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SPATIO-TEMPORAL MODEL FOR CPUE STANDARDIZATION: APPLICATION TO BLUE SHARK CAUGHT BY JAPANESE TUNA LONGLINE FISHERY IN THE NORTH ATLANTIC FROM 1994 TO 2021

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SUMMARY

Abundance indices of blue shark caught by Japanese longline fishery from 1994 to 2021 in the North Atlantic were estimated. Since the catch data of sharks caught by commercial tuna longline fishery is usually underreported due to discard of sharks, the author filtered the logbook data using the similar filtering methods applied in the previous analysis. The nominal CPUE of filtered data was then standardized using the spatio-temporal generalized linear mixed model (GLMM) to provide the annual changes in the abundance. The author focused on interannual variations of the density in the model to account for spatially and annually changes in the fishing location due to the target changes of tuna and tuna-like species. The estimated CPUE revealed downward trend from 1994 to 2004, and then sharply increased until 2008. Thereafter the CPUE was stable until 2015 with annual fluctuations and then decreased in recent years. The estimated CPUE using the spatio-temporal model with a large amount of data collected in the wide waters in the North Atlantic is a very useful information about the abundance of blue sharks.

RÉSUMÉ

Les indices d'abondance du requin peau bleue capturé par la pêcherie palangrière japonaise de 1994 à 2021 dans l'Atlantique Nord ont été estimés. Étant donné que les données de capture des requins capturés par la pêcherie palangrière commerciale de thonidés sont généralement sous-déclarées en raison des rejets de requins, l'auteur a filtré les données des carnets de pêche en utilisant les méthodes de filtrage similaires appliquées dans l'analyse précédente. La CPUE nominale des données filtrées a ensuite été standardisée à l'aide du modèle mixte linéaire généralisé spatio-temporel (GLMM) afin de fournir les changements annuels de l'abondance. L'auteur s'est concentré sur les variations interannuelles de la densité dans le modèle afin de tenir compte des changements spatiaux et annuels de la localisation de la pêche en raison des changements de cible des thonidés et des espèces apparentées. La CPUE estimée a révélé une tendance à la baisse de 1994 à 2004, puis une forte augmentation jusqu'en 2008. Par la suite, la CPUE est restée stable jusqu'en 2015, avec des fluctuations annuelles, puis a diminué au cours des dernières années. La CPUE estimée en utilisant le modèle spatio-temporel avec une grande quantité de données collectées dans une vaste zone de l'Atlantique Nord est une information très utile sur l'abondance du requin peau bleue.

RESUMEN

Se estimaron los índices de abundancia del tiburón azul capturado por la pesquería de palangre japonesa entre 1994 y 2021 en el Atlántico norte. Dado que los datos de capturas de tiburones por parte de la pesquería comercial atunera de palangre suelen estar infradeclarados debido al descarte de tiburones, el autor filtró los datos del cuaderno utilizando métodos de filtrado similares a los aplicados en el análisis anterior. A continuación, la CPUE nominal de los datos filtrados se estandarizó mediante el modelo lineal mixto generalizado espaciotemporal (GLMM) para obtener los cambios anuales en la abundancia. El autor se centró en las variaciones interanuales de la densidad en el modelo para dar cuenta de los cambios espaciales y anuales en la localización de la pesca debidos a los cambios de objetivo de los túnidos y especies afines. La CPUE estimada reveló una tendencia descendente de 1994 a 2004, que luego aumentaba bruscamente hasta 2008. A partir de entonces, la CPUE se mantuvo estable hasta 2015, con fluctuaciones anuales, y disminuyó en los últimos años. La CPUE estimada utilizando el modelo espaciotemporal con una gran cantidad de datos recogidos en una amplia área del Atlántico norte es una información muy útil sobre la abundancia de tiburón azul.

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KEYWORDS:

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

1. Introduction

The blue shark (*Prionace glauca*) is a highly migratory species and widely distributed in the world's oceans from tropical to temperate waters (Nakano and Stevens 2008). Blue sharks are relatively productive in the elasmobranchs and the most abundant pelagic sharks. Blue sharks are a major bycatch of Japanese tuna longline fleets operating in the Atlantic Ocean targeting to albacore (*Thunnus alalunga*), yellowfin tuna (*Thunnus albacares*), bigeye tuna (*Thunnus obesus*), bluefin tuna (*Thunnus thynnus*), southern bluefin tuna (*Thunnus maccoyii*) and swordfish (*Xiphias gladius*). Blue sharks are considered to have two distinct stocks in the Atlantic Ocean due to their opposite reproductive biology between north and south Atlantic delineated by equator.

The benchmark stock assessments for North Atlantic blue sharks were conducted in 2015 (Anon 2015). All scenarios considered with the Bayesian surplus production model and the integrated model (SS3) indicated that the stock was not overfished, and that overfishing was not occurring. However, the Committee acknowledged that there still remained a high uncertainty in data inputs and model structural assumptions. In 2019, ICCAT adopted a total TAC for northern stock (39,102 t) with a quota allocation (Japan is 4,010 t) to prevent from the overexploitation in their uncertain stock status.

In the previous benchmark stock assessment in 2015, Japan provided standardized CPUE (catch per unit effort) of blue sharks caught by Japanese tuna longline fleets operating in the North Atlantic (Kai et al. 2015). Since the logbook records of Japanese fleets in the early period from 1971 to 1993 contain only aggregated catch of shark species, the standardized CPUEs of Japanese fleets were computed separately using the logbook data from 1971 to 1993 and 1994 to 2012, respectively. Since the reporting rates of bycatch species such as blue sharks are commonly low due to the lower value compared to the target species, a filtering method introduced by Nakano and Honma (1996) was applied to remove the set-by-set data with low reporting rates of sharks smaller than 80 % (Nakano and Clarke 2006; Matsunaga 2009). Then, the nominal CPUEs in the early and late periods (1971-1993, 1994-2012) for northern stock were standardized using a generalized linear model (GLM) assuming lognormal and negative binomial error distributions. The standardized CPUEs with the best (lognormal) model showed some fluctuations and relatively increasing trends since 1994 for the northern stock (Kai et al. 2015). However, the lognormal model has an issue as a constant value (e.g., 0.1) must be given for the response variable. In addition, the GLMs commonly assign the spatial area with low resolution and main interaction terms such as "year-area" and "quarter and area" are frequently unavailable due to a lack of data.

The VAST (Vector Autoregressive Spatio-Temporal) software package for R (Thorson 2019), which enables us to analyze fishery data using the spatio-temporal generalized linear mixed model (GLMM) (Thorson et al. 2015), has recently attracted attention as a new approach and is now commonly used globally to predict spatial changes in species distribution and temporal variations in a population range and density. The basic model structure of VAST adopts a delta-GLMM which can consider spatio-temporal correlations among categories such as species (Thorson et al. 2017) and length frequency (Kai et al. 2017). This spatiotemporal model can overcome the above issues of GLMs and improve the CPUE standardization by adding the functions such as random effects for the vessels and interaction terms.

The objective of this working paper is to estimate the standardized CPUE of blue sharks caught by Japanese tuna longline fishery operating in the North Atlantic for 1994-2021 using the spatio-temporal GLMM in consideration with spatial and interannual changes in the density.

2. Materials and Methods

2.1 Data sources

Set-by-set logbook data from Japanese tune longline fisheries in the North Atlantic was used to estimate the annual standardized CPUE of blue sharks for 1994-2021. 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), number of branch lines between floats (hooks between float: HBF) as a proxy for gear configuration, location (longitude and latitude) of set by resolution of 1 × 1 degree square, and vessel identity (vessel name/call sign).

2.2 Data filtering

The logbook data in the North Atlantic was filtered to remove unrealistic records and set-by-set data including discard and under-reporting catch. First, the set-by-set data was filtered using the number of hooks between floats (HBF; 3~30) to remove unrealistic records on the gear-settings. Second, the set-by-set data was filtered using a reporting rate of positive catch for sharks (RR; number of sets with shark recorded/total number of sets in a cruise ≥ 0.8) based on the previous study (Nakano and Clarke 2006; Matsunaga 2009; Kai et al. 2015). The 80% of reporting rate had already been approved in the previous stock assessment for blue sharks in the Atlantic Ocean (Anon 2015).

2.3 Catchability covariate

Except for the effect of year, the nominal CPUEs of blue shark were largely influenced by station, quarter, vessel, sea surface temperature (SST), and target change (**Figure A1**). In the North Atlantic, Japanese longline fisheries change the target species by altering the operational area, gear configuration, and season etc. The number of HBF is one of the useful information to identify the target change through changing the depth of hook distribution (Bigelow et al. 2006). Cluster analysis based on the k-means clustering of observed catch proportions for tunas and swordfish (Carvalho et al. 2010; Chang et al. 2011) is another useful method to identify the target species. The number of HBF however had a strong correlation with station (cell) (**Figures A2**), the author decided not to use this effect in the model. The SST also had a strong correlation with station (cell), so that the SST was not included in the model.

2.4 CPUE standardization with spatio-temporal model

The spatio-temporal model is consisted of two components of encounter probability and positive catch in a delta model. The first predictor was fixed at a constant value because of high positive catches (> 91%). Second predictor was modeled using a negative binomial (NB) model to account for the count data with over-dispersion (variance/mean =37.4):

$$c \sim NegBin\,(c^*, c^*(1+\sigma_1) + c^{*2}\sigma_2),$$
$$\log\,(d) = d_0(t) + \gamma(s) + \theta(s,t) + \epsilon(v) + \sum_{j=1}^{n_j} \beta_j x_j, \qquad (1)$$

where c is observed catch, $NegBin\,(a, b)$ is a negative binomial distribution with mean a and variance b (Lindén and Mäntyniemi 2011), c^* is an expected catch and a function of density d and fishing effort f(number of hooks = 1), σ_1 and σ_2 are residual variations, $d_0(t)$ represents temporal variation (the intercept for each year t), $\gamma(s)$ represents spatial variation (s), $\theta(s,t)$ represents spatio-temporal variation (station s and year t), $\epsilon(v)$ represents random variation in catchability for the vth vessel, and β_j represents the impact of covariate j with value x_j on catchability. The three-month quarters and targeting cluster (i.e. $n_j = 2, x_j = q\ and\ l$) are used as covariates (changing the catchability) corresponding to Eq. (1).

The VAST (version VAST_v13_0_0) software package for R (Thorson 2019) was applied to standardize the nominal CPUE of blue shark in the North Atlantic from 1994 to 2021. Annual abundance index I was estimated as:

$$I(t) = \sum_{s=1}^{n_s} f(s) \times c^*(s,t) / \{\sum_{t=1}^{n_t} \sum_{s=1}^{n_s} f(s) \times c^*(s,t)\}, \qquad (2)$$

where n_s is total number of knots (i.e., 200 locations) and f is fishing effort (number of hooks) at location s.

2.5 Model selection and diagnostics

To select the best model, the explanatory variable was sequentially added to the simple model (Model-1). The best model was selected using the AIC (Akaike 1973) and BIC (Schwarz 1978). For the best model, the goodness of fits was examined using the Pearson residuals and QQ-plot. The residuals were computed using a randomized quantile (Dunn and Smyth 1996) to produce continuous normal residuals.

3. Results

3.1 Summary of data filtering

The preliminary filtering based on the HBF reduced the number records for this analysis from 378,005 sets to 376,863 sets. The follow-up filtering based on the RR reduced the number of records for this analysis to 97,877 sets. The follow-up filtering appeared to be reasonable because the low catch rates for sharks disappeared (**Figure 1**). The difference of annual changes in catch number for blue shark, number of hooks, and the nominal CPUE between the data with and without follow-up filtering are shown in **Figure 2**. The spatial maps of mean nominal CPUE for blue shark, total fishing effort (number of hooks), and total catch of blue shark are shown in **Figure A3**.

3.2 Selection of the best model

Complicated models (Models-4,5, and 6) were reasonably converged with the positive definite of hessian matrix and a small value of maximum gradient, while the simpler models (Models-1,2, and 3) were not converged (**Table 1**). The saturated model (Model-6) including spatial (station/cell), spatio-temporal variance (year and station) and variation over vessel as random effects was identified by AIC and BIC as the most parsimonious model (**Table 1**). The predicted CPUE changed substantially if random effect components were sequentially added to the simple model which had no random effects (Model-1) (**Figure 3**). The fixed effect components (quarter and cluster) had a small effect on the annual trends in the CPUE (**Figure 3**) but those decreased the values of both information criteria (**Table 1)**. Lists of all parameters and estimates of the best models are shown in **Table 2**.

3.3 Annual trends in CPUE

The estimated annual changes in the CPUE of blue shark revealed downward trend from 1994 to 2004, and then sharply increased until 2008. Thereafter the CPUE was stable until 2015 with annual fluctuations and then decreased in recent years (**Fig. 4**). The 95% confidence intervals of the CPUEs were larger after 2007 (**Figure 4**) due to the reduction in fishing effort and shrinkage of operational area of longline fisheries in the North Atlantic.

3.4 Model diagnostics

Diagnostic plots of goodness-of-fit for the best model didn't show a serious deviation from normality and model misspecification (**Figure 5**). These results suggested that the fitting of the best model to the data was good.

3.5 Spatial maps of predicted CPUE

The annual spatial maps of predicted CPUE clearly showed the higher CPUEs of blue sharks at the higher latitudes (35-50° N) (**Figure 6**). Meanwhile, the lower CPUEs of blue sharks were observed in the sub-tropical areas (15-25° N) and cold areas (> 50° N). This tendency was remarkable from 2008 to 2013.

4. Discussions

This document paper estimated a historical trend in abundance indices of blue shark caught by Japanese tuna longline fishery in the North Atlantic from 1994 to 2021 using a spatio-temporal GLMM. The main advantage of the spatio-temporal model is an imputation for the missing data using spatial and temporal correlations through random effects (Thorson 2019). Unlike the design based GLM used in the previous assessment (Kai et al. 2015), the spatio-temporal GLMM developed by Thorson et al. (2015) enabled us to include interaction terms between spatial and temporal effects with high spatial resolutions. The spatio-temporal variations with high spatial resolution had a large impact on the annual trends in the estimated CPUE (**Figure 3**).

The annual trends of the selected model (Model-6) suggested that the abundance indices of blue shark significantly increased in the second half of 2000s and then remained stable with higher CPUEs until 2015 (**Figure 4**). Thereafter, the abundance indices have been declining. Since the fishing effort of Japanese longline fishery has been declining (**Figure 2**) due to shrinkage of operational areas, the recent decreasing trends in the abundance might be attributed to the high fishing pressure of foreign fisheries (ICCAT 2022).

The reporting rates of catch for sharks increased in the late 2000s (**Figure 1**) due to the conservation and management measure for the sharks (Fishery Agency 2009). The Japanese government demanded Japanese longliners to land all parts of sharks in possession in order to promote effective utilization of all the usable parts of sharks.

High CPUE of blue shark observed in the higher latitudinal waters (35-50° N) (**Figure 6**) along with the northern extension of the Gulf stream as well as North Atlantic Drift where Japanese longliners historically targeting bluefin tuna and bigeye tuna.

The author recommends using the predicted annual CPUEs of blue shark caught by Japanese tuna longline fishery in the North Atlantic from 1994 to 2021 as a representative of abundance indices for North Atlantic blue shark because a wide coverage of the main distributional areas (tropical to temperate waters) of blue shark as well as sufficient long time series of data, and statistical soundness of the spatio-temporal model.

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Table 1. Summary of model structure and outputs among different models. All models include fixed effects. "Δ" denotes a difference between the value of criteria and the minimum value.

Model	*Catch rate predictors of random effect*	*Number of parameters*	*Deviance*	*ΔAIC*	*ΔBIC*	*Maximum gradient*
Model-1	Year	31	314769	16356	16282	< 0.1
Model-2	Year + Station	35	303291	9654	9612	< 0.1
Model-3	Year + Station + Vessel	36	299713	4922	4889	< 0.1
Model-4	Year + Station + Vessel + Year and Station	38	290675	76	59	< 0.0001
Model-5	Year + Station + Vessel + Year and Station + Cluster	39	290672	51	43	< 0.0001
Model-6	Year + Station + Vessel + Year and Station + Cluster +Quarter	40	290158	0	0	< 0.001

Table 2. List of all parameters and estimates of the selected model (Model-6).

No	*Parameter name*	*Symbol*	*Type*	*Estimates*
1	Distance of correlation (Spatial random effect)	κ	Fixed	0.0030
2	Variation over vessel	σ_ϵ	Fixed	2.09
3	Northings anisotropy	h_1	Fixed	1.09
4	Anisotropic correlation	h_2	Fixed	1.01
5	Parameter governing pointwise variance (Spatial random effect)	η_γ	Fixed	0.58
6	Parameter governing pointwise variance (Spatio-temporal (year) random effect)	η_θ	Fixed	0.42
7	Parameter governing autocorrelation (Spatio-temporal: year random effect)	ρ_θ	Fixed	1.54
8	Residual variation 1 of negative binomial model	σ_1	Fixed	0.63
9	Residual variation 2 of negative binomial model	σ_2	Fixed	0.52
10	Coefficient of cluster	β_1	Fixed	-0.0014
11	Coefficient of three month quarters	β_2	Fixed	0.13
12-40	Intercept for year	d_0	Fixed	Not shown
41	Vessel effect	ϵ	Random	Not shown
42	Spatial residuals	γ	Random	Not shown
43	Spatio-temporal (year) residuals	θ	Random	Not shown

Table 3. Summary of annual CPUE predicted by spatio-temporal model along with corresponding estimates of the coefficient of variation (CV), annual nominal CPUE, and number of hooks in millions. Values are predicted using the best fitting model (Model-6) and scaled by average CPUE.

Year	*Predicted CPUE*	*Nominal CPUE*	*CV*	*Number of hooks (millions)*
1994	1.03	1.41	0.12	6.05
1995	1.17	0.94	0.11	8.36
1996	1.01	1.06	0.11	5.81
1997	1.06	0.96	0.12	5.51
1998	0.93	1.00	0.11	6.34
1999	0.64	0.66	0.12	3.98
2000	0.71	0.56	0.14	3.68
2001	0.74	0.60	0.11	4.91
2002	0.53	0.54	0.11	5.83
2003	0.77	0.75	0.10	5.32
2004	0.53	0.65	0.09	11.82
2005	0.69	0.82	0.07	14.16
2006	0.87	1.11	0.08	14.08
2007	1.02	1.50	0.09	15.03
2008	1.49	1.27	0.08	20.26
2009	1.24	0.90	0.11	22.66
2010	1.44	0.83	0.16	22.34
2011	1.15	0.89	0.18	14.76
2012	1.63	1.03	0.20	13.23
2013	1.26	1.21	0.23	6.43
2014	1.36	1.42	0.22	9.29
2015	1.37	1.54	0.18	9.55
2016	1.17	1.34	0.20	10.61
2017	1.13	1.30	0.21	12.25
2018	0.74	1.08	0.21	12.17
2019	0.91	1.04	0.21	11.71
2020	0.64	0.74	0.21	8.58
2021	0.77	0.83	0.21	3.44

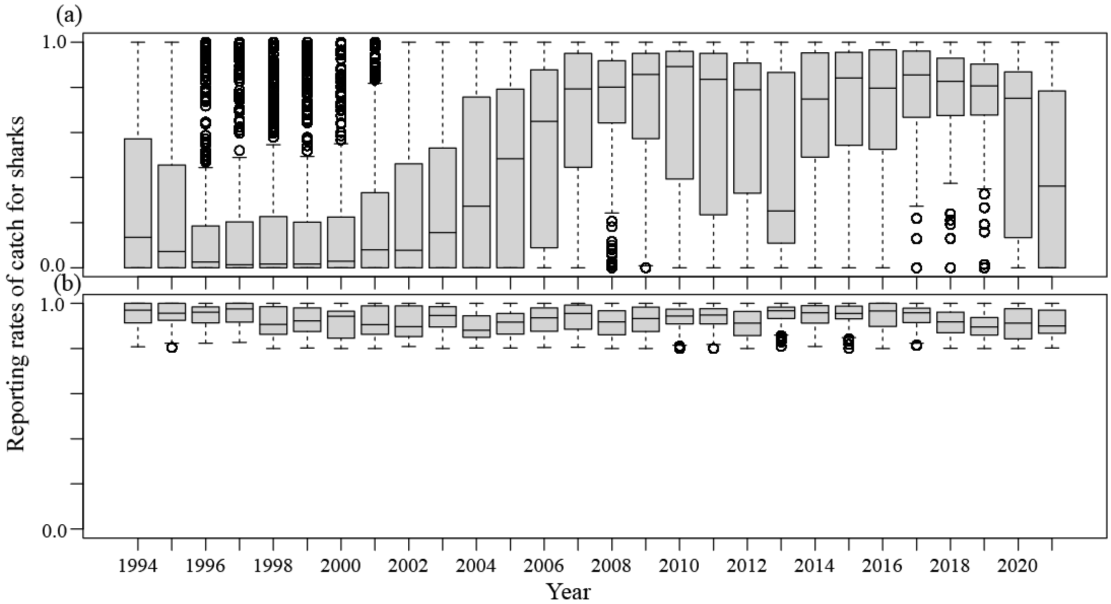

Figure 1. Annual reporting rates (RR) of catch for sharks (a) before filtering and (b) after filtering.

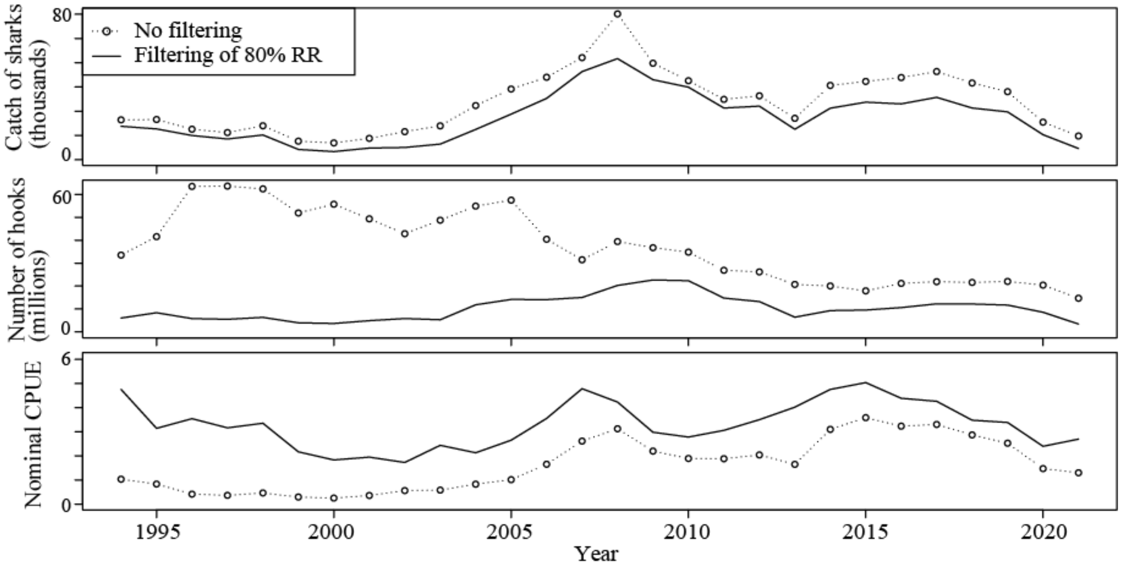

Figure 2. Annual catch in numbers (thousands) (a), number of hooks (millions) (b), and nominal CPUE (per 1000 hooks) (c) for blue shark before filtering (broken line with open circle) and after filtering (solid line).

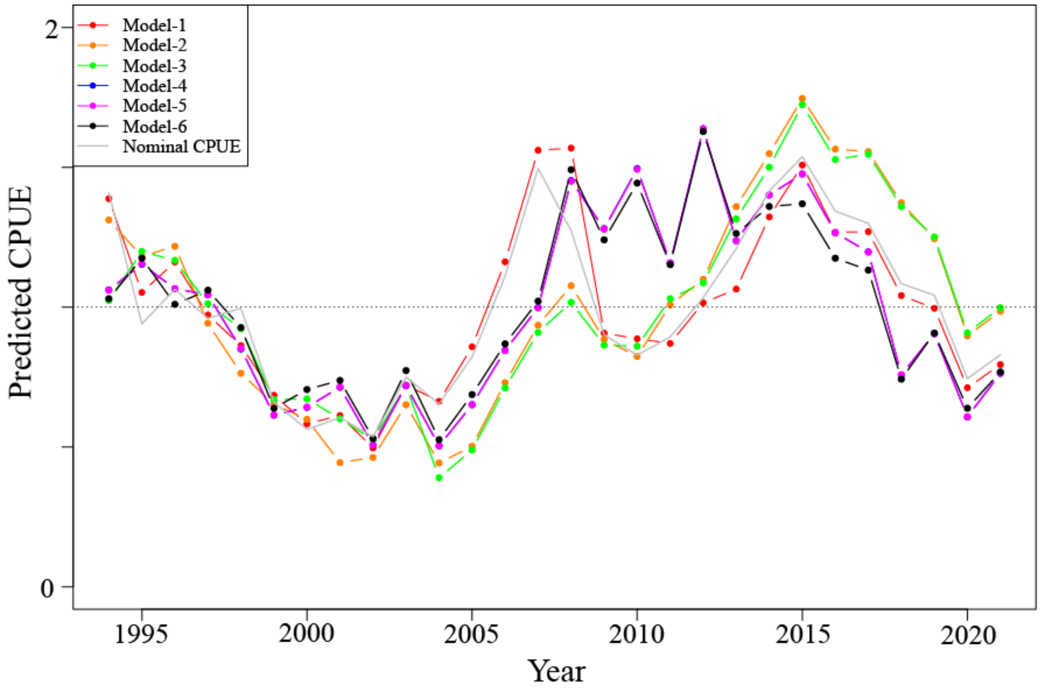

Figure 3. Comparisons of annual predicted CPUE relative to its average among different structures of the spatio-temporal model. For details of the models, see **Table 1**.

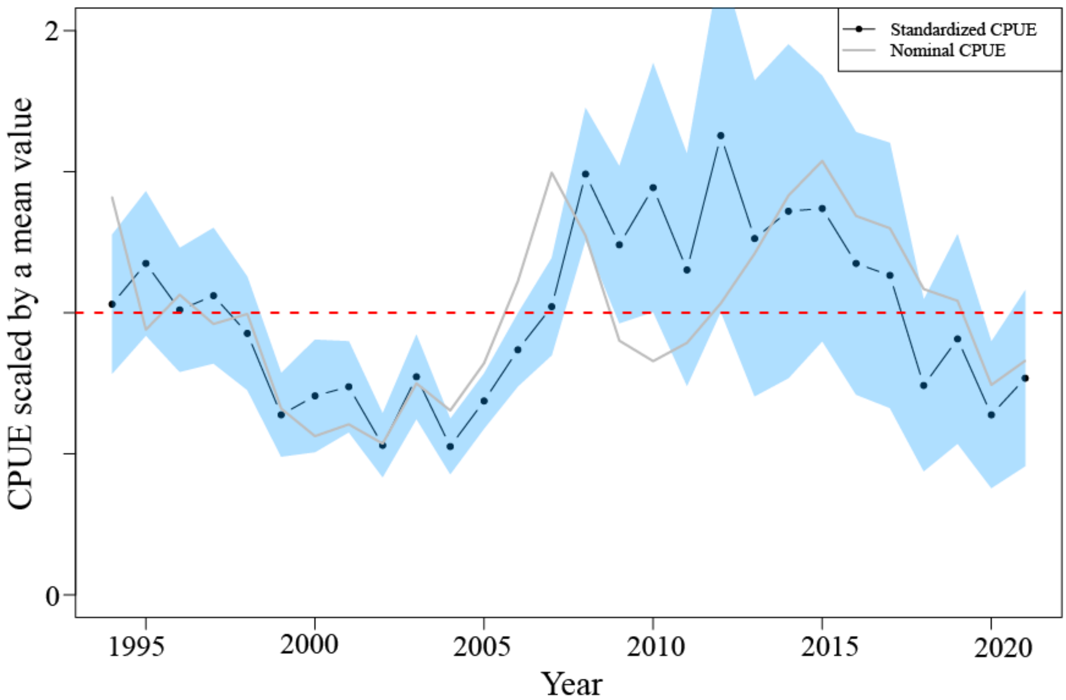

Figure 4. Annual predicted CPUE relative to its average. Gray solid line denotes nominal CPUE relative to its average, shadow denotes 95% confidence intervals, and horizontal dotted line denotes mean of relative values (1.0).

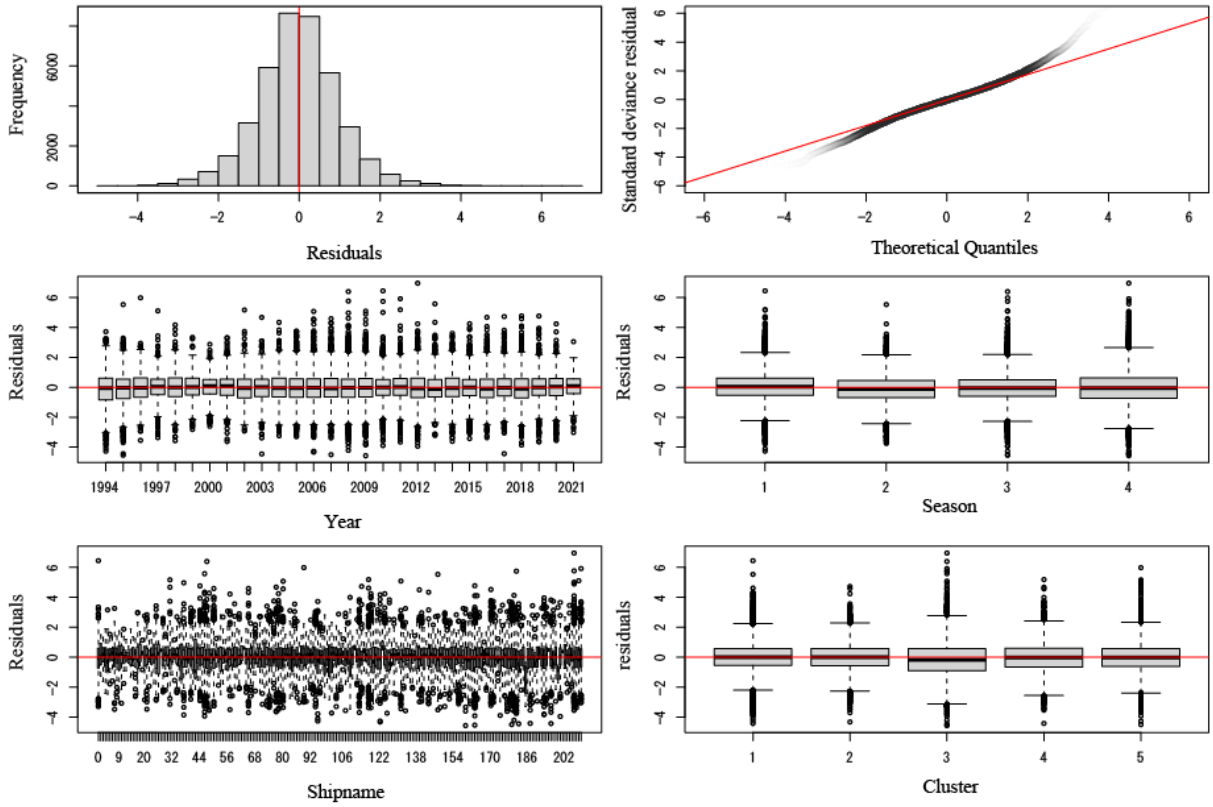

Figure 5. Diagnostic plots of goodness-of-fit for the most parsimonious model (Model-6).

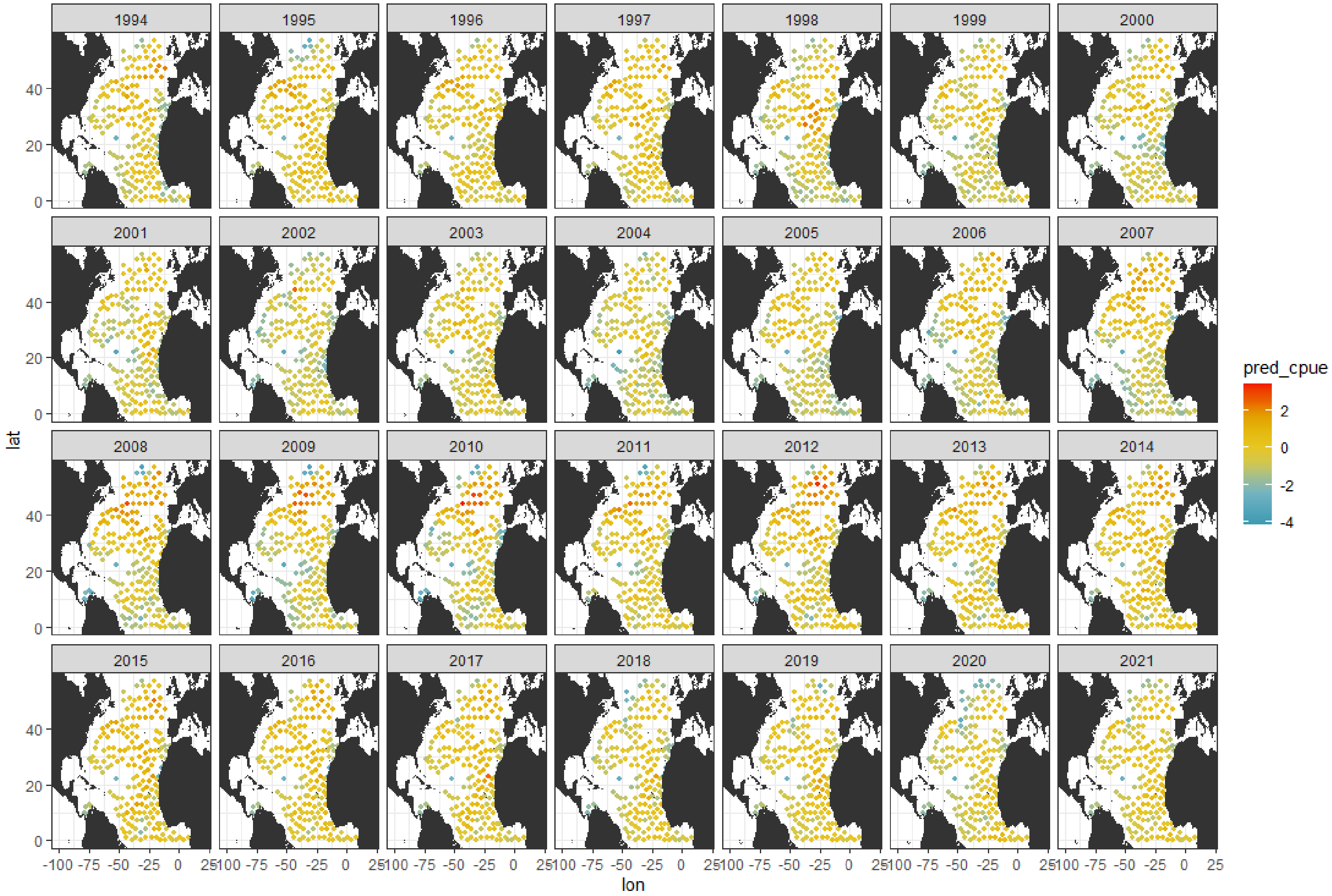

Figure 6. Annual spatial distribution of log-scaled predicted CPUE for blue shark. Two hundred knots are given in the estimation of the standardized CPUE.

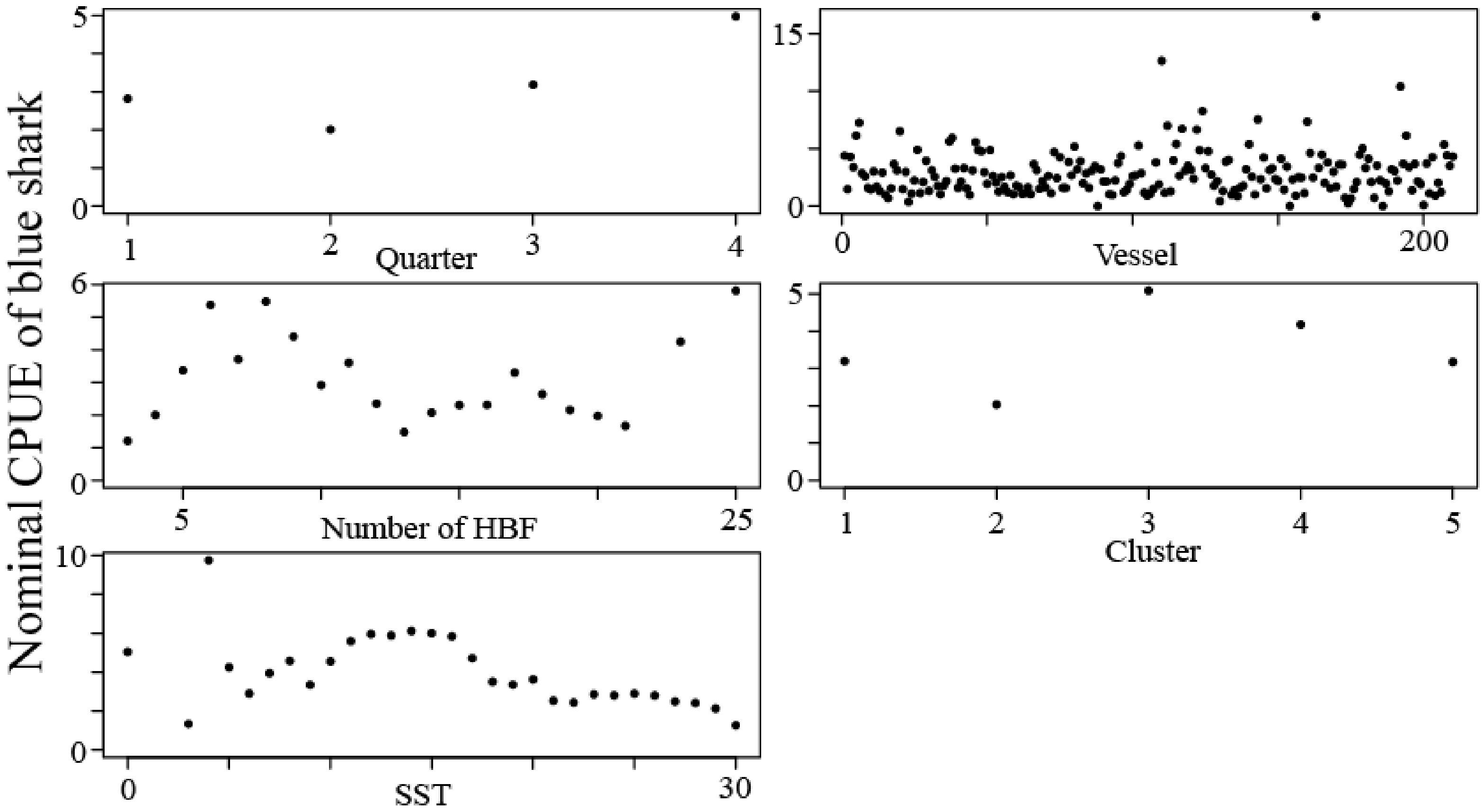

Figure A1. Changes in nominal CPUE (catch of blue shark per 1000 hooks) by quarter, vessel, number of hooks between floats (HBF), targeting cluster, and sea surface temperature (SST).

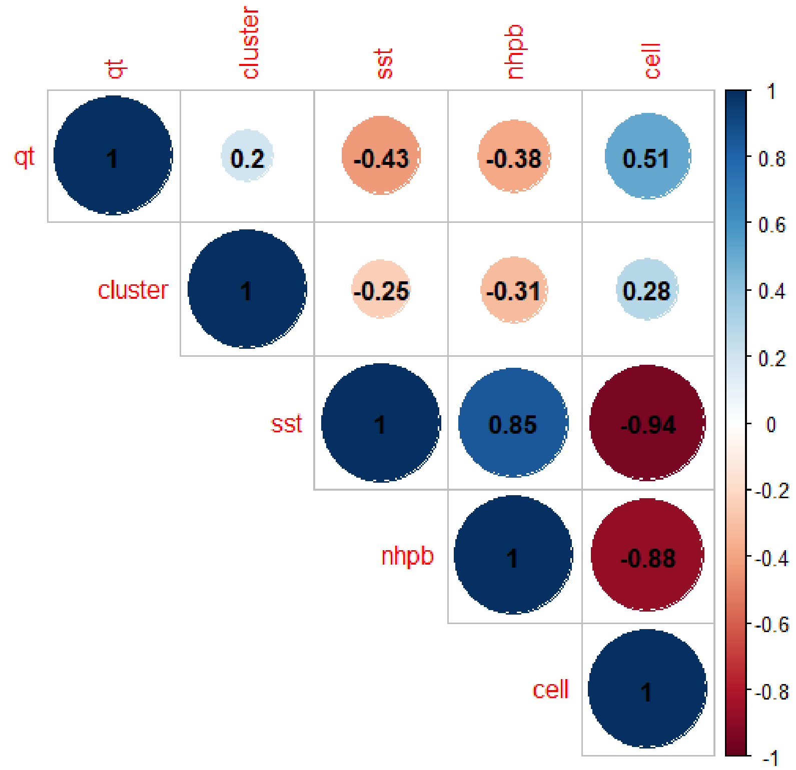

Figure A2. Correlation among quarter, number of hooks between floats (HBF), sea surface temperature (SST), cell (station), and cluster.

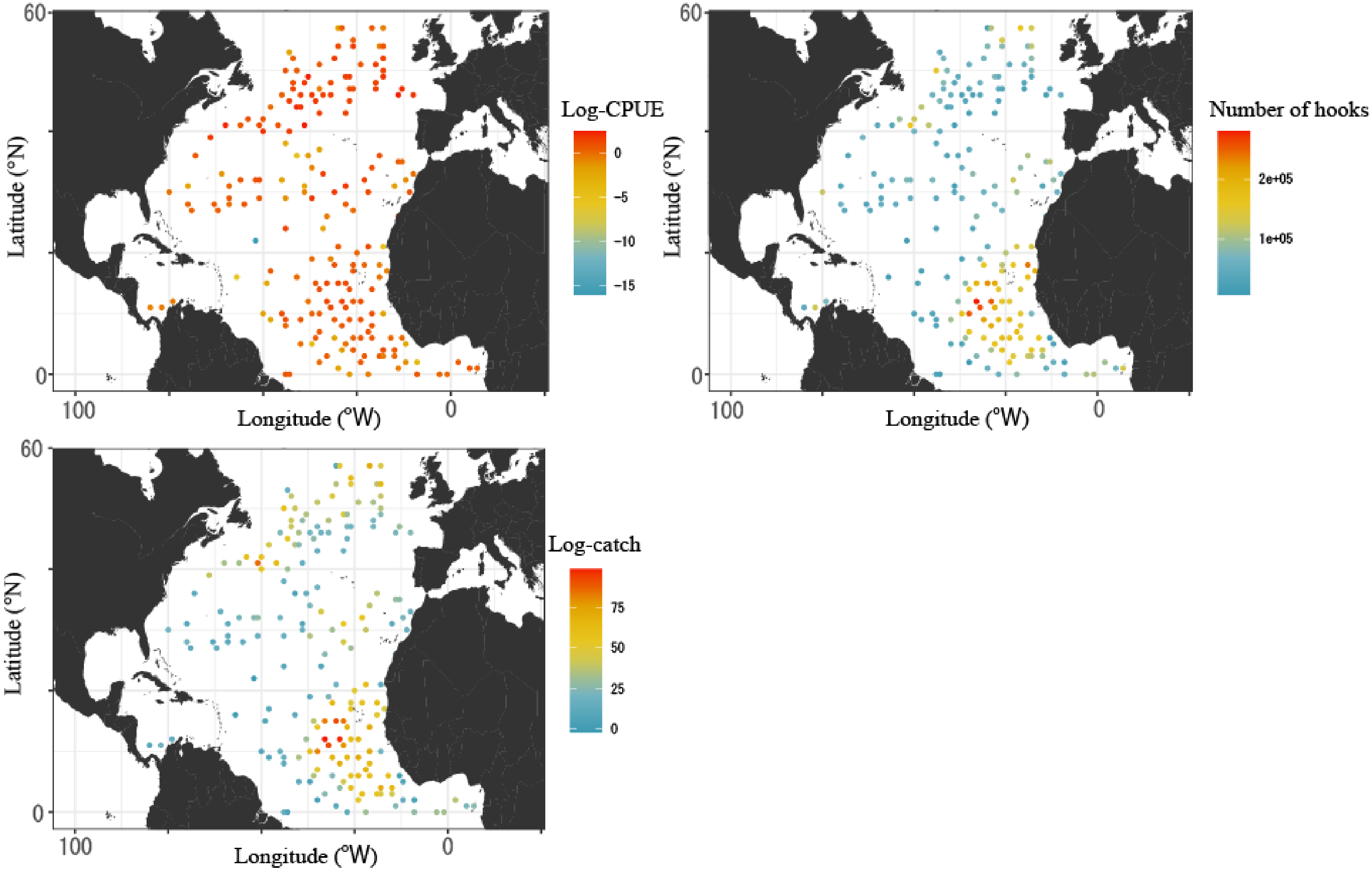

Figure A3. Spatial maps of log-scaled nominal CPUE (catch of blue shark per 1000 hooks), fishing effort (number of hooks) and log-scaled catch (catch of blue shark). Two hundred knots are given in the estimation of the standardized CPUE.