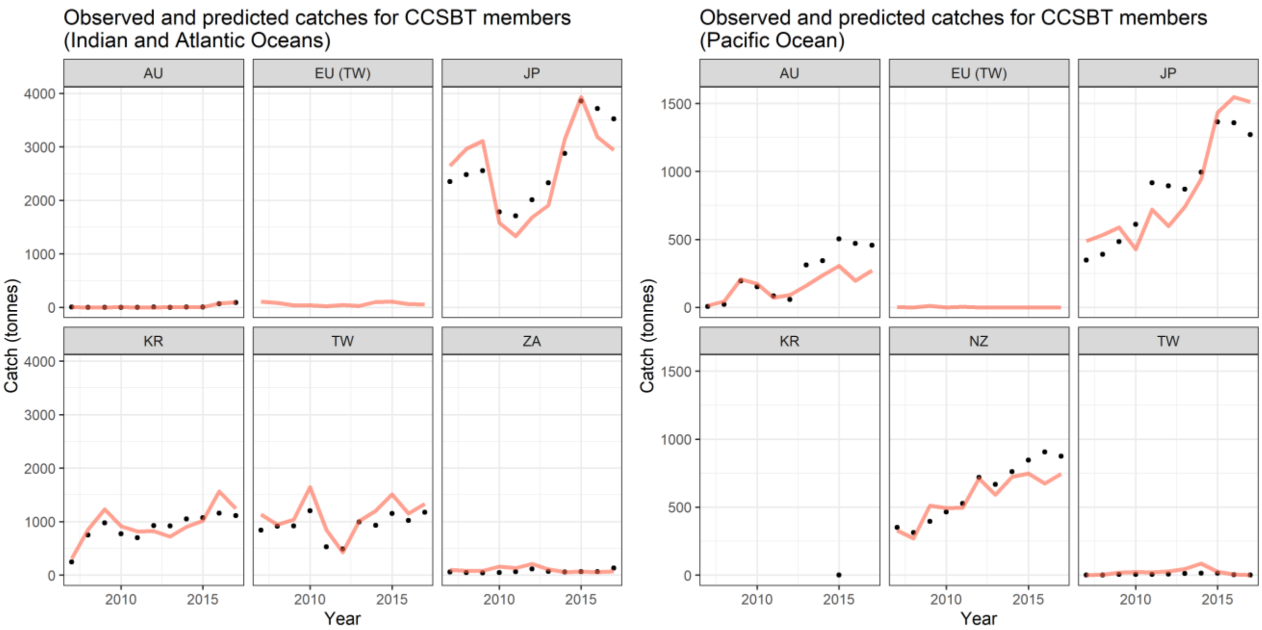


Figure 11. Observed and GLM predicted catches for CCSBT members. EU catches are predicted using effort reported to the CCSBT and assuming a TW surrogate flag. Average annual catches for the Indian/Atlantic and Pacific Oceans are estimated to be 684 and 18 tonnes.

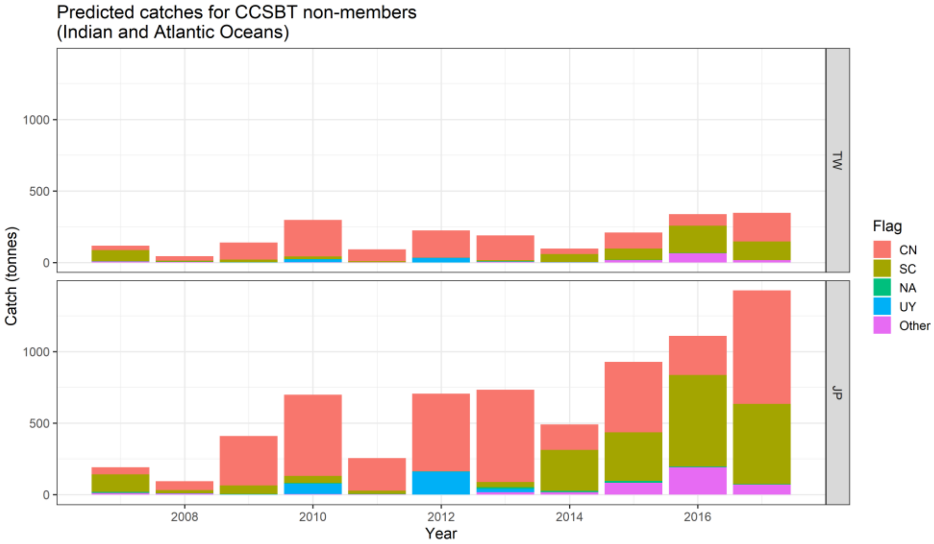


Figure 12. Predicted GLM non-member catches for the Indian and Atlantic Oceans using the adjusted CCSBT effort data and non-member effort obtained from the IOTC and ICCAT. “Other” flag states included MU, BR, BZ, VC, TT, VU, TH, GH, SN, MY. Flag state abbreviations are given in Appendix G.

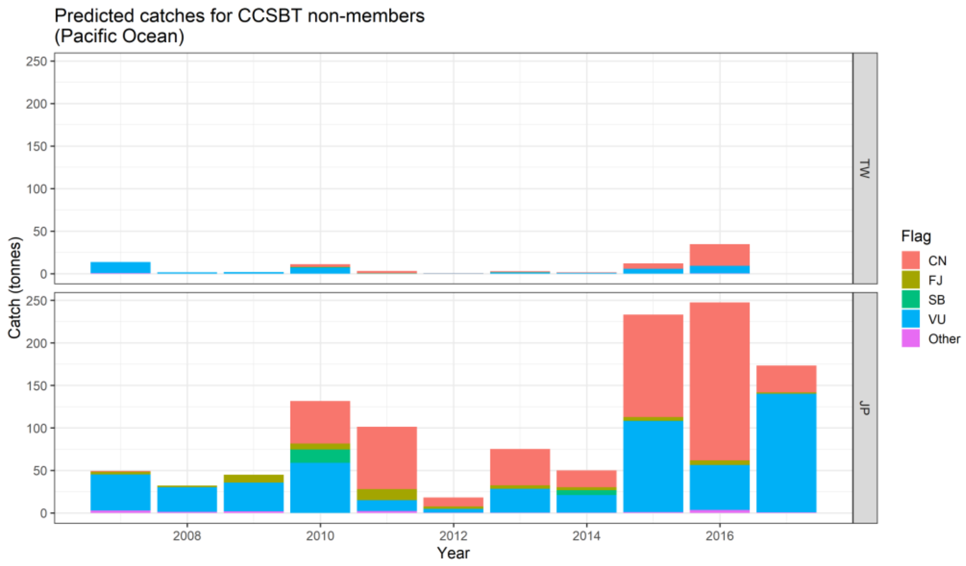
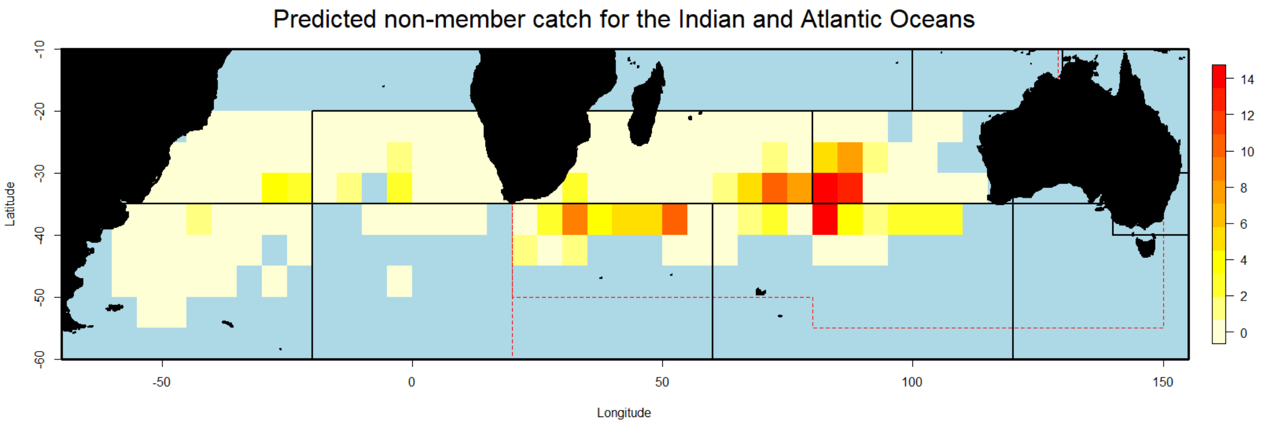


Figure 13. Predicted GLM non-member catches for the Pacific Ocean using the adjusted CCSBT effort data and non-member effort obtained from the WCPFC. "Other" flag states included CK, NC, SN, BZ, TO, NU, PF, US, FM, KI, WS, PG. Flag state abbreviations are given in Appendix G.



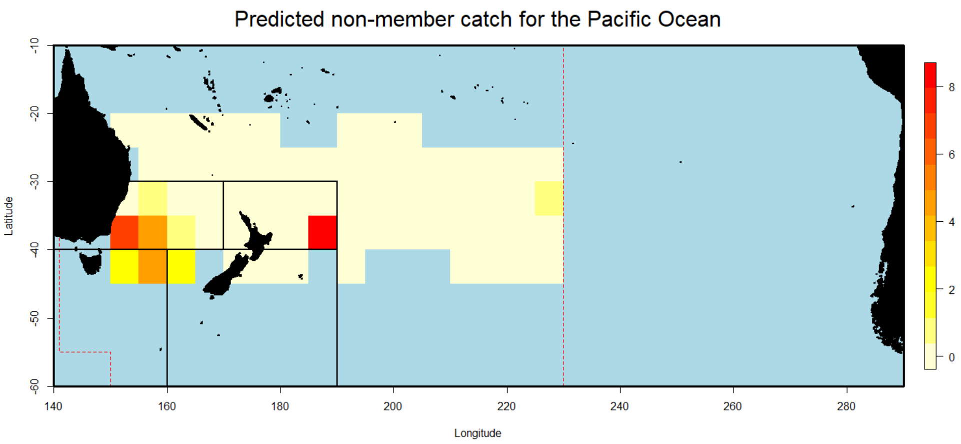


Figure 14. Spatial distributions of predicted GLM non-member catches for the Indian and Atlantic, and Pacific oceans using the adjusted CCSBT effort data and non-member effort obtained from the IOTC, ICCAT and WCPFC. Average catches per year and surrogate flag are shown in tonnes.

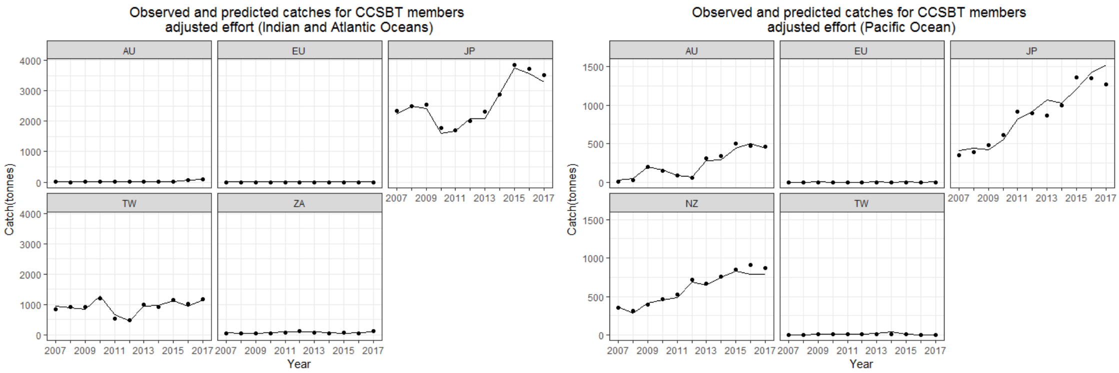


Figure 15 Comparison of observed (circles) and predicted (lines) catches in the Indian and Atlantic, and Pacific Oceans for CCSBT Members, from the random forest models with adjusted effort, based on multiplying the predicted catch rate in kilograms per hook by adjusted effort in the CCSBT data. No observed catch data were available for the EU fleet, and the predictions shown assume TW catchability. Using the random forest model, the average predicted EU catch was less than one tonne in each case (and less than two tonnes assuming JP catchability)

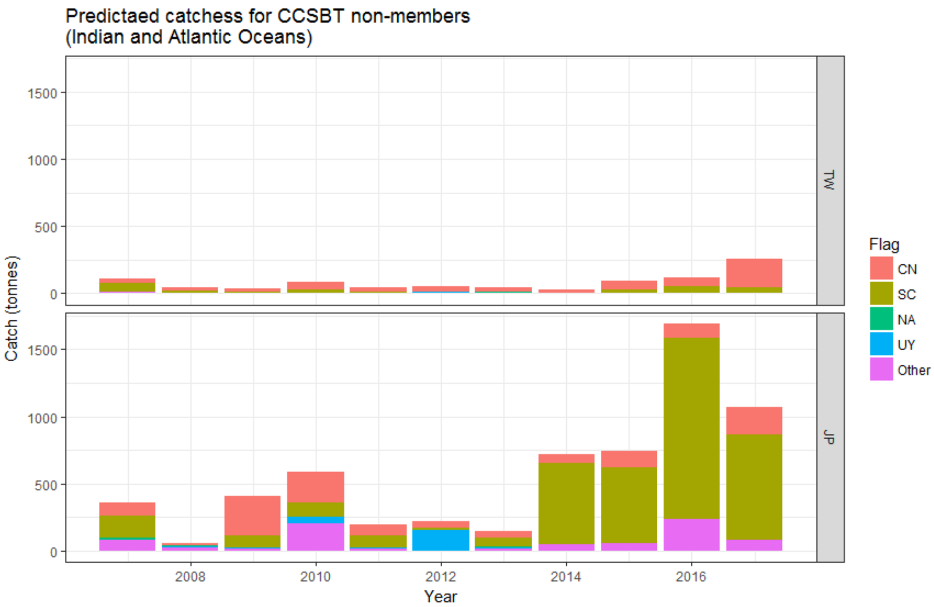


Figure 16. Total catches per year for the Indian and Atlantic Oceans, predicted by the random forest model. Outputs from the alternative flag assumptions are shown, in addition to the effect of using the adjusted or unadjusted CCSBT catch rate.

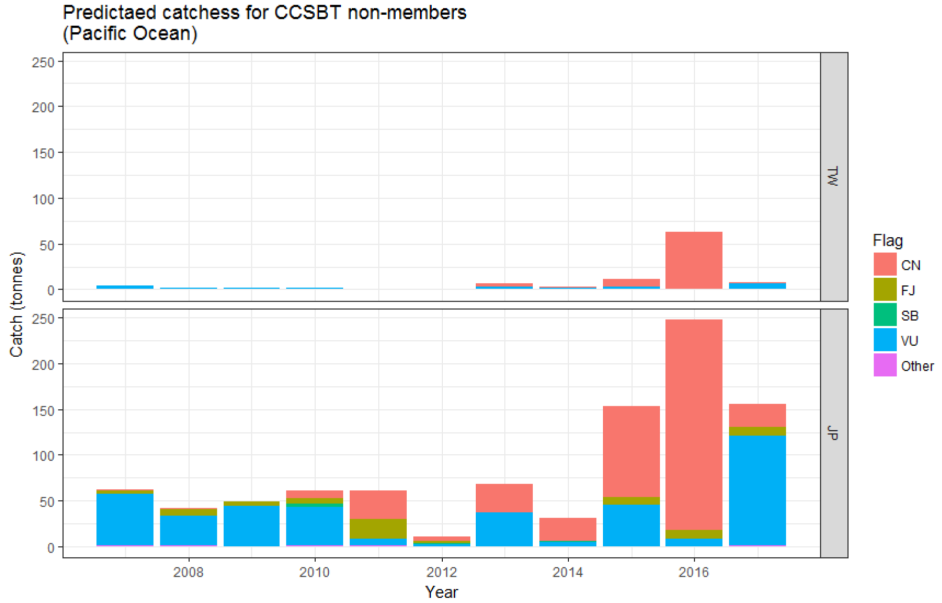
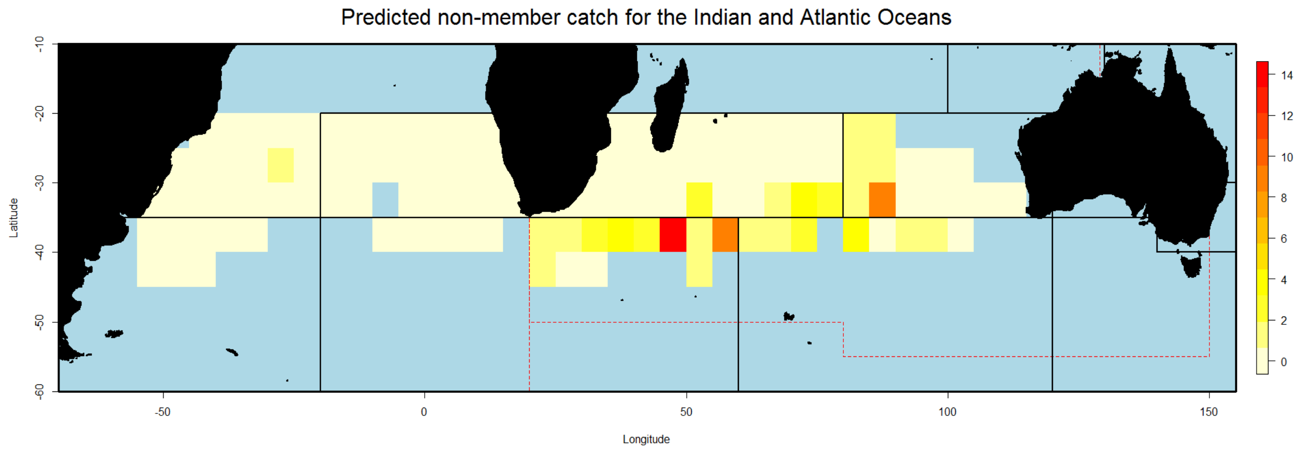


Figure 17. Total catches per year for the Pacific Ocean, predicted by the random forest model. Outputs from the alternative flag assumptions are shown, in addition to the effect of using the adjusted or unadjusted CCSBT catch rate



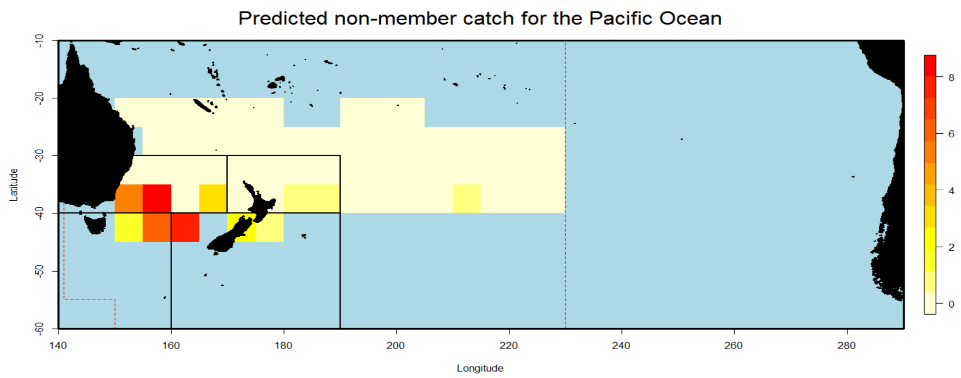


Figure 18. Map of average annual predicted non-Member catch in the Indian and Atlantic, and Pacific Oceans, in tonnes, from the random forest analyses. Results average two alternate assumptions concerning catchability of the non-Member fleet (i.e. assumed JP or TW catchability) and use the adjusted CCSBT catch rate data used to parameterise the model

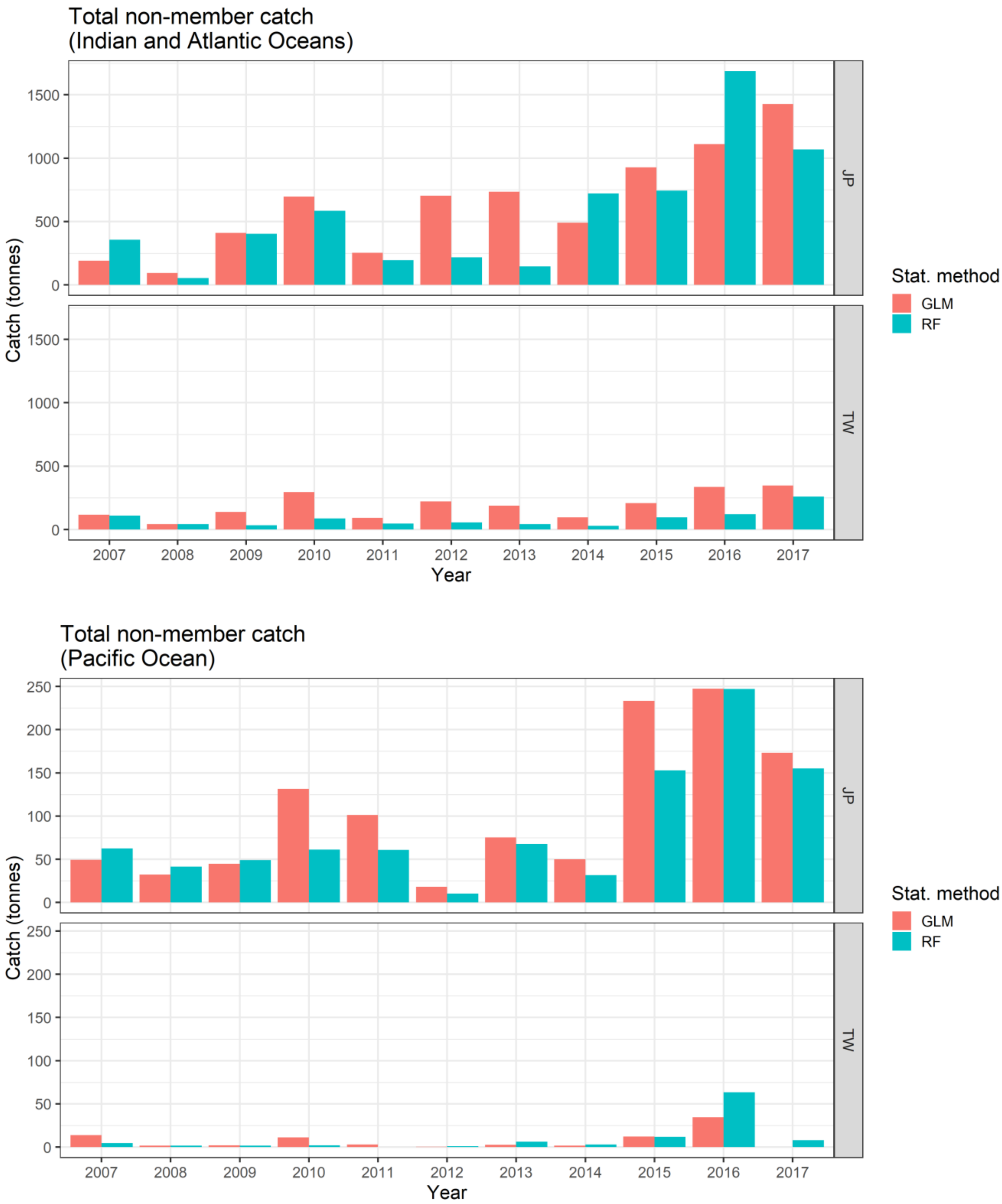


Figure 19. Comparison of total non-member catches using either the GLM or random forest methods, under alternate catch assumptions (JP and TW).

Tables

Table 1 Estimated non-member catches (tonnes) from the GLM for the Indian/Atlantic Oceans, per year and non-member flag state. "Other" flag states included MU, BR, BZ, VC, TT, VU, TH, GH, SN, MY. Flag state abbreviations are given in Appendix G.

Surrogate	Year	Non-Member state					
flag		CN	SC	NA	UY	Other	Total
JP	2007	49.77	123.90	6.29	0.00	11.81	191.77
	2008	63.59	20.58	1.39	0.24	8.05	93.85
	2009	345.73	61.82	0.25	2.43	0.12	410.35
	2010	567.50	50.30	2.42	74.67	2.74	697.64
	2011	226.44	24.99	0.47	0.73	1.97	254.59
	2012	540.48	1.95	1.66	160.62	0.08	704.78
	2013	645.79	37.20	10.71	24.76	15.63	734.09
	2014	179.22	285.89	9.94	0.00	15.88	490.92
	2015	492.96	338.33	14.66	0.00	80.52	926.47
	2016	274.96	639.08	5.41	0.00	190.74	1110.19
	2017	793.98	559.82	4.43	0.00	68.73	1426.97
TW	2007	31.04	76.45	2.80	0.00	6.16	116.46
	2008	29.77	8.74	0.41	0.07	3.85	42.83
	2009	119.52	19.65	0.05	0.41	0.03	139.64
	2010	254.49	19.59	0.62	21.35	0.76	296.81
	2011	83.17	7.64	0.10	0.13	0.49	91.53
	2012	190.54	0.57	0.30	31.21	0.01	222.64
	2013	171.74	8.97	1.56	3.50	2.28	188.04
	2014	37.56	55.35	1.22	0.00	2.00	96.13
	2015	111.73	79.20	1.84	0.00	15.37	208.15
	2016	80.69	190.83	1.03	0.00	64.13	336.68
	2017	201.65	129.71	0.69	0.00	15.49	347.54

Table 2 Estimated non-member catches (tonnes) from the GLM for the Pacific Ocean, per year and non-member flag state. "Other" flag states included CK, NC, SN, BZ, TO, NU, PF, US, FM, KI, WS, PG. Flag state abbreviations are given in Appendix G.

Surrogate flag	Year	Non-Member state CN	FJ	SB	VU	Other	Total
JP	2007	1.10	2.98	0.00	42.59	2.74	49.40
	2008	0.00	1.94	0.00	28.93	1.28	32.15
	2009	0.00	9.36	0.00	33.72	1.78	44.86
	2010	50.14	6.88	15.48	58.94	0.09	131.52
	2011	73.38	13.21	0.00	12.49	2.32	101.38
	2012	10.28	2.90	0.21	4.22	0.43	18.04
	2013	42.84	4.05	0.03	28.03	0.26	75.21
	2014	19.82	3.28	5.82	20.89	0.15	49.96
	2015	120.51	4.45	0.26	107.12	0.89	233.23
	2016	185.65	5.30	0.00	53.04	3.41	247.40
	2017	31.37	1.79	0.00	139.66	0.46	173.27
TW	2007	0.06	0.24	0.00	12.84	0.59	13.73
	2008	0.00	0.03	0.00	1.51	0.01	1.54
	2009	0.00	0.20	0.00	1.65	0.04	1.88
	2010	3.36	0.22	0.74	6.79	0.00	11.11
	2011	2.47	0.31	0.00	0.30	0.03	3.12
	2012	0.28	0.03	0.00	0.06	0.00	0.38
	2013	1.16	0.03	0.00	1.63	0.00	2.82
	2014	0.77	0.03	0.07	0.75	0.00	1.61
	2015	6.48	0.09	0.00	5.51	0.01	12.10
	2016	25.40	0.06	0.00	9.01	0.04	34.51
	2017	0.00	0.00	0.00	0.00	0.00	0.00

Table 3 Predicted catches in tonnes by non-Member fleet from the random forest model for the Indian and Atlantic Oceans, based on alternative assumptions that non-Member catchabilities match those of Taiwan (TW) or Japan (JP), and assuming adjusted CCSBT effort. Flag state abbreviations are given in Appendix G.

Surrogate flag	Year	Non-member state CN	SC	NA	UY	Other	Total
JP	2007	93.29	163.73	14.48	0.00	84.52	356.02
	2008	11.24	6.90	0.43	13.04	23.37	54.97
	2009	288.15	91.10	0.02	6.83	18.30	404.41
	2010	228.34	106.91	0.10	49.69	200.63	585.68
	2011	81.24	88.20	0.18	12.80	12.69	195.11
	2012	48.61	10.20	1.25	153.56	3.29	216.91
	2013	44.51	69.79	9.70	6.20	16.04	146.25
	2014	71.03	599.70	0.16	0.00	50.59	721.47
	2015	123.16	561.66	0.26	0.00	59.27	744.35
	2016	100.80	1348.63	0.30	0.00	236.89	1686.62
	2017	205.77	777.00	0.14	0.00	84.95	1067.85
TW	2007	34.64	61.79	1.58	0.00	12.94	110.96
	2008	21.54	17.52	0.32	0.13	3.44	42.95
	2009	21.21	13.44	0.05	0.12	0.16	34.98
	2010	61.50	19.22	2.16	2.01	1.88	86.76
	2011	37.20	8.60	0.05	0.45	0.34	46.63
	2012	44.54	0.55	0.06	10.21	0.12	55.47
	2013	27.51	5.54	1.51	6.06	1.30	41.92
	2014	23.67	4.02	0.78	0.00	0.80	29.27
	2015	68.45	25.64	0.29	0.00	1.78	96.16
	2016	70.26	45.56	0.38	0.00	4.14	120.34
	2017	217.03	39.25	0.28	0.00	3.77	260.33

Table 4 Predicted catches in tonnes by non-Member fleet from the random forest model for the Pacific, based on alternative assumptions that non-Member catchabilities match those of Taiwan (TW) or Japan (JP), and assuming adjusted CCSBT effort. "Other" flags consist of summed values from CK, NC, PF and TO. Flag state abbreviations are given in Appendix G.

Surrogate	Year	Non-Member flag state					
Flag		CN	FJ	SB	VU	Other	Total
JP	2007	1.42	3.93	0.00	56.14	1.09	62.58
	2008	0.34	7.14	0.00	33.05	0.93	41.46
	2009	0.00	5.32	0.00	43.24	0.52	49.08
	2010	8.81	5.89	4.10	41.67	0.87	61.34
	2011	31.21	20.91	0.00	7.46	1.19	60.77
	2012	4.79	2.30	0.27	2.79	0.12	10.27
	2013	30.07	1.00	0.03	36.37	0.17	67.64
	2014	25.74	0.40	0.52	4.93	0.09	31.67
	2015	98.92	8.25	0.13	45.36	0.20	152.86
	2016	229.39	9.67	0.00	7.88	0.18	247.13
	2017	24.49	9.75	0.00	119.72	1.21	155.18
TW	2007	0.06	0.35	0.00	3.92	0.14	4.48
	2008	0.00	0.24	0.00	1.17	0.13	1.55
	2009	0.00	0.41	0.00	1.12	0.20	1.73
	2010	0.01	0.01	0.01	2.02	0.01	2.06
	2011	0.07	0.01	0.00	0.00	0.01	0.10
	2012	0.47	0.00	0.00	0.33	0.06	0.87
	2013	3.14	0.00	0.00	3.00	0.00	6.15
	2014	1.40	0.00	0.00	1.65	0.02	3.08
	2015	8.47	0.00	0.00	3.32	0.05	11.85
	2016	63.14	0.04	0.00	0.06	0.05	63.29
	2017	0.85	0.25	0.00	6.76	0.03	7.89

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Appendix A: Data revisions

Pacific

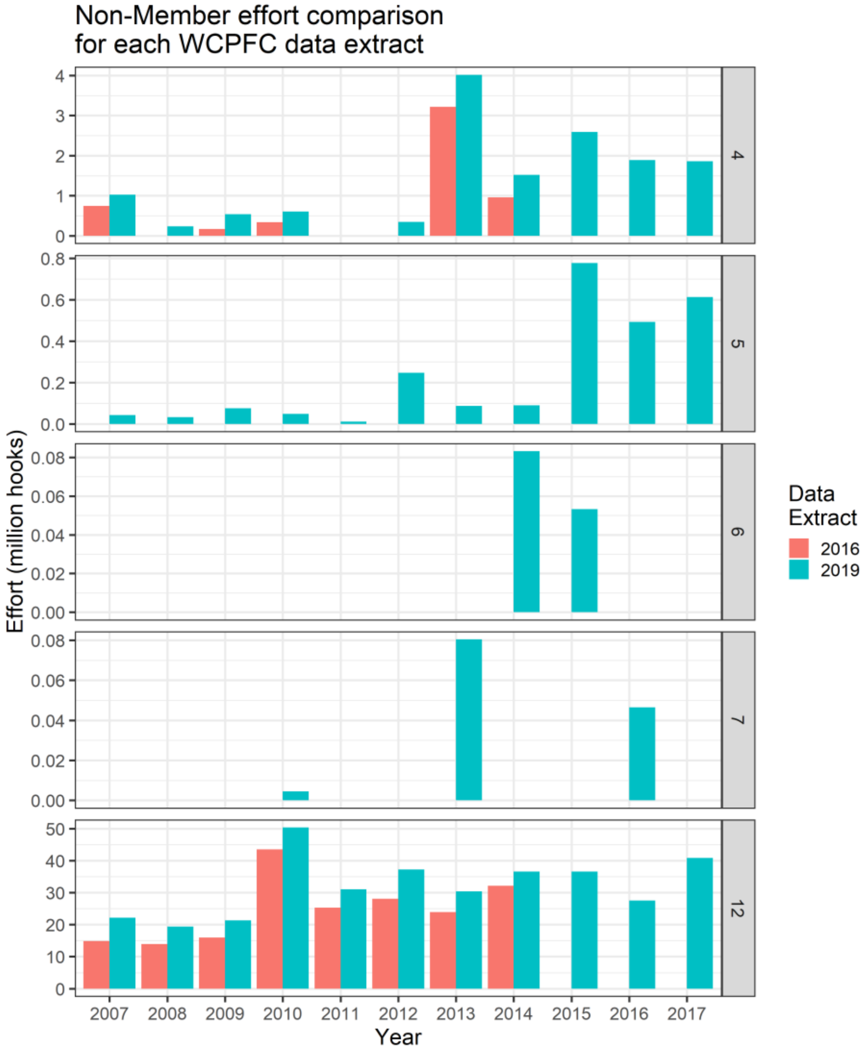


Figure 20. Changes in the effort and the distribution of effort extracted from the WCPFC data, with an increase in the total effort, including statistical areas 5, 6, and 7.

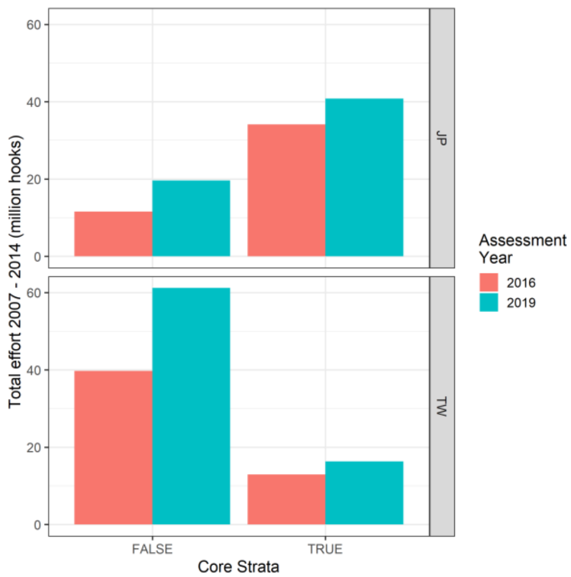


Figure 21. Core strata effort for JP and TW reported to the WCPFC. There has been an increase in the JP and TW effort reported to the WCPFC, compared to the previous analysis.

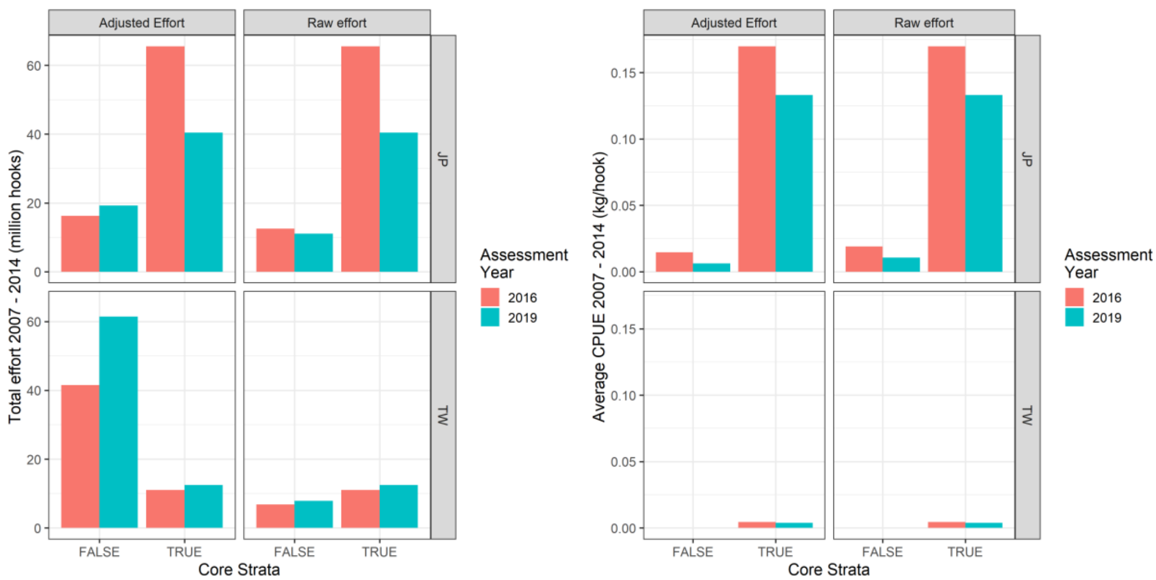


Figure 22. Effort adjustment for CCSBT data, for JP and TW fishing in the Pacific, with associated change in the empirical catch rate. Adjustment of the effort leads to an overall increase, particularly for TW. This is even more pronounced than for the previous assessment year, since the effort available from the WCPFC has also increased (Figure 20). However, the catch rate for TW is small, particularly outside of the core strata. In summary therefore, even though more effort data are available from the WCPFC, the influence on estimates of the adjusted catch rate for JP and TW are small.

Indian and Atlantic Oceans

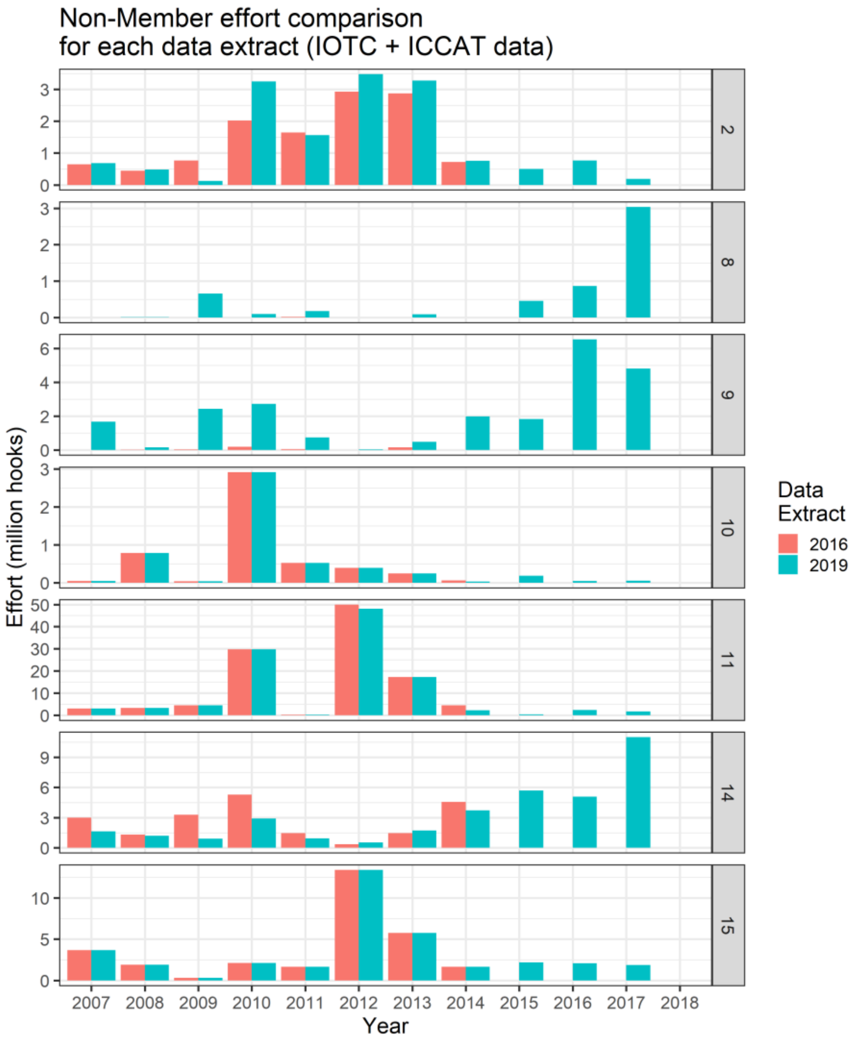


Figure 23. Changes in the distribution of effort extracted from the IOTC and ICCAT data, with a spatial shift south into statistical areas 8 and 9.

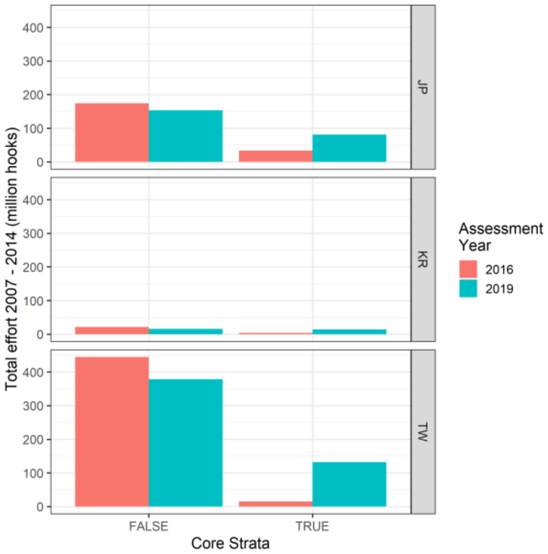
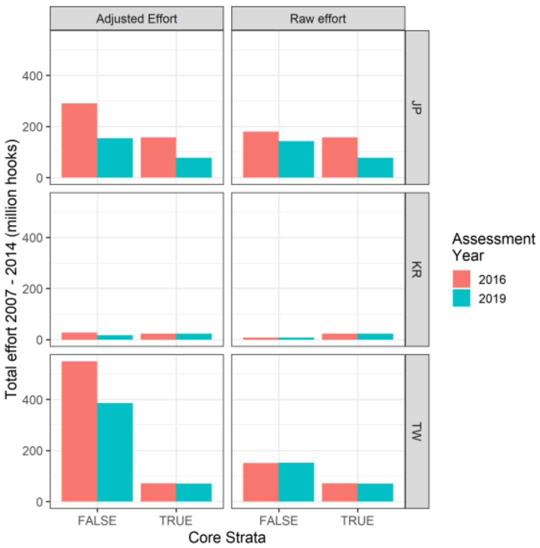


Figure 24. Core strata effort for JP, TW and KR reported to the IOTC/ICCAT. There has been a shift in the effort reported from outside to inside the core strata, compared to the previous analysis.



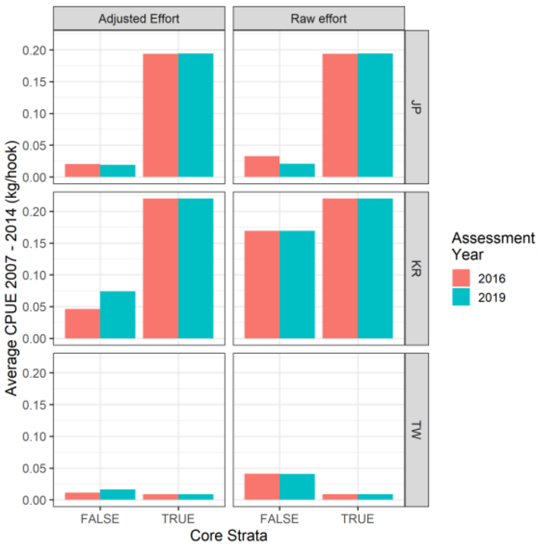
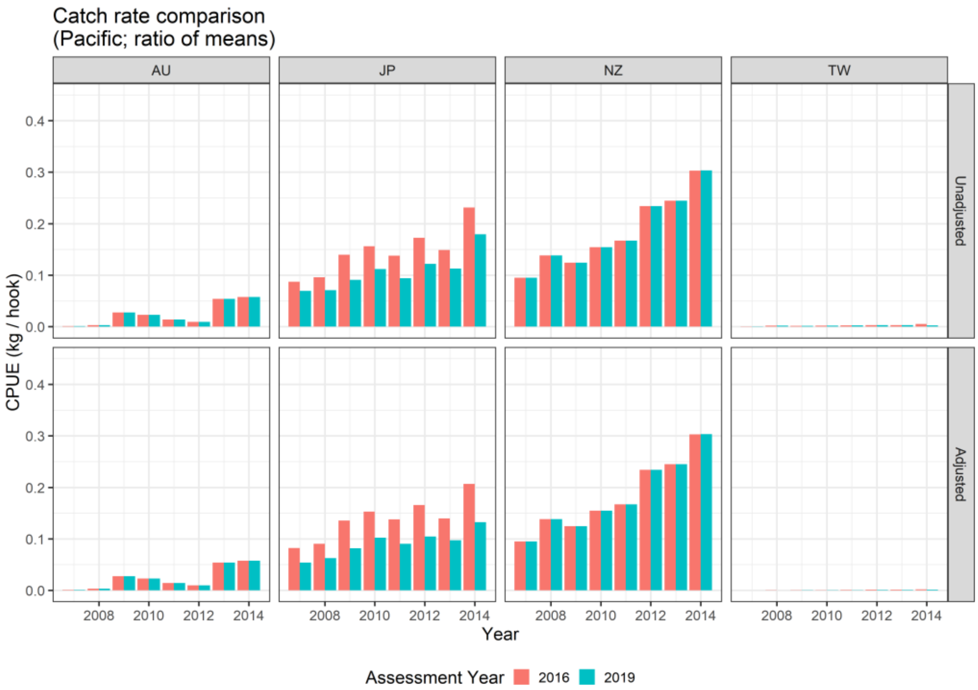
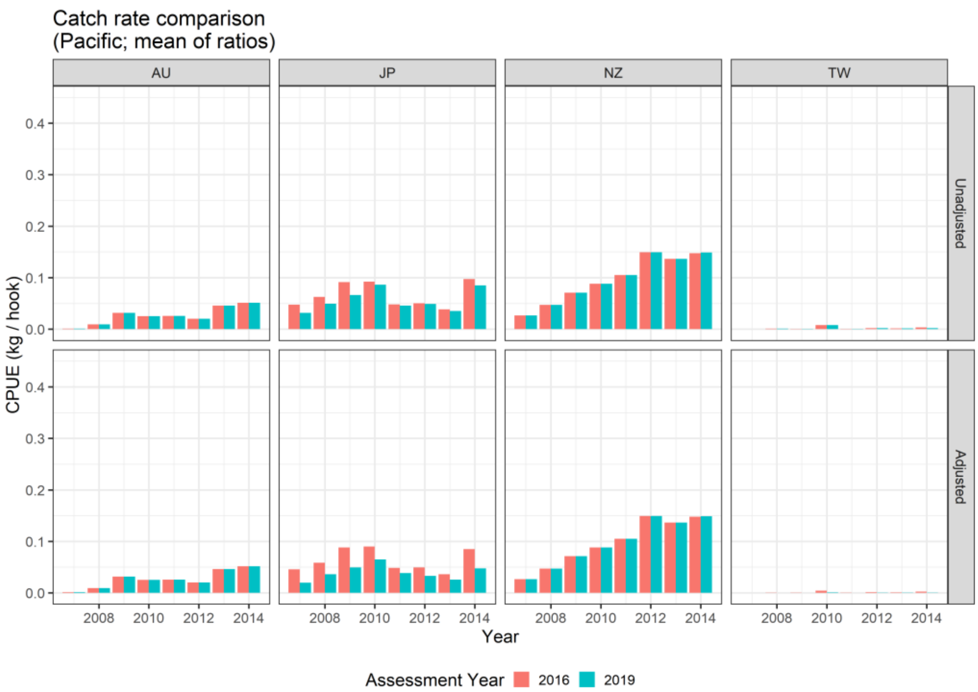


Figure 25.Effort adjustment for CCSBT data, for JP, KR and TW fishing in the Indian and Atlantic Oceans, with associated change in the empirical catch rate. A reallocation of IOTC/ICCAT effort into the core strata has led to a less pronounced adjustment to the CCSBT effort. Therefore the reduction in JP catch rate due to revisions in the CCSBT data extract are less apparent after the CCSBT effort has been adjusted, whereas the adjusted empirical catch rates for KR and TW have increased compared to the previous analysis.

Appendix B: Comparison of catch rates with previous assessment

Pacific





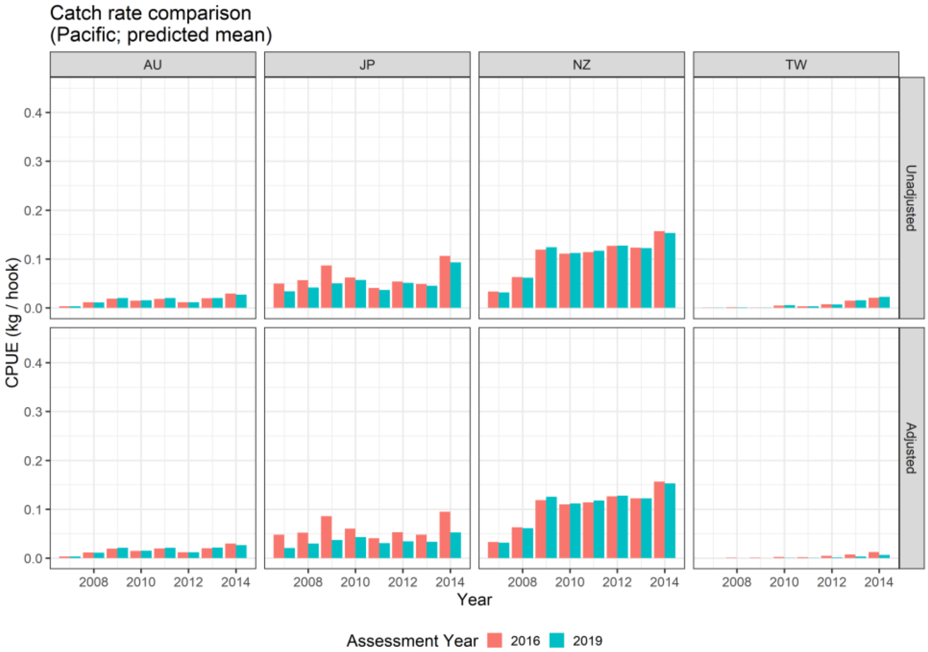
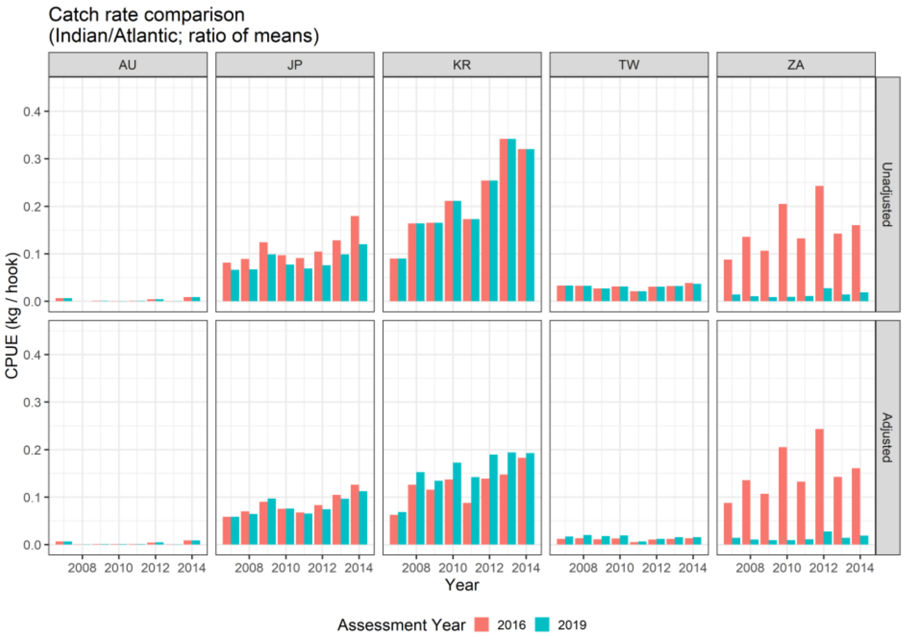
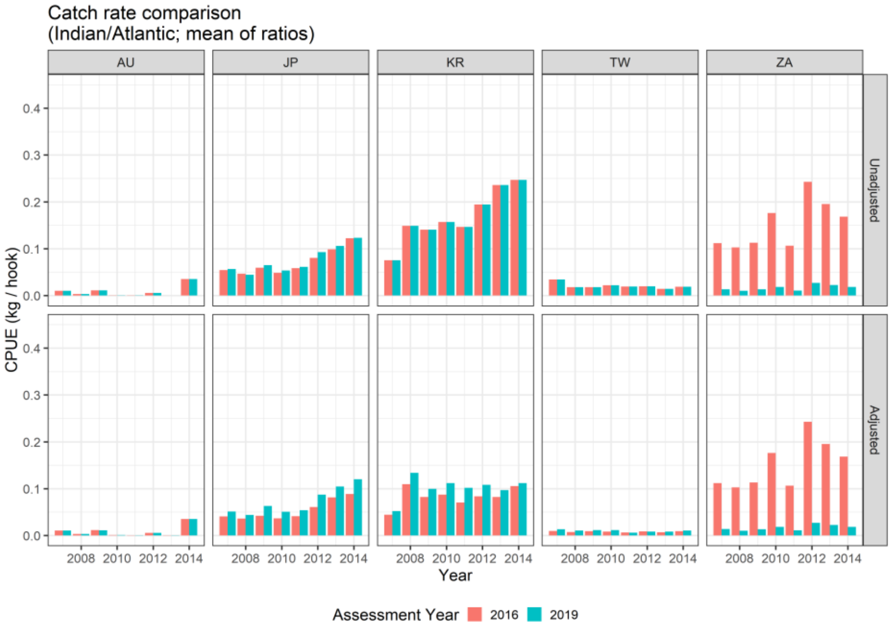


Figure 26.Raw and adjusted CCSBT catch rates for the Pacific Ocean, compared by assessment year. Three catch rate calculations are shown: ratio of means; mean of ratios; and the model predicted mean. Observed differences in the ratio of means reflect changes to the raw JP CCSBT data (leading to lower catch rates). A left skew of the distribution of catch rates is apparent, since the mean of ratios is much lower than the ratio of means. This skew is more pronounced in the previous data extract, since the difference between the two assessment years narrows. Nevertheless, the mean of ratios for the current assessment year is smaller than the previous year's assessment, and this is reflected in the model predicted catch rates.

Indian and Atlantic Oceans





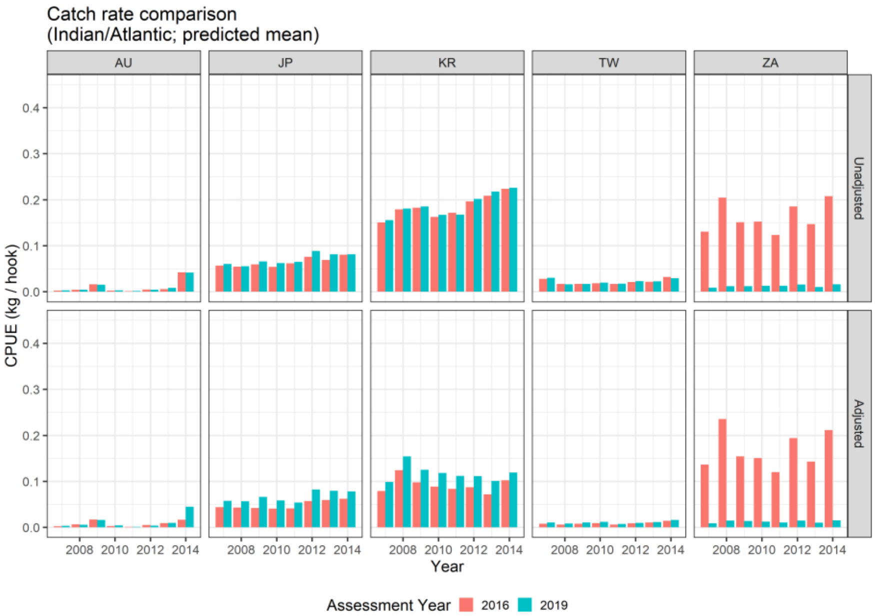


Figure 27. Raw and adjusted CCSBT catch rates for the Indian and Atlantic oceans, compared by assessment year. Three catch rate calculations are shown: ratio of means; mean of ratios; and, the model predicted mean. Observed differences in the ratio of means reflect changes to the raw JP CCSBT data (leading to lower unadjusted catch rates), plus changes in the distribution of the IOTC data, which has led to a less pronounced reduction in the adjusted catch rate. In addition to these changes, the new JP data has a different distribution of catch rates, being less skewed towards smaller values. The mean of the ratios is more sensitive to this left skew, and in the new data therefore this estimator shows an increase in the empirical catch rates compared to the previous year. The model fit to the catch rate data is a prediction of the mean of the ratios and therefore follows this pattern. Overall these combined changes have led to an increase in the predicted catch rates, particularly for the adjusted data.

Appendix C: Diagnostics for predictive model of weight per fish

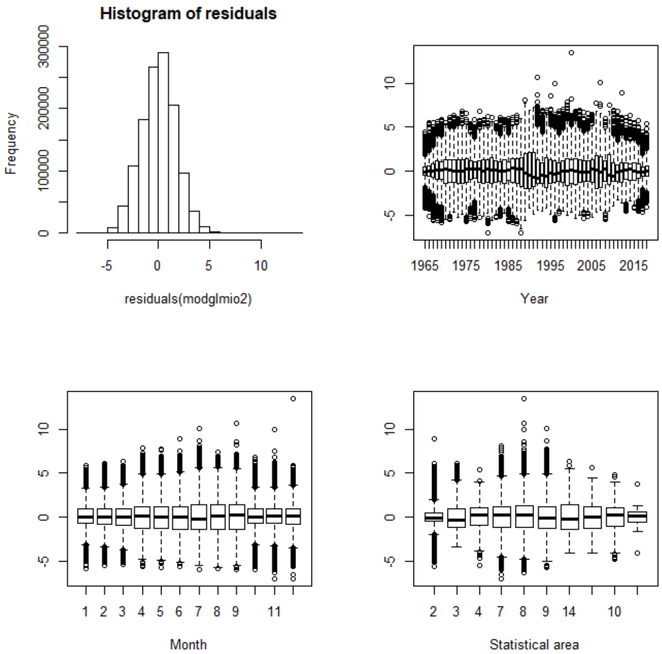


Figure 28. Residual diagnostics for GLM fit to weight per fish for the Indian and Atlantic Oceans

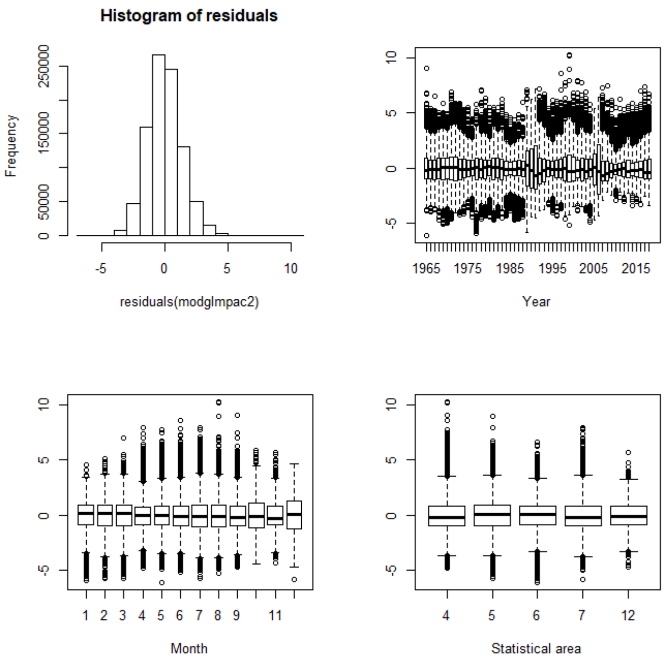


Figure 29. Residual diagnostics for GLM fit to weight per fish for the Pacific Ocean

Appendix D: Diagnostics for GLM model fit to catch rate data

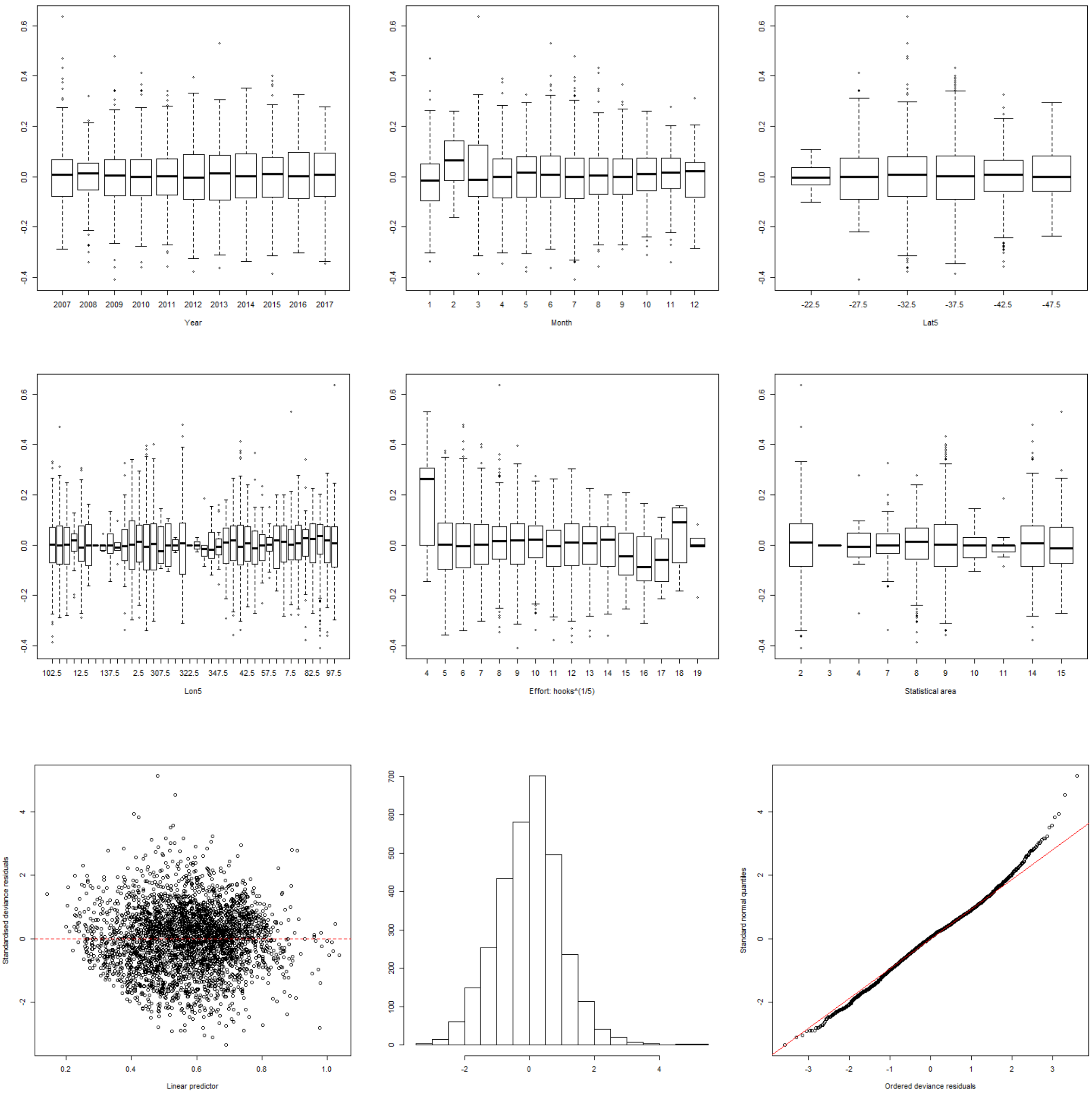


Figure 30. Residual diagnostics for the Indian and Atlantic Oceans positive catch GLM

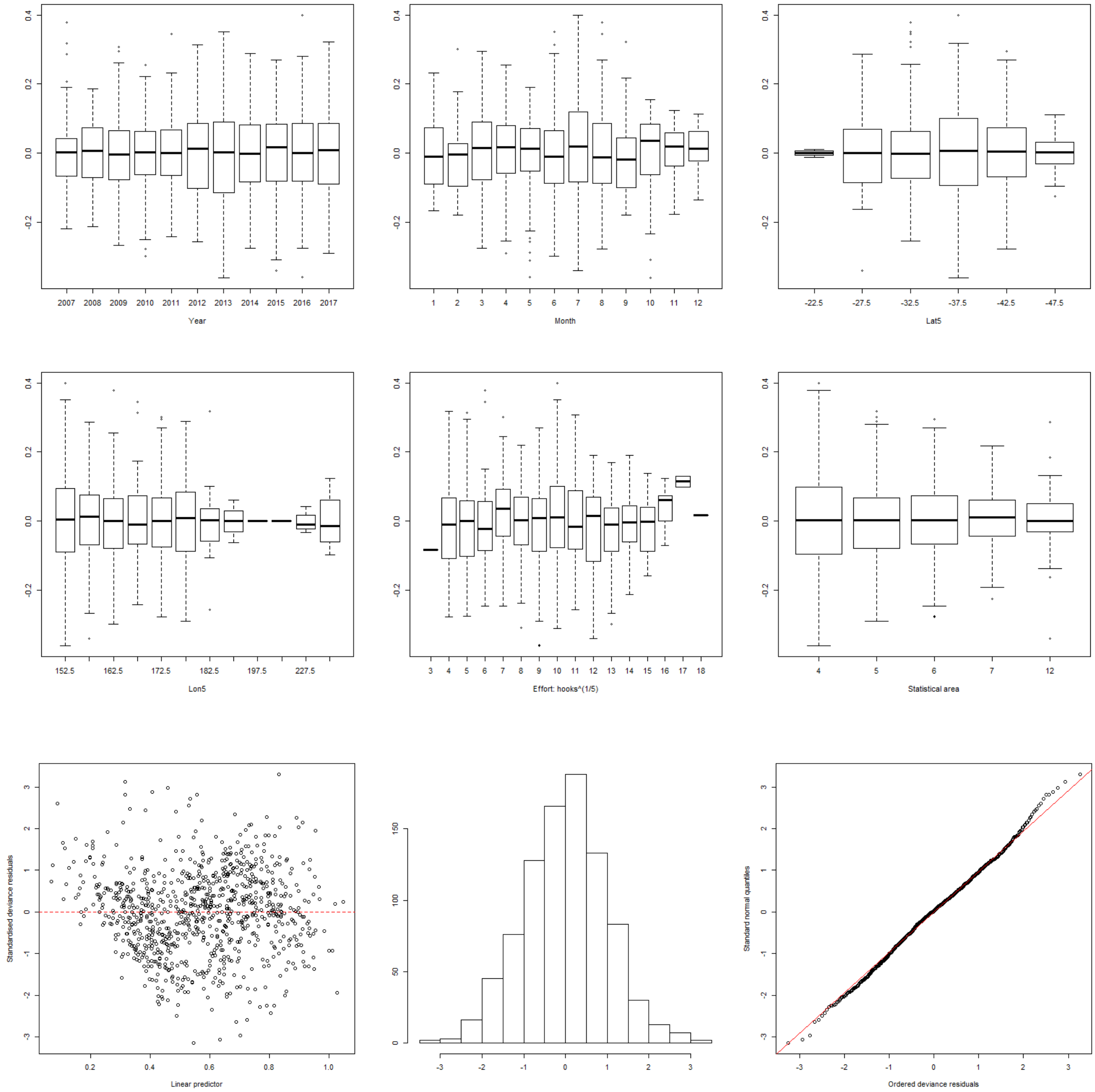


Figure 31. Residual diagnostics for the Pacific Ocean positive catch GLM

Appendix E: Diagnostics for Random Forest model fit to catch rate data

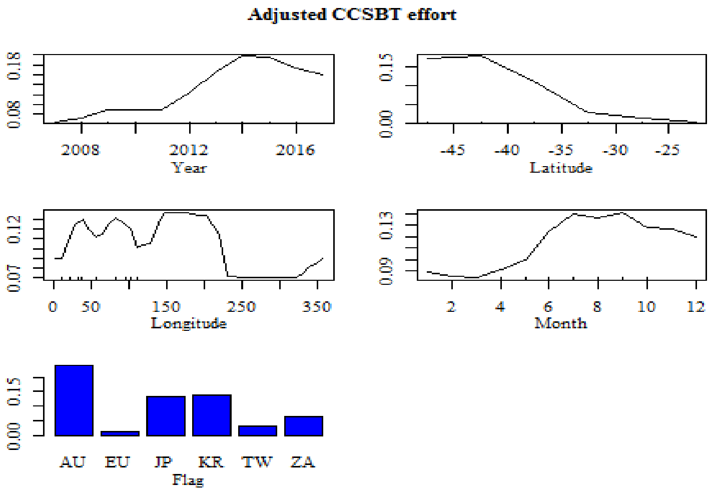


Figure 32: Partial effects of variables in the random forests model for predicting catch rates of SBT in the Indian and Atlantic Oceans.

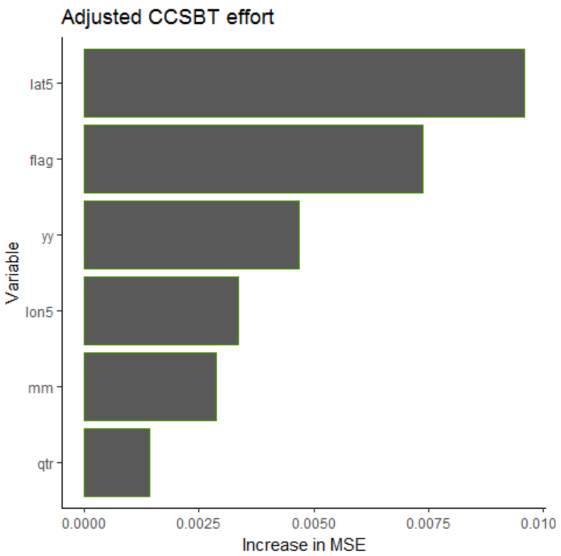


Figure 33 Variable importance for predicting catch rates of SBT using random forests for the Indian and Atlantic Oceans. MSE is the mean squared error.

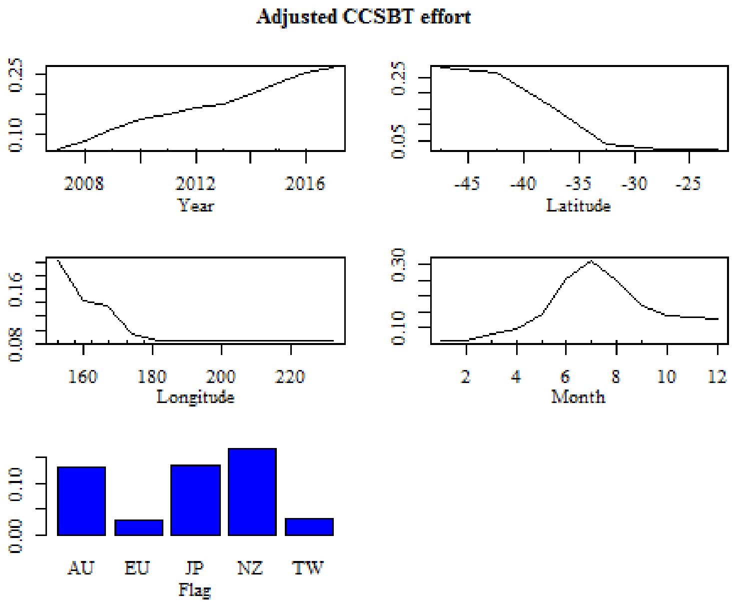


Figure 34 Partial effects of variables in the random forests model for predicting catch rates of SBT in the Pacific Ocean.

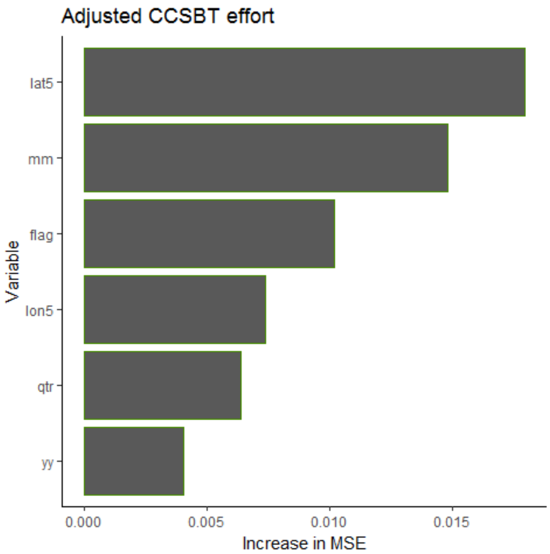


Figure 35 Variable importance for predicting catch rates of SBT using random forests for the Pacific Ocean. MSE is the mean squared error

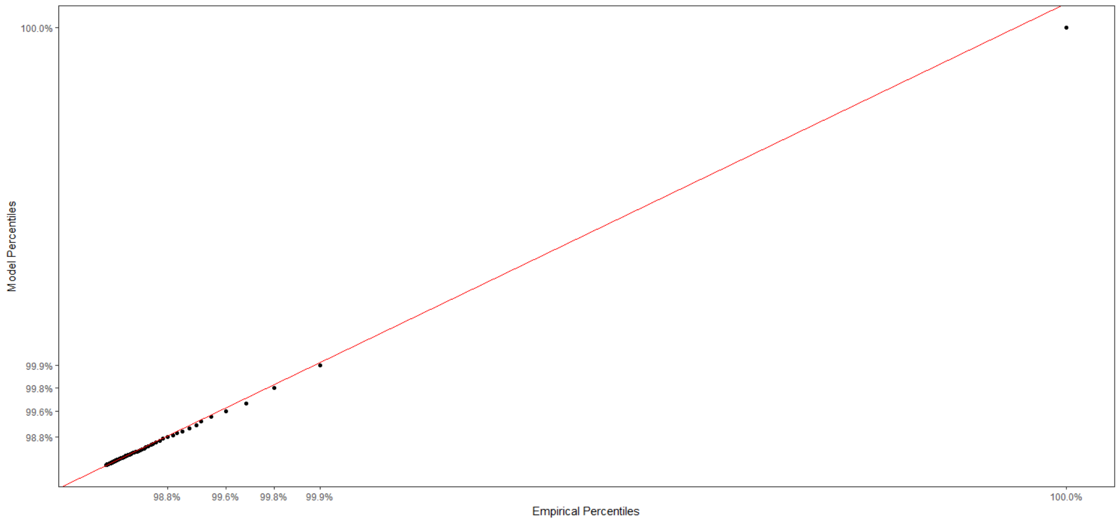


Figure 36 P–P plot of the predictive distribution against the empirical distribution for the Indian and Atlantic oceans

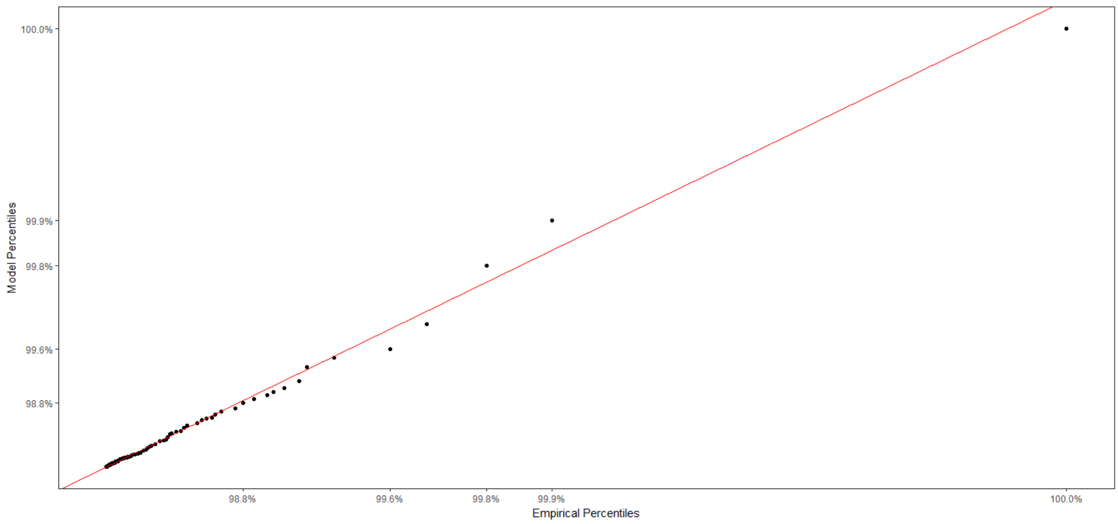


Figure 37 P–P plot of the predictive distribution against the empirical distribution for the Pacific Ocean.

Appendix F: Tuning tables for Random Forest regression

To find the optimal random forest model we perform a large grid search across several hyper parameters of the model. We created a grid and loop through each hyper parameter combination and evaluate the model. We searched across 100 different models with varying the number of variables to randomly sample as candidates at each split (mtry), minimum node size, and sample size. This allows us to consistently sample the same observations for each sample size and make it more clear the impact that each change makes. Our analyses show that the out-of-bags errors for the adjusted effort data are smaller than the error in models with unadjusted effort data. The top 10 performing models all have root mean square error (RMSE) values right around 0.104 (Pacific Unadjusted effort), 0.07 (Pacific adjusted effort), 0.08 (Indian and Atlantic Oceans Unadjusted effort), and 0.07 (Indian and Atlantic Oceans adjusted effort). The results show that models with deeper trees (3-5 observations in a terminal node) and less candidate variables (4-5 variables to sample at each split) perform best.

Table 5 The hyper parameters of top ten random forest models for the PACIFC Ocean and with unadjusted CCSBT effort data

id	mtry	node_size	sample_size	OOB_RMSE
1	4	5	0.70	0.1043222
2	4	5	0.75	0.1044021
3	4	3	0.70	0.1044085
4	3	3	0.70	0.1046143
5	4	3	0.65	0.1046394
6	4	3	0.75	0.1047085
7	5	5	0.75	0.1049101
8	4	5	0.65	0.1049212
9	4	7	0.75	0.1049482
10	3	3	0.80	0.1051182

Table 6 The hyper parameters of top ten random forest models for the PACIFC Ocean and with adjusted CCSBT effort data

id	mtry	node_size	sample_size	OOB_RMSE
1	4	5	0.80	0.0746879
2	4	3	0.70	0.0747407
3	4	3	0.65	0.0748012
4	4	5	0.75	0.0748562
5	4	3	0.75	0.0748584
6	4	5	0.70	0.0748677
7	4	3	0.60	0.0749877
8	4	5	0.65	0.0752098
9	4	7	0.80	0.0752685
10	4	7	0.75	0.0753067

Table 7 The hyper parameters of top ten random forest models for the Indian & Atlantic Oceans and with unadjusted CCSBT effort data

id	mtry	node_size	sample_size	OOB_RMSE
1	4	3	0.60	0.0848851
2	4	3	0.65	0.0849094
3	4	3	0.70	0.0849282
4	4	3	0.80	0.0850536
5	4	3	0.75	0.0850972
6	4	5	0.80	0.0851072
7	3	3	0.80	0.0851168
8	5	3	0.65	0.0851380
9	5	3	0.60	0.0852342
10	4	5	0.65	0.0852482

Table 8 The hyper parameters of top ten random forest models for the Indian & Atlantic Oceans and with adjusted CCSBT effort data

id	mtry	node_size	sample_size	OOB_RMSE
1	4	5	0.80	0.0746879
2	4	3	0.70	0.0747407
3	4	3	0.65	0.0748012
4	4	5	0.75	0.0748562
5	4	3	0.75	0.0748584
6	4	5	0.70	0.0748677
7	4	3	0.60	0.0749877
8	4	5	0.65	0.0752098
9	4	7	0.80	0.0752685
10	4	7	0.75	0.0753067

Appendix G: List of flag state abbreviations

Members and co-operating non-members		Non-cooperating non-members	
AU	Australia	BR	Brazil
EU	European Union	BZ	Belize
JP	Japan	CK	Cook Islands
KR	Korea	CN	China
TW	Taiwan	FJ	Fiji
ZA	South Africa	FM	Federated States of Micronesia
		GH	Ghana
		KI	Kiribati
		MU	Mauritius
		MY	Malaysia
		NA	Namibia
		NC	New Caledonia
		NU	Niue
		PF	French Polynesia
		PG	Papua New Guinea
		SB	Solomon Islands
		SC	Seychelles
		SN	Senegal
		SN	Senegal
		TH	Thailand
		TO	Tonga
		TT	Trinidad and Tobago
		US	United States
		UY	Uruguay
		VC	Saint Vincent and the Grenadines
		VU	Vanuatu
		WS	Samoa