Updated CPUE of blue shark (*Prionace glauca*) in the Indian Ocean estimated from Japanese observer data between 1992 and 2019

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Abstract

We updated the Japanese observer data until 2019 and standardized nominal catch-per-unit-effort (CPUE) of blue shark caught by Japanese tuna longline fisheries in the Indian Ocean from 1992 to 2019. We used generalized linear model (GLM) with negative binomial error distribution to standardize the nominal CPUEs. The most parsimonious model was selected by Akaike Information Criterion (AIC) as the best model for the estimation of annual CPUEs. The goodness-of-fits were diagnosed by residual plots. The 95% confidence intervals were estimated from the bootstrapping method. The annual CPUEs had a similar trend to those shown in the previous analysis except in 2000. The annual CPUE increased in 1990s and reached to the peak in 2000, and then gradually decreased with a large fluctuation until 2013. Since 2014, the annual CPUE showed an increasing trend. We suggest that the estimated annual CPUE should be utilized as one of the candidates of primary abundance indices in the next stock assessment of blue shark in the Indian Ocean scheduled in 2021 because the Japanese observer data covers a wide range of the main distribution area (temperate water) of blue shark in the Indian Ocean and a longer time period compared to the other fleets' CPUE data.

Key words

Blue shark, Japanese observer data, Standardized CPUE, Longline fishery, *Prionace glauca*, Negative binomial model

Introduction

Blue shark, *Prionace glauca*, is the most abundant pelagic shark species and widely distributed in the tropical and warm-temperate oceans worldwide (**Compagno, 2001; Nakano and Stevens, 2008**). It is one of the common bycatch shark species for Japanese tuna longline fishery in the Indian Ocean. Japanese tuna longline fishery in the Indian Ocean is largely divided into two types of operations targeting southern bluefin tuna (*Thunnus maccoyii*) and those targeting other tuna species (**Semba *et al.*, 2015**). Although the area and season of the operation of Japanese tuna longline fleet targeting *T. maccoyii* is limited, its operation area in the Indian Ocean is generally overlapped with the distribution area of blue shark including the main distribution area (temperate water).

In the previous analysis, annual CPUEs of blue shark in the Indian Ocean were estimated using zero-inflated negative binomial model (ZINB) with observer data collected from Japanese commercial tuna longline fishery (**Semba *et al.*, 2016**). They added newly available data; 1) observer data with deep set and set operated in the tropical water: 2) the observer data collected outside the traditional CCSBT observer program in the Indian Ocean. However, the estimated annual CPUE trends were almost the same as those in 2015 (**Semba *et al.*, 2015**) because the added data mainly consisted of set from tropical area where the abundance of blue shark was relatively small.

We update standardized CPUE for blue shark caught by Japanese tuna longline fisheries in the Indian Ocean from 1992 to 2019 using the generalized linear model with Japanese observer data. We also examine the appropriateness of the estimated CPUEs for the stock assessment of blue shark scheduled in 2021.

Material and Method

1) Data sources

The Japanese observer data in the Indian Ocean covering the CCSBT area, the IOTC area including data collected by Indonesian observer, and the ICCAT area. The observer data collected in the jurisdiction of IOTC was extracted based on the map for fisheries statistical areas defined by FAO.

We updated Japanese observer data from 1992 to 2019 (**Table 1**). We particularly added the newly available observer data in the period between 2016 and 2019. In addition, we added a large amount of observer data collected at the CCSBT area through experimental fishing program in the period between 1998 and 2000 that were not used in the previous analysis. Then, we removed erroneous dataset that had no information about the operation locations (i.e., latitude and longitude), observed number of hooks, and number of hooks between floats (HBF). Similarly, the datasets with extremely small and large number of HBF (less than 4 and more than 40) were also removed from the analysis. The IOTC observer data finally reduced from 15,601 to 15,416 datasets.

2) *CPUE standardization*

Since the updated observer data for blue shark indicated 25 % zero catch ratio with overdispersion (27.95 of dispersion: variance/mean ratio) on average in the period between 1992 and 2019, we determined to use ZINB and negative binomial model (NB) to standardize the nominal CPUE.

However, we finally used only NB due to the convergence issue of ZINB. We used the same covariates (year, area, and season) as used in the previous analysis. We also added HBF to remove the targeting effect for tropical tunas in the subtropical/tropical area. The HBF was simply classified into shallower sets (HBF < 12) and deeper sets (HBF ≥ 12). The area definition was changed from east/west separation at 90 °E to 65.5 °E (see **Fig. 1**) because **Kai (2019)** found more reasonable longitudinal line for area separation using the GLM tree (**Ichinokawa and Brodziak, 2010**) with logbook data for pelagic sharks in the Indian Ocean. The definition of season was the same as that used in the previous analysis. Season was separated into 1) April-July and 2) August-December.

3) *Model structure*

The negative binomial model with a log-link function is as follows:

$$Y_i \sim NegBin\ (\mu_i, k),$$
$$\log\ (\mu_i) = \beta_0 + \beta_1 year + \beta_2 qt + \beta_3 area + \beta_4 hbf + Interaction + \text{offset}(\log(hooks)), \quad (1)$$

where Y_i is negative binomial distributed with mean μ_i and parameter k, β represents coefficients, "*year*" represents year-effect (signifying each year from 1992 to 2019), "*qt*" represents season-effect (signifying season 1 and 2), "*area*" represents area-effect (signifying area 1 and 2), "*hbf*" represents gear-effect (signifying shallow set and deep set, **Fig. A1**), "*Interaction*" represents interaction terms, and "$hooks$" represents a fishing effort (observed number of hooks) given as an offset term. For the full model including all covariates and three interaction terms (i.e., year:area, gear:season, and area:gear), model selection was conducted by Akaike Information Criterion (AIC). We removed each explanatory variable and the interaction terms one by one from the full model and compared the AICs to select the best model. The other interaction terms were not included in the model due to the convergence issue (i.e., year:gear, and year:season) or insignificant effect on the result (area:season). The least-square mean of standardized CPUE by year was calculated, and then the annual CPUE was scaled by the mean CPUE in the period between 1992 and 2019.

4) *Model diagnostics*

We evaluated the fitting of the model to the data using the Pearson residuals, QQ-plot and type-II analysis. The residuals were calculated using a randomized quantile (**Dunn and Smyth, 1996**) to produce continuous normal residuals.

To evaluate the uncertainties in the estimates of annual CPUE, we estimated the 95 % confidence intervals (95% CI) using a bootstrapping method (i.e., randomly resampling of the set-by-set data from the datasets in the same year) with 1,000 iterations for the selected model.

Results

The most parsimonious model (**Model 8**, **Eq. 1**) was selected as the best model based on the model selection by AIC (**Table 2**). The fittings of the best model to the data were not bad (**Figs. 2 and 3**). Interaction terms of the selected model were confirmed to be significant from type-II analysis, while the single factor of area was not significant (**Table 3**).

The estimated CPUE was weighted by the relative size of two-areas (i.e., number of 1 x 1 degrees of grid) because the selected model included the interaction term of year and area.

Overall, complicated models with interaction terms (e.g., Models 6, 7, and 8) tended to decrease the magnitude of annual fluctuations (**Fig. 4**). The factors of gear and interaction term between year and area had a large impact on the trends in the estimated CPUEs (**Table 3**).

The estimated annual CPUEs showed a similar trend to those shown in the previous analysis except the value in 2000 (**Fig. 5**) due to the increase of datasets in 2000 (**Table 1**). The annual CPUEs sharply increased in the end of 1990s and reached to the peak in 2000, and then gradually decreased with large fluctuations until 2013 (**Fig. 5**). Thereafter, the annual CPUEs showed an increasing trend. The 95 % CIs for the best model were narrow and the coefficient of variation (CV) for the best model was small over the period of this analysis (the mean value of CV from 1992 to 2019 was 0.07) (**Table 4** and **Fig. 5**).

Discussions

This paper presented standardized annual CPUEs of blue shark in the Indian Ocean estimated from negative binomial model with Japanese observer data collected between 1992 and 2019. We updated the Japanese observer data for recent four years until 2019 and added a large volume of datasets throughout the whole periods. Additionally, we changed the model structure and error distribution of GLM from ZINB to NB. Moreover, we changed the area definition and added a factor of gear configuration (i.e., HBF) to the model as a catchability coefficient. Although we updated the data and model with major several changes, the annual CPUE estimated from Japanese observer data showed a similar trend to that estimated in the previous analysis (**Semba et al., 2016**). These results suggested that the estimated annual CPUE in this study is robust to the uncertainties in the model structure as well as quantity of the data. Current estimates are based on observer data which includes both retained sharks and released sharks, and thus it is considered to be appropriate to estimate the trend of population abundance. The advantage of using the Japanese observer data in the Indian Ocean is, compared to CPUEs of the other fleets, that the main operation area covered by the data collected at the CCSBT area overlapping a wide range of main distribution area (temperate water) of blue shark and a long time period from 1992 to 2019. Additionally, in the previous IOTC stock assessment of blue shark in 2017 (**IOTC, 2017**), the CPUE estimated from the Japanese observer data was used. These facts suggest that the estimated Japanese observer CPUE should be utilized as one of the candidates of primary abundance indices in the next stock assessment of blue shark in the Indian Ocean scheduled in 2021.

Although the ZINB was not applied to standardize the nominal CPUE of blue shark in this study, there was no large impact of this process on the annual trends in the estimated CPUE (**Fig. 5**). **Minami and Lennert-Cody (2007)** revealed that the ZINB can provide a better fit to the data than NB, and NB may overestimate model coefficients when fitted to data with many zero-valued observations. However, the zero-catch ratio used in their study was more than 50%. Probably, the 25 % zero catch ratio in this study may not be regarded as an excess zero-valued data. Therefore, it is not unreasonable to use the NB for the data with 25% zero catch ratio.

The annual change in number of HBF showed a clear decadal shift of depth (Fig. A1). Specifically, the numbers of HBF were lower than 12 until 2009, and then the number of HBF remarkably increased due to the addition of observer data collected in the tropical waters. Although we attempted to include the interaction term of year and gear into the model to reduce the effect, the model was removed from the analysis due to the convergence issue.

The sharp decline of fishing effort since 2006 may contribute to the recent increasing trends in the CPUE since 2012. Overall, the estimated CPUE indicated a stable trend from 1993 to 2019 except in 1999 and 2000. The annual CPUE indicated a large spike in 1999 and the standardized CPUE in 1999 sharply increased approximately 2.4 times compared to that in 1998 (**Table 4**). **Yokoi et al. (2017)** revealed that the estimated median population growth rate (r) of blue shark was 0.384 with a range of minimum and maximum values of 0.195-0.533 from global data. The estimated value suggests that the blue shark population may increase 1.47 times in a year without exploitation and density dependent. Therefore, the sharp increase of CPUE in 1999 is unrealistic in this context. In future work, we need to investigate the reasons for the spike and improve the standardization method.

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Table 1. Summary of data used in the analyses for previous study (Semba et al. 2016) and this study (after filtering).

Year	Semba et al.(2016)			This study		
	Catch number of blue shark	Observed number of hook	Nominal CPUE (per 1000 hooks)	Catch number of blue shark	Observed number of hook	Nominal CPUE (per 1000 hooks)
1992	2549	1,310,404	1.945	2549	1,533,623	1.662
1993	1323	656,373	2.016	1323	735,486	1.799
1994	1981	986,045	2.009	1981	1,028,879	1.925
1995	2892	1,252,228	2.309	2892	1,312,029	2.204
1996	4222	1,007,713	4.190	4222	1,152,149	3.664
1997	2552	1,289,690	1.979	2552	1,452,998	1.756
1998	2724	731,948	3.722	6309	2,124,331	2.970
1999	3682	533,777	6.898	14132	2,110,940	6.695
2000	1655	395,313	4.187	2818	520,479	5.414
2001	3777	1,090,940	3.462	3777	1,234,660	3.059
2002	2043	623,211	3.278	2043	652,265	3.132
2003	3423	794,412	4.309	3423	799,931	4.279
2004	2922	1,221,501	2.392	2922	1,480,667	1.973
2005	4845	1,724,604	2.809	4845	1,884,161	2.571
2006	4797	2,004,561	2.393	4797	2,457,329	1.952
2007	2898	1,122,223	2.582	2898	1,205,363	2.404
2008	958	295,009	3.247	958	302,186	3.170
2009	1916	433,950	4.415	1916	449,355	4.264
2010	743	589,901	1.260	935	996,457	0.938
2011	1363	513,921	2.652	2724	1,216,732	2.239
2012	1738	537,239	3.235	2291	1,122,627	2.041
2013	1010	875,151	1.154	1010	1,001,325	1.009
2014	3174	1,707,821	1.859	3121	2,001,977	1.559
2015	3915	1,075,236	3.641	4123	1,501,702	2.746
2016				1438	1,244,666	1.155
2017				1978	1,657,007	1.194
2018				4292	1,382,296	3.105
2019				4442	1,589,815	2.794

Table 2. Summary of model selection information for blue shark from multiple models. ΔAIC denotes the reduction in AIC from the best-fitting model. Model 8 (shade) was selected as the best model.

Model	Structure of NB	ΔAIC	Deviance	Degree of freedom
1	log(hook)	4080	83,018	2
2	year + log(hook)	2361	81,244	29
3	year + area + log(hook)	2298	81,179	30
4	year + area + season + log(hook)	2133	81,013	31
5	year + area + season + gear + log(hook)	688	79,565	32
6	year + area + season + gear + year:area + log(hook)	111	78,935	59
7	year + area + season + gear + year:area + area:gear + log(hook)	24	78,845	60
8	year + area + season + gear + year:area + area:gear + season:gear + log(hook)	0	78,820	61

Table 3. Type-II analysis of deviance table for model components produced by the negative binomial model (Best model). LR Chisq denotes Likelihood Ratio Chi-Square statistics, DF is degree of freedom, and Pr is significant probability for each factor.

Factor	LR Chisq	Df	Pr (>Chisq)
Year	1449	27	< 0.001
Area	0.02	1	0.885
Season	20.50	1	< 0.001
Gear	1683	1	< 0.001
Year:Area	716	27	< 0.001
Area:Gear	85	1	< 0.001
Season:Gear	26	1	< 0.001

Table 4. Summary of outputs.

Year	Scaled nominal CPUE	Standardized CPUE	Scaled standardized CPUE	Coefficient of variations (CV)	Lower value (scaled CPUE) of 95% CI	Upper value (scaled CPUE) of 96% CI
1992	0.632	0.929	0.520	0.077	0.448	0.601
1993	0.684	0.990	0.554	0.083	0.471	0.650
1994	0.732	1.120	0.627	0.075	0.539	0.721
1995	0.838	1.255	0.703	0.065	0.621	0.793
1996	1.393	2.238	1.253	0.059	1.113	1.402
1997	0.668	1.044	0.585	0.072	0.505	0.672
1998	1.129	1.573	0.880	0.052	0.794	0.971
1999	2.544	3.758	2.103	0.086	1.759	2.465
2000	2.058	3.999	2.238	0.124	1.752	2.807
2001	1.163	2.128	1.191	0.071	1.030	1.367
2002	1.190	2.361	1.322	0.089	1.102	1.550
2003	1.626	2.690	1.506	0.055	1.347	1.670
2004	0.750	1.334	0.747	0.069	0.651	0.849
2005	0.977	1.665	0.932	0.055	0.830	1.033
2006	0.742	1.170	0.655	0.063	0.580	0.736
2007	0.914	1.638	0.917	0.084	0.778	1.077
2008	1.205	1.516	0.849	0.080	0.728	0.986
2009	1.620	2.711	1.518	0.073	1.316	1.736
2010	0.357	0.967	0.541	0.073	0.470	0.620
2011	0.851	1.209	0.677	0.064	0.597	0.763
2012	0.776	1.504	0.842	0.056	0.751	0.936
2013	0.383	0.838	0.469	0.084	0.400	0.552
2014	0.592	1.185	0.664	0.048	0.604	0.727
2015	1.043	1.858	1.040	0.059	0.920	1.167
2016	0.439	1.924	1.077	0.063	0.948	1.209
2017	0.454	2.290	1.282	0.057	1.142	1.431
2018	1.180	2.064	1.155	0.078	0.997	1.347
2019	1.062	2.060	1.153	0.049	1.048	1.271

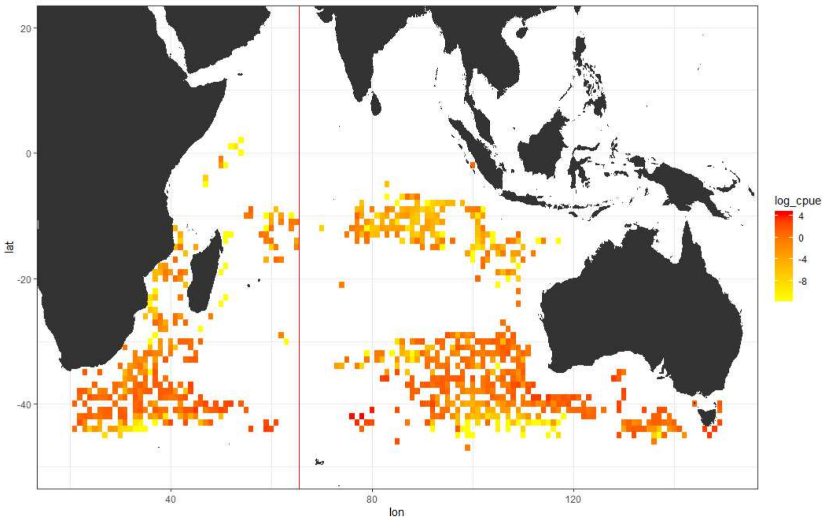

Fig.1 Spatial distribution of logarithmic nominal CPUE (catch number per 1,000 hooks) of blue shark from the Japanese observer data and experimental fishing program recorded in Japanese tuna longline fishery operated in the Indian Ocean from 1992 to 2019. The red vertical line denotes the delineation of the area separation used in the analysis.

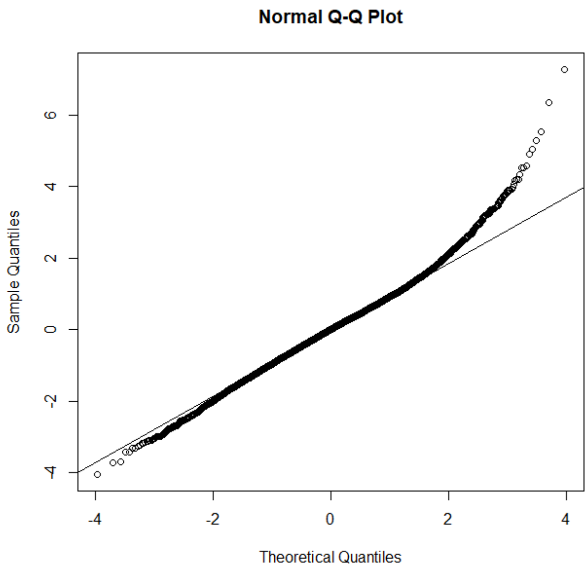

Fig. 2 Diagnostic plots of goodness-of-fit for the negative binomial model (best model).

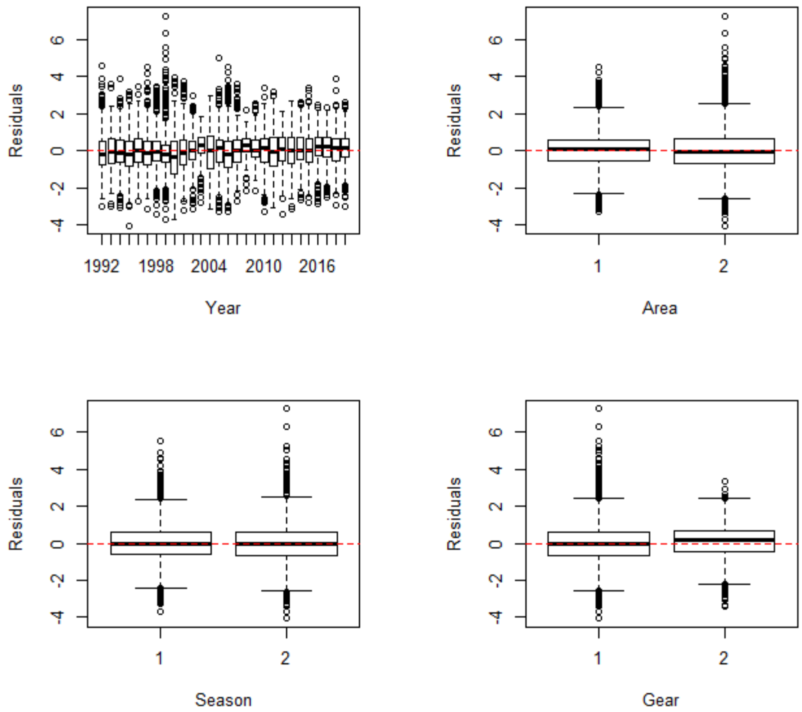

Fig. 3 Residual plots of the negative binomial model (best model) for each explanatory variable.

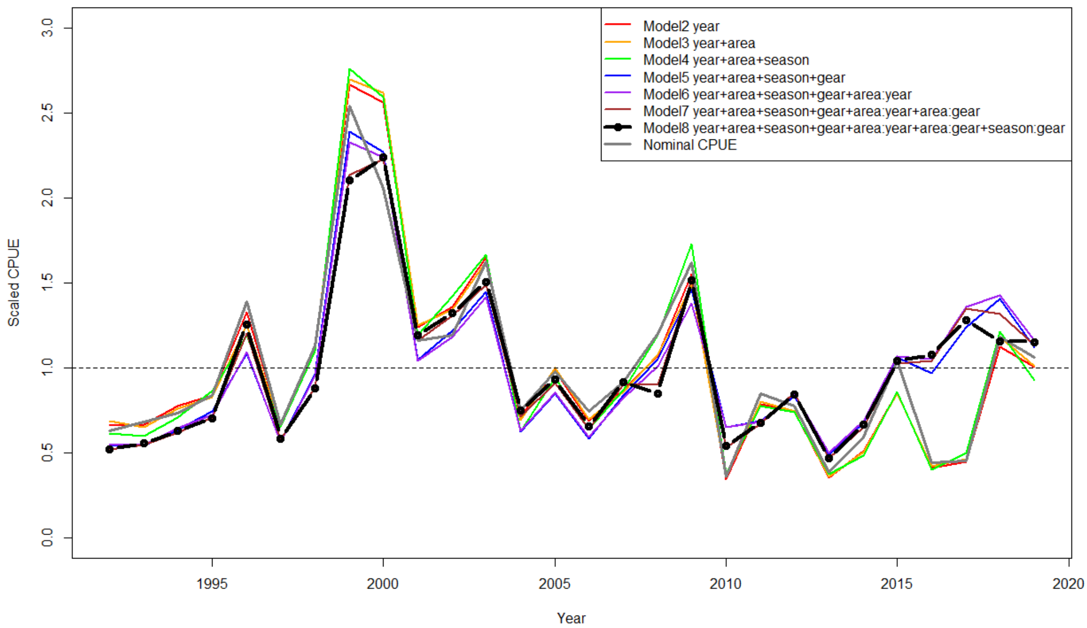

Fig.4 Comparisons of standardized CPUEs (scaled by a mean value) of blue shark among the different model structures.

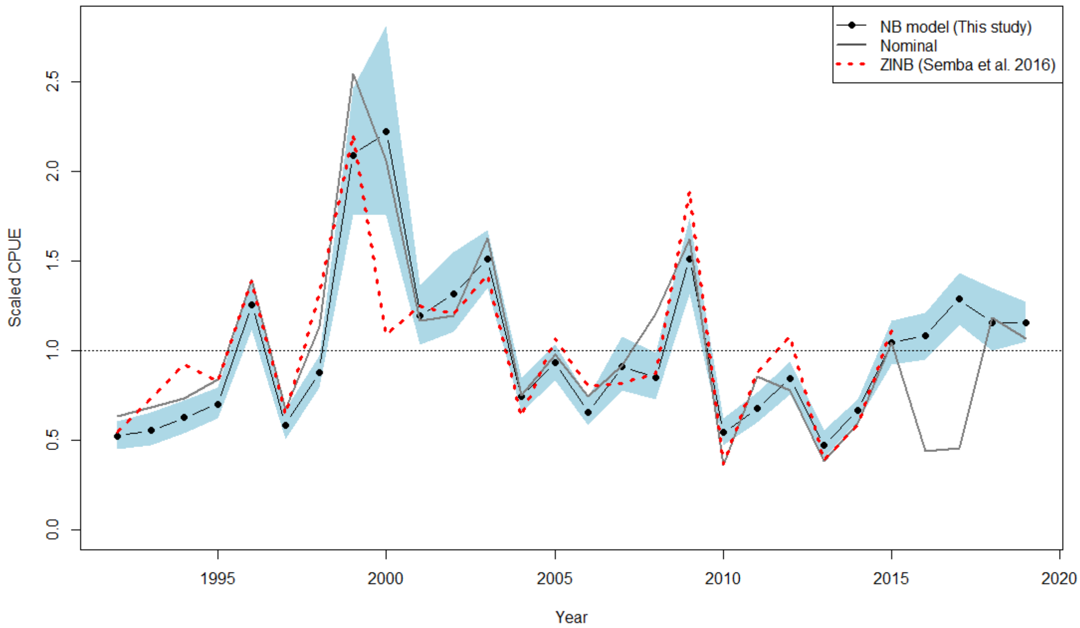

Fig.5 Standardized CPUEs (best model: scaled) of blue shark and its 95% confidence intervals (ranges of light blue) estimated from 1,000 bootstrapping.

Appendix

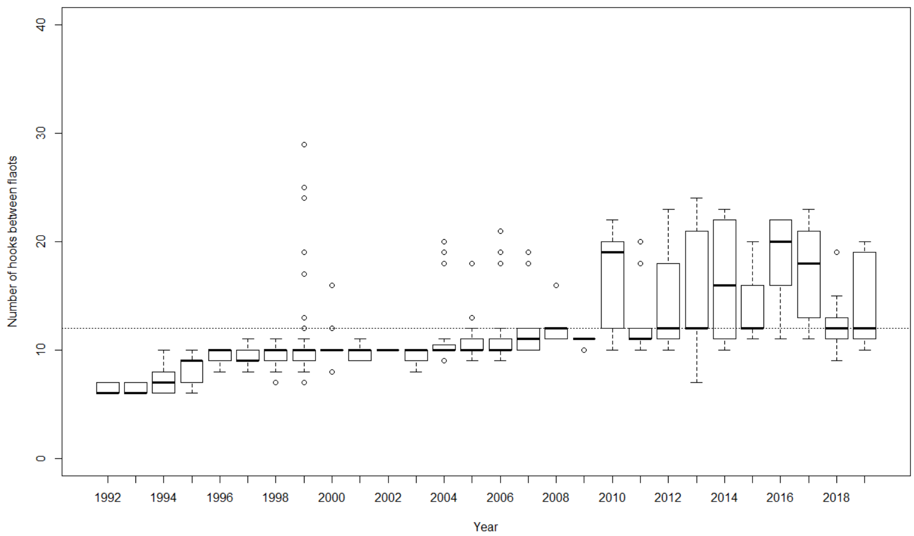

Fig. A1 Annual change in number of hooks between floats. Horizontal dotted line denotes the distinction of shallow and deep set.