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Standardized CPUE of shortfin mako caught by Japanese shallow-set longline fisheries from 1975 to 1993[1]

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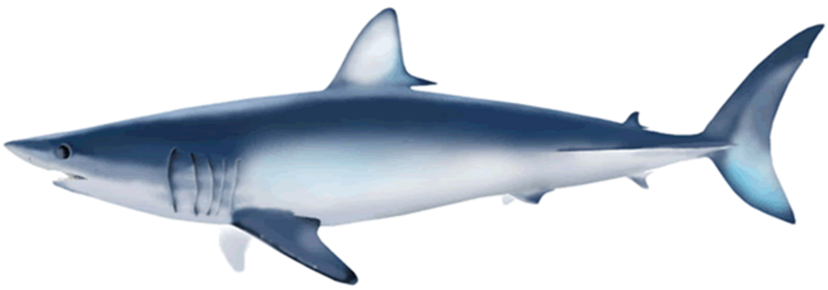

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Abstract

This working paper provides the yearly changes in standardized CPUE of shortfin mako caught by Japanese shallow-set longline fishery from 1975 and 1993 in the western and central North Pacific. Since Japanese logbook data before 1994 have no/little information about species of sharks, we estimated the catch number of shortfin mako using the catch ratio of shortfin mako to sharks from 1994 to 1999. The nominal CPUE was standardized using a spatio-temporal generalized linear mixed model (GLMM). The best model was selected using AIC for several candidate models which have different random effects as explanatory variables. The full model was selected and the standardized CPUE showed a decreasing trend from 1976 to 1987 and then it gradually increased up to 1993.

Introduction

At the data preparatory meeting in December 2017 for the stock assessment of shortfin mako (*Isurus oxyrinchus*) in the North Pacific, shark working group (WG) of International Scientific Committee for Tuna and Tuna-like Species in the North Pacific Ocean (ISC) had determined to use the fishery data from 1994 to 2016 (ISC 2017) due to the difficulty in the estimation of the catch and CPUE for the time before 1994 due to a lack of the species specific data on the Japanese longline fishery that is the main fishery catching the shortfin mako by bycatch in the North Pacific. However, if we can use the longer time series of the data, it could be useful to improve the accuracy and precision of the stock assessment because it covers their life span (i.e. 31 years old for female) and give us the data contrasts before 1994 and after 1993. It can estimate the catch number of shortfin mako for the data before 1994 with a fixed accuracy level, if the annual differences are small for the catch ratio of shortfin mako to sharks by area and quarter for the shallow-set longline data since 1994.

The objectives of this working paper are to estimate the catch number of shortfin mako caught by Japanese shallow-set longline fishery from 1975 and 1993 in the North Pacific and to provide the yearly changes in standardized CPUE of shortfin mako using a spatio-temporal generalized linear mixed model (GLMM) (Thorson et al. 2015a; Kai et al. 2017a, b). The spatio-temporal model may yield more precise, biologically reasonable, and interpretable estimates of abundance than common methods such as GLM (generalized linear model) (Shelton et al. 2014; Thorson et al. 2015a) by reducing sample selection bias and filling in the spatial gaps common in fishery-dependent data (Walter et al. 2014; Carruthers et al. 2011; Thorson et al. 2016).

Materials and Methods

Data source

We used set by set logbook data of Japanese offshore and distant water longline fishery from 1975 to 1993 and the data from 1994 to 2016.

Data filtering

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Only the shallow-set commercial data were used in the analysis. The shallow-set data could be determined because fishermen changed the depth of the gear to change the target species, and the number of HBF varied depending on the depth (Nakano et al. 1997). We defined the shallow-set fishery using a small number of HBF (3 - 6). We also used the data in Tohoku and Hokkaido (and Toyama prefecture) areas (Eastern and Northern parts of Japan) because fishermen in the areas tend to report the shark's catch well (Hiraoka et al. 2016). Finally, we used only set by set data that have 100 % reporting rates for sharks that defined by the number of sets recorded with sharks divided by the total number of sets for a trip (Nakano and Clarke, 2006).

Estimation of catch number

Since Japanese logbook data before 1994 have no/little information about species of sharks, we estimated the catch number of shortfin mako using the catch ratio of shortfin mako to sharks by area (area1: 20–30°N; area2: 30–50°N and 130–170°E; area3: 30–50°N and 170°E–160°W) and quarter (quarter1: Jan.–Mar.; quarter2: Apr.–Jun.; quarter3: Jul.–Sep.; quarter4: Oct.–Dec.) from 1994 to 1999 (Table 1). The data after 1999 were not used for this analysis to avoid the effects of the operational change in 2000s due to the changes in the targeting (Hiraoka et al. 2016) and the ratios were not stable (Fig. A1). The estimates of catch number are continuous values, so that a continuous model was used for the CPUE standardization.

Spatio-temporal model

We developed a model that accounts for both seasonal and inter-annual variability in the distribution of shark species in the western and central North Pacific, while accounting for differences in sampling intensity between locations, seasons and years. We used a hierarchical spatio-temporal model, so that we could explicitly decompose variance into components representing among-year and within-year variation. We then used the model to predict density at unsampled locations and times, to provide the best-estimate of the yearly changes in the CPUE. Spatio-temporal modelling of CPUE data assumes that species density at nearby locations should have similar density estimates during each time interval. The correlation between statistical stations (latitude and longitude) in each time interval (governed by fixed effects that are estimated from the data) was then used to estimate catch rates in a period (year and quarter) for all stations, including stations that do not have data in each period. We then compared the predicted CPUE with nominal CPUE to examine the impact of the standardization on the trends in the abundance indices of shortfin mako in the North pacific.

Model description

The spatio-temporal model estimated the density d (s, t, q) in each station s (latitude and longitude with a resolution of 2 × 2 degree square), year-quarter t (signifying a three-month quarter, where t = 1 in signifies quarter-1 1975 and t = 76 signifies quarter-4 1993), and quarter q (signifying a three-month quarter, where q = 1 in signifies quarter1 and q = 4 in signifies quarter4). We modelled the temporal variation at the scale of

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3-month intervals, given that the species showed strong variable distributions among seasons and years. Each station, year-quarter, and quarter had the density:

$$d(s,t,q) = \exp\big(d_0(t,q) + \gamma(s) + \theta(s,t) + \omega(s,q)\big), \tag{1}$$

where $d_0(t,q)$ represents temporal variation (the intercept for each year-quarter *t* and quarter q), $\gamma(s)$ represents spatial variation (the average density in station *s* relative to the average station), and $\theta(s,t)$ and $\omega(s,q)$ represents spatio-temporal variation (additional variation in density for station *s* and year-quarter *t*, and for station *s* and quarter *q*, respectively, after accounting for purely spatial and temporal variation). Spatial variation $\gamma(s)$ is modeled as a Gaussian random field (GRF), which reduces to a multivariate normal distribution (MVN) when evaluated at a finite set of stations (Thorson et al. 2015b):

$$\boldsymbol{\gamma} \sim MVN(\mathbf{0}, \sigma_\gamma^2 \cdot \mathbf{R}_{\boldsymbol{spatial}}), \tag{2}$$

where σ_γ is the marginal standard deviation (SD) of spatial variation $\boldsymbol{\gamma}$ and $\mathbf{R}_{\boldsymbol{spatial}}$ is spatial covariance for the random field and approximated using a Matérn correlation function with smoothness $\nu = 1$:

$$\mathbf{R}_{\boldsymbol{spatial}}(s,s') = \frac{1}{\Gamma(\lambda)2^{\nu-1}} \cdot (\kappa|\mathbf{H}(s-s')|)^\nu K_\nu(\kappa|\mathbf{H}(s-s')|)\ , \tag{3}$$

where |*s*-*s*'| is the Euclidian distance between two generic locations *s* and *s*', σ_γ is the marginal variances of the spatial random field, Γ is the gamma function, and K_ν is the modified Bessel function of second kind (Lindgren et al. 2011). This covariance function calculates the correlation between $\boldsymbol{\gamma}$ at stations *s* and *s*' given their distance |*s*-*s*'| after linear transformation **H** which accounts for geometric anisotropy (see supplementary in Thorson et al. 2015a). The spatial-temporal variation, $\theta(s,t)$, was modeled by combining the GRF for spatial variation with first-order autoregressive process for temporal variation at each site:

$$\mathrm{vec}(\boldsymbol{\theta}) \sim MVN(\mathbf{0}, \sigma_\theta^2 \cdot \mathbf{R}_{\boldsymbol{spatial}} \otimes \mathbf{R}_{\boldsymbol{AR1}}), \tag{4}$$

where $\mathrm{vec}(\boldsymbol{\theta})$ is the vectorized value of matrix $\boldsymbol{\theta}$, σ_θ is the marginal SD of spatio-temporal variation $\boldsymbol{\theta}$**,** $\otimes$ is the Kronecker product where if **A** is an *m* x *n* matrix and **B** is a *p* x *q* matrix, then the Kronecker product $\mathbf{A} \otimes \mathbf{B}$ is the *mp* x *nq* block matrix:

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} \boldsymbol{a_{11}}\mathbf{B} & \cdots & \boldsymbol{a_{1n}}\mathbf{B} \\ \vdots & \ddots & \vdots \\ \boldsymbol{a_{m1}}\mathbf{B} & \cdots & \boldsymbol{a_{mn}}\mathbf{B} \end{bmatrix}, \tag{5}$$

and $\mathbf{R}_{\boldsymbol{AR1}}$ is the temporal component of variance in spatio-temporal variation $\boldsymbol{\theta}$**:**

$$\mathbf{R}_{AR1}(t,t') = \rho^{|t-t'|}, \tag{6}$$

where ρ is a parameter governing autocorrelation and |*t*-*t*'| is the difference in time among samples in year-quarter *t*. The other spatial-temporal variation, $\omega(s,q)$ was modeled by the same methods as $\theta(s,t)$. We estimated a separate SD for spatial (σ_γ) and spatio-temporal (σ_θ, and σ_ω) components, but estimated the same decorrelation distance (κ) for the processes, using the implicit assumption that dynamics were defined by a “characteristic scale” that defined decorrelation distance for both. Following the parameterization from Lindgren et al. (2011), we estimated a magnitude parameter η for each spatial and spatio-temporal process, and the corresponding marginal SD was then calculated as:

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$$\sigma_\gamma = 1/\sqrt{4\pi\eta_\gamma^2}, \tag{7}$$

where other marginal SDs (i.e., σ_θ, and σ_ω) were calculated similarly (from η_θ, and η_ω).

Expected catch c_i^* is a function of density and fishing effort f_i (number of hooks), $c_i^* = d(s_i, t_i, q_i)f_i$, and was then compared with the observed catch (in numbers) c_i for the i-th observation, in station s_i, year-quarter t_i, and quarter q_i. The compiled spatio-temporal data (by each station and year-quarter) of shortfin mako showed a lognormal distribution, so that we assumed that available catch data c arises from the lognormal distribution:

$$\Pr(C = c) = \text{Lognormal}(C; \log(c), \sigma^2) \tag{8}$$

where Lognormal ($x; m, \sigma^2$) is the lognormal probability density function evaluated at x, given log-mean m and log-standard deviation σ, σ is the time-varying (i.e. year-quarter changes in) log-standard deviation for catch rates.

Parameters representing temporal variation (d_0), spatial covariance (κ and η_γ), and spatial-temporal covariance (η_θ, η_ω, ρ_θ, and ρ_ω) were estimated as fixed effects while integrating across random effects representing spatial (station) and spatio-temporal (station and year-quarter, and station and quarter) variations (Table A1). This integral was approximated using the Laplace approximation, and the fixed effects were estimated using gradient information as provided by Template Model Builder (TMB; Kristensen, 2015), which is an R package (R Core Team, 2016) for fitting statistical latent variable models to data. It was inspired by ADMB (Fournier et al. 2012). The details of TMB are described on the website (see http://www.admb-project.org/developers/tmb/, accessed 28 Mar. 2018). Further details regarding GRF estimation can be found in Thorson et al. (2015a, b).

After estimating the fixed effects (year and quarter, and parameters for the random effects) by maximizing the marginal likelihood of the data, the relative trends of CPUE were predicted from the fixed and random effects. Coefficient of variation (*CV*) for estimated CPUE was estimated using TMB.

Model convergence was confirmed using the hessian matrix (confirming that the hessian is positive definite) and by ensuring that the maximum absolute value of the final gradient of parameters was less than 0.01. The changes in predicted catch rates were compared among multiple models (Fig. 1). We used Akaike Information Criterion (AIC; Akaike, 1973) to identify which model had greater support given available data (Table 2). This model-selection is appropriate given that TMB implements maximum marginal likelihood estimation.

We chose the best model with regards to the combinations of the explanatory variables for the four candidate models. We also compared the yearly changes in predicted catch rates among multiple models for model selection. The CV and confidence intervals of annual changes in the CPUE were calculated for the

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best-fitting model using the information matrix and delta-method (Fournier et al. 2012). We also examined the Pearson residuals for the best-fitting model to identify model misspecification and heteroscedascity (Maunder and Punt 2004)

Results

The most complicated model (M-4) included purely spatial variation, spatio-temporal variation among seasons, and spatio-temporal variation among all periods. AIC identified this saturated model as the most parsimonious model (Table 1) and the maximum gradient was less than 0.01. Including the seasonal component for spatio-temporal variation substantially decreased the marginal SD of spatial and spatio-temporal variation among all periods (e.g., compare the M-3 with M-4). We therefore used the saturated model (M-4) to predict the yearly changes in the CPUE of shortfin mako.

Overall, the trend in predicted CPUE was almost similar among four models, however, the difference of the random field (i.e. spatial-temporal random effects) had a large impact on the trends in predicted CPUE (Table 1, Fig. 1). The standardized CPUE showed a decreasing trend from 1976 to 1987 and then it gradually increased up to 1993, and the CV of predicted CPUE ranged from 0.9 to 1.1 (Table 1, Fig. 2).

Diagnostic plots of goodness-of-fit to the data for the most parsimonious model (Model 4) were shown in Fig. 3. The Pearson residuals indicated a slight negative skewness, however the model fits at each observation for the model were good.

Spatial distributions of predicted CPUE relative their averages were shown in Appendix figures (Figs. A2-5). These spatial distributions indicated that the hotspots of shortfin mako were distributed in the water of coastal and offshore nearby eastern part of Japan.

Discussion

This working paper provided the yearly changes in standardized CPUE of shortfin mako caught by Japanese shallow-set longline fishery from 1975 and 1993 in the western and central North Pacific. There is no problem to readily use the predicted CPUE for the stock assessment of shortfin mako, if the catch number of "shortfin mako" is recorded instead of the catch number of "sharks". However, there is a large uncertainty in the estimation of the catch number because we estimated catch number of shortfin mako using the catch ratio of shortfin mako to sharks for a different decade. For that reason, it is questionable that the predicted CPUE of shortfin mako in this study can represent the actual trends in the abundance in the North Pacific.

Shortfin mako is a bycatch species and susceptible to overexploitation due to slow growth rates, maturity at a late age, and low fecundity (Compagno 2001). The considerable increase of the fishing effort in 1970s and 1980s was caused by the expansion of the shallow-set longline fishery and the existence of the driftnet fisheries at high seas. These fisheries must have a large impact on the abundance of shortfin mako. These

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facts can explain the decline of the abundance in 1970s and 1980s and an increase of the abundance in the late of 1980s and the beginning of 1990s due to the decrease in the fishing effort. As the result, the trends of the predicted CPUE is likely to be reasonable. However, it is better to use a large CV (e.g. 0.2) when this index is applied to the assessment model.

To examine the consistency of the spatial distribution of shortfin mako between early period (1975-1993) and latter period (1994-1999), we compared the variograms (a function describing the degree of spatial dependence of a spatial random field or stochastic process) (Cressie 1993) for the data of two periods. The sample variogram for the early period showed a clear spatial correlation up to around 0.01 km (Fig. A6), whereas the sample variogram for the latter period showed a clear spatial correlation up to around 0.02 km (Fig. A7). These results suggested that there was a spatial correlation present for both data. In addition, there was a different spatial dependency in the residuals for both data. Therefore, the degree of spatial dependency may be different between the data of early period and latter period. However, it is difficult to judge whether the estimated spatial distribution of early period is incorrect because the spatial distribution can be changed by year and quarter. In future work, we need to explore the relationships between the spatial dependency and the catch ratio of shortfin mako to sharks.

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Table 1. Catch rate of shortfin mako to sharks by area and quarter. The definitions of area and quarter are as follows: area1: 20–30°N; area2: 30–50°N and 130–170°E; area3: 30–50°N and 170°E–160°W; quarter1: Jan.–Mar.; quarter2: Apr.–Jun.; quarter3: Jul.–Sep.; quarter4: Oct.–Dec..

Area	Q1	Q2	Q3	Q4
1	0.0217	0.0136	0.0096	0.0253
2	0.0177	0.0106	0.0096	0.0284
3	0.0223	0.0105	0.0058	0.0287

Table 2. Summary of the model selection information from four analyses, including the catch rate predictor as random effect, the number of parameters, the deviance, the reduction in AIC (ΔAIC) from the best-fitting model, maximum gradient, marginal standard deviation (SD) of spatial variation and spatio-temporal variations.

Model	Catch rate predictors of random effect (RE)	Number of parameters	Deviance	ΔAIC	Maximum gradient	Marginal SD of spatial variation	Marginal SD of spatio-temporal (year-quarter) variation	Marginal SD of spatio-temporal (quarter) variation
M-1	Null	152	36090	2491	< 0.01			
M-2	Station	156	34590	999	< 0.01	0.489		
M-3	Station + Year-quarter and station	158	33632	45	< 0.01	0.217	0.493	
M-4	Station + Quarter and station + Year-quarter and station	160	33583	0	< 0.01	0.195	0.469	0.178

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Table 3. Summary of yearly changes in CPUE predicted by spatio-temporal model along with the corresponding estimates of the coefficient of variation (CVs), and yearly changes in the nominal CPUE and fishing effort (number of hooks x 1millions). The values are predicted using the best fitting model and scaled by average CPUE.

Year	Predicted	CV	Nominal	Effort
1975	1.06	0.11	1.31	12.0
1976	1.30	0.09	1.46	16.7
1977	1.21	0.09	1.35	21.5
1978	1.26	0.09	1.18	20.2
1979	1.15	0.10	1.29	21.0
1980	1.24	0.09	1.30	18.8
1981	0.93	0.10	1.06	19.0
1982	1.00	0.10	1.13	17.3
1983	1.07	0.11	1.04	22.8
1984	0.98	0.10	0.89	23.7
1985	0.78	0.11	0.77	28.2
1986	0.94	0.11	0.92	29.8
1987	0.71	0.10	0.70	29.8
1988	0.82	0.11	0.74	24.2
1989	0.86	0.11	0.64	23.7
1990	0.82	0.11	0.63	20.6
1991	0.91	0.12	0.82	20.7
1992	0.90	0.12	0.80	21.9
1993	1.06	0.12	0.98	19.5

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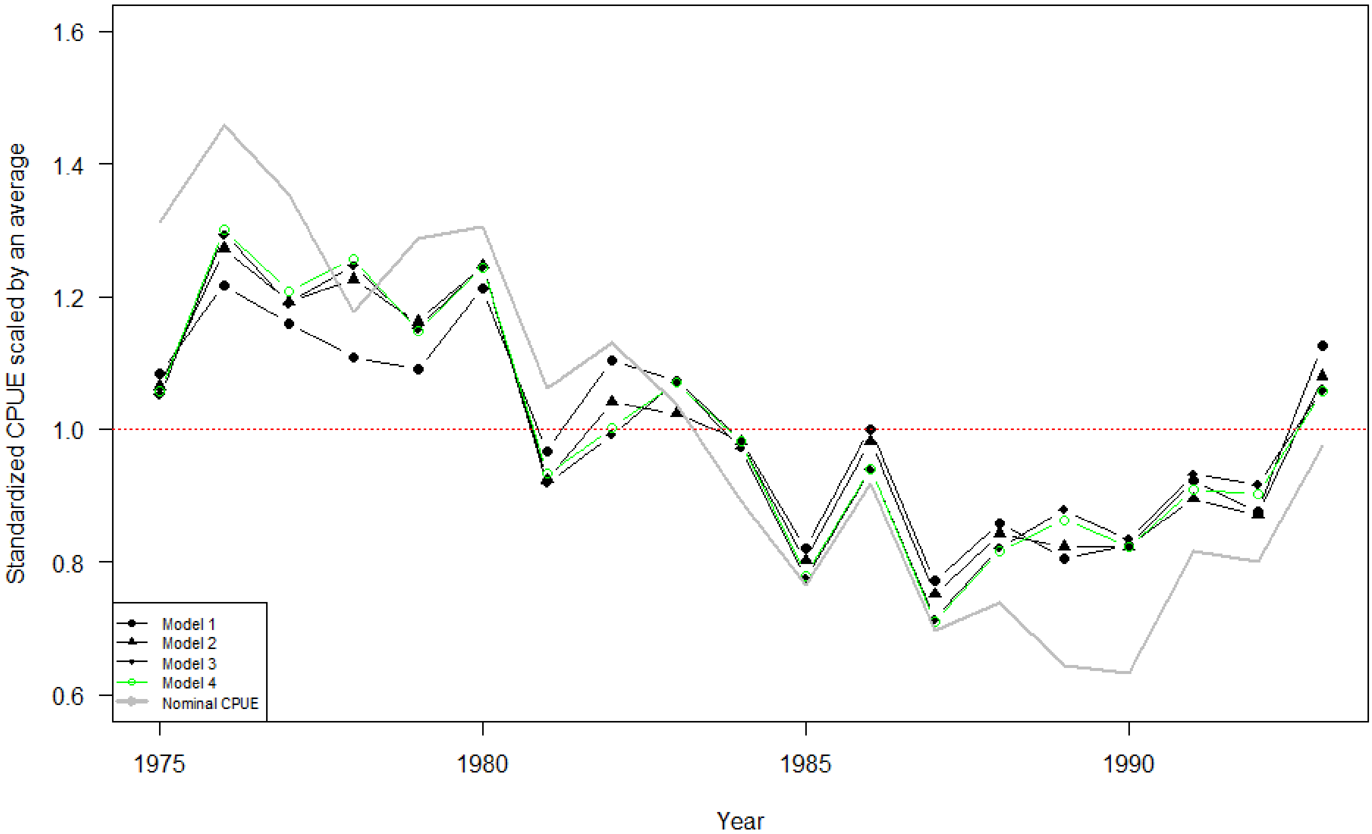

Figure 1. Yearly changes in predicted CPUE relative its average for shortfin mako for four models with the explanatory variables sequentially added to the null model. Please see Table 2 for the model structure.

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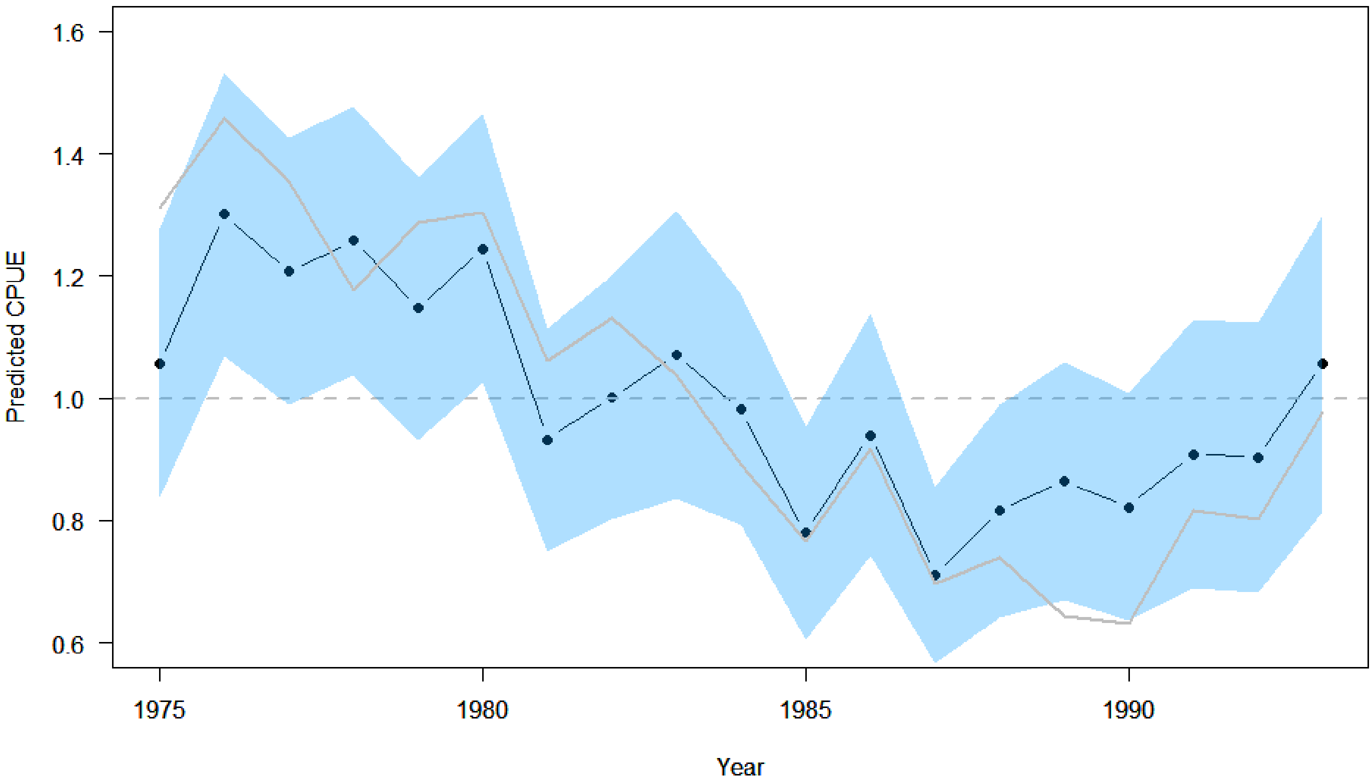

Figure 2. Yearly changes in predicted CPUE relative its average for shortfin mako (black solid line with filled circle). Grey solid line denotes the nominal CPUE relative to its average, shadow denotes the 95 % confidence intervals, and the horizontal dotted line denotes mean value of relative values (1.0).

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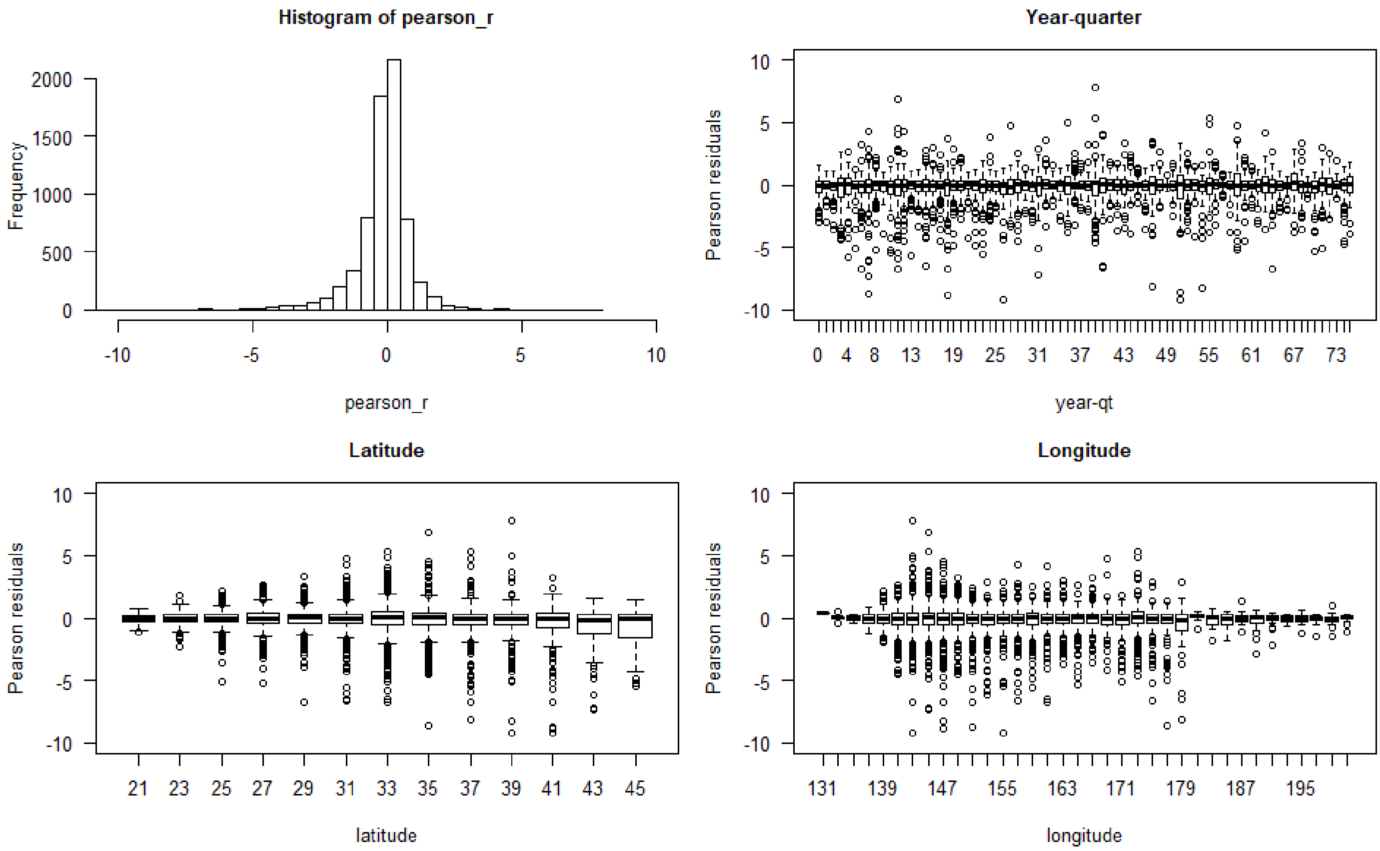

Figure 3. Diagnostic plots of goodness-of-fit to the data for the most parsimonious model (Model 4) selected by AIC. Histogram of Pearson residuals (upper left): Pearson residuals against year-quarter (upper right) : Pearson residuals against latitude (lower left): Pearson residuals against longitude :(lower right)

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Appendix figure and tables

Table A1. List of all parameters and the estimates for the best-fitting model.

No	Parameter name	Symbol	Type	Estimates
1	Distance of correlation (Spatial random effect)	κ	Fixed	0.31
2	Northings anisotropy	h_1	Fixed	0.51
3	Anisotropic correlation	h_2	Fixed	0.29
4	Parameter governing pointwise variance (Spatial random effect)	η_γ	Fixed	1.45
5	Parameter governing pointwise variance (Spatio-temporal (year-quarter) random effect)	η_θ	Fixed	0.60
6	Parameter governing pointwise variance (Spatio-temporal (quarter) random effect)	η_ω	Fixed	1.59
7	Parameter governing autocorrelation (Spatio-temporal: year-quarter random effect)	ρ_θ	Fixed	0.38
8	Parameter governing autocorrelation (Spatio-temporal quarter random effect)	ρ_ω	Fixed	0.10
9-84	Intercept for year-quarter	d_0	Fixed	Not shown
85-160	Log-standard deviation for catch rates for year-auarter	σ	Fixed	Not shown
161	Spatial residuals	γ	Random	Not shown
162	Spatio-temporal (year-quarter) residuals	τ	Random	Not shown
163	Spatio-temporal (quarter) residuals	θ	Random	Not shown

[1] Working document submitted to the ISC Shark Working Group Workshop, April, 10-16, 2017, La Jolla, CA, USA. **Document not to be cited without author’s permission.**

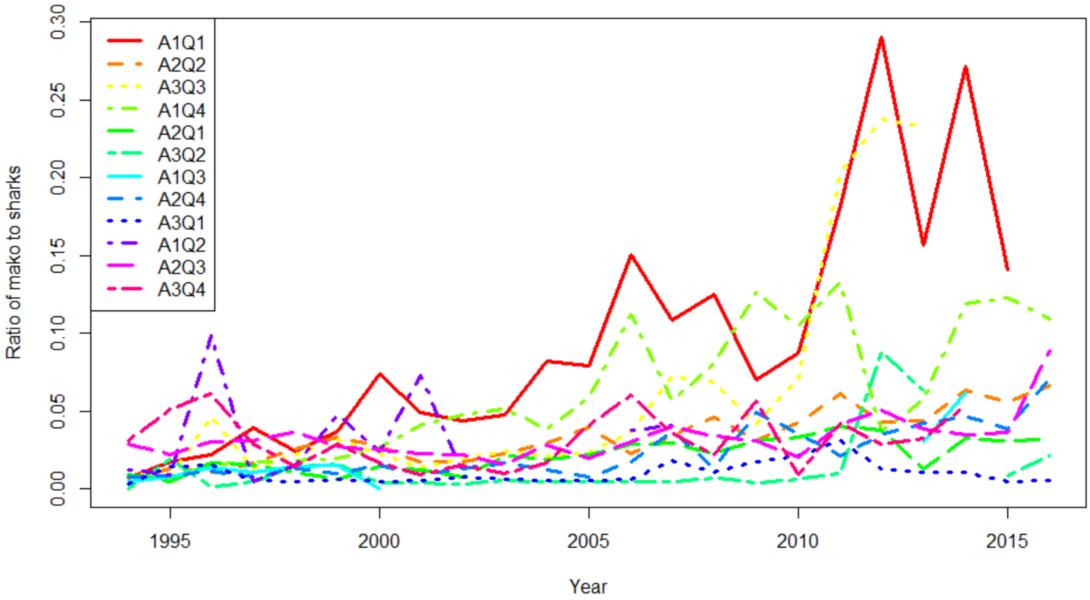

Figure A1. Catch ratio of mako shark to sharks by area and quarter from 1994 to 2016.

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[1] Working document submitted to the ISC Shark Working Group Workshop, April, 10-16, 2017, La Jolla, CA, USA. **Document not to be cited without author's permission.**

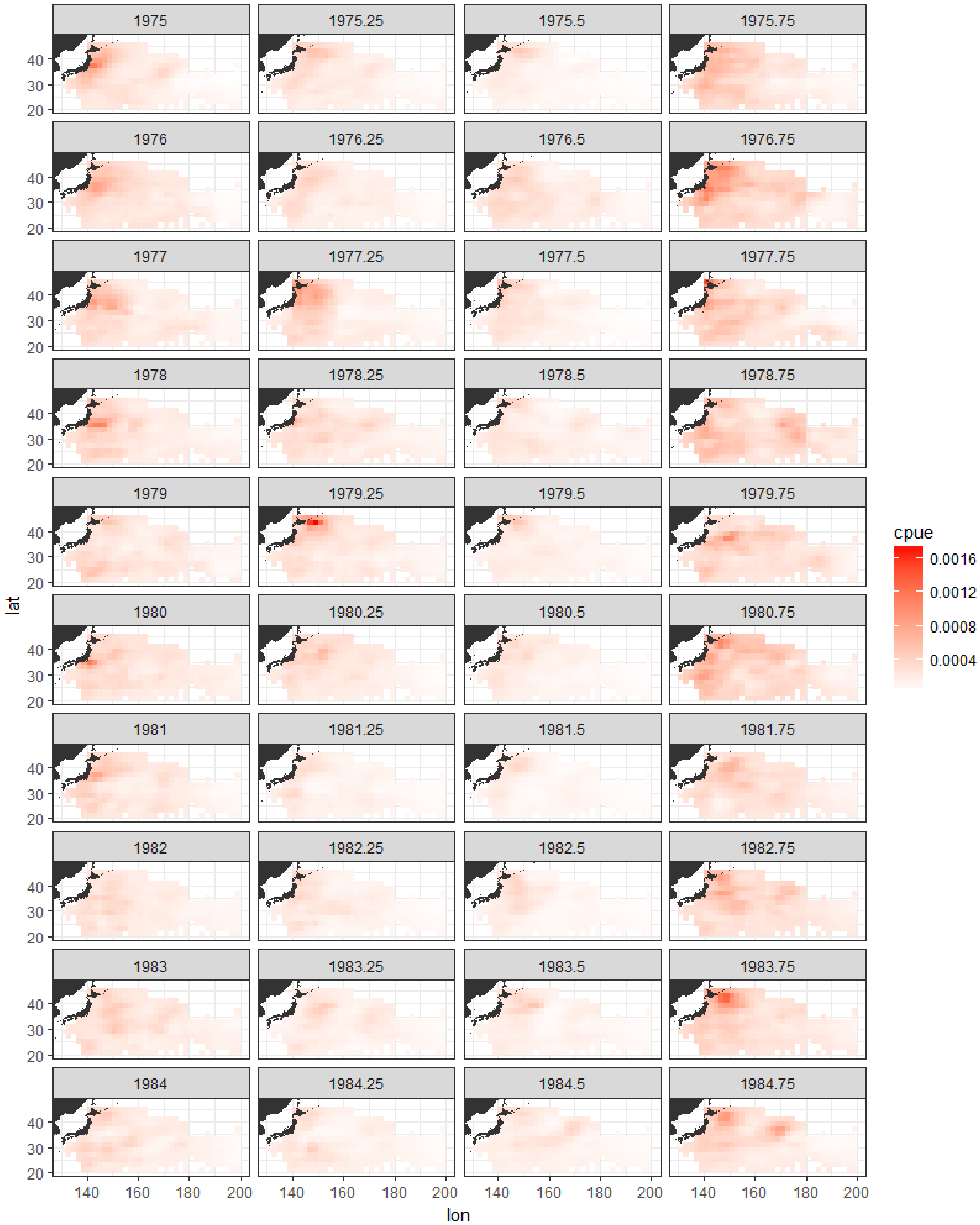

Figure A2. Year-quarter specific spatial distribution of predicted CPUE relative its average from 1975 and quarter 1 to 1993 and quarter 4.

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Figure A2. Continued.

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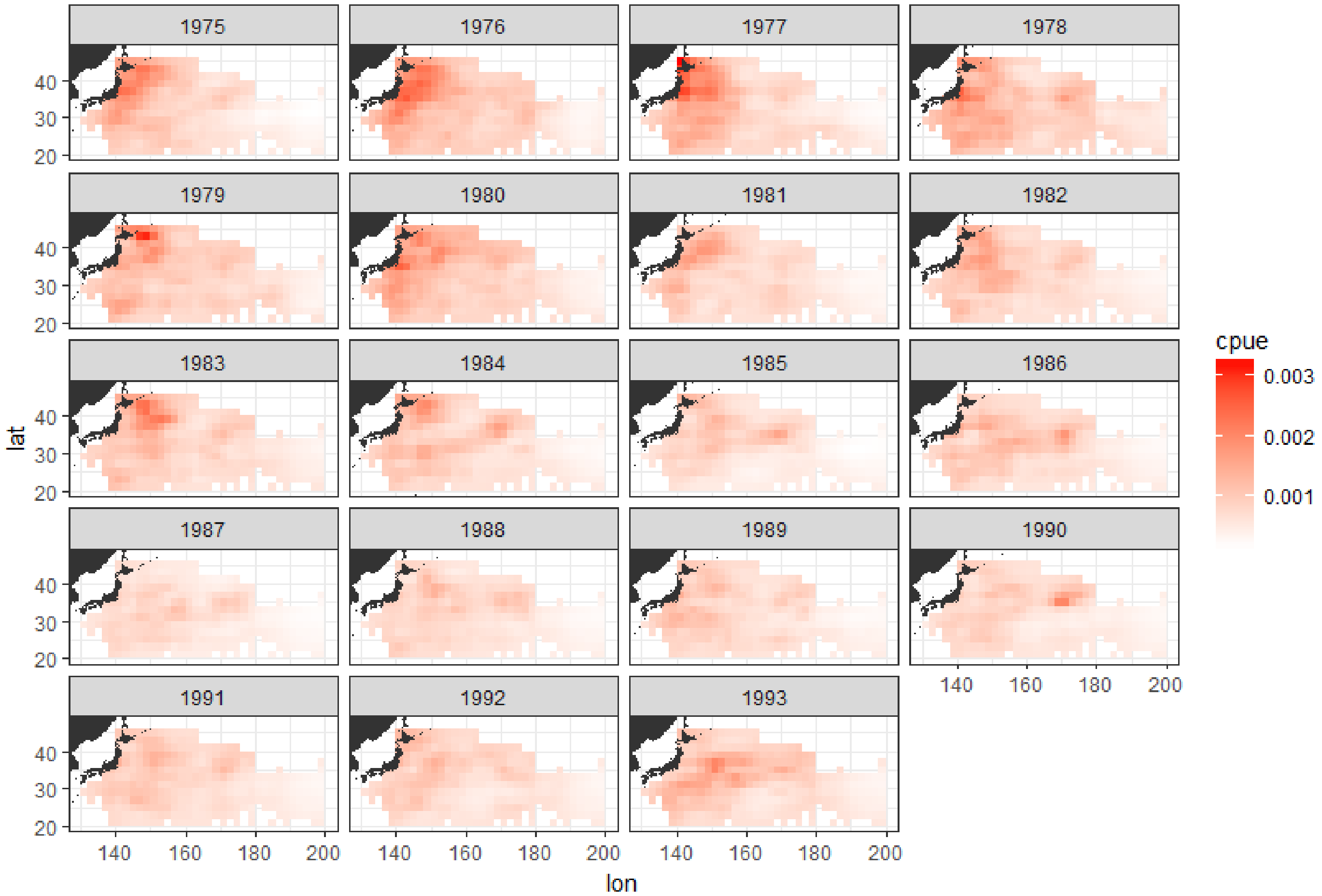

Figure A3. Year-specific spatial distribution of predicted CPUE relative its average.

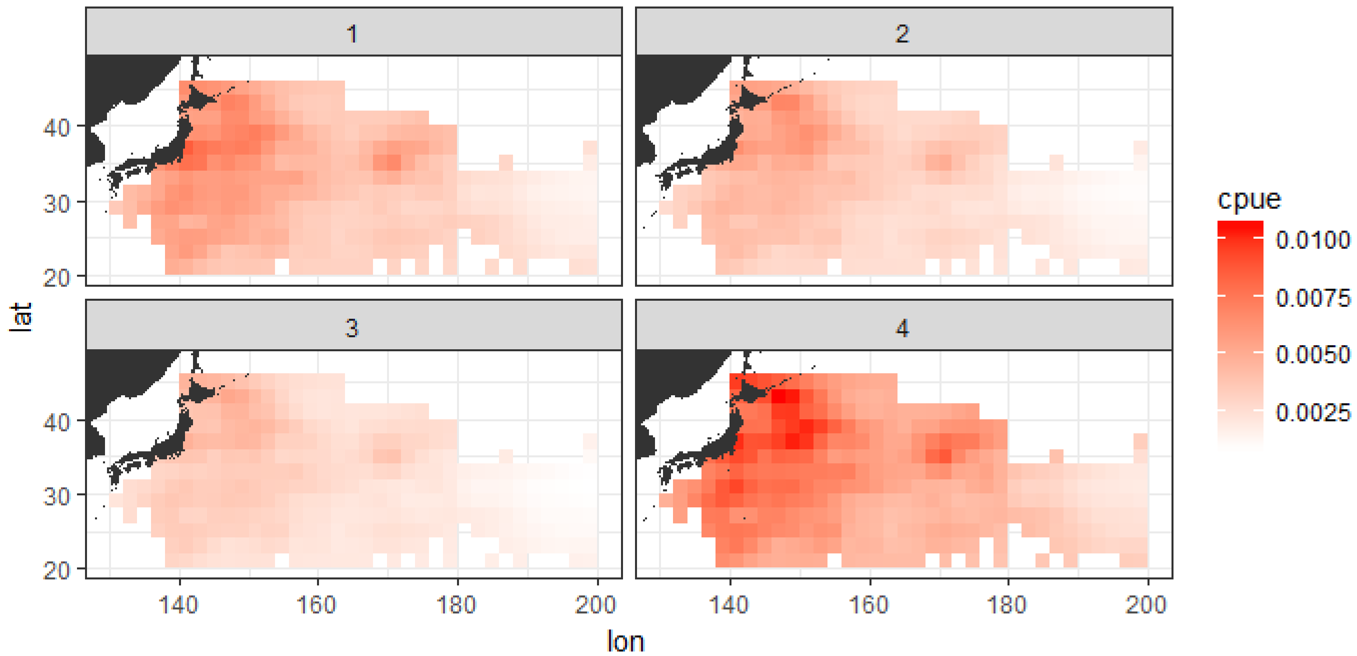

Figure A4. Quarter-specific spatial distribution of predicted CPUE relative its average.

[1] Working document submitted to the ISC Shark Working Group Workshop, April, 10-16, 2017, La Jolla, CA, USA. **Document not to be cited without author's permission.**

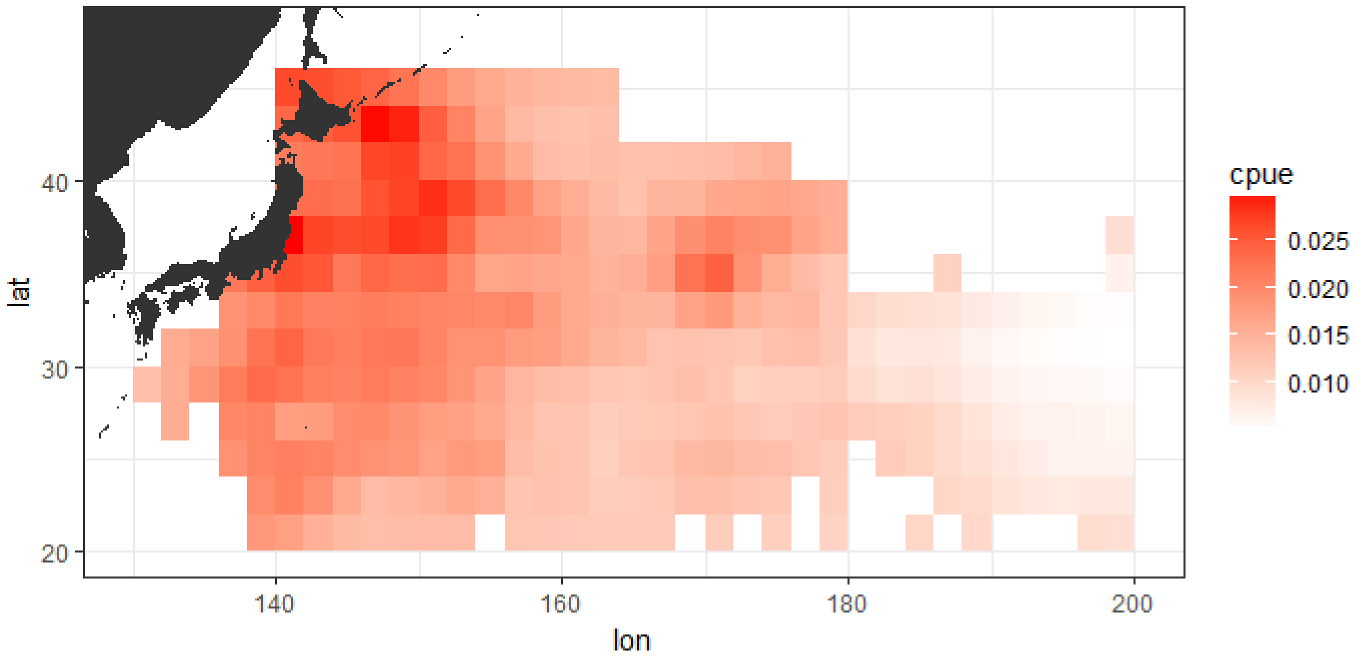

Figure A5. Overall spatial distribution of predicted CPUE relative its average.

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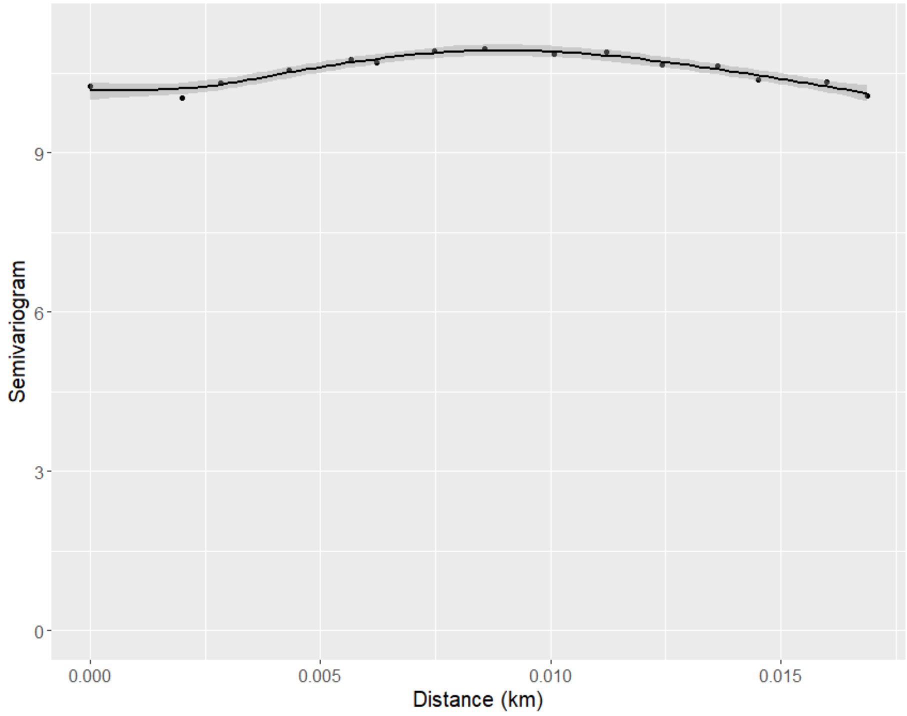

Figure A6. Sample variogram of the Pearson residuals obtained by the null model for the data from 1994 to 1999.

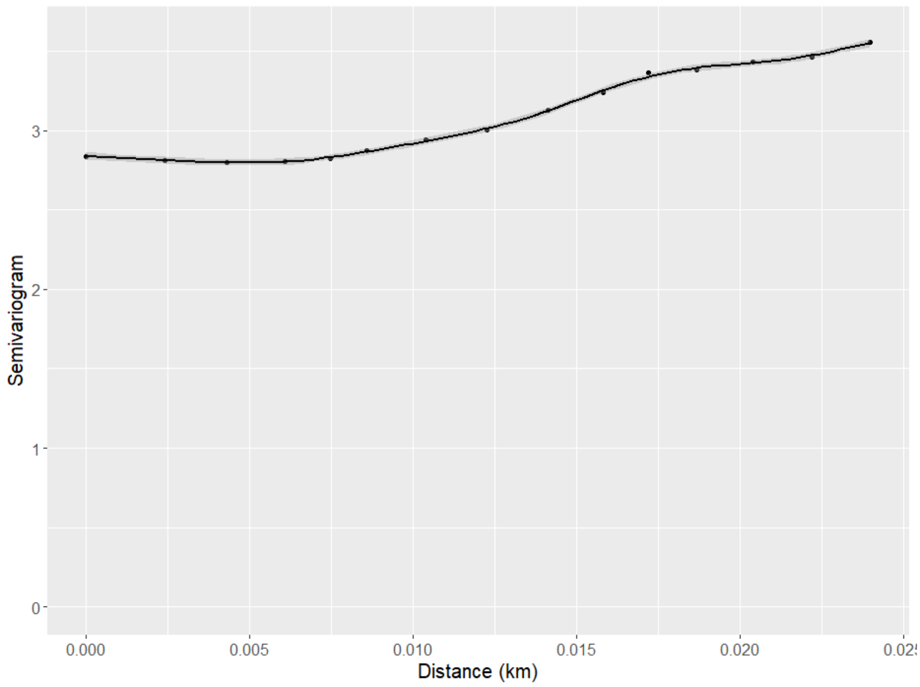

Figure A7. Sample variogram of the Pearson residuals obtained by the null model for the data from 1975 to 1993.

[1] Working document submitted to the ISC Shark Working Group Workshop, April, 10-16, 2017, La Jolla, CA, USA. **Document not to be cited without author's permission.**