CPUE standardization of the Indian Ocean swordfish (*Xiphias gladius*) by Japanese longline fisheries: Using negative binomial GLMM and zero inflated negative binomial GLMM to consider vessel effect.

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Highlights

1. Using R software package glmmTMB, I applied the GLM with a negative binomial distribution (NB-GLM), the GLMM with a negative binomial distribution (NB-GLMM) and the GLMM with a zero-inflated negative binomial distribution (ZINB-GLMM) for the CPUE standardization of the Indian Ocean swordfish. The random effects were used for the vessel name and the 5 x 5 grid area.

2. I set two time-series that are 1976-1993 and 1994-2015 to the IOTC management area. Because 1) the Japanese logbook format changed in 1994, 2) The shallow sets changed to the deep sets during mid of the 1990s, 3) Number of operated vessels were changed. In detail, a lot of vessels moved to another Ocean between 1980 and mid of the 1990s then these vessels came back to the Indian Ocean.

3. I used BIC for the model selection because Japanese logbook is a big data. Using the selected model, standardized CPUE were calculated by R software package “lsmeans”. In some models, the effect of hooks between floats was not statistically significant. The reason is thought that the gear effect might be included the vessel effect.

4. I used the Pearson residuals for the model validation. Most of the selected models showed a good fitting. However, the Pearson residuals of South West area (1976-1993) showed the different trends by the covariate.

5. Calculating the CPUE for the whole Indian Ocean might be misunderstood to realize trends of adult swordfish biomass, because length frequency of swordfish varies by the four areas. It is better to use CPUE of North West area where the data is substantial to the production models such as ASPIC and BSPM.

6. Since 2010, the number of operating vessels have drastically decreased, and area coverage also reduced, hence the standardized CPUE after 2010 might be unreliable. Furthermore, there is a possibility that data after 2010 would have an impact on past estimates quality. Therefore, it is necessary to standardize before 2010 or to use geostatistical models to fill time-spatial defects. In this analysis, I did not use the interaction to avoid overfitting for the GLMMs. In actual, there

might be a correlation between year and area. Such a relationship can also be handled with the geostatistical models in the future assessment.

Abstract

The IOTC has conducted the stock assessment of swordfish by dividing the Indian Ocean into four areas. For the benchmark stock assessment, I standardized the Japanese longline CPUE of swordfish for each of these regions. To properly handle information included by vessel names such as differences in targeting and equipment, and zero inflated catch data, I applied the GLM with negative binomial distribution, the GLMM with negative binomial distribution and the zero-inflated negative binomial distribution. The model selection was performed using the BIC, and the R software package lsmeans were used to calculate the standardized CPUE.

Introduction

The Indian Ocean Tuna Commission (IOTC) has divided the Indian Ocean into four areas and conducted the stock assessment for swordfish (Figure 1) (IOTC 2014). Nishida and Wang (2014) calculated the standardized CPUE for this stock assessment. They defined the targeting operation by cluster analysis to estimate the realistic CPUE of the Indian Ocean swordfish because targeting information have not been listed in the Japanese log book data. Targeting information is strongly critical information for CPUE standardization because it makes change the catchability for fish. However, the targeting information does not contain any other vital information (e.g., radar equipment and operational technique of crew, etc.). These differences also have a significant influence on the catchability which is the essential issue for standardization of CPUE. I considered this information and targeting effect are included in the "vessel name" of the Japanese logbook data. However, it has not been taken into consideration in the CPUE analysis of the previous studies. It is better to use random effect rather than the fixed effect to consider the vessel effect because a lot of Japanese vessels operated in the Indian Ocean. In detail, if over hundred covariates are used for GLM analysis, the standardized CPUE tend to be over fit to nominal CPUE. Meanwhile, swordfish is the bycatch species for Japanese longliners in the Indian Ocean, and the number of catch in one operation tends to be zero. To treat these zero-catch data is also a major problem for CPUE standardization. Improving these difficulties, I used the GLM with a negative binomial distribution (NB-GLM), GLMM with a negative binomial distribution (NB-GLMM) and the GLMM with a zero-inflated negative binomial distribution (ZINB-GLMM) in the standardization of the CPUE of Indian Ocean swordfish.

Material and Method

Data sets

I used a logbook of the Japanese longline fishery in the Indian Ocean for CPUE standardization. Japanese logbook data has been reported the detail of fishery operation. The number of vessels operated in the Indian Ocean has been historically changed (Figure 2). The number of operating vessels increased to mid 1980 and then declined over the next the 1990s (Figure 2). From the mid of the 1990s to the 2000s, the number of operated vessels increased again (Figure 2). However, the number of vessels dropped sharply in the 2010s (Figure 2). It is thought that in this historical change was occurred by the vessel moving to another Oceans. In the 1970s, Japanese tuna longliners operated near the equator, and the southern bluefin tuna fishery operated near the 50 degrees south (Figure 3). After that, the fishing ground of Japanese longline spread throughout the Indian Ocean from the 1990s to the 2000s (Figure 3). Since 2010, the fishing ground has shrunk rapidly (Figure 3). The high CPUE in the wide area throughout is North West area (Figure 4). However, due to the influence of pirates, there is no operation in 2011.

Area definition

Based on the IOTC area definition, I calculated CPUE for each of the four areas (Figure 1). This area definition is considered relatively reasonable. The reasons are as follows:

1) Due to the difference of the targeting species, the operational style greatly differs between North area and South area (Figure 5).
2) The historical trend of zero catch rate varies by area (Figure 6).
3) the length frequency of swordfish is different by area (Figure 7).

Thus, standardized CPUE by area can be fit to the area based fishery defined by SS3. North West is the most appropriate for CPUE standardization to fit the production models such as ASPIC and BSPM, because the data is substantial and that CPUE is relatively higher than another area.

Time periods

I used Japanese logbook data which period is between 1976 and 2015 because the vessel names for each operation began to be compiled accurately since 1976. I also set two time periods as 1976-1993 and 1994-2015. The reasons are as follows:

1) The data quality might be different because of the logbook format change.
2) The gear configuration of Japanese longline fishery has drastically changed in the middle of the 1990s (Figure 5). In detail, hooks between floats (HBF) changed from shallow to deep rope operation (Figure 5).
3) The operated vessels were decreased in middle of the 1990s (Figure 2).

Considering these facts, I divided data sets into two time periods.

Statistical models

I applied simple GLM with negative binomial distribution (NB-GLM), GLMM with negative binomial distribution (NB-GLMM), and GLMM with zero inflated negative binomial distribution (ZINB-GLMM) to the swordfish CPUE standardization. The random effect is appropriate to consider vessel effect, and zero-inflated model estimates "true" zero catch. In this analysis, I used R software package "glmmTMB" (Brooks et al., 2017). Japanese logbook data is huge thus I used Bayesian information criterion (BIC) that is considered the effect of the number of the data sets for model selection. I also used the R software package "lsmeans" to calculate the standardized swordfish CPUE (Lenth 2016). It needs to the additional script from the GitHub (https://github.com/glmmTMB) to apply "lsmeans" for the "glmmTMB".

The simple negative binomial GLM can be described as follows:

$$Catch_i \sim NB(\mu_i, k),$$

$$E(Catch_i) = \mu_i,\ \mathrm{var}(Catch_i) = \mu_i(1 + \mu_i/k) \text{ and}$$

$$\log(\mu_i) = \beta_0 + \mathbf{X}_i\boldsymbol{\beta} - \log(hooks_i).$$

Where $catch_i$ is the number of catch by the operation. μ_i is expected value, k is the dispersion parameter. The link function was used for log function. β_0 is the intercept, $\mathbf{X}_i$ is the matrix of variables, $\boldsymbol{\beta}$ is the covariates vectors, and hooks denote the hooks/1000 of the operation.

I used NB-GLMM to consider the vessel effect for the CPUE standardization. In this model, I assumed random intercept as vessel names. Alternatively, I applied 5x5 grid area effect as random part. The detail of the NB-GLMM is as follows:

$$Catch_i \sim NB(\mu_i, k),$$

$$E(Catch_i) = \mu_i,\ \mathrm{var}(Catch_i) = \mu_i(1 + \mu_i/k) \text{ and}$$

$$\log(\mu_i) = \beta_0 + \mathbf{X}_i\boldsymbol{\beta} - \log(hooks_i) + v_i,\ v_i \sim N(0, \sigma^2_{vessel}) \text{ or}$$

$$\log(\mu_i) = \beta_0 + \mathbf{X}_i\boldsymbol{\beta} - \log(hooks_i) + v_i + a_i,\ v_i \sim N(0, \sigma^2_{vessel})\ \ a_i \sim N(0, \sigma^2_{area}).$$

Where v_i is the random effect of vessels, and that variance is σ^2_{vessel}, a_i is the random effect for 5x5 area and that variance is σ^2_{area}.

Finally, I applied ZINB-GLMM to handle the zero-catch data and vessel effect as follows:

$$Catch_i \sim NB(\pi_i, \mu_i, k),$$

$$E(Catch_i) = \mu_i(1 - \pi_i),$$

$$\mathrm{var}(Catch_i) = (1 - \pi_i)\mu_i(1 + \pi_i\mu_i + \mu_i/k),$$

$$\log(\mu_i) = \beta_0 + \mathbf{X}_i\boldsymbol{\beta} - \log(hooks_i) + v_i + a_i,$$

$$\mathrm{logit}(\pi_i) = \gamma_0 + \mathbf{Z}_i\boldsymbol{\gamma} + v*_i,$$

$$v_i \sim N(0, \sigma^2_{vessel}),\ a_i \sim N(0, \sigma^2_{area}) \text{ and } v*_i \sim N(0, \sigma^2_{*vessel}).$$

Where π_i is the probability of zero catch of the operation *i*. π_i is estimated by logit link function that variable matrix is $\mathbf{Z}_i$, the covariate vector is $\boldsymbol{\gamma}$, respectively. We applied the random effect for vessel name and 5x5 area. However, ZINB-GLMM did not convergence when the random effect of 5x5 area was used for the zero-part regression.

For all models, I used the fixed effect variables for the year, the quarter, the 5×5 area, and the HBF. All variables were applied the categorical variables. I selected the best model by the several combinations of random and fixed variables. In this process, I used the BIC rather than AIC. It needs to consider the data size effect for the model selection because Japanese logbook data is the big data. I also calculated the Pearson residual of the selected models for the model validation. I did not use the interaction for the all statistical model to avoid overfitting. However, there might be a correlation between year and area. To consider this phenomenon, I addressed the random slope GLMM to treat annual interactions for the variables. However, this model did not converge.

Result and Discussion

North East area (Early period:1976-1993)

The selected model was the NB-GLMM that variables of random effect was the vessel name and that fixed effect variables were the year, the quarter and the 5x5 area, respectively (Table.5). Some models showed a smaller BIC than the selected model however the effects of the HBF were not significant in these models. Thus, I excluded the variable of the HBF (Table 5). The ZINB-GLMM was not selected in this analysis. The reason is thought that the zero-catch rate is relatively lower, on the order of 50% (Figure. 6 (a)).

The standardized CPUE was below the nominal CPUE since 1986 (Figure.9 (a), Table 1). Pearson residuals for each predicted value roughly and uniformly varied (Figure. 9 (b)). On the other hand, Pearson residuals showed the specific trend by variables (the year, the quarter and the 5x5 area). (Figure. 9 (c)-(e)). Thus, it is considered that this model is a relatively good fit model.

North East area (Late period:1994-2015)

The selected model in North East area (1993-2015) was ZINB-GLMM. The covariate of the count part is the year, the quarter and the 5x5 area with the random vessel effect and the covariate of the zero-part model was the year, the quarter (Table 6). BIC of some model was smaller than the selected model. I excluded these models because all the gear or all year effects were not significant (Table.6).

The standardized CPUE is higher than the national CPUE before 2006 (Table 1, Figure. 10 (a)). Conversely the nominal CPUE is higher than the standardized CPUE after 2006 (Table 1, Figure. 10 (a)). The standardized CPUE increases rapidly after 2012 (Figure. 10 (a), Table 6). When the predicted values become the smaller, the Pearson residual tend to be the larger. However, the Pearson residuals are relatively uniformly dispersed against the predicted value (Figure. 10 (b)). The Pearson residuals by the variables were plotted uniformly dispersed (Figure. 10 (c), (d)). Thus, it is considered that this model is a good fitted model.

North West area (Early period:1976-1993)

The selected model was NB-GLMM that variables for random effect are the vessel name and the 5x5 area and that fixed effect variables are the year and the quarter (Table. 7). Some models showed a smaller BIC than the selected model however the covariates of HBF of these models were not significant. Thus, I excluded the variable of the HBF (Table 7).

The trend of standardized CPUE is similar for the nominal CPUE (Table 2, Figure. 11 (a)). The Pearson residuals are roughly related to predicted values however it is almost uniformly distributed (Figure. 11 (b)). The Pearson residuals are also uniformly distributed by year and quarter (Figure (c), (d)). From the tendency of these Pearson residuals, the selected model is considered well standardized.

North West area (Late period:1994-2015)

The selected model is NB-GLMM that random effects are the vessel name and the 5x5 area. The fixed effects of this model are the year, the quarter, and the HBF (Table.8).

The standardized CPUE showed a similar trend to the nominal CPUE until 2010 (Figure. 12 (a)). Because of the pirate effect, the number of vessels have rapidly decreased after 2011 (Figure. 2). As a result, the number of samples also decreased. Thus, it is considered that the selected model might be unreliable after 2011. The Pearson residual shows a substantially uniform variation with respect to the predicted value (Figure. 12 (b)). However, Pearson residuals tend to increase with the specific elements of the year and the HBF (Figure.12 (c), (e)). Considering the model validation result, this model is approximately well estimated.

South East area (Early period:1976-1993)

The selected model is NB-GLMM, its random effect is the vessel name and 5x5 area and that fixed effects are the year, the quarter and the HBF (Table.9).

BIC of some models are smaller than the selected model. However, the effects of all HBF were not significant for smaller BIC models. Therefor I excluded these models (Table.9). The standardized CPUE showed a flat trend against the nominal CPUE until 1987 and showed a sharp decline from 1988 to 1992 (Figure. 13 (a)). The Pearson residual tend to be higher when the catch was estimated zero (Figure. 13 (b)). The Pearson residuals roughly uniformly fluctuate for each year (Figure 13 (c)). The Pearson residuals by quarter tend to increase as the season progresses (Figure 13 (d)). Excluding HBF of four, the residuals decreased with the HBF increasing (Figure 13 (e)). Therefor it is considered that this model not fully standardized. In South East area, zero catch is periodically fluctuating (Figure. 6). Thus, zero catch might not be standardized well.

South East area (Late period:1994-2015)

The selected model is ZINB-GLMM that the random effect of the count part is the vessel name and the 5x5 area, and that fixed effects are the year, the quarter. The covariate of zero parts is the year and the quarter (Table. 10).

BIC of some models was smaller than the selected model however the effects of all HBF were not significant. Thus, they were excluded from the best model (Table. 10). Nominal CPUE sharply rises after 2005, however standardized CPUE showed the flat fluctuate (Figure.14 (a)). The Pearson residuals become higher near the zero-estimated catch (Figure. 14 (b)). However, there is no tendency in the Pearson residuals for each variable (Figure.14 (c), (d)). Therefore, it seems that this model is approximately well estimated.

South West area (Early period:1976-1993)

The model selected by BIC is NB-GLMM that random effect is the vessel name and the 5x5 area, and that the fixed effect is the year, the quarter, the HBF (Table. 11).

The standardized CPUE shows similar trends as the nominal CPUE till 1984, however it changed lower than the nominal CPUE after 1985 (Figure. 15 (a)). The Pearson residual tends to decrease with the estimated value increases (Figure. 15 (b)). The Pearson residuals by quarter are almost uniform (Figure. 15 (c), (d)). However, the Pearson residual tends to increase when the HBF are 5-10 (Figure. 15 (e)). From these results, it is considered that this model is approximately presumed.

South West area (Late period:1994-2015)

The selected model is ZINB-GLMM that the count part of random effects are the vessel name and the 5 x5 area, and that the fixed effect are the year and the quarter, fixed effect of zero part are the year and the quarter (Table.12).

BIC of some models is smaller than the selected model. However, the covariates of all HBF were not significant thus I excluded covariates of all HBF (Table. 12). The standardized CPUE shows similar trends to the nominal CPUE till 2003, however, after 2004, the standardized CPUE is smaller than the nominal CPUE (Figure. 16 (a)). Although the Pearson residual tends to be larger when predicted values are lower (Figure.16 (b)), the variation of the Pearson residual per year and quarter is small (Figure.16 (c)-(d)). Therefore, this model is considered relatively well estimated.

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Table 1. Standardized swordfish CPUE for the North East Indian Ocean calculated by Japanese longline fishery (1976-1993 and 1994-2015).

Year	Nominal CPUE	Standardized CPUE	lower	upper
1976	0.58	0.59	0.49	0.71
1977	0.95	0.87	0.72	1.05
1978	1.17	0.87	0.73	1.03
1979	0.77	0.86	0.73	1.02
1980	1.01	0.97	0.83	1.13
1981	0.85	0.79	0.67	0.92
1982	0.87	0.77	0.67	0.90
1983	0.80	0.76	0.66	0.88
1984	0.81	0.86	0.75	0.99
1985	1.00	1.01	0.87	1.16
1986	1.00	0.88	0.76	1.01
1987	1.44	0.98	0.85	1.12
1988	1.30	0.94	0.82	1.09
1989	1.11	0.86	0.74	1.01
1990	0.97	0.83	0.72	0.96
1991	1.19	0.90	0.77	1.04
1992	0.90	0.63	0.54	0.75
1993	1.14	0.91	0.77	1.07
1994	1.07	1.30	1.08	1.56
1995	1.08	1.22	1.02	1.44
1996	1.18	1.37	1.16	1.62
1997	1.37	1.51	1.29	1.77
1998	1.24	1.33	1.14	1.56
1999	1.11	1.35	1.15	1.58
2000	0.94	0.98	0.83	1.14
2001	0.72	1.14	0.97	1.35
2002	0.61	0.96	0.81	1.13
2003	0.79	1.18	0.99	1.40
2004	0.60	0.83	0.70	1.00
2005	0.79	0.97	0.81	1.17
2006	0.68	0.69	0.59	0.82
2007	1.01	0.86	0.73	1.01
2008	1.13	0.90	0.77	1.05
2009	1.00	0.93	0.79	1.08
2010	0.89	0.83	0.71	0.97
2011	0.87	0.78	0.66	0.92
2012	0.82	0.80	0.68	0.94
2013	1.14	0.98	0.83	1.15
2014	1.57	1.32	1.13	1.55
2015	1.57	1.38	1.17	1.62

Table 2. Standardized swordfish CPUE for the North West Indian Ocean calculated by Japanese longline fishery (1976-1993 and 1994-2015).

Year	Nominal CPUE	Standardized CPUE	lower	upper
1976	1.36	1.44	1.24	1.67
1977	1.27	1.33	1.15	1.54
1978	2.36	2.09	1.85	2.35
1979	1.58	1.30	1.13	1.48
1980	1.12	0.94	0.83	1.07
1981	1.11	0.99	0.88	1.11
1982	1.51	1.09	0.97	1.21
1983	1.22	1.03	0.92	1.15
1984	1.44	1.21	1.08	1.35
1985	2.21	1.61	1.45	1.80
1986	1.89	1.46	1.30	1.63
1987	1.77	1.56	1.39	1.74
1988	2.23	1.93	1.73	2.16
1989	1.51	1.32	1.18	1.48
1990	1.75	1.38	1.23	1.55
1991	1.34	1.22	1.07	1.38
1992	2.48	2.27	1.99	2.58
1993	2.84	2.36	2.09	2.66
1994	2.65	3.22	2.64	3.93
1995	2.19	2.48	2.03	3.02
1996	1.99	2.02	1.66	2.46
1997	2.13	1.99	1.64	2.42
1998	2.10	2.15	1.76	2.61
1999	1.55	1.60	1.31	1.95
2000	1.56	1.60	1.31	1.95
2001	1.98	1.94	1.59	2.37
2002	1.64	1.71	1.40	2.08
2003	1.35	1.34	1.10	1.63
2004	1.27	1.13	0.92	1.37
2005	1.27	1.11	0.91	1.35
2006	1.32	1.02	0.84	1.24
2007	1.63	1.25	1.03	1.52
2008	1.61	1.23	1.01	1.50
2009	1.51	1.36	1.12	1.66
2010	1.51	1.52	1.22	1.89
2011	-	-	-	-
2012	2.64	1.71	1.29	2.28
2013	2.09	1.18	0.90	1.55
2014	1.11	0.84	0.65	1.08
2015	2.01	1.91	1.46	2.49

Table 3. Standardized swordfish CPUE for the South East Indian Ocean calculated by Japanese longline fishery (1976-1993 and 1994-2015).

Year	Nominal CPUE	Standardized CPUE	lower	upper
1976	0.14	0.39	0.26	0.60
1977	0.42	0.52	0.35	0.79
1978	1.17	0.45	0.30	0.67
1979	0.48	0.29	0.19	0.44
1980	0.49	0.49	0.33	0.73
1981	0.49	0.44	0.30	0.66
1982	0.26	0.39	0.26	0.60
1983	0.50	0.37	0.25	0.55
1984	0.80	0.48	0.33	0.72
1985	0.96	0.47	0.32	0.69
1986	0.20	0.35	0.24	0.51
1987	0.53	0.40	0.27	0.60
1988	0.67	0.61	0.41	0.91
1989	0.50	0.42	0.28	0.62
1990	0.39	0.29	0.19	0.43
1991	0.57	0.20	0.13	0.29
1992	0.29	0.12	0.08	0.18
1993	0.67	0.25	0.17	0.36
1994	0.49	0.57	0.44	0.75
1995	0.56	0.65	0.50	0.84
1996	0.80	0.56	0.43	0.72
1997	1.12	0.69	0.53	0.89
1998	0.53	0.49	0.38	0.65
1999	0.76	0.56	0.43	0.73
2000	0.67	0.67	0.51	0.87
2001	0.44	0.46	0.36	0.60
2002	0.51	0.64	0.49	0.83
2003	0.41	0.48	0.37	0.63
2004	0.63	0.49	0.37	0.63
2005	0.31	0.45	0.34	0.60
2006	0.80	0.38	0.29	0.50
2007	1.50	0.44	0.34	0.58
2008	1.02	0.39	0.30	0.51
2009	0.88	0.36	0.28	0.47
2010	1.34	0.43	0.33	0.55
2011	1.56	0.55	0.42	0.72
2012	1.44	0.40	0.31	0.52
2013	1.64	0.58	0.44	0.75
2014	1.68	0.72	0.55	0.94
2015	1.35	0.52	0.40	0.68

Table 4. Standardized swordfish CPUE for the South West Indian Ocean calculated by Japanese longline fishery (1976-1993 and 1994-2015).

Year	Nominal CPUE	Standardized CPUE	lower	upper
1976	1.13	1.01	0.83	1.21
1977	1.38	1.09	0.89	1.34
1978	1.11	0.96	0.80	1.15
1979	1.47	1.16	0.98	1.38
1980	1.26	1.24	1.05	1.47
1981	1.17	1.02	0.87	1.20
1982	0.69	0.84	0.71	0.98
1983	0.88	0.99	0.84	1.17
1984	1.31	1.51	1.28	1.77
1985	2.49	1.78	1.52	2.10
1986	1.29	1.34	1.14	1.57
1987	1.55	1.51	1.28	1.77
1988	2.58	1.59	1.35	1.87
1989	1.74	1.29	1.10	1.51
1990	2.28	1.39	1.18	1.63
1991	1.93	1.13	0.96	1.33
1992	1.94	1.34	1.14	1.57
1993	1.75	1.08	0.92	1.27
1994	1.76	1.36	1.18	1.57
1995	1.11	0.84	0.73	0.97
1996	0.91	0.79	0.69	0.92
1997	1.01	0.82	0.71	0.94
1998	0.76	0.65	0.56	0.75
1999	0.64	0.56	0.48	0.64
2000	0.73	0.48	0.42	0.56
2001	0.55	0.39	0.34	0.45
2002	0.49	0.42	0.37	0.49
2003	0.35	0.35	0.30	0.41
2004	0.52	0.44	0.38	0.51
2005	0.61	0.46	0.40	0.54
2006	0.80	0.52	0.45	0.60
2007	0.73	0.43	0.37	0.50
2008	0.95	0.55	0.47	0.63
2009	1.20	0.75	0.64	0.87
2010	1.20	0.79	0.68	0.92
2011	1.17	0.82	0.71	0.95
2012	1.01	0.75	0.64	0.86
2013	0.91	0.62	0.53	0.72
2014	0.88	0.55	0.47	0.64
2015	0.96	0.60	0.51	0.70

Table 5. Deviance table for swordfish CPUE in the North East Indian Ocean by Japanese longline fishery (1976-1993). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	107647	107664	107643	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	104693	104719	104687	2956	0
yr+offset(log(hooks/1000))	19	107116	107279	107078	0	1
yr+offset(log(hooks/1000))+(1| vessel)	20	104448	104619	104408	2670	0
yr+qtr+offset(log(hooks/1000))	22	106965	107153	106921	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	23	104382	104579	104336	2584	0
yr+offset(log(hooks/1000)) yr	37	NA	NA	NA	NA	NA
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	40	103321	103664*	103241	NA	NA
yr+qtr+offset(log(hooks/1000)) yr+qtr	43	106775	107144	106689	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	45	NA	NA	NA	NA	NA
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	61	103274	103797*	103152	NA	NA
yr+qtr+area+offset(log(hooks/1000))	66	105245	105811	105113	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	**67**	**103296**	**103870**	**103162**	**1951**	**0**
yr+qtr+area+gear+offset(log(hooks/1000))	82	105101	105803	104937	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	83	103236	103947	103070	1867	0
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	85	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+(1| vessel)	86	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	88	103243	103997	103067	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	101	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	104	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	104	103201	104092	102993	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	131	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	132	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	148	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	148	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	163	NA	NA	NA	NA	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

Table 6. Deviance table for swordfish CPUE in the North East Indian Ocean by Japanese longline fishery (1994-2015). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	212837	212855	212833	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	205234	205262	205228	7605	0
yr+offset(log(hooks/1000))	23	210348	210560	210302	0	1
yr+offset(log(hooks/1000))+(1| vessel)	24	203730	203952	203682	6620	0
yr+qtr+offset(log(hooks/1000))	26	210277	210517	210225	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	27	203692	203941	203638	6587	0
yr+offset(log(hooks/1000)) yr	45	210012	210428	209922	0	1
yr+qtr+offset(log(hooks/1000)) yr+qtr	51	209635	210107	209533	388	8.83E-81
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	53	201504	201994**	201398	8135	0
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	54	201759	202258	201651	0	1
yr+qtr+area+offset(log(hooks/1000))	65	207079	207680	206949	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	66	201948	202558	201816	5133	0
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	79	201195	201926*	201037	779	5.23E-158
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	88	201551	202364	201375	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+(1| vessel)	89	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))	91	206614	207455	206432	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	**91**	**201397**	**202239**	**201215**	**5216**	**0**
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	92	201636	202487	201452	0	1
yr+qtr+area+gear+offset(log(hooks/1000)) yr+(1| vessel)	114	203363	204417	203135	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	114	201245	202299	201017	2118	0
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	117	203221	204302	202987	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	117	201094	202175*	200860	2127	0
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	129	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	130	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	156	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	156	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	181	NA	NA	NA	NA	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

** BIC is lower than the selected model, however predictor variables of year effect are not statistically significant.

Table 7. Deviance table for swordfish CPUE in the North West Indian Ocean by Japanese longline fishery (1976-1993). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	247381	247399	247377	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	240248	240276	240242	7135	<0.0001
yr+offset(log(hooks/1000))	19	244788	244962	244750	0	1
yr+offset(log(hooks/1000))+(1| vessel)	20	238396	238579	238356	6394	<0.0001
yr+qtr+offset(log(hooks/1000))	22	243251	243452	243207	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	23	237539	237749	237493	5714	<0.0001
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area)	**24**	**236712**	**236932**	**236664**	**829**	**<0.0001**
yr+offset(log(hooks/1000)) yr	37	244747	245085	244673	0	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	41	236367	236742*	236285	8388	<0.0001
yr+qtr+offset(log(hooks/1000)) yr+qtr	43	242987	243380	242901	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	45	236551	236963	236461	6440	<0.0001
yr+qtr+area+offset(log(hooks/1000))	59	241906	242445	241788	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	60	236623	237171	236503	5285	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	62	236241	236807*	236117	386	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))	76	241304	241998	241152	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	77	236281	236985	236127	5025	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	78	236638	237351	236482	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	81	236500	237240	236338	145	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000)) yr+(1| vessel)	95	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	95	236309	237177	236119	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	98	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	98	236178	237074	235982	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	117	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	118	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	135	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	135	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	151	NA	NA	NA	NA	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

Table 8. Deviance table for swordfish CPUE in the North West Indian Ocean by Japanese longline fishery (1994-2015). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	377684	377703	377680	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	367065	367094	367059	10620	<0.0001
yr+offset(log(hooks/1000))	22	374055	374266	374011	0	1
yr+offset(log(hooks/1000))+(1| vessel)	23	364350	364570	364304	9707	<0.0001
yr+qtr+offset(log(hooks/1000))	25	372079	372319	372029	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	26	362100	362349	362048	9982	<0.0001
yr+offset(log(hooks/1000)) yr	43	373994	374406	373908	0	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	**48**	**359260**	**359720**	**359164**	**14744**	**<0.0001**
yr+qtr+offset(log(hooks/1000)) yr+qtr	49	371801	372271	371703	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	51	359361	359850	359259	12444	<0.0001
yr+qtr+area+offset(log(hooks/1000))	63	367711	368314	367585	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	64	359408	360022	359280	8304	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	72	359058	359748	358914	366	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))	84	366101	366906	365933	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	85	359133	359948	358963	6970	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	85	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	88	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+(1| vessel)	106	360311	361327	360099	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	106	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	109	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	109	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	125	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	126	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	147	360084	361493	359790	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	147	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	167	NA	NA	NA	NA	NA

Table 9. Deviance table for swordfish CPUE in the South East Indian Ocean by Japanese longline fishery (1976-1993). Bold is the best model that by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000)	2	113359	113377	113355	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	103376	103403	103370	9985	<0.0001
yr+offset(log(hooks/1000)	19	111379	111553	111341	0	1
yr+offset(log(hooks/1000))+(1| vessel)	20	101428	101611	101388	9953	<0.0001
yr+qtr+offset(log(hooks/1000)	22	105016	105217	104972	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	23	94186	94396	94140	10832	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	**35**	**79348**	**79667**	**79278**	**14862**	**<0.0001**
yr+offset(log(hooks/1000)) yr	37	109992	110330	109918	0	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) qtr	39	79333	79688	79255	30664	<0.0001
yr+qtr+offset(log(hooks/1000)) yr+qtr	43	95352	95744	95266	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	45	NA	NA	NA	NA	NA
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	56	79078	79589*	78966	NA	NA
yr+qtr+area+offset(log(hooks/1000)	78	84414	85126	84258	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	79	79420	80140	79262	4996	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000)	89	83948	84760	83770	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	90	79176	79997	78996	4775	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	97	79191	80076	78997	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	100	79093	80006	78893	104	<0.0001
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr+area	101	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	108	79004	79990	78788	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	111	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	111	78916	79928	78694	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	155	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	156	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	167	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	177	NA	NA	NA	NA	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

Table 10. Deviance table for swordfish CPUE in the South East Indian Ocean by Japanese longline fishery (1994-2015). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	272253	272272	272249	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	259077	259106	259071	13178	<0.0001
yr+offset(log(hooks/1000))	23	268411	268635	268365	0	1
yr+offset(log(hooks/1000))+(1| vessel)	24	256933	257166	256885	11480	<0.0001
yr+qtr+offset(log(hooks/1000))	26	262873	263125	262821	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	27	252730	252993	252676	10145	<0.0001
yr+offset(log(hooks/1000)) yr	45	261881	262318	261791	0	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	50	233189	233675	233089	28702	<0.0001
yr+qtr+offset(log(hooks/1000)) yr+qtr	51	255225	255720	255123	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	**53**	**231490**	**232005**	**231384**	**23739**	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	75	230700	231429 *	230550	834	<0.0001
yr+qtr+area+offset(log(hooks/1000))	82	241635	242432	241471	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	83	233855	234661	233689	7783	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))	104	240292	241303	240084	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	105	232986	234007	232776	7308	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	105	231467	232487	231257	1519	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	108	231315	232365	231099	158	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	127	230674	231908 *	230420	680	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	130	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	130	230542	231805 *	230282	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	163	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	164	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	186	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	186	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	207	NA	NA	NA	NA	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

Table 11. Deviance table for swordfish CPUE in the South West Indian Ocean by Japanese longline fishery (1976-1993). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Pr(>Chisq)
offset(log(hooks/1000))	2	259076	259095	259072	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	242806	242833	242800	16272	<0.0001
yr+offset(log(hooks/1000))	19	256278	256453	256240	0	1
yr+offset(log(hooks/1000))+(1| vessel)	20	241883	242068	241843	14396	<0.0001
yr+qtr+offset(log(hooks/1000))	22	256037	256240	255993	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	23	240310	240523	240264	15729	<0.0001
yr+offset(log(hooks/1000)) yr	37	256113	256455	256039	0	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	**40**	**233447**	**233817**	**233367**	**22672**	**<0.0001**
yr+qtr+offset(log(hooks/1000)) yr+qtr	43	255621	256019	255535	0	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	45	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))	54	241458	241957	241350	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	55	234531	235039	234421	6929	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	61	233340	233904	233218	1203	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))	70	238685	239332	238545	0	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	71	233389	234045	233247	5298	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	73	234437	235111	234291	0	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	76	234407	235109	234255	36	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	89	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	92	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	92	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	107	NA	NA	NA	NA	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	108	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	124	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	124	NA	NA	NA	NA	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	139	NA	NA	NA	NA	NA

Table 12. Deviance table for swordfish CPUE in the South West Indian Ocean by Japanese longline fishery (1994-2015). Bold is the best model selected by BIC.

Model (Count part / Zero part)	Df	AIC	BIC	deviance	Chisq	Chi Df	Pr(>Chisq)
offset(log(hooks/1000))	2	428680	428700	428676	NA	NA	NA
offset(log(hooks/1000))+(1| vessel)	3	410037	410068	410031	18644	1	<0.0001
yr+offset(log(hooks/1000))	23	420572	420803	420526	0	20	1
yr+offset(log(hooks/1000))+(1| vessel)	24	405141	405382	405093	15433	1	<0.0001
yr+qtr+offset(log(hooks/1000))	26	418348	418609	418296	0	2	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)	27	402435	402706	402381	15915	1	<0.0001
yr+offset(log(hooks/1000)) yr	45	419446	419898	419356	0	18	1
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area)	46	394843	395305	394751	24605	1	<0.0001
yr+qtr+offset(log(hooks/1000)) yr+qtr	51	414409	414921	414307	0	5	1
yr+qtr+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	**53**	**394274**	**394806**	**394168**	**20139**	**2**	**<0.0001**
yr+qtr+area+offset(log(hooks/1000))	62	405725	406347	405601	0	9	1
yr+qtr+area+offset(log(hooks/1000))+(1| vessel)	63	395737	396369	395611	9990	1	<0.0001
yr+qtr+gear+offset(log(hooks/1000))+(1| vessel)+(1|area) yr+qtr	71	393317	394029*	393175	2436	8	<0.0001
yr+qtr+area+gear+offset(log(hooks/1000))	80	403338	404141	403178	0	9	1
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel)	81	394751	395564	394589	8589	1	<0.0001
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr	85	NA	NA	NA	NA	4	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr	88	394236	395119	394060	NA	3	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr	103	NA	NA	NA	NA	15	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+(1| vessel)	106	396213	397276	396001	NA	3	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr	106	393289	394353*	393077	2923	0	<0.0001
yr+qtr+area+offset(log(hooks/1000)) yr+qtr+area	123	NA	NA	NA	NA	17	NA
yr+qtr+area+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	124	NA	NA	NA	NA	1	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+(1| vessel)	142	NA	NA	NA	NA	18	NA
yr+qtr+area+gear+offset(log(hooks/1000))+(1| vessel) yr+qtr+area	142	NA	NA	NA	NA	0	NA
yr+qtr+area+gear+offset(log(hooks/1000)) yr+qtr+area+gear	159	NA	NA	NA	NA	17	NA

* BIC is lower than the selected model, however predictor variables of all gear effect are not statistically significant.

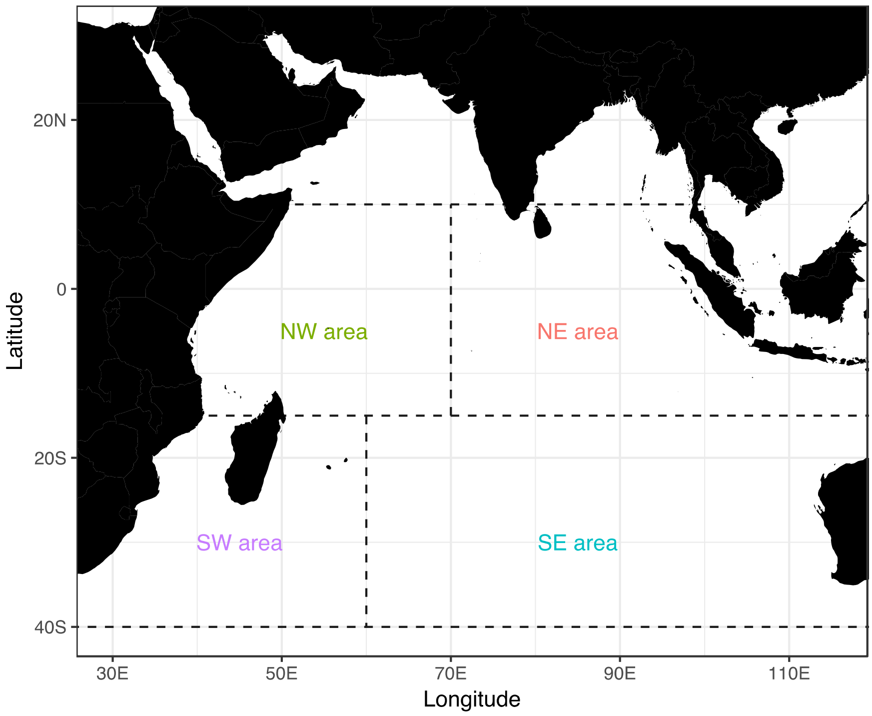

Figure 1. Analysis area for the swordfish CPUE standardization given by Japanese longline fishery in the Indian Ocean.

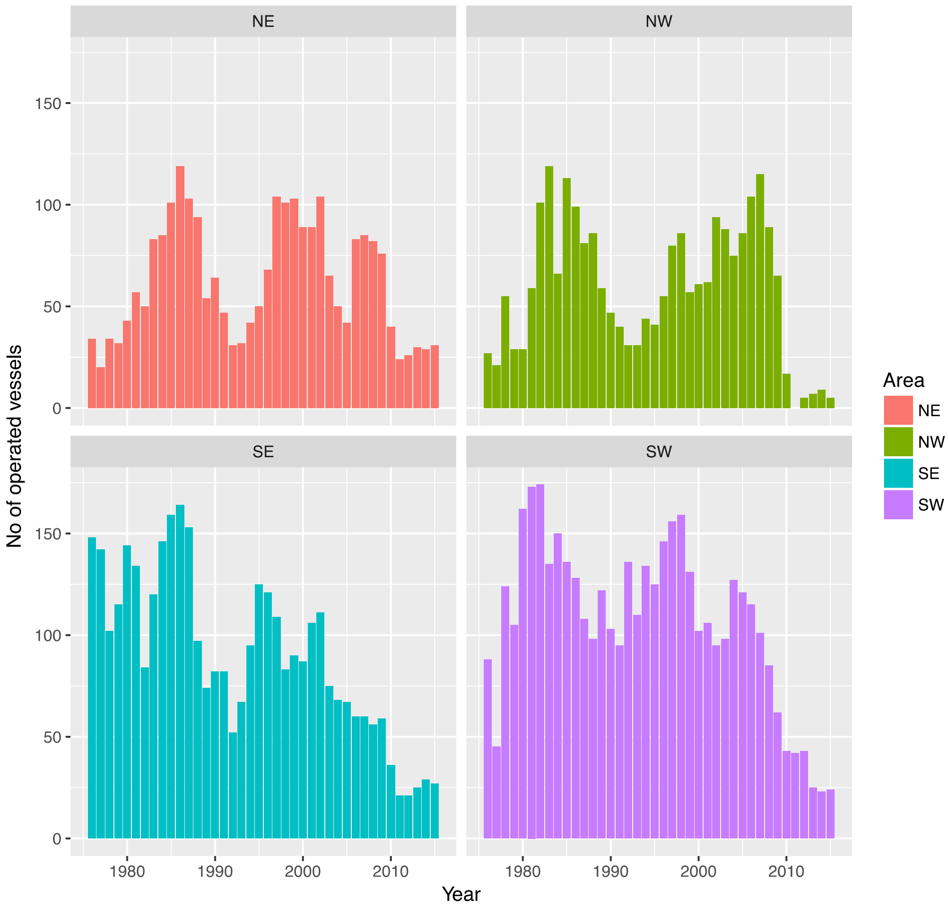

Figure 2. Historical change of the number of the operated Japanese vessel in Indian Ocean.

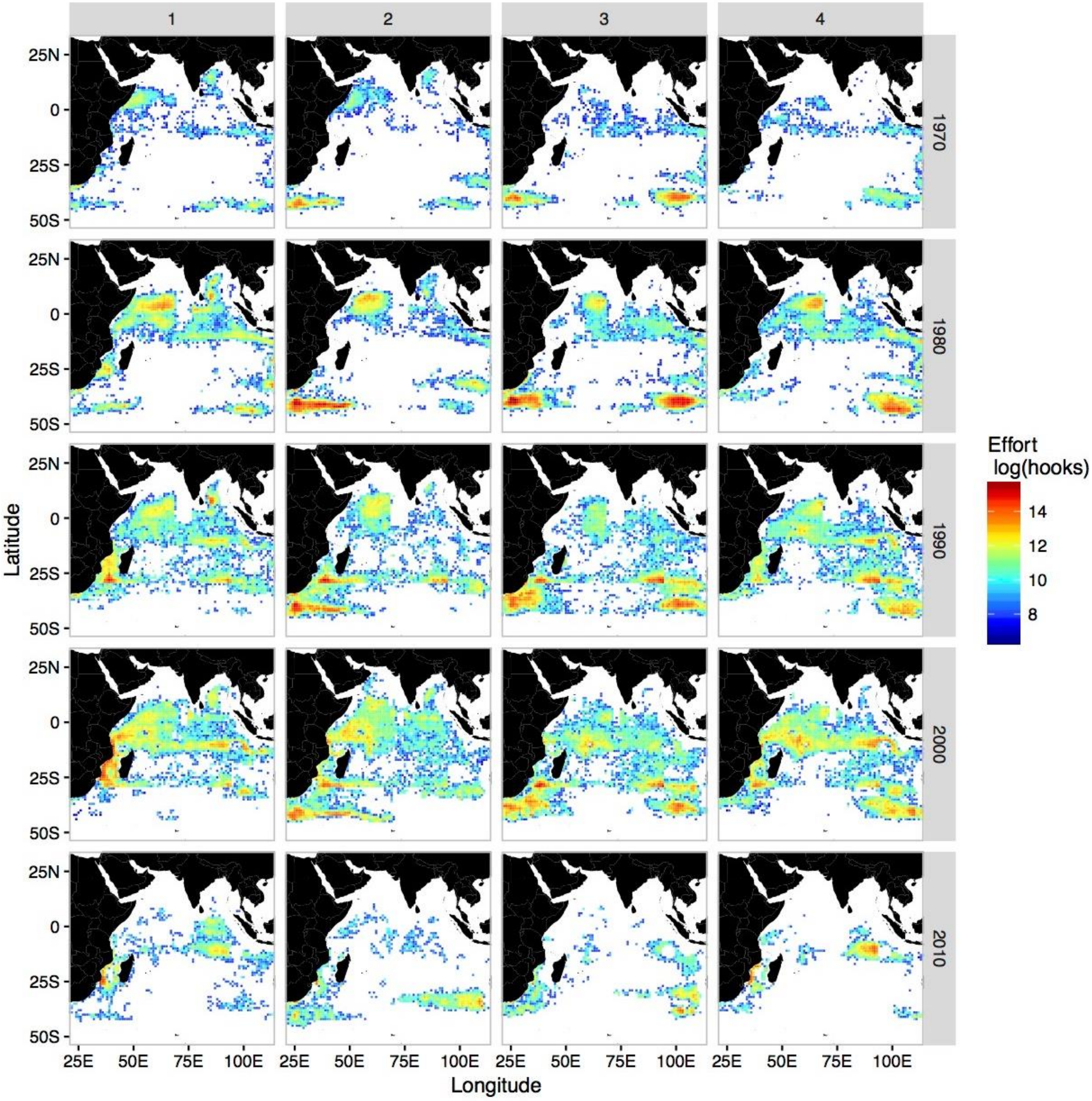

Figure3. Time spatial change of the effort of Japanese distant water longline in Indian Ocean.

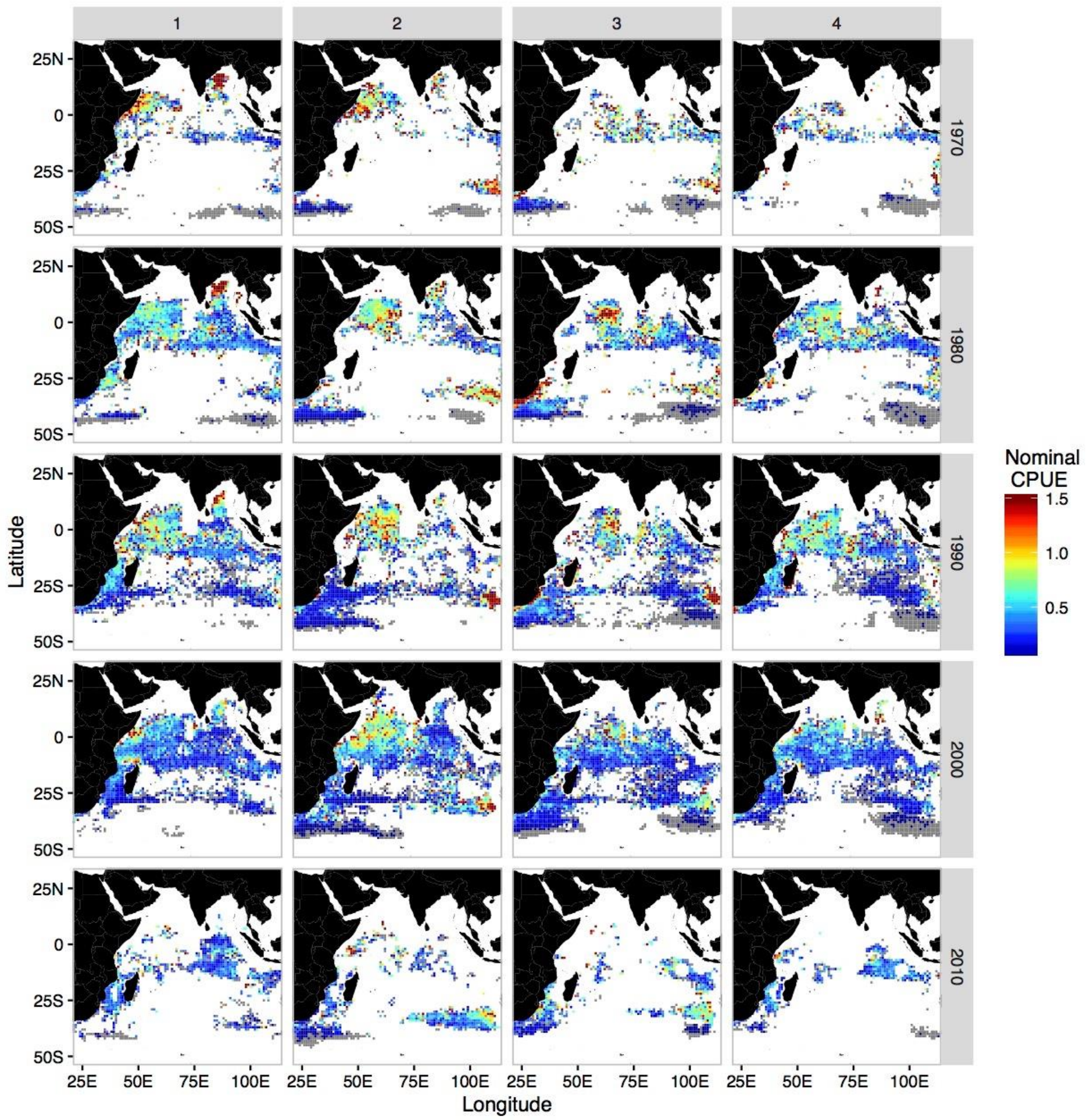

Figure 4. Time spatial change of the nominal sword fish CPUE by Japanese distant water longline in Indian Ocean.

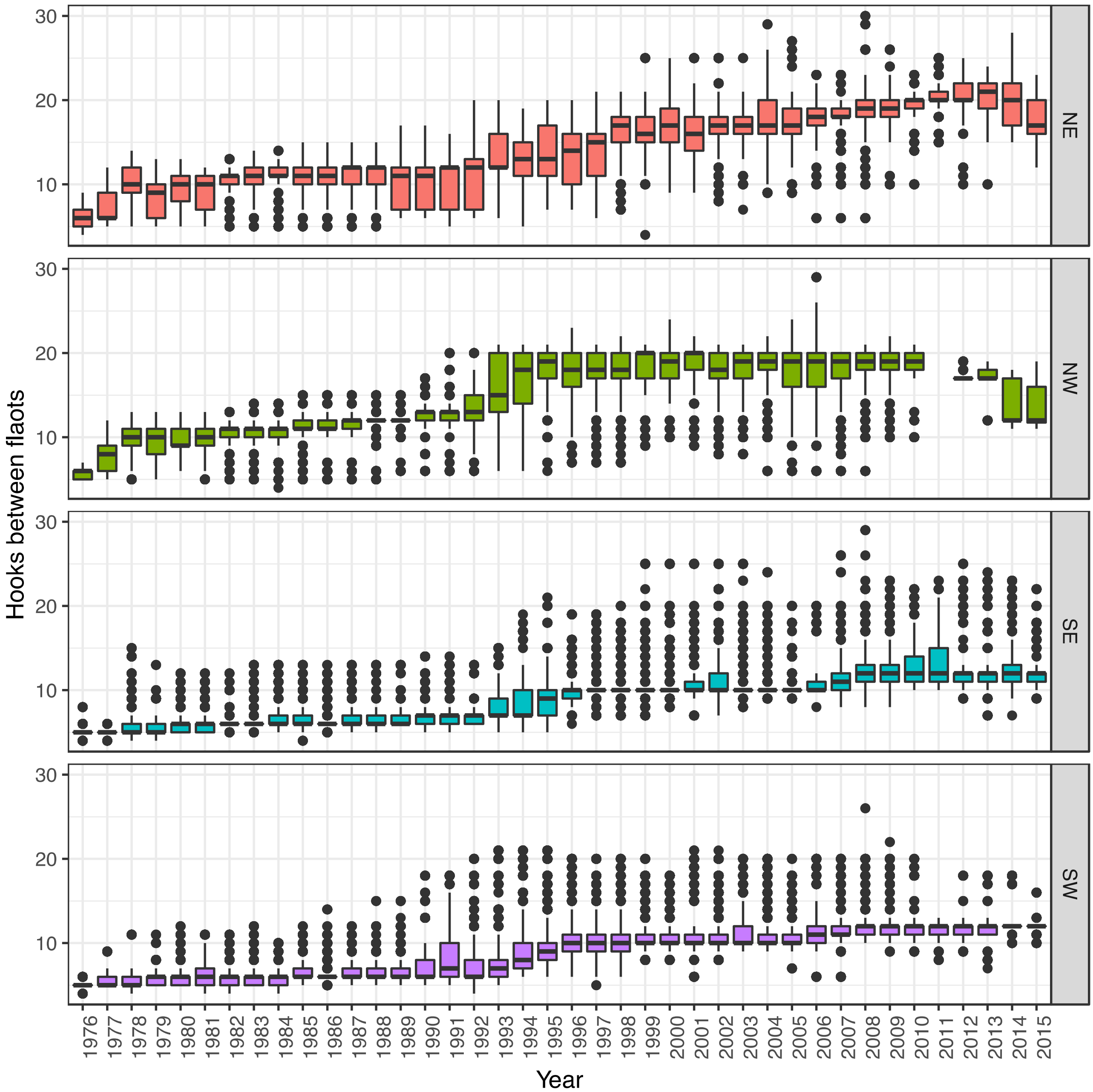

Figure 5. Historical change of the hooks between floats in Indian Ocean.

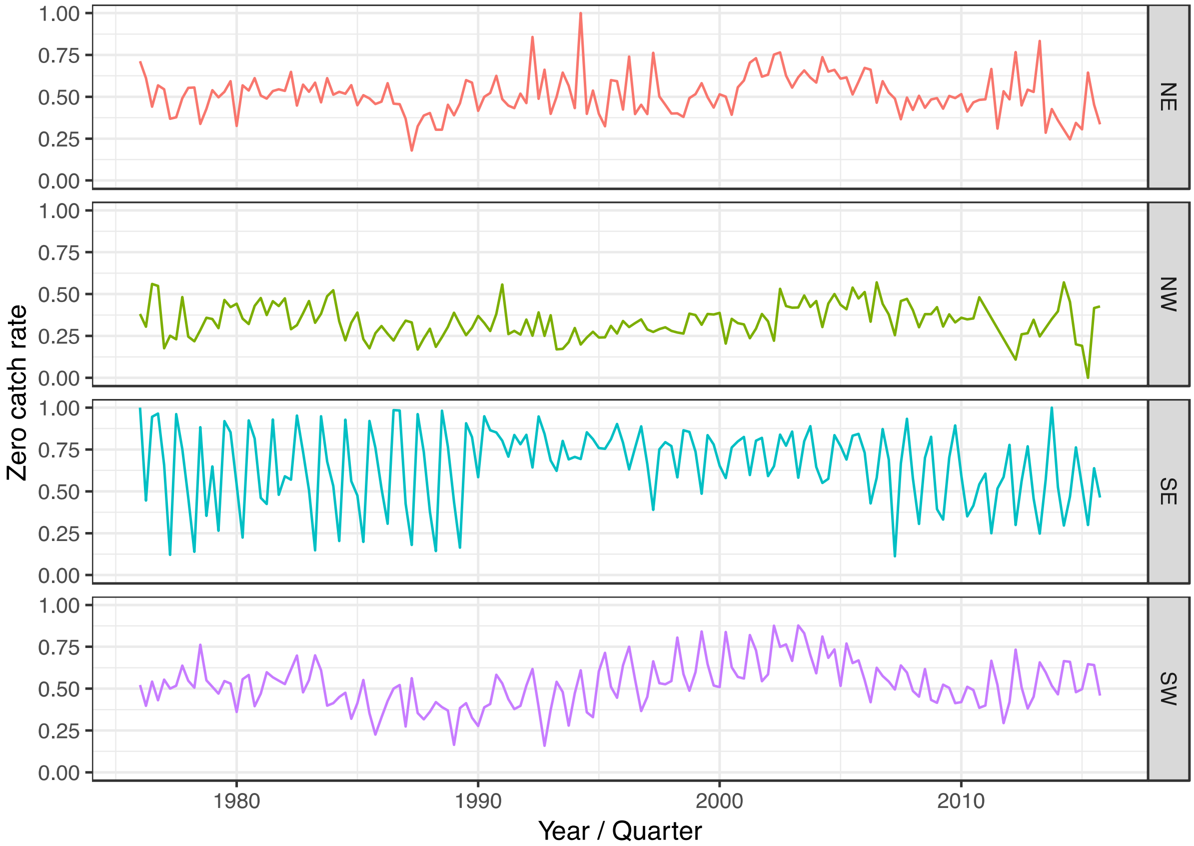

Figure 6. Zero catch rate of the swordfish by Japanese long line fishery.

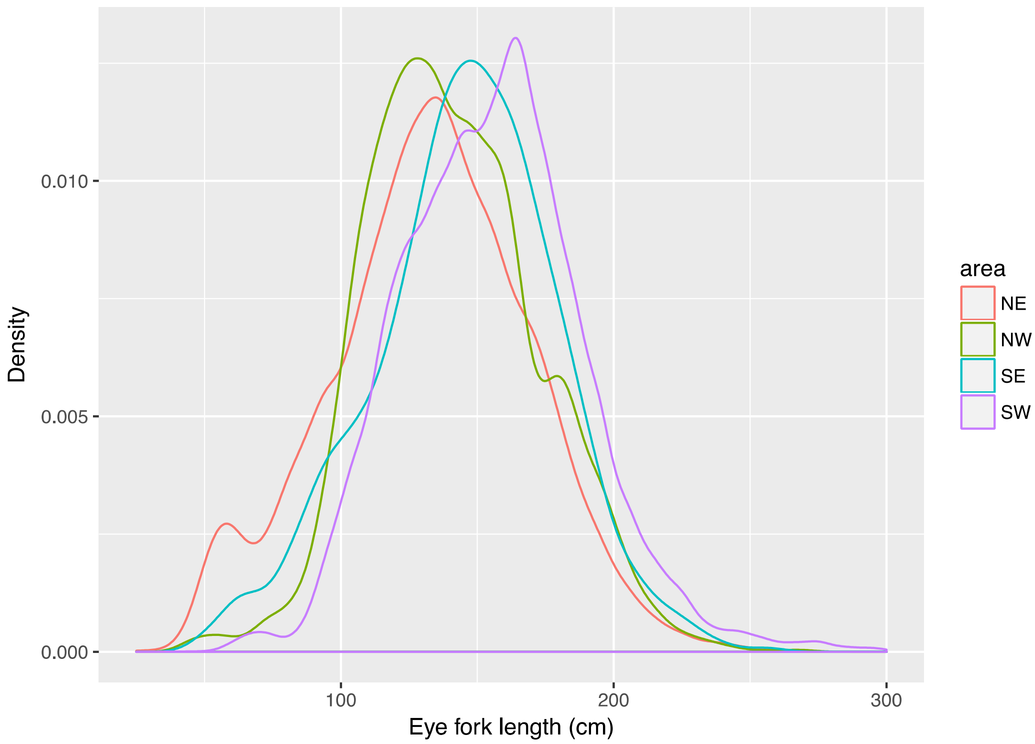

Figure 7. Length frequency of swordfish observed by each analysis area.

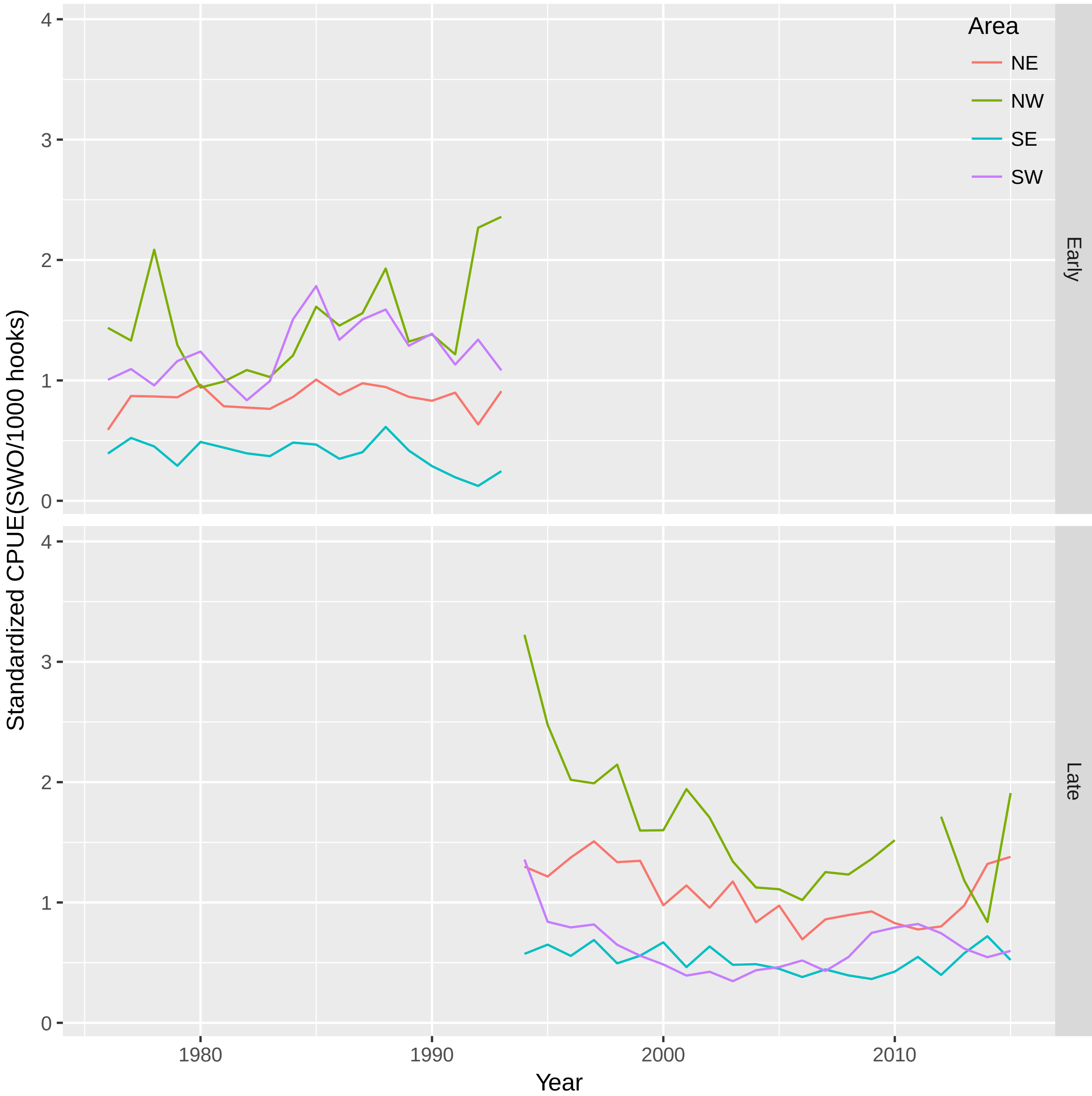

Figure 8. Standardized swordfish CPUE (Least squares mean) by Japanese longline fishery. The best models were selected by BIC. Filled areas denote 95% confidence interval of standardized CPUE.

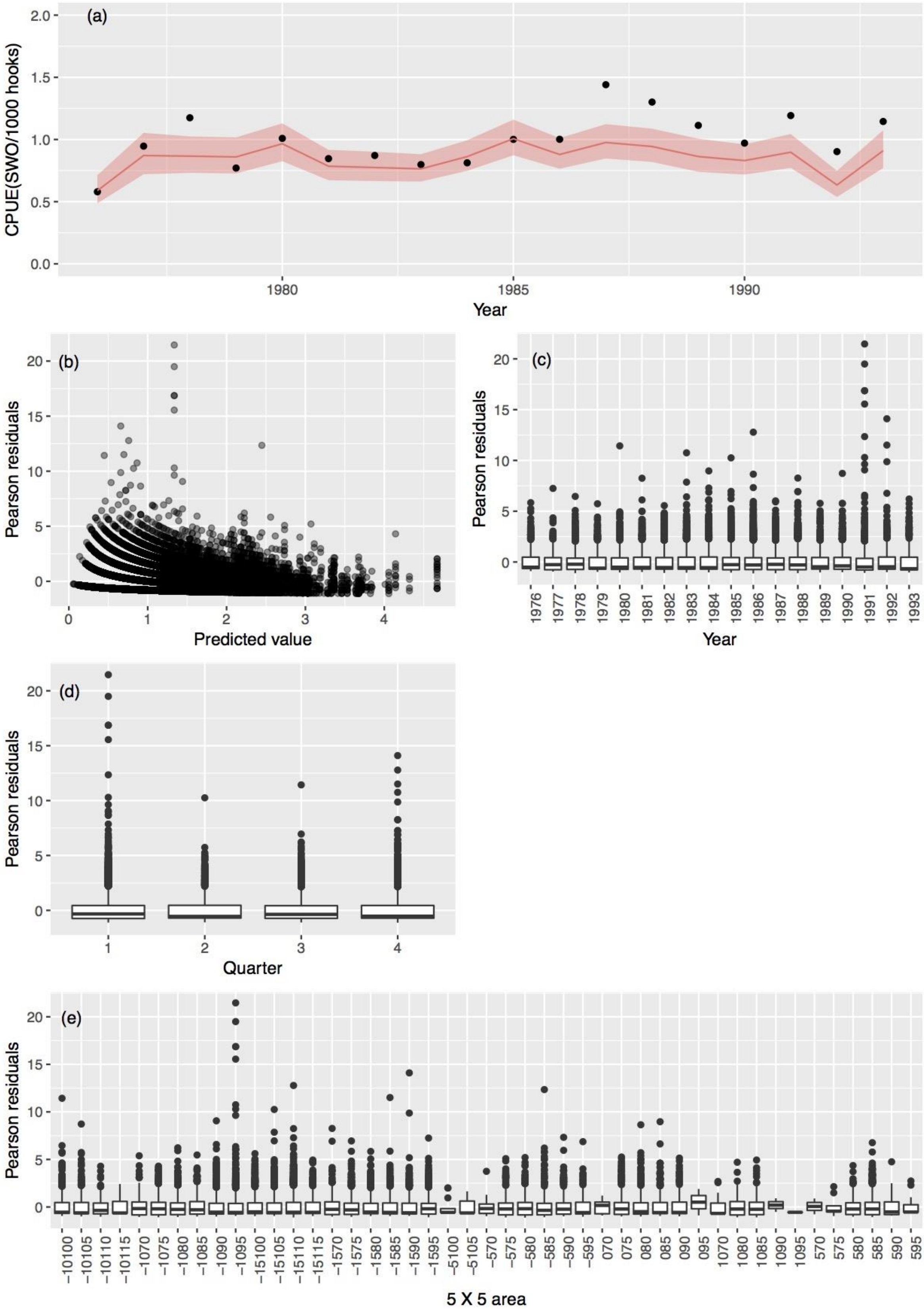

Figure 9. The result of CPUE standardization analysis of North East Indian Ocean swordfish by Japanese longline fishery (1976-1993). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(e) The plots of the Pearson residual trend.

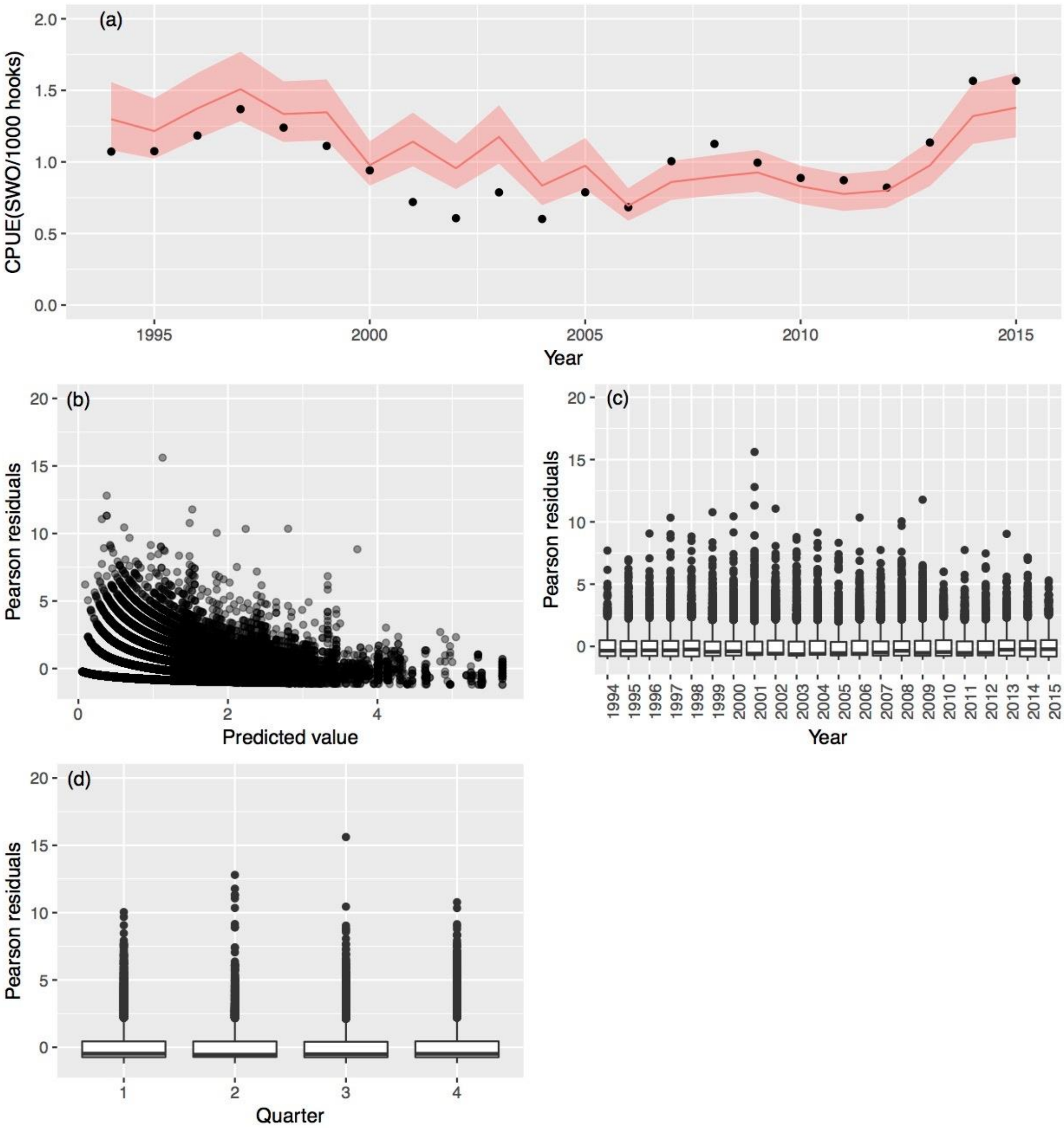

Figure 10. The result of CPUE standardization analysis of North East Indian Ocean swordfish by Japanese longline fishery (1994-2015). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(d) The plots of the Pearson residual trend.

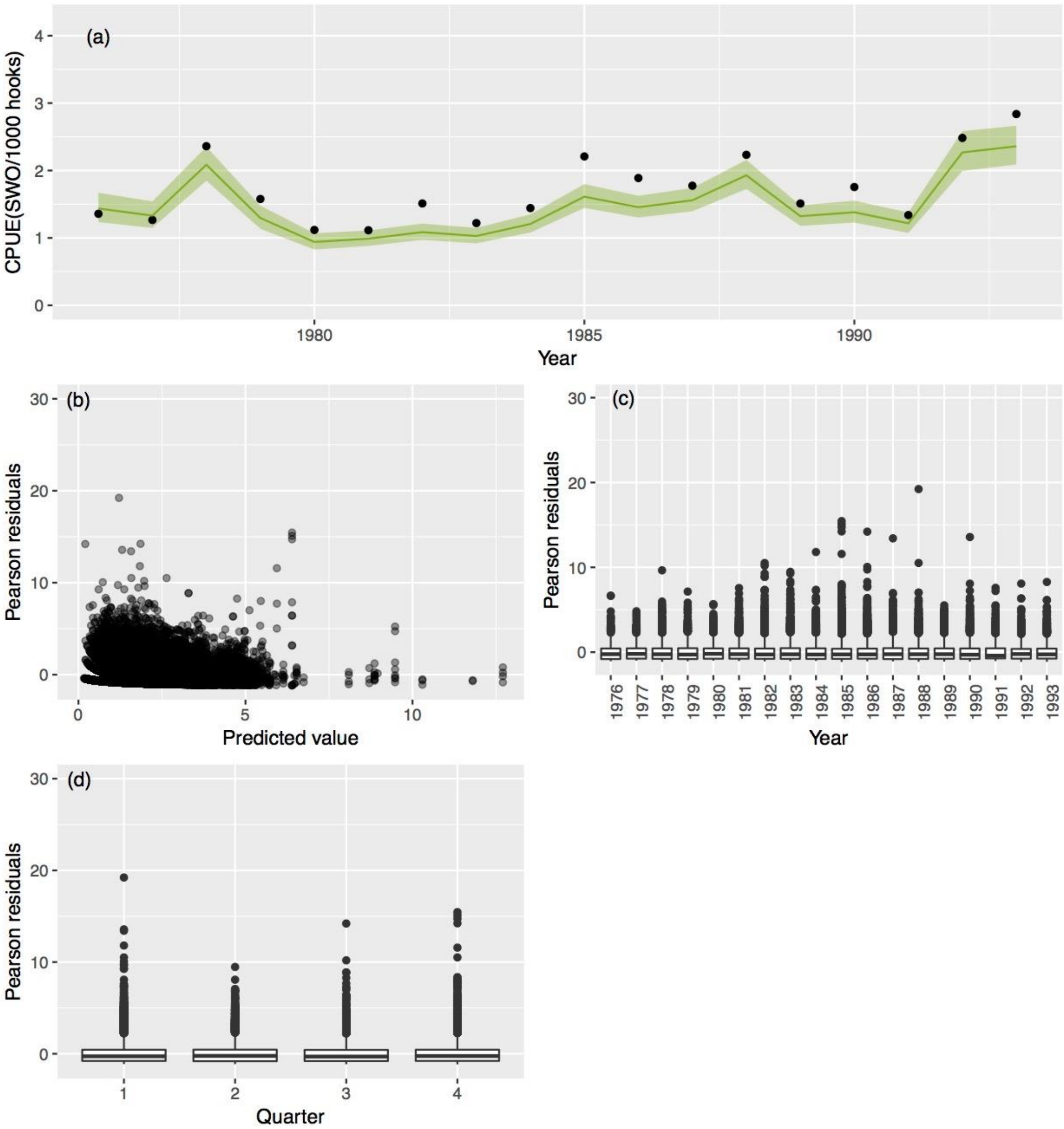

Figure 11. The result of CPUE standardization analysis of North West Indian Ocean swordfish by Japanese longline fishery (1976-1993). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(d) The plots of the Pearson residual trend.

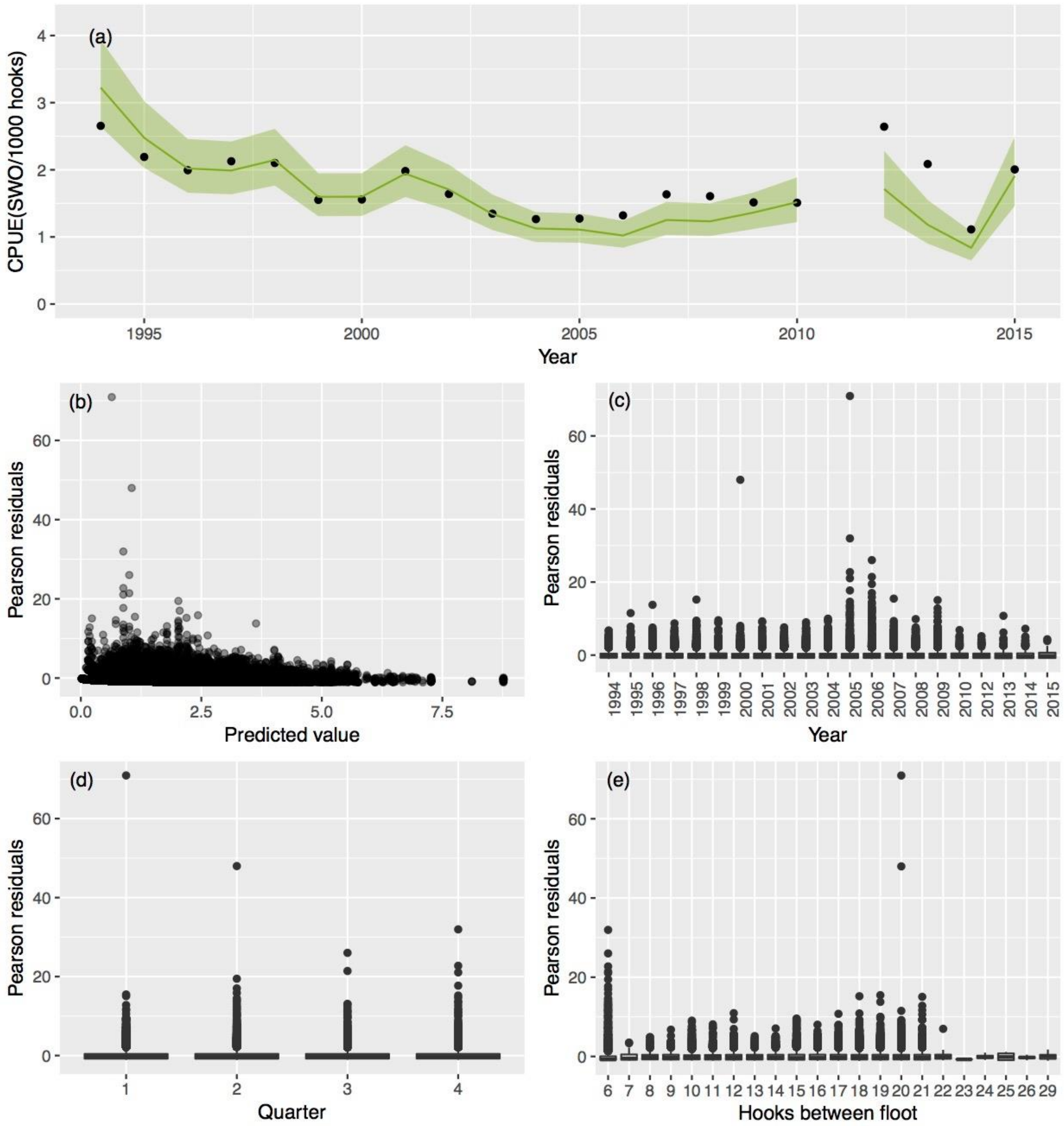

Figure 12. The result of CPUE standardization analysis of North West Indian Ocean swordfish by Japanese longline fishery (1994-2015). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(e) The plots of the Pearson residual trend.

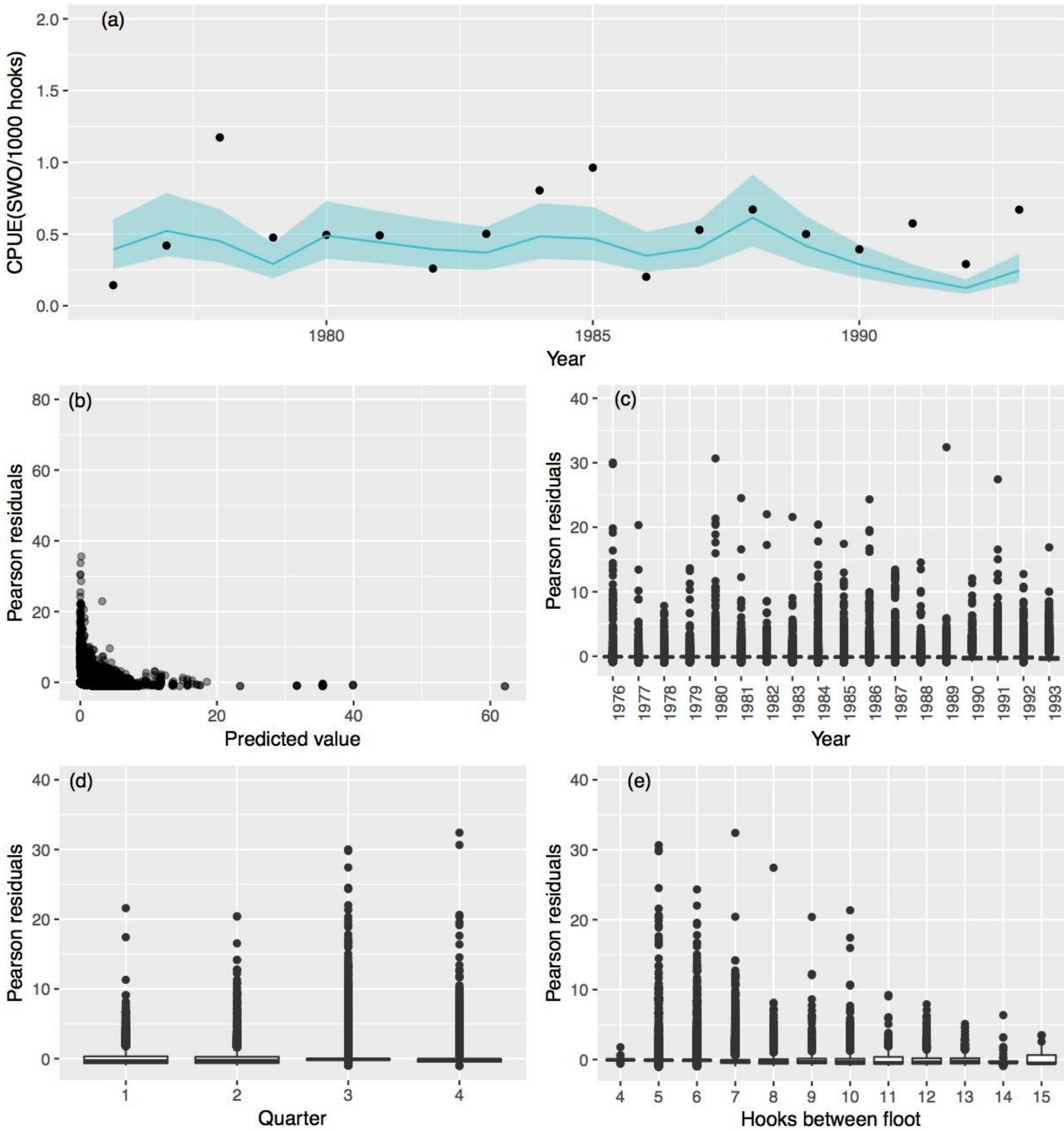

Figure 13. The result of CPUE standardization analysis of South East Indian Ocean swordfish by Japanese longline fishery (1976-1993). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(e) The plots of the Pearson residual trend.

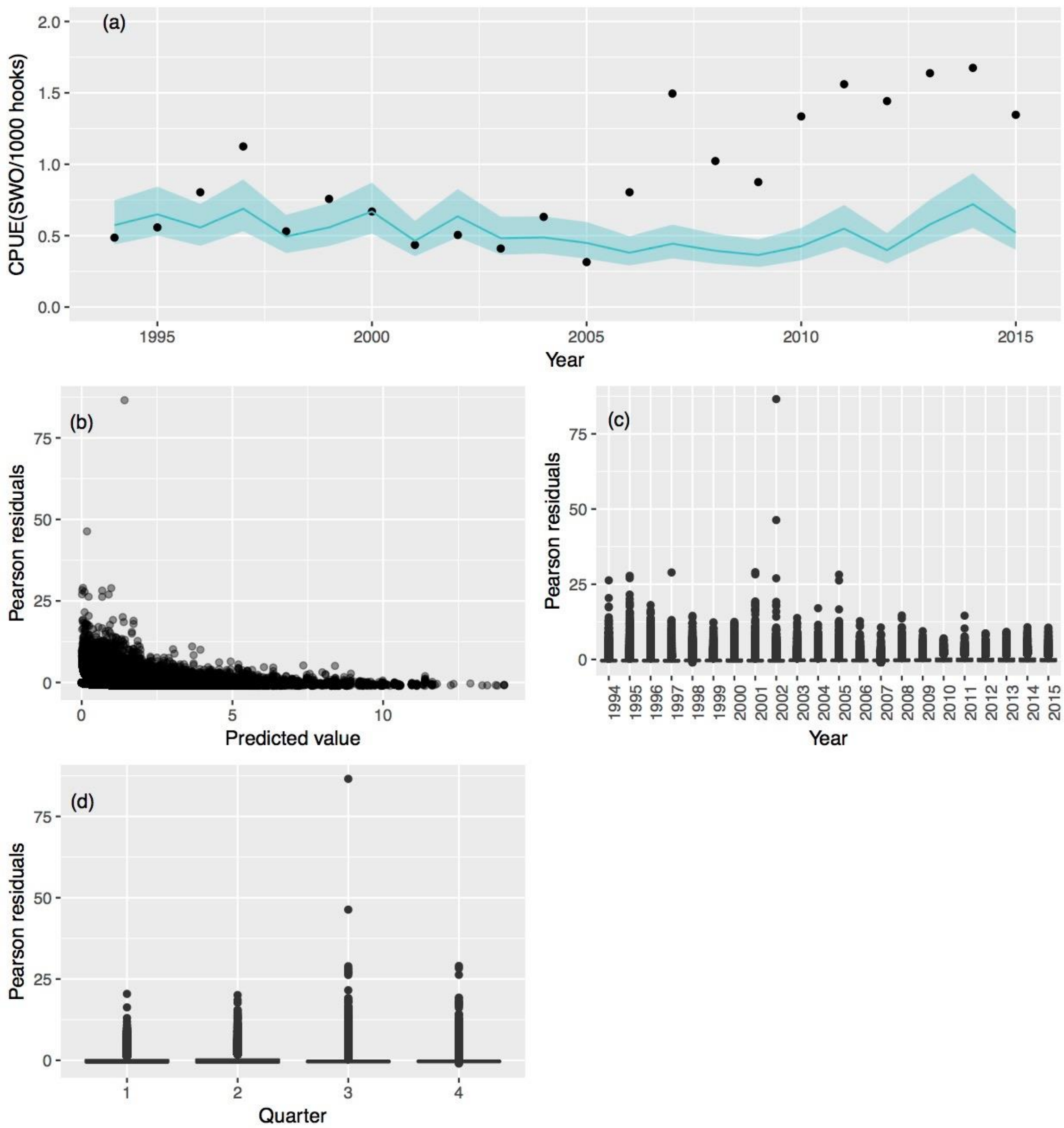

Figure 14. The result of CPUE standardization analysis of South East Indian Ocean swordfish by Japanese longline fishery (1994-2015). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(d) The plots of the Pearson residual trend.

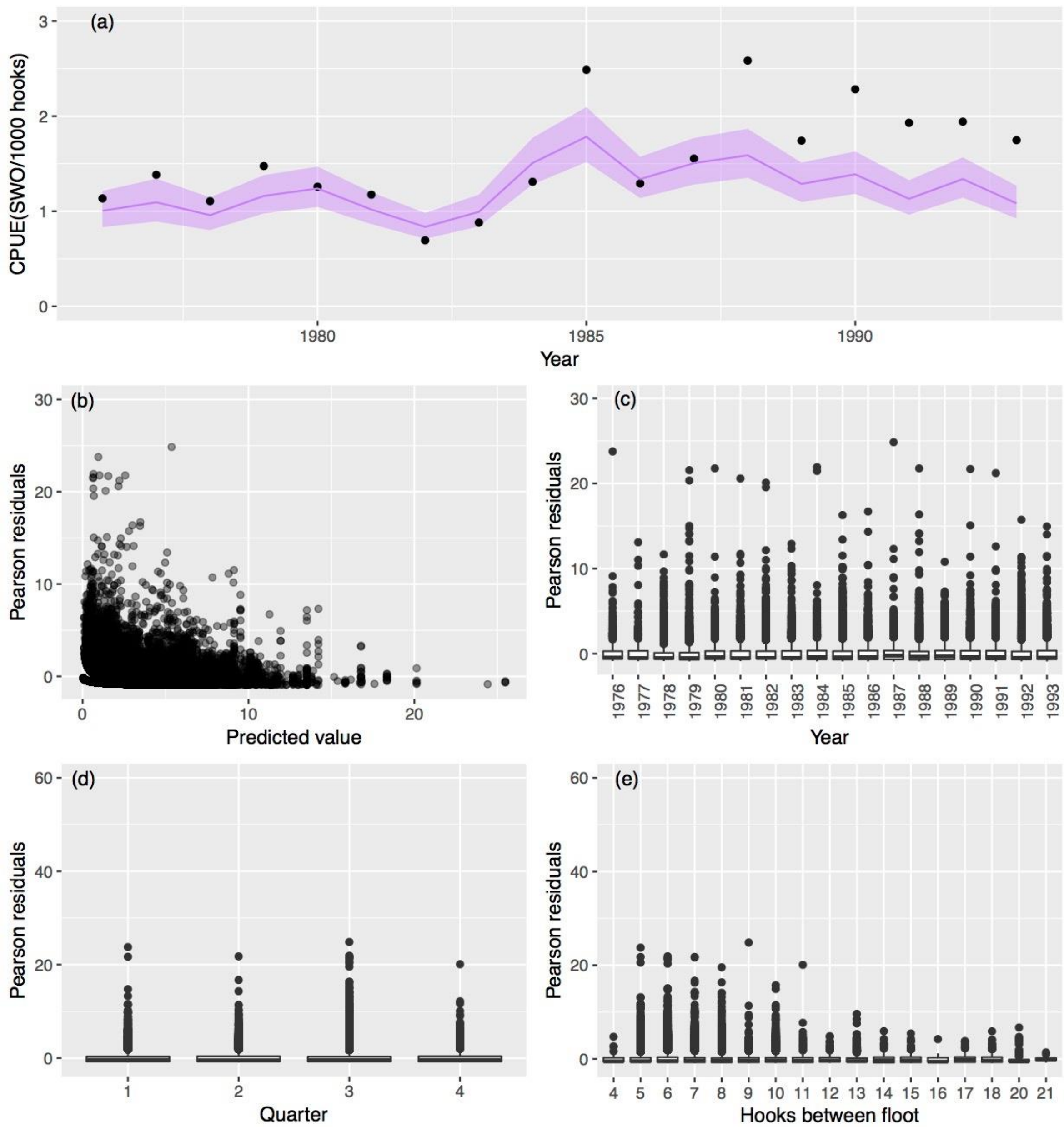

Figure 15. The result of CPUE standardization analysis of South West Indian Ocean swordfish by Japanese longline fishery (1976-1993). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(e) The plots of the Pearson residual trend.

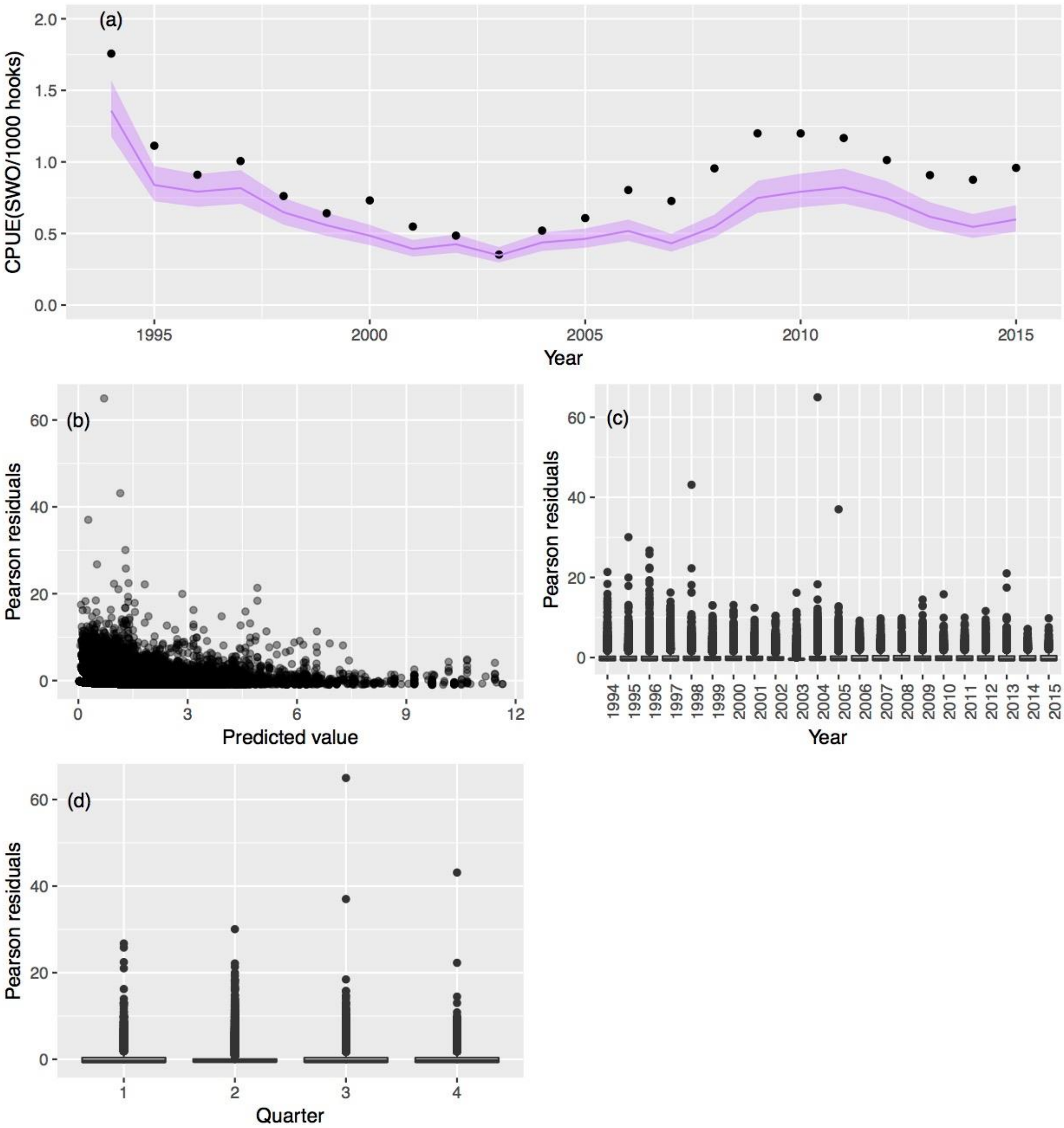

Figure 16. The result of CPUE standardization analysis of South West Indian Ocean swordfish by Japanese longline fishery (1994-2015). (a) The comparison between nominal and standardized CPUE (Lines denote standardized CPUE, Points denote nominal CPUE, and filled areas denote 95% confidence interval of standardized CPUE). (b)-(d) The plots of the Pearson residual trend.