# SPATIO-TEMPORAL MODEL FOR CPUE STANDARDIZATION: APPLICATION TO BLUE SHARK CAUGHT BY JAPANESE TUNA LONGLINE FISHERY FROM 1994 TO 2023

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*SUMMARY*

*Abundance indices of blue shark caught by Japanese tuna-longline fishery in the Indian Ocean were estimated using logbook data from 1994 to 2023. Since the blue sharks in this area are non-target species and frequently discarded, the data was filtered based on the reporting rate of observer data. The nominal CPUEs were standardized using the spatio-temporal generalized linear mixed model (GLMM, sdmTMB) to update the annual changes in the abundances. We focused on spatial and interannual variations of the density in the model to account for spatiotemporal changes in the fishing location due to the target changes of tuna and tuna-like species. The predicted annual CPUEs revealed a gradual increase overall. However, the recent decrease in fishing effort and reduced area and data coverage have widened the confidence intervals significantly since 2019. In 2023, the CPUE values were very high, with a notably wide confidence interval. The predicted CPUE using the spatio-temporal model with a large amount of data collected in the wide area in the Indian Ocean is very useful information about the spatiotemporal changes in the abundance.*

*KEYWORDS*

*Blue shark, Prionace glauca, Japanese tuna longline, CPUE standardization, GLMM, spatio-temporal model*

## 1. Introduction

The blue shark (*Prionace glauca*) is the most abundant pelagic shark species, widely distributed in tropical and warm-temperate oceans worldwide (Compagno 2001; Nakano and Stevens 2008). This species is a major bycatch of Japanese tuna longline fleets operating in the Indian Ocean, through deep-set longline operations targeting bigeye tuna (*Thunnus obesus*) in tropical regions and shallow-set longline operations targeting southern bluefin tuna (*Thunnus maccoyii*) in temperate regions (Semba *et al*. 2015). Although the area and season of operation for the Japanese tuna longline fleet targeting *T. maccoyii* are limited, their operational area in the Indian Ocean generally overlaps with the distribution area of blue sharks, including their main distribution area in temperate waters.

The benchmark stock assessment for the blue sharks was conducted in 2021 using stock synthesis (SS3) model with fishery data for 1950-2019 (IOTC 2021). The model indicated that the stock is currently neither overfished nor subject to overfishing when using maximum sustainable yield as the management reference point.

In the previous benchmark stock assessment in 2021, Japan provided standardized CPUEs (catch per unit effort) of blue shark caught by Japanese tuna longline fishery operating in the Indian Ocean from 1992 to 2019. The annual CPUEs were estimated using generalized linear model (GLM) assuming a negative binomial model (NB) with observer data collected from Japanese commercial tuna longline fishery (Kai and Semba 2020). The model included year, two seasons (April-July and August-December), area, and gear configuration (number of hooks between floats: nhbf) as fixed effect and three interaction terms (i.e. year-area, gear-season, and area-gear). The gear configuration was classified into shallow-set (nhbf < 12) and deep-set (nhbf ≥ 12) in consideration of the

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change in target fish species. The area was separated into two sub-areas based on GLMtree (Ichinokawa and Brodziak 2010). Annual changes in the standardized CPUEs showed that it sharply increased at the end of the 1990s, reaching a peak in 2000, and then gradually decreased with large fluctuations until 2013. Thereafter, the annual CPUEs showed an increasing trend.

In the previous analysis, GLM was used, but GLM cannot adequately account for spatiotemporal effects. Recently, spatiotemporal statistical GLMM models such as INLA (Rue *et al*. 2009), VAST (Thorson 2019), and sdmTMB (Anderson *et al*. 2022) have been used to standardize the CPUE of tuna and tuna-like species. Among these, sdmTMB, which is an R package designed for spatiotemporal modeling using Template Model Builder (TMB), is the newest and has advantages on several aspects such as user-friendly interface and fast estimation.

The objective of this working paper is to estimate the standardized CPUE of blue shark caught by Japanese tuna longline fishery operating in the Indian Ocean from 1994 to 2023 using spatio-temporal GLMM (sdmTMB) in consideration of spatial and temporal changes in the density.

## 2. Materials and Methods

One of the issues with observer data is the low coverage in terms of operation area (**Fig. 1**). Additionally, in 2021 and 2022, observer data was not obtained due to COVID-19. To address these issues, we decided to use logbook data to standardize the CPUE of blue sharks in the Indian Ocean. In the data analysis, using observer data ensures a high rate of reporting for shark catches during the observation period. In contrast, with logbook data, the reporting rate is not necessarily 100% for all vessels due to the issue of discards depending on the fishing strategy of the vessel. Therefore, it is necessary to remove the logbook data that has a low reporting rate of blue sharks based on the actual reporting rate of observer data.

### *2.1 Data sources*

Set-by-set logbook data from Japanese tuna longline fisheries in the Indian Ocean was used to estimate the annual standardized CPUEs of blue sharks in the area for 1994-2023. Data from 1992 and 1993 were not used due to the impact of changes in the format. The logbook data includes information about date of operation, catch number of tuna and tuna-like species and bycatch species such as sharks and billfishes, amount of effort (number of hooks), nhbf as a proxy for gear configuration, location/station/cell (longitude and latitude) of set by resolution of 1 × 1 degree square, and vessel identity (vessel name).

Set-by-set observer data from Japanese tuna longline fisheries in the Indian Ocean was also used to filter the logbook data based on the reporting rate of blue sharks. The observer data includes details of biological information as well as size information, in addition to the same items of logbook data. Reporting rate of blue sharks defined by the following equation:

Reporting rate ＝ total number of operation with positive catch of blue sharks/total number of operation

where this rate was calculated for each cruise and annually.

### *2.2 Data filtering and separation*

The logbook data in the Indian Ocean were filtered to remove records with high ratio of discard and separated into categorical datasets for appropriate analysis.

1. The set-by-set data from the areas other than the Indian Ocean were removed.
2. The set-by-set data in 1992 and 1993 were removed.
3. The set-by-set data were divided into four seasons: Autumn (April-June), Winter (July-September), Spring (October-December), and Summer (January-March).
4. The set-by-set data with the number of hooks between floats (hbf) between 3 and 25 were used to remove unrealistic records on the gear settings.
5. The set-by-set data with a reporting rate of less than 0.589 were removed based on the third quartile of the combined reporting rate over the years (**Fig. 2**).

### *2.3 Catchability covariate*

Except for the effect of station, the nominal CPUEs of blue sharks were largely influenced by year, quarter, vessel, number of hbf, and target change (**Fig. A1**). In the Indian Ocean, Japanese tuna longline fisheries change the target species by altering the operational area, gear configuration, season, etc. (**Fig. A2**). The number of hbf (**Fig. A3**) is commonly used to identify target change through changes in the depth of hook distribution (Bigelow et al. 2006). Cluster analysis based on k-means clustering of observed catch proportions for southern bluefin tuna, yellowfin tuna, bigeye tuna, and albacore (Carvalho et al. 2010; Chang et al. 2011) was also used to identify target species (**Fig. A4**). The issue of multicollinearity was evaluated using correlations among quarters, number of hbf, station, and cluster (**Fig. A5**). Since high correlations were observed among the station (cell), nhbf, and cluster, nhbf was not used in this analysis. Vessel name was treated as a random effect to account for individual differences in vessel catchability.

### *2.4 CPUE standardization with spatio-temporal model*

The sdmTMB model (Anderson *et al*. 2022) can be written as

$$E[y_{s,t}] = \mu_{s,t},$$
$$\mu_{s,t} = f^{-1}(\mathbf{X}_{s,t}\boldsymbol{\beta} + O_{s,t} + \alpha_g + \omega_s + \epsilon_{s,t}), \qquad (1)$$

where $y_{s,t}$ represents the response data (catch number of blue sharks) at station $s$ (knot) and time $t$ (year); $\mu$ represents the mean; $f$ represents a link function (logit or log); $\mathbf{X}$ represents design matrices of main effects; $\boldsymbol{\beta}$ represents a vector of fixed-effect coefficients (year, season, and cluster); $O$ represents an offset (log-transformed number of hooks); $\alpha_g$ represents random intercept by group $g$ (vessel names): $\omega_s$ represents a spatial component (a random field) : $\epsilon_{s,t}$ represents a spatiotemporal component (a random field).

To account for count-data of blue sharks with over-dispersion and high zero catch ratio (**Table 1**), we used four observation models (Poisson model, Negative binomial model, Tweedie model, and Zero-inflated negative binomial model).

The sdmTMB (version sdmTMB_0_6_0) software package for R (Anderson *et al*. 2022) was applied to standardize the nominal CPUE of blue sharks in the Indian Ocean from 1994 to 2023. The annual abundance index relative to the average $\hat{I}$ was estimated as:

$$\hat{I}(t) = \sum_{s=1}^{n_s}(E[y_{s,t}])/\{\sum_{t=1}^{n_t}\sum_{s=1}^{n_s}E[y_{s,t}])\}, \qquad (2)$$

where $n_s$ is total number of knots. One hundred knots were given in consideration of the computational cost and spatial density.

The 95 % confidence intervals were calculated using the standard error estimated from the generalized delta method in TMB.

### *2.5 Model selection and diagnostics*

Model selection was conducted in two stages. First, the four observation models were compared using the full model structure. Next, the optimal model structure was compared by sequentially adding explanatory variables to the simple null model (Model-0). The best model was selected using AIC (Akaike 1973) and BIC (Schwarz 1978) for both stages. If different models were selected based on AIC and BIC, the optimal model was chosen using 10-fold cross-validation (Hastie 2009). The performance of cross-validation was compared using the root mean square error (RMSE) and absolute mean error (AME). For the best model, the goodness of fit was examined using residual plot for each explanatory variable and QQ plot. The residuals were computed using a simulation-based approach to create scaled residuals for GLMM in package R (DHARMa), which uses a randomized quantile (Dunn and Smyth 1996) to produce continuous normal residuals.

## 3. Results

### *3.1 Summary of data filtering and basic annual trends*

The data filtering based on the number of hbf, reporting rate, and operational area reduced the number of records for this analysis from 658,690 sets to 113,766 sets. Annual catch numbers, number of hooks, nominal CPUE, and positive catch ratio for this species before and after data filtering are shown in **Fig. 3**. Annual catches of blue sharks were slightly changed, but the annual trends were almost the same before and after data filtering. The annual catch number was stable from 1994 to 2007, but it increased sharply in 2008-2009. After that, it gradually decreased, showing a slight downward trend since 2016, although the catch number has remained stable. The levels of annual fishing effort, annual nominal CPUE, and annual positive catch ratio significantly changed after data filtering. The annual change in actual fishing effort was stable from around 1994 to 2006, but it decreased sharply from 2007 to 2010. Since then, it has shown a slight downward trend. Due to data filtering, much of the set-by-set data that did not catch blue sharks from 1994 to 2009 was removed. After data filtering, the CPUE and positive catch ratio from 1994 to 2007 increased significantly. The nominal CPUE showed a gradual upward trend from 1994 to 2012, and although it fluctuated thereafter, the level remained stable. As for the positive catch ratio, it has shown a slightly monotonically increasing trend since 1994.

### *3.2 Selection of the best model*

All models reasonably converged with a positive definite Hessian matrix and a small maximum gradient (< 0.001) (**Tables 2, 3**). Zero-inflated negative binomial model was selected by both AIC and BIC as the most parsimonious model for the model selections of first stage (**Table 2**). Then, the best model was selected using cross-validation because the AIC and the BIC chose Model-5 and Model-4, respectively (**Table 3**). Cross-validation finally selected Model-5 that is the saturated model, which includes spatial variance (knots), spatial-temporal variance, variation over vessel effects as random effects, and the effects of cluster and quarter as fixed effects.

The differences in the observation model did not significantly affect the overall trend, but the values for the years 2000, 2003, and 2023 varied greatly due to the assumption of error structure (**Fig. 4**). The predicted CPUE changed substantially when random effect components were sequentially added to the simple model, which had no random effects (Model-0) (**Fig. 4**). The fixed effect components of quarter and cluster had a small effect on the annual trends in the CPUE (**Fig. 4**), but the effect of cluster decreased the AIC and increased the BIC (**Table 3**). Lists of all parameters and estimates of the best models are shown in **Table 4**.

### *3.3 Annual trends in CPUE*

The predicted CPUE showed a gradual increasing trend overall (**Fig. 5**). However, due to the recent decrease in fishing effort and the resulting reduction in area and data coverage, the 95 % confidence intervals have significantly widened since 2019. In the most recent year, 2023, the CPUE values were very high, and the 95% confidence interval was very wide.

### *3.4 Model diagnostics*

Diagnostic plots of goodness-of-fit for the best model (Model-5) didn’t show a serious deviation from normality and model misspecification (**Fig. 6**). These results suggested that the fittings of the best model to the data were good.

### *3.5 Spatial maps of estimated CPUE*

The spatial maps of predicted CPUEs clearly showed higher CPUEs of blue sharks in the temperate waters throughout the years (**Fig. 7**). The areas of high estimated CPUE (i.e., hotspots) were observed in the areas off the coasts of South Africa, Mozambique, and Madagascar between 40°S and 20°S, as well as the offshore regions along the west coast of Australia, were notably high.

## 4. Discussions

This paper predicted the historical trend in abundance indices of blue sharks caught by the Japanese tuna longline fishery in the Indian Ocean from 1994 to 2023 to provide the abundance indices for the upcoming benchmark stock assessment in 2025. We applied spatio-temporal GLMM (sdmTMB) after filtering the logbook data based on the reporting rate of observer data. The average reporting rate of observer data was 0.777 (SD = 0.226), whereas the average reporting rate of logbook data was significantly lower at 0.279 (SD = 0.335). Particularly, from 1994 to 2008, the average reporting rate in the logbook data was 0.210 (SD = 0.290), and it has shown an increasing trend since around 2008 (mean = 0.545, SD = 0.361). This trend may have been influenced by the shark-related resolution adopted by the IOTC in 2005 [Resolution 05/05: IOTC_sharks_Res-05-05_ConservationOf.pdf]. By using a reporting rate threshold of 0.589, we were able to improve the nominal CPUE and positive catch ratio, which were extremely low until 2007 (**Fig. 3**). However, since this value greatly affects the annual trend of CPUE, it is considered that appropriateness of this threshold can be further improved by developing statistical methods using the latest data, referring to past filtering methods (Nakano and Honma, 1996; Nakano and Clarke, 2006; Kai and Yokawa, 2015).

By using the spatiotemporal statistical model, it is considered that the estimation precision has improved compared to the GLM used previously. Spatiotemporal statistical models allow us to predict CPUE for missing years using spatiotemporal autocorrelation. Therefore, it is possible to directly apply spatiotemporal statistical models to observer data. Even though the effort data in logbook records has been decreasing annually (**Fig. A6**), the method presented here may be more suitable for representing the overall abundance index in the Indian Ocean for the time being, as coverage of observer data is low and restricted to particular area and season.

We recommend using the predicted annual CPUEs of blue sharks caught by Japanese tuna longline fishery in the Indian Ocean from 1994 to 2023 as a representative of abundance indices in the Indian Ocean due to a wide coverage of the main distributional areas (temperate waters) of blue sharks over time, sufficient long time series of data, and statistical soundness of the spatiotemporal model.

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**Table 1.** Summary of dispersion ratio, percentage of zero catch, and sample number used in the model for blue sharks in the Indian Ocean.

| Year | Dispersion ratio | Percentage of zero catch | sample number (×1000) | Year | Dispersion ratio | Percentage of zero catch | sample number (×1000) |
|---|---|---|---|---|---|---|---|
| 1994 | 11.1 | 55 | 2,834 | 2009 | 25.9 | 24 | 12,035 |
| 1995 | 23.3 | 61 | 3,887 | 2010 | 36.5 | 23 | 8,089 |
| 1996 | 52.1 | 62 | 3,614 | 2011 | 40.0 | 24 | 6,962 |
| 1997 | 20.8 | 55 | 4,927 | 2012 | 25.3 | 22 | 6,940 |
| 1998 | 15.5 | 57 | 3,618 | 2013 | 28.5 | 25 | 5,193 |
| 1999 | 49.9 | 62 | 2,684 | 2014 | 14.9 | 26 | 4,823 |
| 2000 | 27.4 | 48 | 2,544 | 2015 | 32.8 | 22 | 4,395 |
| 2001 | 14.2 | 43 | 3,116 | 2016 | 25.2 | 26 | 3,146 |
| 2002 | 20.0 | 40 | 2,186 | 2017 | 18.7 | 24 | 3,432 |
| 2003 | 26.3 | 43 | 1,264 | 2018 | 44.7 | 24 | 2,310 |
| 2004 | 9.9 | 35 | 1,757 | 2019 | 39.8 | 28 | 1,057 |
| 2005 | 12.5 | 31 | 2,719 | 2020 | 8.9 | 24 | 1,015 |
| 2006 | 10.8 | 33 | 2,304 | 2021 | 29.9 | 28 | 1,641 |
| 2007 | 35.7 | 31 | 3,097 | 2022 | 10.7 | 20 | 1,283 |
| 2008 | 28.1 | 26 | 10,511 | 2023 | 2.8 | 19 | 383 |

**Table 2.** Summary of structures and outputs for different observation models of blue sharks in the Indian Ocean. "Δ" denotes a difference between the value of criteria and the minimum value.

| Model | Observation model | Number of parameters | AIC | ΔAIC | BIC | ΔBIC | Maximum gradient |
|---|---|---|---|---|---|---|---|
| 1 | Poisson | 42 | 768207 | 284695 | 768612 | 284299 | < 0.0001 |
| 2 | Negative binomial | 43 | 495660 | 12147 | 496074 | 11761 | < 0.0001 |
| 3 | Tweedie | 44 | 513323 | 29810 | 513747 | 29434 | < 0.0001 |
| 4 | Zero-inflated negative binomial model | 83 | 483513 | 0 | 484313 | 0 | < 0.0001 |

**Table 3.** Summary of structures and outputs for different models of blue sharks in the Indian Ocean. "Δ" denotes a difference between the value of criteria and the minimum value. RMSE and AME denote root mean square error and absolute mean error, respectively, calculated from the outputs of the cross-validation.

| Model | Catch rate predictors of random effect | Number of parameters | AIC | ΔAIC | BIC | ΔBIC | RMSE | AME | Maximum gradient |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Year | 61 | 564297 | 80784 | 564885 | 80607 | | | < 0.0001 |
| 1 | Year + Station | 67 | 527588 | 44075 | 528234 | 43956 | | | < 0.0001 |
| 2 | Year + Station + Year and Station | 69 | 500406 | 16893 | 501072 | 16793 | | | < 0.0001 |
| 3 | Year + Station + Year and Station + Vessel | 71 | 484508 | 995 | 485193 | 915 | | | < 0.0001 |
| 4 | Year + Station + Year and Station + Vessel + Season | 77 | 483536 | 23 | 484278 | 0 | 10.405 | 4.061 | < 0.0001 |
| 5 | Year + Station + Year and Station + Vessel + Season + Cluster | 83 | 483513 | 0 | 484313 | 35 | 10.153 | 3.990 | < 0.0001 |

**Table 4.** List of all parameters and estimates of the selected models (Model-5) for blue sharks in the Indian Ocean.

| No | Parameter name | Symbol | Type | Binomial | Negative binomial |
|---|---|---|---|---|---|
| 1 | Spatial decorrelation rate | $\kappa$ | Fixed | 0.186 | 0.187 |
| 2 | IID random intercept variance | $\sigma_\epsilon$ | Fixed | 1.12 | 2.00 |
| 3 | Northings anisotropy | $h_1$ | Fixed | 1.18 | 1.18 |
| 4 | Anisotropic correlation | $h_2$ | Fixed | 0.99 | 0.99 |
| 5 | Spatial random field marginal variance | $\sigma_{\omega 2}$ | Fixed | 1.12 | 2.00 |
| 6 | Spatiotemporal random field marginal variance | $\sigma_{\epsilon 2}$ | Fixed | 0.52 | 1.10 |
| 7 | IID random intercept variance | $\sigma_{g2}$ | Fixed | 2.78 | 0.55 |
| 9 | Coefficient of year, three month quarter, and cluster | $\beta$ | Fixed | Not shown | Not shown |
| 10 | IID random intercept deviation for group g | $\alpha_g$ | Random | Not shown | Not shown |
| 11 | Spatial random field at point *s* (knot) | $\omega_s$ | Random | Not shown | Not shown |
| 12 | Spatiotemporal random field at point *s* and time *t* (knot) | $\varepsilon_{s,t}$ | Random | Not shown | Not shown |

**Table 5.** Summary of annual CPUE predicted by spatio-temporal model along with corresponding estimates of the coefficient of variations (CV), annual nominal CPUE, and number of hooks in millions for blue sharks in the Indian Ocean. Values are predicted using the best fitting model (Model-5) and CPUEs are scaled by average CPUE.

| Year | Predicted CPUE | Nominal CPUE | CV | Number of hooks (millions) | Year | Predicted CPUE | Nominal CPUE | CV | Number of hooks (millions) |
|---|---|---|---|---|---|---|---|---|---|
| 1994 | 0.40 | 0.76 | 0.10 | 7.6 | 2009 | 0.80 | 1.16 | 0.03 | 38.7 |
| 1995 | 0.68 | 0.65 | 0.09 | 10.8 | 2010 | 0.82 | 1.18 | 0.03 | 26.4 |
| 1996 | 0.76 | 0.54 | 0.11 | 10.4 | 2011 | 1.03 | 1.32 | 0.05 | 21.9 |
| 1997 | 0.75 | 0.70 | 0.09 | 14.3 | 2012 | 1.04 | 1.41 | 0.06 | 22.3 |
| 1998 | 0.57 | 0.73 | 0.09 | 10.6 | 2013 | 0.98 | 1.30 | 0.08 | 16.5 |
| 1999 | 1.52 | 1.30 | 0.14 | 7.6 | 2014 | 0.68 | 0.83 | 0.07 | 15.7 |
| 2000 | 0.97 | 0.97 | 0.11 | 7.3 | 2015 | 0.94 | 1.35 | 0.07 | 14.2 |
| 2001 | 0.65 | 0.89 | 0.06 | 9.3 | 2016 | 0.84 | 0.81 | 0.13 | 10.2 |
| 2002 | 0.56 | 0.89 | 0.09 | 6.6 | 2017 | 0.92 | 0.78 | 0.11 | 11.2 |
| 2003 | 1.21 | 1.43 | 0.15 | 3.7 | 2018 | 1.30 | 1.08 | 0.14 | 7.4 |
| 2004 | 0.84 | 1.01 | 0.15 | 5.2 | 2019 | 1.31 | 1.40 | 0.15 | 3.3 |
| 2005 | 0.81 | 1.09 | 0.10 | 7.9 | 2020 | 1.69 | 0.93 | 0.25 | 3.1 |
| 2006 | 0.68 | 0.85 | 0.11 | 7.1 | 2021 | 1.17 | 0.82 | 0.20 | 5.1 |
| 2007 | 0.80 | 1.22 | 0.08 | 9.8 | 2022 | 1.26 | 0.68 | 0.24 | 4.0 |
| 2008 | 1.07 | 1.26 | 0.03 | 33.9 | 2023 | 2.94 | 0.68 | 0.50 | 1.2 |

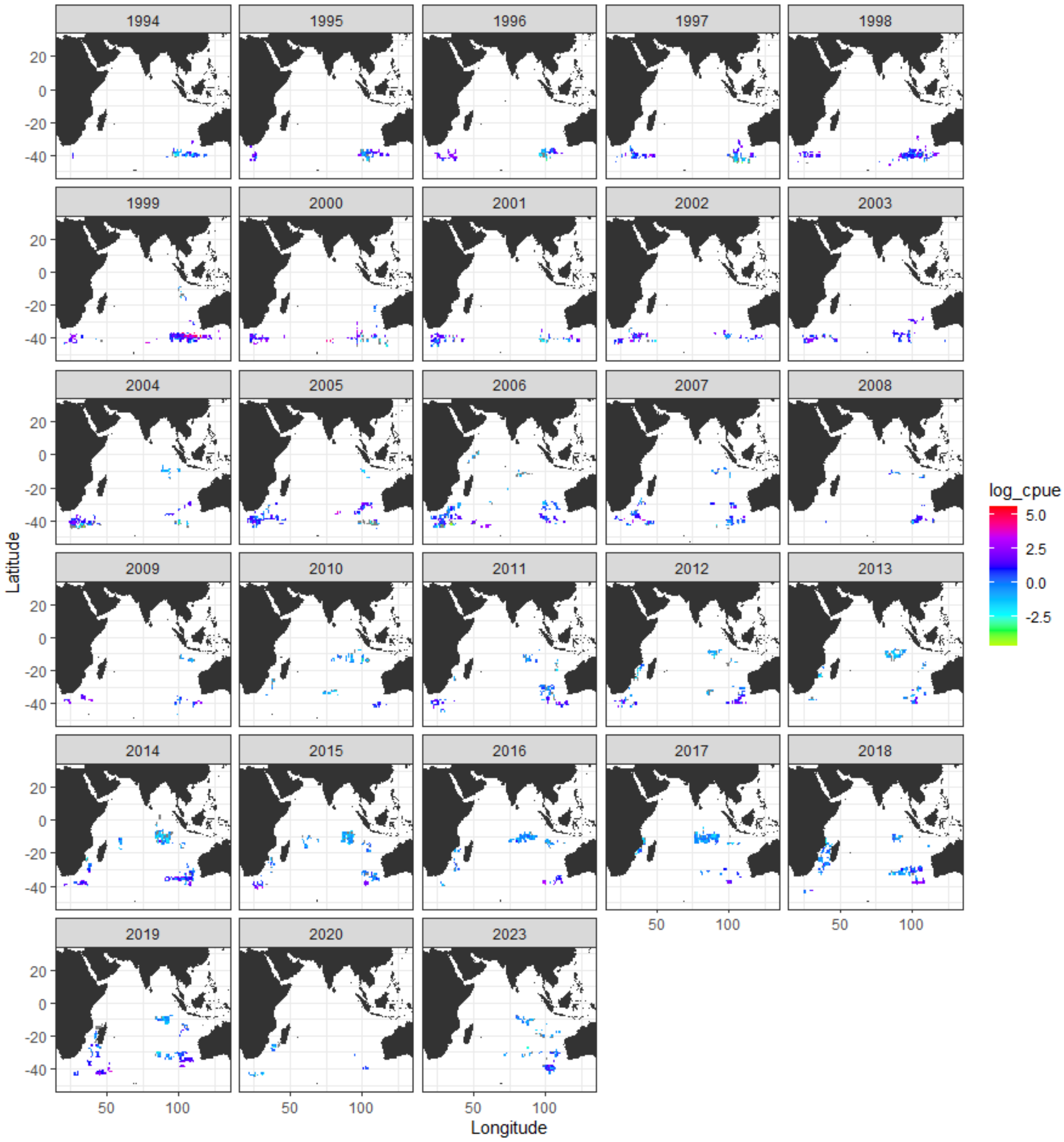


**Fig. 1** Spatiotemporal changes in the log-transformed CPUE of blue sharks based on observer data. Observers were not available in 2021 and 2022.

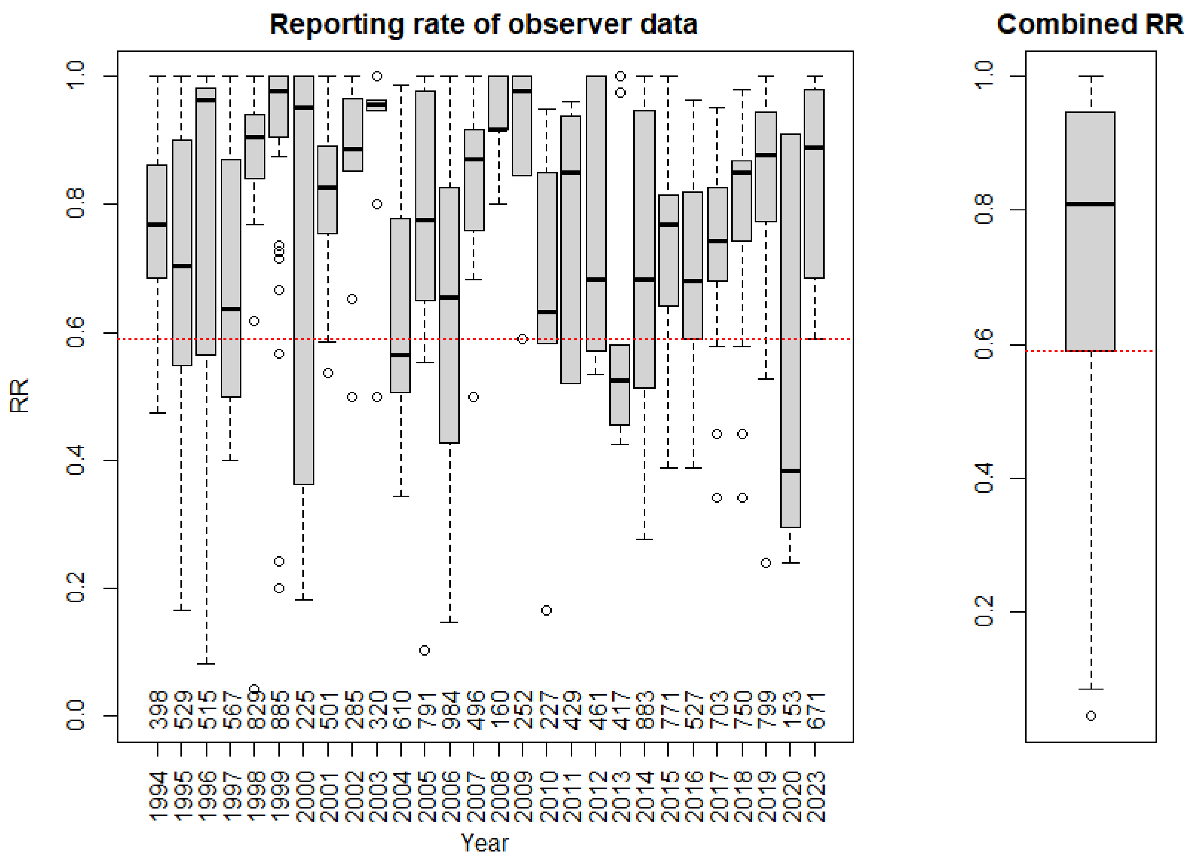


**Fig. 2** Reporting rate (RR) of blue sharks in the Indian Ocean based on observer data. The left panel shows annual changes in the RR, while the right panel shows RR combined by year. The red dotted line indicates the threshold for data filtering (third quartile of the box for combined RR: 0.589). The numerical value at the bottom indicates the number of operations per year.

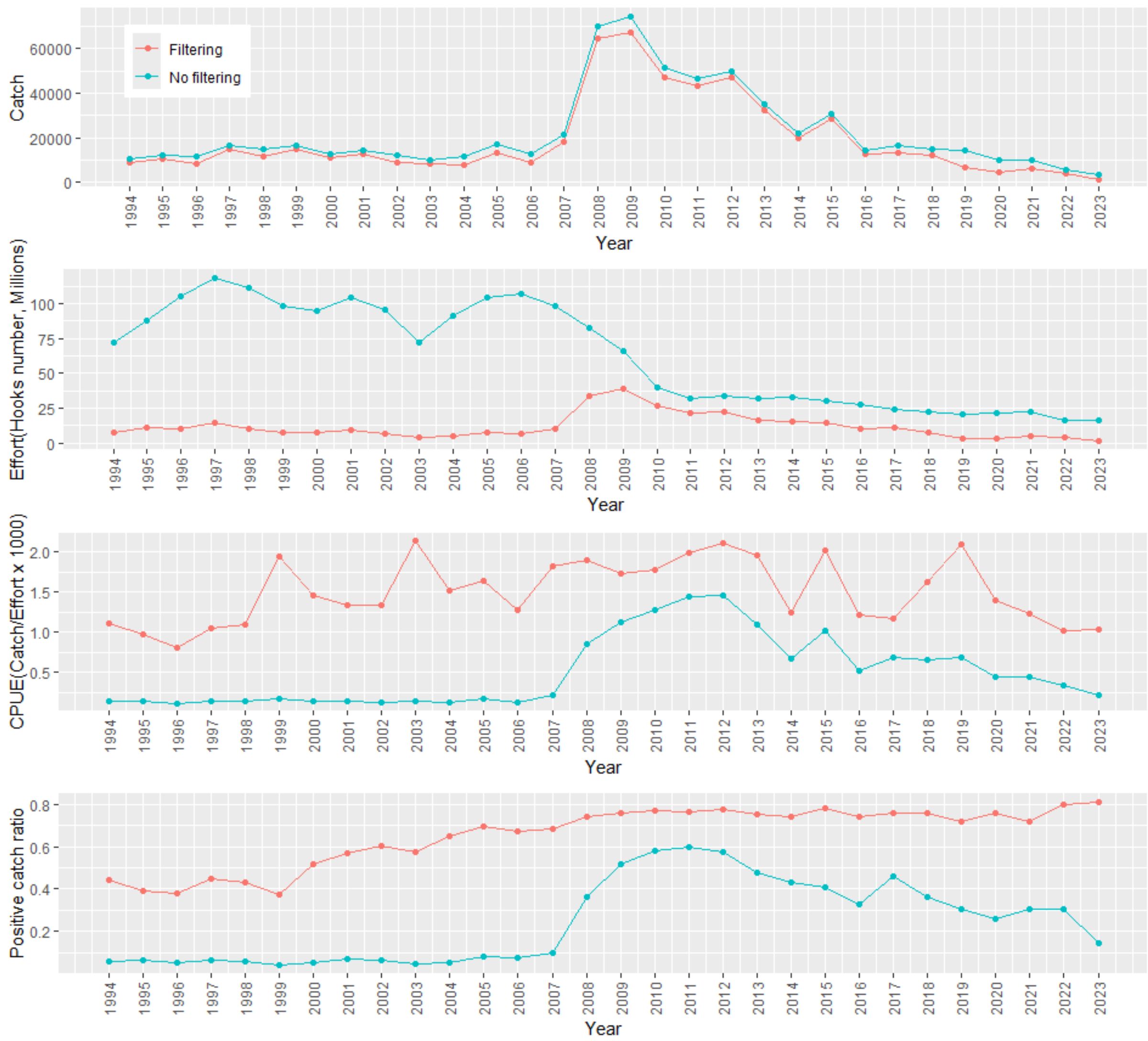


**Fig. 3** Annual catch in numbers, number of hooks (millions), nominal CPUE (per 1000 hooks), and positive catch ratio for blue sharks in the Indian Ocean before and after data filtering from 1994 to 2023. CPUE is scaled by the mean value of annual CPUE

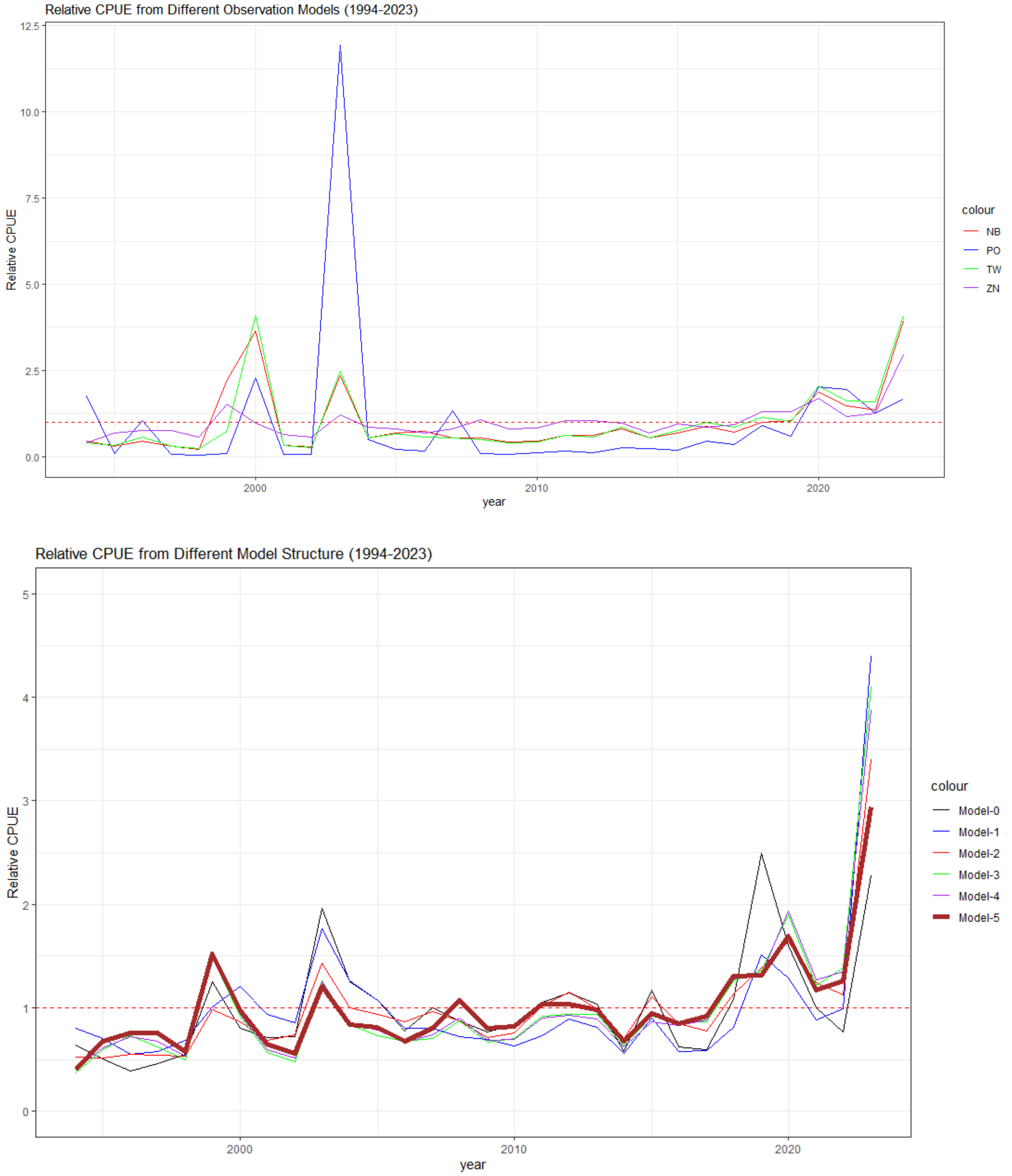


**Fig. 4** Comparisons of predicted annual CPUE relative to its average among different observation model (upper panel) and different model structures (lower panels) for blue sharks in the Indian Ocean. For details of the models, see **Tables 2, 3**.

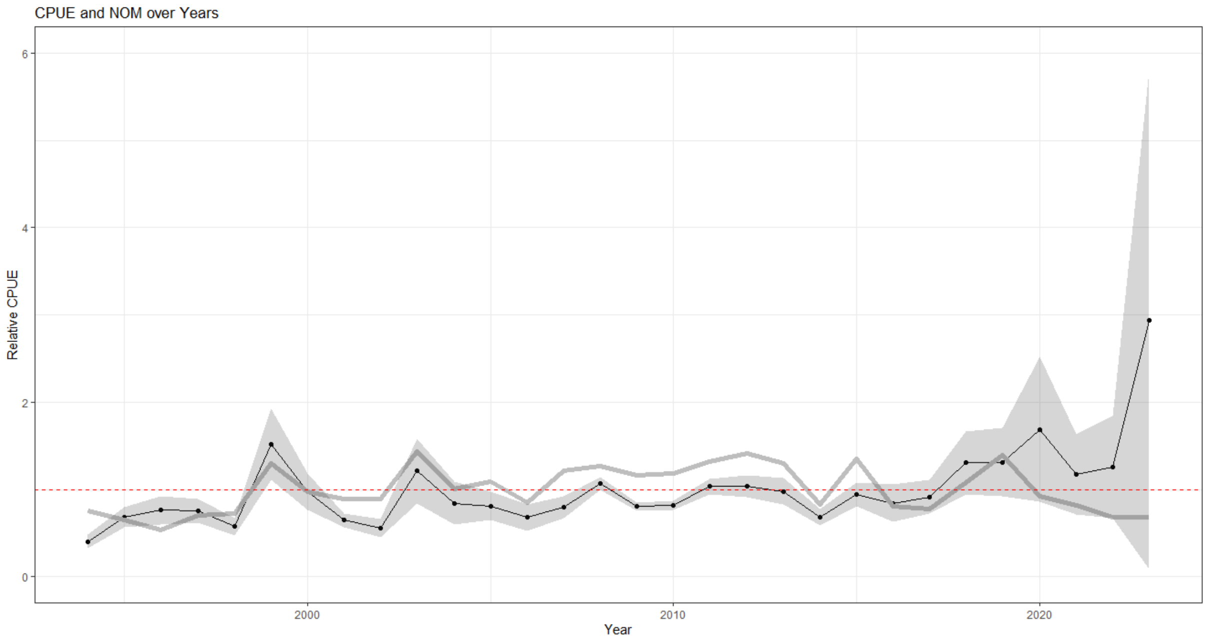


**Fig. 5** Annual predicted CPUE relative to its average for blue sharks in the Indian Ocean from 1994 to 2023. Gray solid line denotes nominal CPUE relative to its average, shadow denotes 95% confidence intervals, and horizontal red broken line denotes mean of relative values (1.0).

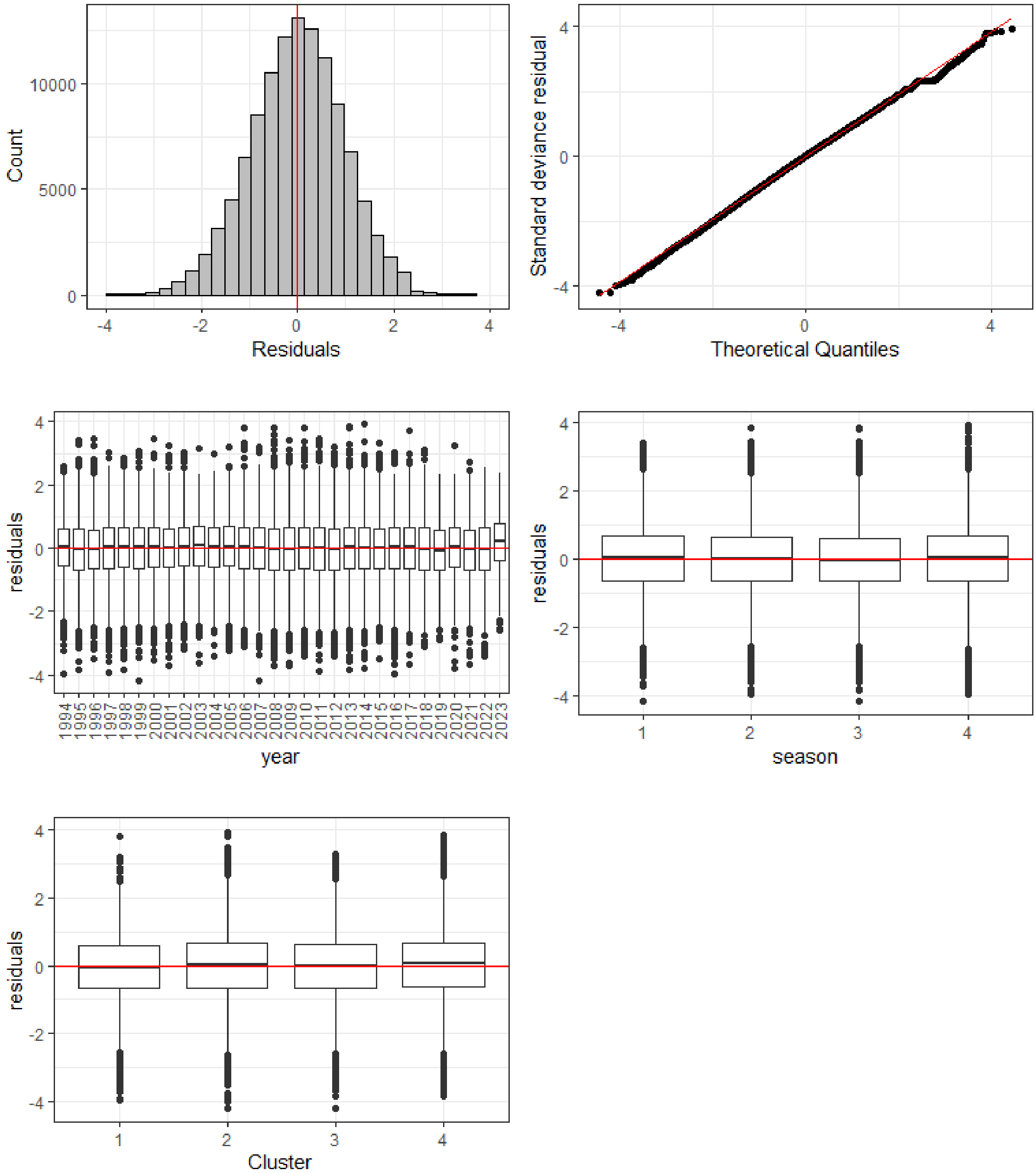


**Fig. 6** Diagnostic plots of goodness-of-fit for the most parsimonious model (Model-5) for blue sharks in the Indian Ocean.


**Fig. 7** Spatial distribution of log-scaled predicted CPUE for blue sharks in the Indian Ocean. One hundred knots are given in the estimation of the standardized CPUE.

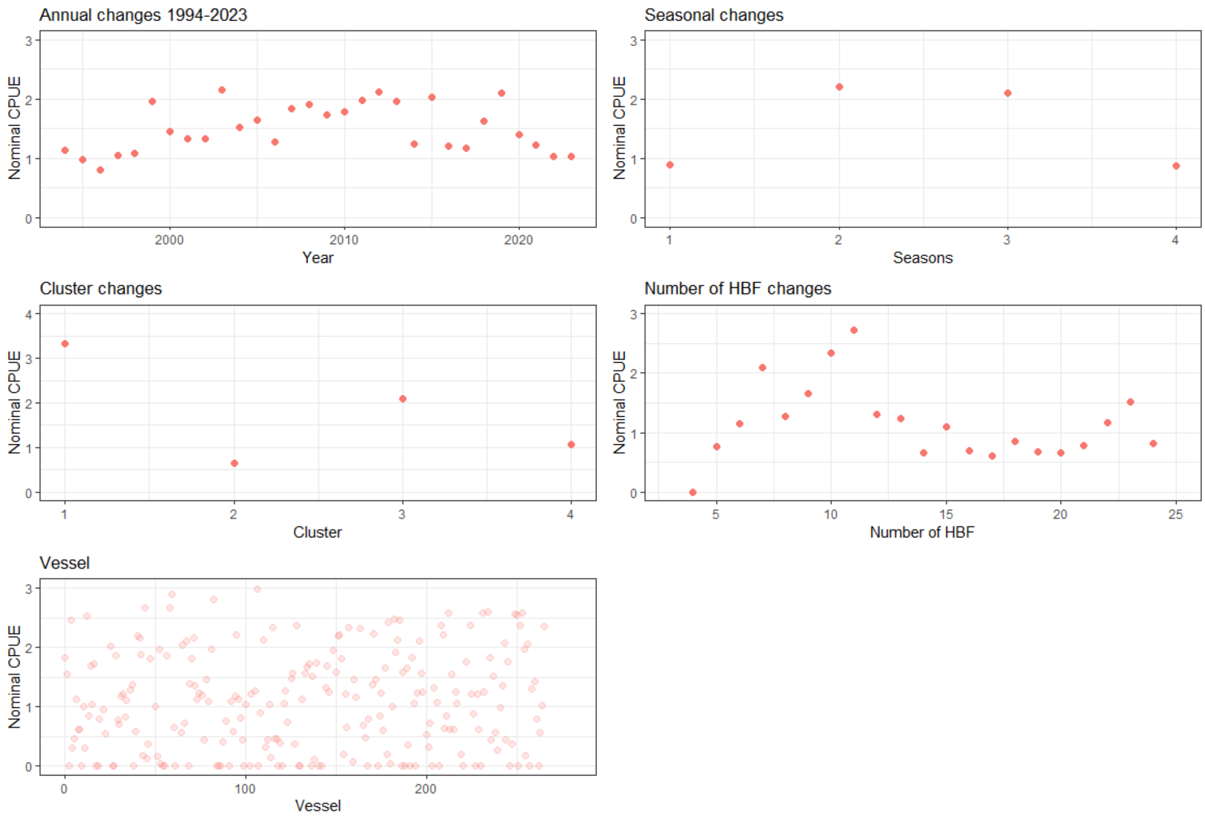


**Fig. A1** Changes in nominal CPUE (per 1000 hooks) by year, season, targeting cluster, number of hooks between floats (HBF), and vessel for the filtered data of blue sharks in the Indian Ocean.

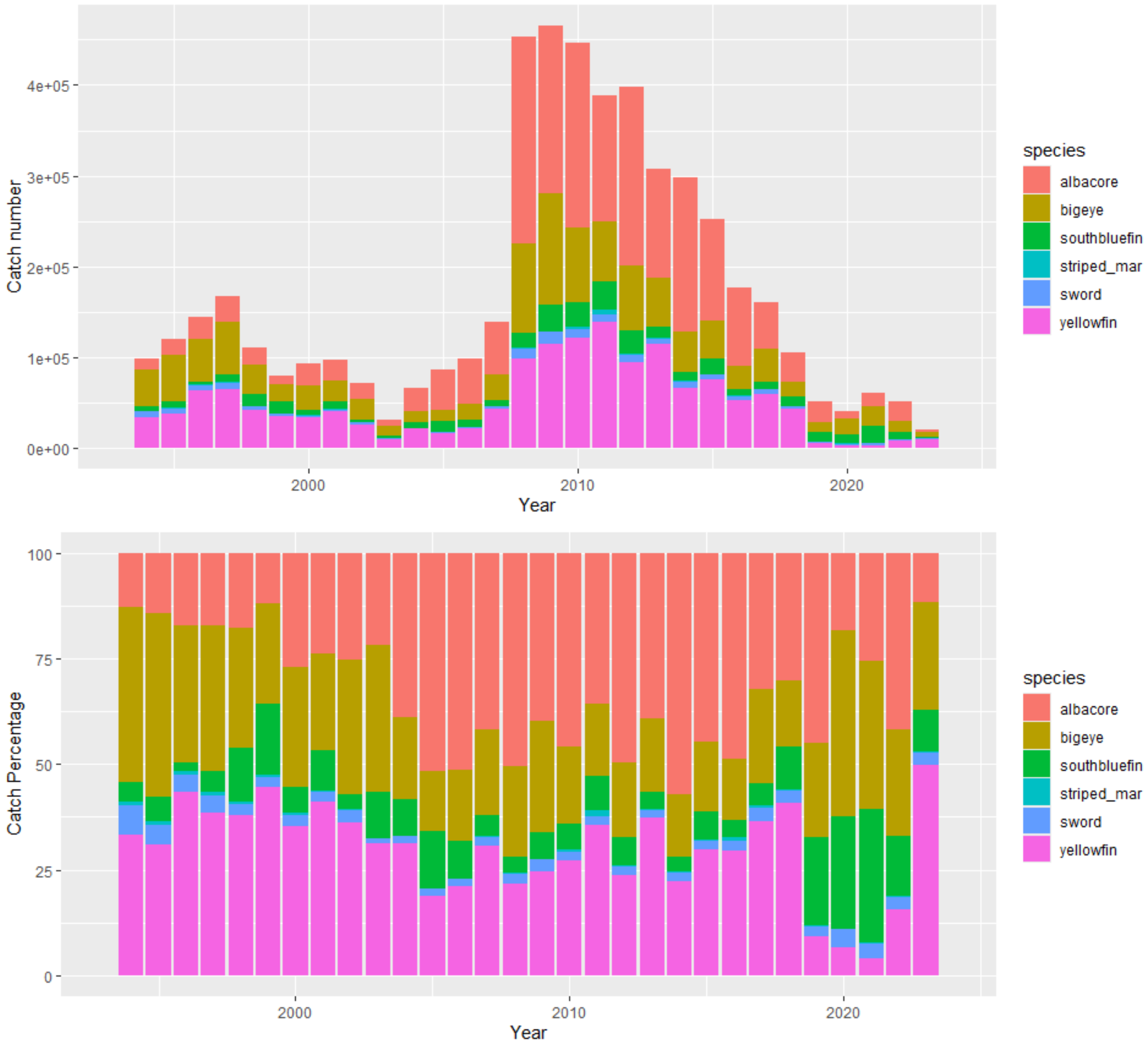


**Fig. A2** Annual changes in the species composition of catch numbers (upper panel) and the proportion of catch numbers (lower panel) for tunas and tuna-like species caught by the Japanese longline fishery in the Atlantic Ocean from 1994 to 2023.

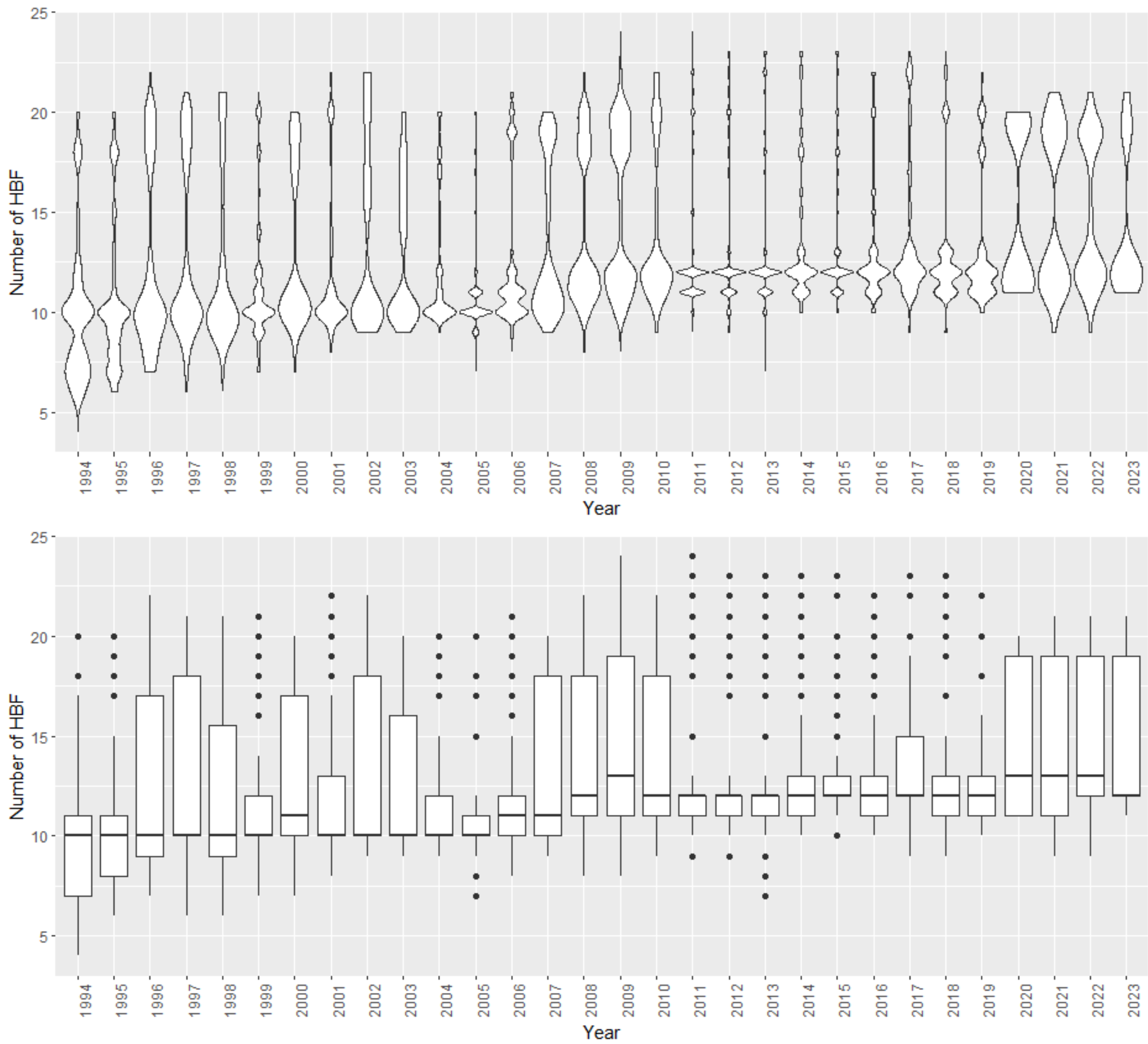


**Fig. A3** Annual changes in the number of hooks between floats (HBF) (upper panel shows a violin plot, and lower panel shows a boxplot).

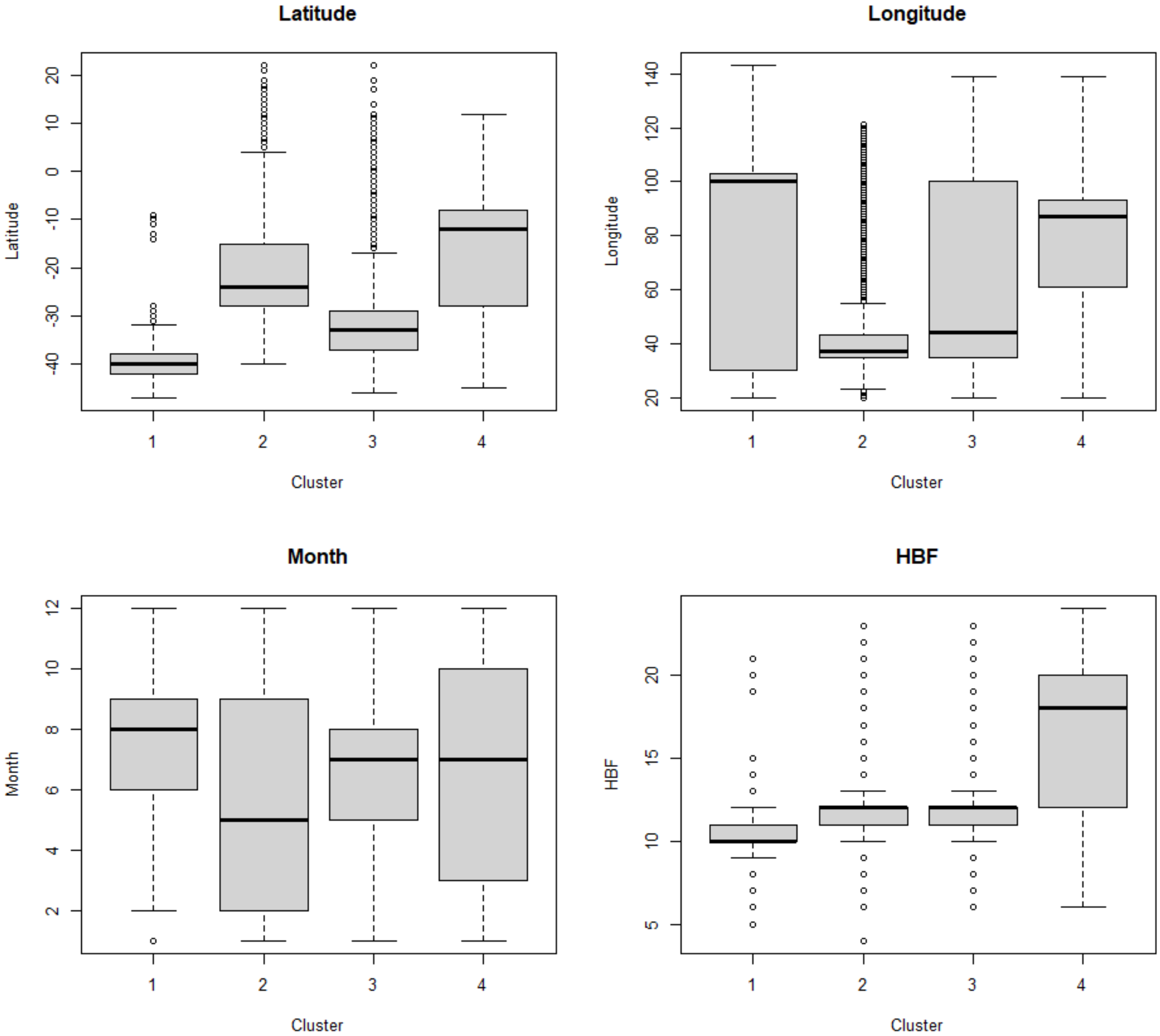


**Fig. A4** Boxplots of latitude, longitude, month, and HBF for each cluster. The thick line represents the median, and the upper and lower bounds of the box represent the third quartile and first quartile, respectively.

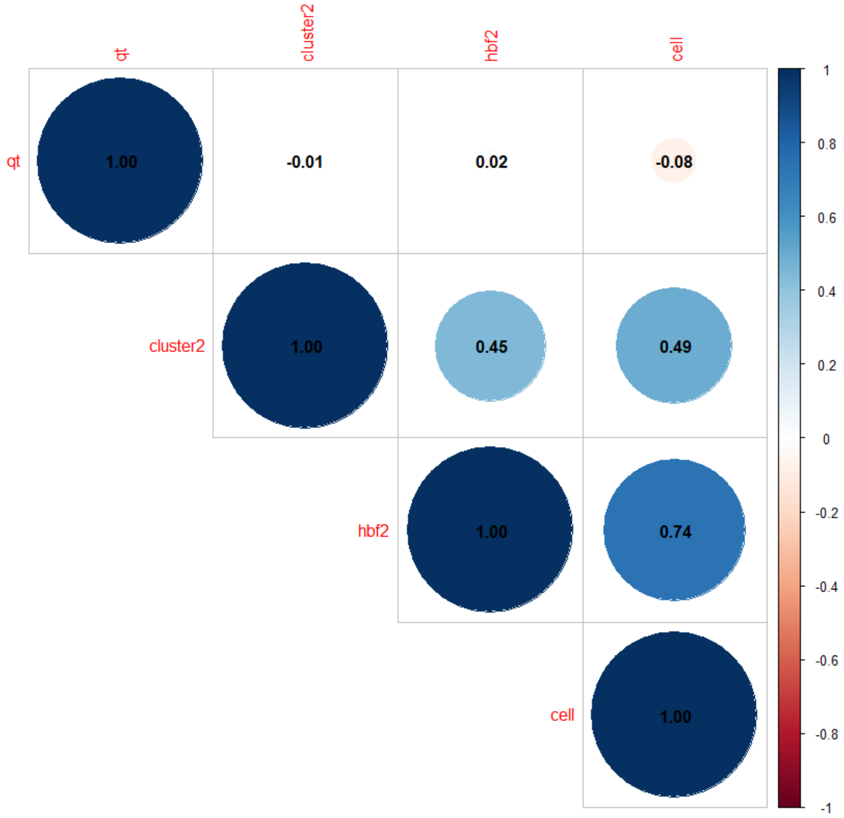


**Fig. A5** Correlation among quarters, number of hooks between floats (HBF), cell (station), and cluster using filtered datasets in the Indian Ocean.

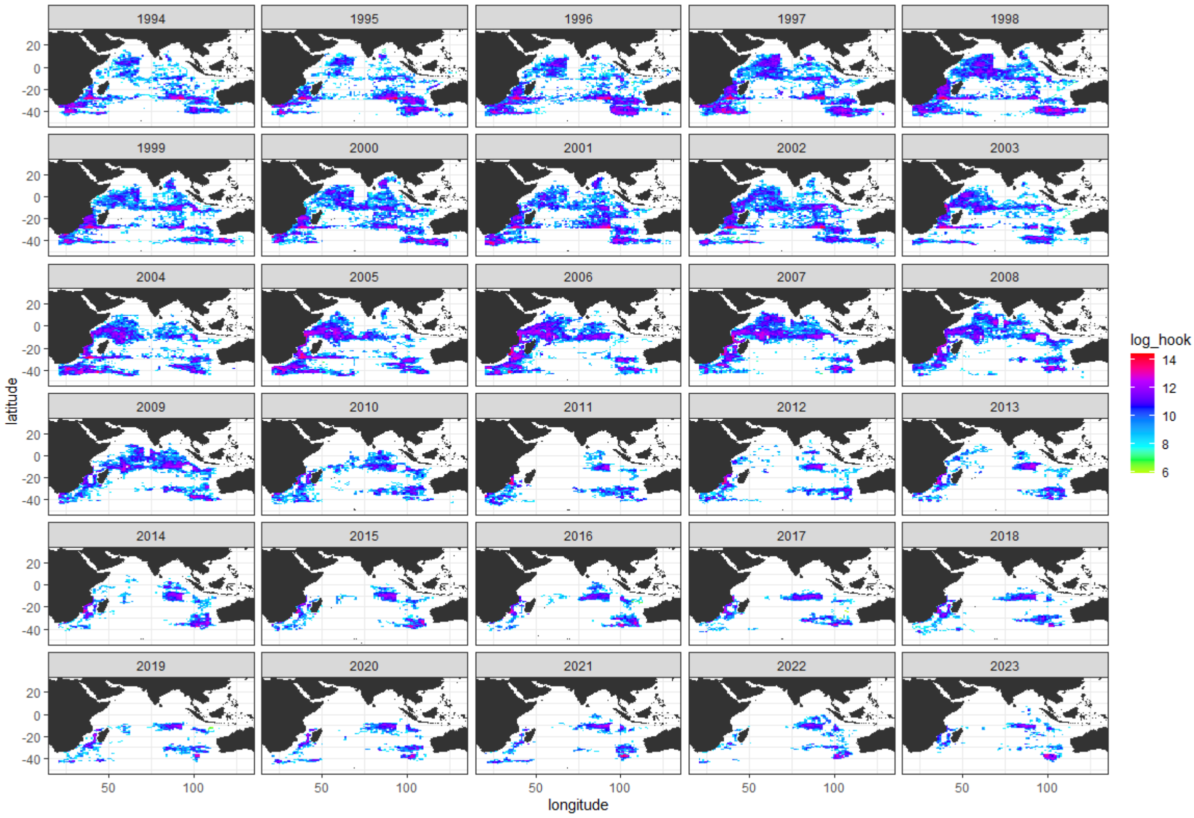


**Fig. A6** Annual changes in the spatial maps of fishing effort (log scale of the total number of hooks) by Japanese tuna longline fleets in the Atlantic Ocean from 1994 to 2023.