UPDATED ON THE CPUE STANDARDIZATION OF THE BLUE SHARK (*Prionace glauca*) CAUGHT BY INDONESIAN TUNA LONGLINE IN THE EASTERN INDIAN OCEAN

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ABSTRACT

The blue shark or BSH (*Prionace glauca*) is commonly caught as bycatch in tuna longline fishery. It is vulnerable as a consequence of the increasing intensity of tuna harvesting. Despite this species categorized as well-studied compared to other shark species, an update on its abundance is essential for stock assessment and fishery management. This study provided an update on the CPUE standardization of the blue shark as a proxy of relative abundance by removing possible factors that influence the CPUE using a Generalized Linear Model (GLM). The fishery-independent data was gathered through the Indonesian onboard scientific observers program operated in the eastern Indian Ocean from August 2005 to December 2019. Due to the large proportion of the zero catch of blue shark (~62%), the CPUE was standardized using a delta-lognormal model. In general, an increase-fluctuated trend of the CPUE was observed in the last decade. The standardized CPUE of the blue shark as a proxy of its relative abundance decreased during 2006 and to 2011 and showed an increasing trend thereafter and peaked in 2018. The positive catch of blue shark was significantly affected by the variables of year, quarter, and latitude, where the blue shark is more abundant in high latitude waters.

Key Words: abundance, bycatch, stock assessment, relative abundance, delta-lognormal model

INTRODUCTION

Shark conservation and management efforts have been growing as a global concern in the past decade as a decline in shark populations has occurred in many oceans and basins (Baum et al., 2003; Burgess et al., 2005; Megalofonou et al. 2005; Baum and Blanchard 2010). In the Indian Ocean, they are vulnerable to the high intensity of tuna harvesting, where the use of longlines and gillnets were identified as a significant contributor to shark bycatch (Fahmi & Dharmadi, 2015). Therefore, some management measures were established by the Indian Ocean Tuna Commission (IOTC), referred to as IOTC Resolution, to maintain sharks' stock level.

The blue shark (*Prionace glauca*) is one of the cosmopolitan sharks, having a wide-range distribution in the tropical, subtropical, and temperate waters, including the Mediterranean Sea (Compagno 1999). The abundance of blue sharks is relatively high compared to other species of shark. The species has interacted with various and widespread fisheries, plus its circum-global distribution has a consequence in it being a relatively well-assessed elasmobranch. In the Indian Ocean, the latest assessment is carried out on the basis of the 2017 data and stated that blue sharks are not overfished nor subject to overfishing (IOTC, 2020). However, the increased fishing effort could raise concerns about the decline in biomass in the future.

As the blue shark is the dominant catch among other shark species, it is essential to determine its current level of abundance using the independent-fishery data (i.e., onboard observer). In many studies, the catch per unit of effort (CPUE) is assumed to be related to the fish abundance and is known as a relative index of abundance (Campbell, 2004; Maunder & Punt, 2004). However, the CPUE data series commonly were confounded by either fishing configuration and environmental factors. Therefore, removing possible factors that may affect the CPUE is needed to provide a more reliable abundance index, then commonly referred to as the CPUE standardization process. Previous CPUE standardization of the blue shark has been reported in the Indian Ocean by using various GLM-based models (Tsai & Liu 2014; Coelho et al., 2014; Coelho et al., 2015; Semba et al., 2015; Semba & Kai 2016; Novianto et al., 2016, 2017; Jatmiko et al., 2019). This paper filtered out the possible factors that influence the CPUE and provided an update on the CPUE standardization of the blue shark as a proxy of relative abundance, which may use for the latest stock assessment initiation in the Indian Ocean region.

MATERIALS AND METHODS

1. Data Collection

This study analyzed the data collected by the onboard scientific observer scheme on commercial tuna longline vessels based on several fishing bases, namely Benoa, Cilacap, Palabuhanratu, and Jakarta. The program was initiated in 2005 through an Australia-Indonesia collaboration (ACIAR Project FIS/2002/074), and since 2010 it has been conducted by the Research Institute for Tuna Fisheries (RITF Indonesia). The dataset contained information regarding the number of fishes caught by species, the total number of hooks, the number of Hooks Between Floats (HBF), the start time of the set, soak time, and geographic position (latitude and longitude) derived from GPS data as summarized in Table 1. However, to avoid bias due to misidentification issues on the blue shark among other shark species, the datasets of 2005 were excluded from the analysis.

2. CPUE Standardization

The response variable in the standardization model was the catch per unit of effort (CPUE) according to 1000 hooks. The CPUE was calculated according to 1000 hooks using a formula as follows:

$$CPUE = C/E \times 1000 \quad (1)$$

where:

- C = the catch number of the blue shark.
- E = the number of hooks.

The CPUE also was estimated spatially in a 5x5 grid map. A large proportion of zero catch of blue shark (~62%) was identified from the observers' records. Hence, a left-skewed of catch distribution of the blue shark also was produced. Then, the delta-lognormal model was applied to the blue shark CPUE standardization to address these excessive zero catch. The delta-lognormal is a combination of two GLM models; one is used to estimate the positive catches only, and the second is to estimate the proportion of positive submodels. The positive catch event and proportion of positive submodels were modeled assuming a lognormal and binomial model, respectively:

$$\log(CPUE) = \mu + Year + Quarter + Start\_time + HBF + Lat + Lon + Moon + \varepsilon_1 \quad \ldots\ldots\ldots\ldots (2)$$

$$P = \mu + Year + Quarter + Start\_time + HBF + Lat + Lon + Moon + \varepsilon_2 \quad \ldots\ldots\ldots\ldots (3)$$

where:

- Year = analyzed from 2006 and 2019 and categorized as a factor.
- Quarter = defined as a factor and divided into four categories: 1 = January to March, 2 = April to June, 3 = July to September, 4 = October to December.
- Start time = defined as the time when the longline was set. It was treated as a quantitative variable, and the values were rounded to the nearest integer.
- Soak time = calculated as the time elapsed between setting up the longline and the longline being hauled.
- Soak time = treated as a continuous variable. Thus, the value was rounded to the nearest integer.
- Lat5 and Lon5 = abbreviations of latitude and longitude, respectively, defined as the actual position (in decimal format) where the longline was deployed. It is

incorporated as a continuous variable in the GLM analysis. Both geographical information were grouped in a 5x5 grid.

- HBF = abbreviation of the total number of hooks between float. It is categorized as a quantitative variable instead of a factor.
- Moon phase = The moon phase was determined by the sinusoidal formula reported by Sadiyah et al. (2012) to account for the effect of cyclic moon behaviour.

The best fit model selection between both Lognormal and Binominal models was carried out using the AIC method (Venables and Ripley, 2002). The distribution of residuals was used to verify the assumption of the Lognormal distribution of the positive catches. These diagnostic plots also were used to evaluate the fitness of the models. In addition, deviance analysis tables for the proportion of positive observations and for the positive catch rates were also provided. The final estimate of the relative annual abundance index was obtained by the product of the main yearly effect of the Lognormal and Binomial components (Lo et al., 1992).

Standardized CPUE = CPUE * P .... (4)

The 95% confidence intervals were constructed based on the bias corrected percentile method. All the statistical and mapping analyses were carried out using R software (R Core Team, 2020), particularly the package pscl (Jackman, 2017), emmeans (Lenth, 2018), MASS (Venables and Ripley, 2002), Hmisc (Harrell Jr. et al., 2018), lsmeans (Lenth, 2016), and statmod (Giner and Smyth, 2016) for statistical, while for mapping the package ggplot2 (Wickham, 2016), mapdata (Brownrigg, 2018), maps (Deckmyn, 2018), sf (Pebesma, 2018), rnaturalearth (South, 2017), rnaturaleartdata (South, 2017), and rgeos (Bivand & Rundel, 2020) were used in this study.

RESULT AND DISCUSSION

The nominal CPUE of the blue shark showed a strong inter-annual variation. In general, an increasing trend of relative abundance was observed during the last decade. The CPUE of the blue shark decreased during 2006 and to 2011 and showed an increasing trend thereafter and peaked in 2018 (Figure 1). The abundance of the blue shark also described spatially based on a 5x5 grid map. Overall, we found that the blue shark is more abundant in high latitude waters. High CPUE mainly detected in the latitude between 10 – 35º South (Figure 2).

The standardized CPUE series contains the combined effects from two models, one that accounts for the positive catches only through Lognormal distribution and the rest estimates the proportion of positive count per year using Binomial distribution. Some explanatory variables contributed significantly in explaining the deviance of the blue shark CPUE standardization. The ANOVA tables for each model indicated that the main effects were significant (mostly $p < 0.01$) and were selected in the final model (Table 2). The model of Lognormal and Binomial were produced AIC = 2,244 and 3,068, respectively. Therefore, Lognormal model was selected as the best fit model, including the explanatory variables of year, latitude, and quarter are detected to be contributed significantly to the relative abundance indices.

In terms of the model validation, the residuals distribution histogram and Q-Q normal plot showed that error distributions approximate to the normal. These indicated that the model was adequate with no significant outliers or trends in the residuals. The diagnostic of residuals vs. fitted also showed that the Lognormal model does not have a severe deviation from the model assumptions (Figures 3). Overall, the standardized CPUE using the delta-lognormal model can reduce the inter-annual variability in the nominal CPUE. The trends were relatively similar to the nominal CPUE series with less dramatic variation along the period (Figure 4).

In the present study, we have only used the delta-Lognormal model to analyze the observers' data due to a high proportion of zero catch of the blue shark appear as the main problem. Although there has been a decrease in the number of trips and low spatial-coverage on the Indonesian scientific observer program, this study may reveal the relative abundance of blue sharks in the eastern Indian Ocean, where assessment is relatively limited compared to the western part. As a highly migratory species, the blue shark may distribute throughout large areas of the Indian Ocean and are harvested by several nations. Therefore, to get a more reliable analysis of the relative abundance in the eastern Indian Ocean, a joint CPUE analysis, including more data from multi-nation and by applying other models simultaneously, should be a priority in the future.

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Table 1. Summary of observed fishing effort from Indonesian tuna longline fishery during 2006 and 2019. Results are pooled and presented by year of observation. Operational parameters are means and standard deviations (in parenthesis)

Year	Trips	Sets	Total hooks	Hook per set (mean ±s.d.)		Hook per float (mean±s.d.)	
2006	13	400	575,989	1,440	(215.3)	11.2	(3.9)
2007	13	262	403,333	1,539	(323.0)	14.0	(4.4)
2008	15	396	510,702	1,290	(383.7)	12.7	(4.5)
2009	13	288	328,718	1,141	(234.4)	12.2	(4.9)
2010	6	166	221,274	1,333	(457.5)	13.6	(5.2)
2011	3	105	110,384	1,051	(173.9)	12	(0.0)
2012	8	198	290,265	1,466	(559.1)	14.1	(2.3)
2013	7	210	231,990	1,105	(204.4)	12.4	(2.2)
2014	6	184	216,705	1,178	(181.1)	15.0	(1.9)
2015	5	150	174,655	1,164	(144.6)	14.1	(3.2)
2016	3	130	175,868	1,353	(209.0)	11.3	(3.3)
2017	4	139	192,188	1,383	(398.7)	15.3	(1.8)
2018	6	195	262,856	1,348	(230.6)	14.8	(2.5)
2019	9	164	216,836	1,322	(193.9)	10.8	(4.5)

Table 2. Deviance table for final GLM results of the delta-lognormal model. Each parameter indicated the degrees of freedom (Df), the deviance (Dev), the residual degrees of freedom (Resid Df), the residual deviance (Resid. Dev), the Chi-square test statistic and the significance (p-value).

Lognormal Positive Catch rate

Source	Df	Deviance	Resid. Df	Resid. deviance	F	Pr (>F)	
NULL			1108	514.96			
Year	13	19.6082	1095	495.35	3.4658	2.663e-05	***
Lat5	1	13.2893	1094	482.06	30.5361	4.097e-08	***
Quarter	3	7.2563	1091	474.80	5.5578	8.724e-04	***

Binomial Model

Source	Df	Deviance	Resid. Df	Resid. deviance	Pr (>Chi)	
NULL			2986	3752.7		
Year	13	399.50	2973	3353.2	< 2.2e-16	***
Lat5	1	135.83	2972	3217.4	< 2.2e-16	***
Quarter	3	40.17	2969	3177.2	9.803e-09	***
Lon5	1	73.34	2968	3103.9	< 2.2e-16	***
HBF	1	65.79	2967	3038.1	5.019e-16	***
Soak time	1	6.34	2966	3031.7	0.011779	*
Start set	1	7.13	2965	3024.6	0.007574	**

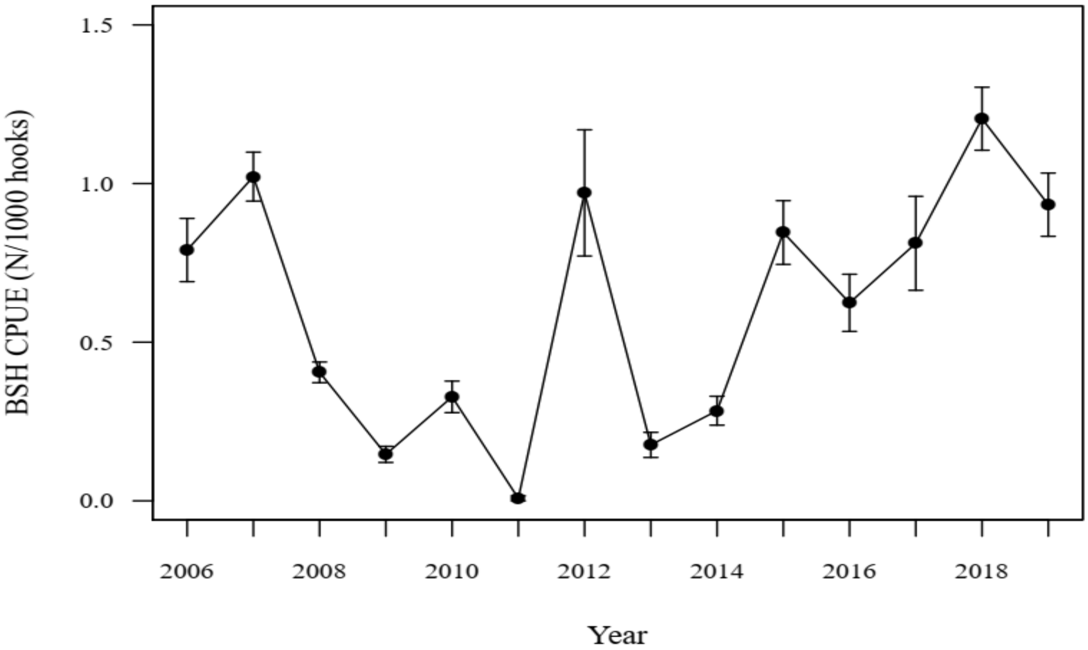

Figure 1. Nominal CPUE series (N/1000 hooks) for the blue shark from 2006 to and 2019. The error bars refer to the standard errors.

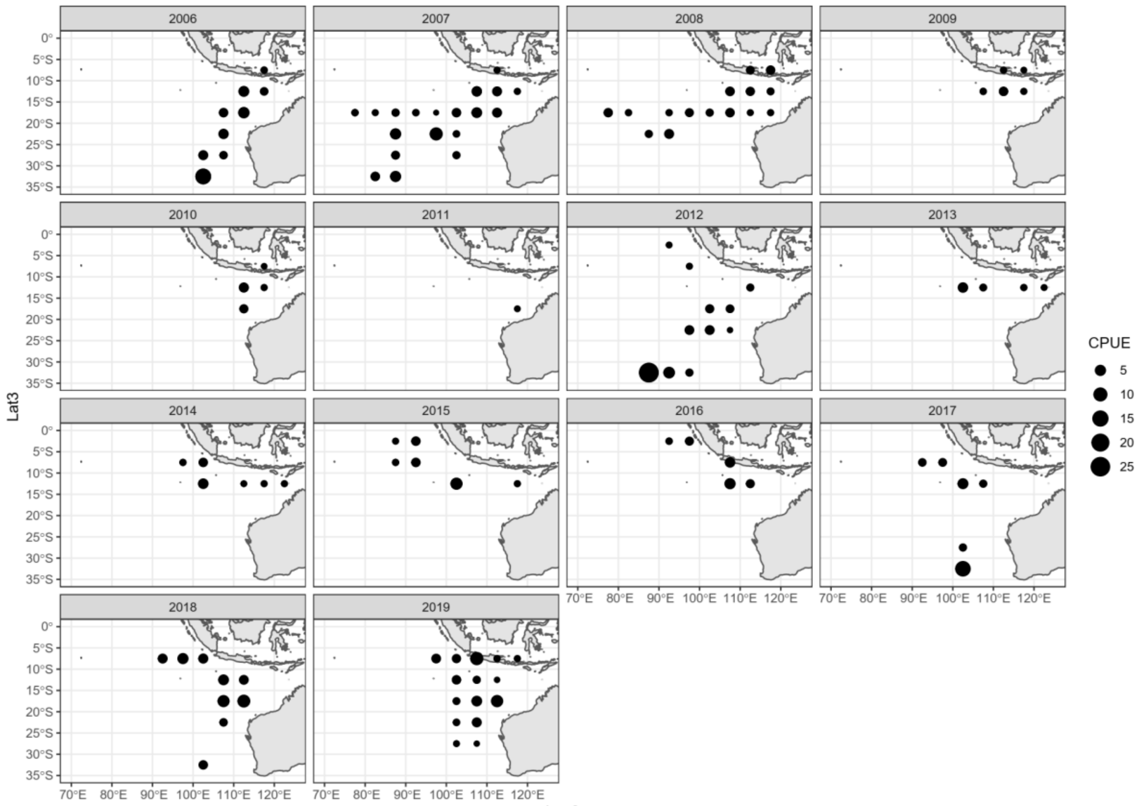

Figure 2. The spatial abundance of the blue shark in the eastern Indian Ocean from 2006 to 2019 provided into 5x5 grid map

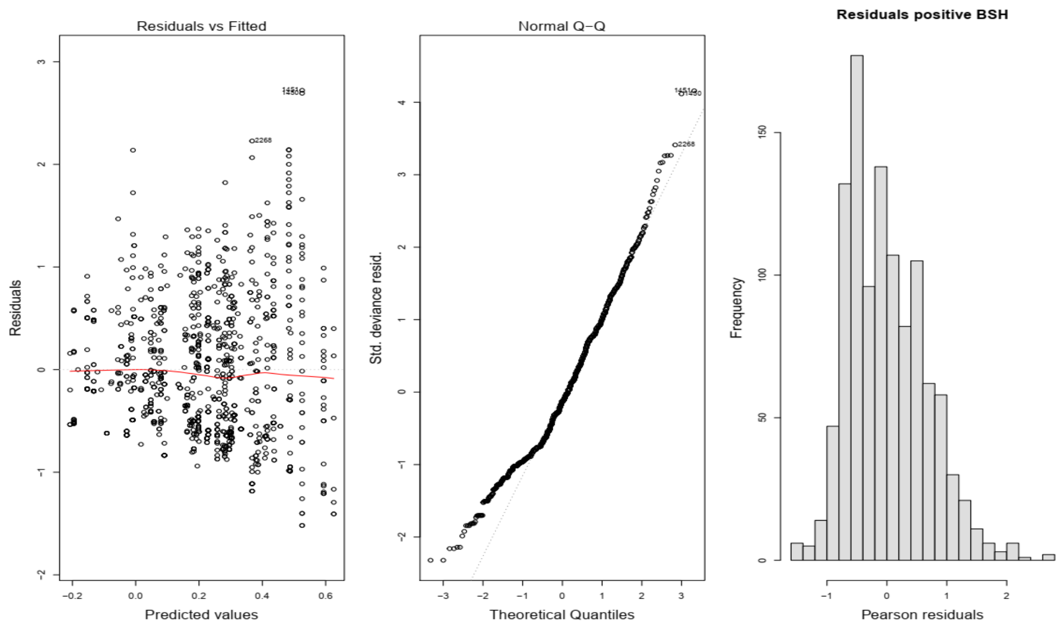

Figure 3. Residual analysis for the final model for the blue shark CPUE standardization during 2006 and 2019 including the residuals along with the fitted values on the log scale (left panel), the QQPlot (middle), and the histogram of the distribution of the residuals (right).

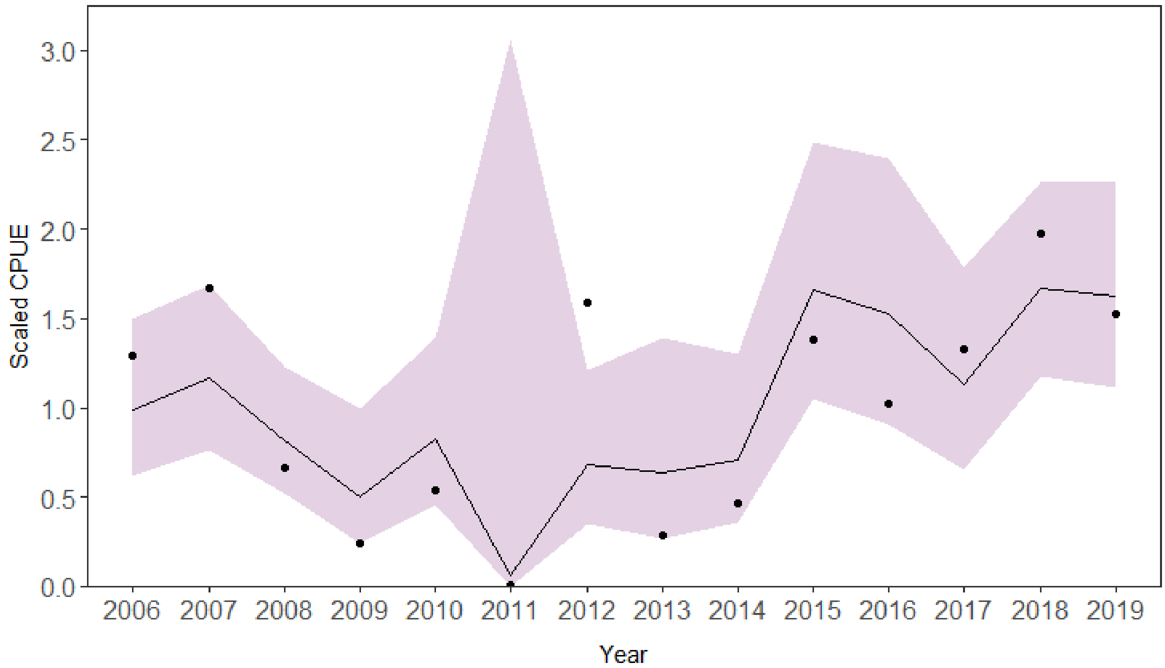

Figure 4. Standardized CPUE series for the blue shark using a delta-lognormal model. The solid lines refer to the standardized index with the 95% confidence intervals, and the dots represent the nominal CPUE series. Both series are scaled by their means.