# Standardized CPUE of blue shark in Indonesian tuna longline fishery estimated from scientific observer data, for the period 2005 – 2016.

Dian Novianto<sup>1</sup>, Eko Susilo<sup>2</sup>, Zulkarnaen Fahmi<sup>1</sup> & Rui Coelho<sup>3</sup>

<sup>1</sup> Research Institute for Tuna Fisheries, Agency for Marine Affairs & Fisheries Research & Human Resources, Ministry of Marine Affairs & Fisheries Republic of Indonesia.

<sup>2</sup>. Institute for Marine Research and Observations, Agency for Marine Affairs & Fisheries Research & Human Resources, Ministry of Marine Affairs & Fisheries Republic of Indonesia.

<sup>3</sup> Portuguese Institute for the Ocean and Atmosphere (IPMA, I.P.). Av. 5 de Outubro s/n, 8700-305 Olhão, Portugal.

#### Abstract

This working document analyses the catch, effort, nominal and standardized CPUE trends for blue shark captured by the Indonesian tuna longline fishery for the period 2005-2016. Nominal annual CPUEs were calculated as number (N)/1000 hooks and were estimated with Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM). Using year, quarter, area, the environment variables (sea surface temperature, chlorophyll-a concentration, eddy kinetic energy, sea level anomaly, and absolute dynamic topography) and Operational characteristics of the gear. Model Goodness-offit and model comparison was carried out with the Akaike Information Criteria (AIC) and the pseudo coefficient of determination  $(R^2)$  and model validation with a residual analysis. The final estimated indexes of abundance were calculated by least square means (LSMeans) or Marginal Means. The results showed the factors that contributed most for the deviance were the Area, followed by Year, SST, NHBF and Quarter, followed by the other effects and the interactions. In general, there were no noticeable trends, with the series varying along the period. This paper presents the update of the index of abundance for the blue shark estimated from captures from the Indonesian pelagic longline fleet in the Eastern Indian Ocean and can be used in future stock assessments models.

KEYWORDS: Blue shark, standardized CPUE, tuna longline fisher.

### Introduction

The blue shark is the most prevalent shark captured in pelagic longline fisheries from Indonesian tuna longline fleet in Indian Ocean and catches can account for more than 50 % of the total of shark catch (Novianto et al., 2014). This species is highly targeted in the fin trade market, in Hong Kong market auctioned fin weight was dominated, which was 17% of the overall market (Clarke et al., 2006).

The CPUE analysis of blue shark has been reported elsewhere by several authors in the different areas where these fisheries take place: in the north Atlantic (Aires-da-Silva et al., 2008; Coelho et al., 2016), in the southwest Atlantic (Carvalho et al., 2011), in the south-western equatorial Atlantic (Hazin et al., 1994; Carvalho et al., 2010), in the central North Atlantic (Vandeperrea et al., 2014), in the Mediterranean (Megalofonou et al., 2009), in the south-east Pacific Ocean (Bustamante & Bennett, 2013) the North Pacific Ocean (Tsai et al., 2015), Indian Ocean (Tsai & Liu 2014; Coelho et al., 2014; Coelho et al., 2015; Semba et al., 2015; Semba & Kai 2016; Novianto et al., 2016).

The fluctuations in the environment can trigger movement and changes in behavior and habitat use for many elasmobranch species was actively select for or exploit specific environmental conditions, often forgoing their home range areas to access a spatially variable resource (Schlaff et al., 2014). The habitat is highly influenced by dynamic oceanographic factors, the different characteristic of oceanographic variabilities can influence on fish distribution. Fish will choose a more suitable habitat for feeding, shelter, reproduction, and migration (Palacios et al., 2006).

The CPUE varied greatly in relation to the season and environmental factors besides operational factors. Previous study about environmental variables for CPUE of the blue shark was reported by several authors (Bigelow et al., 1999; Megalofonou et al., 2009; Mitchell et al., 2014; Vandeperrea et al., 2014).

The objective of the present study was to update standardized blue shark CPUE indices for Indonesian longline fleet estimated using observer data collected by scientific observer program Research Institute for Tuna Fisheries (RITF) conducted 2005 - 2016 and environmental variables data that we expected to influence abundance and catchability of blue shark.

#### Materials and methods

#### Fisheries data

Data collection was conducted by a scientific onboard observer program RITF from August 2005 to December 2016 in the tuna longline vessels mostly based in Benoa Harbour, Bali. Data collections included the number of blue sharks caught, the total number of hooks used, number of hooks between floats, length of float lines, length of branch lines, and the length between branch lines. Spatio-temporal information (date of operation, latitude and longitude), and the number of shark lines used were also collected and used for this analysis.

#### Satellite data analysis (environmental data)

Time series satellite data analysis was carried for the year 2005–2016. Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard Aqua spacecraft were used to derived monthly sea surface temperature (SST) and chlorophyll-a concentration (SSC). SST and SSC Level-3 Standard Mapped Images (L3SMI) with 4-km spatial resolution were processed at Environmental Research Division (ERD-NOAA) and distributed through ERDDAP server (http://coastwatch.pfeg.noaa.gov).

Altimeter derived variables computed from multimission altimeter satellite: Jason-3, Sentinel-3A, HY-2A, Saral/AltiKa, Cryosat-2, Jason-2, Jason-1, T/P, ENVISAT, GFO, ERS1/2. A daily gridded files with a spatial resolution of  $0.25^{\circ} \times 0.25^{\circ}$  was processed with Optimal Interpolation (OI) with respect to a twenty-year mean and distributed by EU Marine Copernicus at <u>http://marine.copernicus.eu</u>. In this study we used sea level anomaly (SLA), absolute dynamic topography (ADT), and Eddy kinetic energy (EKE) as environmental variables. Daily data were averaged at monthly scale in order to calculate SLA, ADT, and EKE assuming linear regression.

SLA is defined as subtraction sea surface height (SSH) above the reference ellipsoid with temporal mean of the sea surface height over a certain period (MSS) as follows:

SLA = SSH - MSS

ADT is defined as dynamical part of the absolute signal calculated from the SLA using the temporal mean of the SSH above the geoid over a certain period (MDT):

ADT = SLA + MDT

EKE is computed following formula:

$$EKE = \left(\frac{1}{2}\right)(u^2 + v^2)$$

where u and v are zonal and meridian geostrophic currents components, respectively.

The SLA, ADT, and EKE data were re-sampled to fit the SST and SSC resolution. Each monthly environmental variables were extracted from each pixel corresponding to the longliner fishing activities. A GAM model using the 'mgcv package' (Wood, 2006) was performed to analyse the effects of environmental variables on the nominal BSH CPUE.

#### **CPUE** standardization

The CPUE analysis was carried out using this official data from the RIFT observer program. Operational data at the fishing set level was used, with the catch data referring to the total numbers (N) of blue shark captured per fishing set. For the CPUE standardization, the response variable was catch per unit of effort (CPUE), measured as numbers (N) of BSH per 1000 hooks deployed. The standardized CPUE series was estimated with Generalized Linear Models (GLM) and Generalized Linear Mixed Models (GLMM).

There were a relatively large number of sets (67.6%) with zero BSH catches that results in a response variable of CPUE=0. As these zeros can cause mathematical problems for fitting the models, the approach chosen was a Tweedie model with link=log that can model both the continuous component of the response variable for the positive observations and the mass of zeros for the zero catches. For this model the nominal CPUE was used directly in the response variable given this specific characteristic of the distribution.

The covariates considered and tested in the models were:

- Year: analyzed between 2005 and 2016;
- Quarter of the year: 4 categories: 1 = January to March, 2 = April to June, 3 = July to September, 4 = October to December;
- Area: defined by regression trees, according to the method developed by Ichinokawa and Brodziak (2010);

- Operational characteristics of the gear (used as proxies for targeting effects): Number of hooks between floats (NHBF), Length of the float line; Length of the branch line, Length between branchline, and Number of shark lines used.
- Environmental variables: sea surface temperature, chlorophyll-a, eddy kinetic energy, sea level anomaly, and absolute dynamic topography.

The significance of the explanatory variables in the CPUE standardization models was assessed with likelihood ratio tests comparing each univariate model to the null model and by analyzing the deviance explained by each covariate. Goodness-of-fit and model comparison was carried out with the Akaike Information Criteria (AIC) and the pseudo coefficient of determination ( $\mathbb{R}^2$ ). Interactions were considered and tested, and the significant interactions were used in the analysis. Model validation was carried out with a residual analysis. The final estimated indexes of abundance were calculated by least square means (LSMeans) or Marginal Means, that for comparison purposes were scaled by the mean standardized CPUE in the time series.

Statistical analysis for this paper was carried out with the R Project for Statistical Computing version 3.4.0 (R Core Team, 2016) using several additional libraries (Venables and Ripley, 2002; Wickham, 2007, 2009; Fox and Weisberg, 2011; Gross and Ligges, 2012; Becker et al., 2013; Bivand and Lewin-Koh, 2013; Dunn, 2013; Stabler et al., 2013; Lenth, 2014).

#### Results

#### Effects of environmental variables

The Effect of the environmental variables on the nominal CPUE is shown in **Figure 1**. The SST values recorded at the fishing ground ranged from  $15.10^{\circ} - 31.87^{\circ}$  C, and BSH were caught in the temperature range between  $26.30^{\circ} - 29.5^{\circ}$  C. In terms of SSC, the fishing records ranged from 0.04 - 1.88 mg/m3 where BSH were mainly caught between 0.09 - 0.16 mg/m3. SLA values ranged between -0.21 m -0.29 m, and BSH were caught in the range 0.02 - 0.11 m. For the EKE, the values ranged between 0 - 0.41 m<sup>2</sup> s<sup>-2</sup> and BSH were mainly concentrated in the range 0 - 0.02 m<sup>2</sup> s<sup>-2</sup>. Finally for ADT the fishing ground values ranged from 0.49 m -1.33 m where BSH were mainly caught in the range 0.94 - 1.33 m.

#### Spatial distribution of the data

The spatial distribution of the data analyzed comes from the Indonesia fishery, and is mostly from the eastern Indian Ocean area, in both tropical and more temperate waters (**Figure 2**). Using the GLM tree method for area definitions (4 areas) resulted in a separation between the more tropical and the more temperate waters, and also a segregation between the more eastern and western locations (**Figure 3**). Those area definitions were used in the BSH CPUE standardization model as the spatial/area effects.

#### **CPUE** data characteristics

The nominal time series of the BSH CPUE is presented in **Figure 4**. In general the series was highly variable, with peaks in 2007 and 2012, and lower values in the remaining years. The series has also shown relatively higher values in the most recent period of 2015 and 2016. The percentage of fishing sets with zero catches of BSH in the fishery was high, specifically 67.6% of the fishing sets, varying annually between a minimum of 36.3% in 2007 and a maximum of 98.2% in 2011 (**Figure 5**). Overall, the nominal blue shark CPUE distribution was highly skewed to the right and become more normal shaped, but still skewed, in a log-transformed scale (**Figure 6**).

#### **CPUE** standardization

Several explanatory variables tested for the BSH CPUE standardization were significant and contributed significantly for explaining part of the deviance. Some interactions were also significant, and were therefore included in the final model. Sensitivities to the model structure were run for comparing the use of operational data with adding environmental data. It is noted that there were some differences when the environmental data was added, particularly in the beguiling and end of the time series (**Figure 7**). On the final model, the factors that contributed most for the deviance were the Area, followed by Year, SST, NHBF and Quarter, followed by the other effects and the interactions (**Table 1**). In terms of model validation, the residual analysis, including the residuals distribution along the fitted values, the QQ plots and the residuals

histograms, showed that the model was adequate with no major outliers or trends in the residuals (**Figure 8**).

The final standardized BSH CPUE index (N/1000 hooks) for the Indonesian data in the Indian Ocean between 2005 and 2016 is shown in **Figure 9** and **Table 2**. The trends were relatively similar to the nominal series, but with smoother peaks. In general, there were no noticeable major trends with the series varying along the period, even though it is noticeable that there are generally higher values in the more recent years (**Figure 9**, **Table 2**).

#### Discussion

The final model showed that SST is important environmental variables besides operational factors. SST for effect on BSH CPUE ranged between 26.30<sup>0</sup>-29.5<sup>0</sup> C, correspond to distributed effort data more operated occurred in the tropical area. Carvalho et al. (2011) recorded significant effects of SST upon CPUE for BSH commercial CPUE in the south-west Atlantic Ocean. The different result from Mitchell et al. (2014) concluded surface chlorophyll a concentration (CHL) significantly affected CPUE compared to SST in the western English Channel. In the eastern Mediterranean blue sharks were more often caught in cooler waters but locally dense concentrations were more likely to occur in warm areas (Damalas & Megalofonou, 2010). Vandeperre et al. (2014) stated that variation in catch rates in relation to SST reflected the varying presence of different sex and life stages of blue shark, furthermore they stated It needs to be noted that although SST was important in explaining trends in catch rates, it does not directly reflect the temperature range of the blue shark habitat that extends to several hundreds of metres depth.

Based on the analysis, the nominal CPUE of blue shark in the Indian Ocean showed a strong inter-annual fluctuation, particularly in the year 2007 and 2012. This high CPUE might be because that the high blue shark catch rate occurred in area 1 and 3. However, this high variability was slightly smoothed in the standardized CPUE series. There were some differences when the environmental data was added, particularly in the beguiling and end of the time series. In 2005-2007 and 2015-2016 most CPUE data from the eastern Indian Ocean. The reasons for these differences might be related to climate in Indian Ocean region especially in the Eastern Indian Ocean, were strongly affected by the Asia-

Australia (AA) monsoon system: the southeast and northwest monsoon. The southeast monsoon (April–October) is associated with easterlies from Australia that carry warm and dry air over the region. On the other hand, the northwest monsoon (wet season) is associated with westerlies from the Asian continent that carry warm and moist air to the region (Susanto et al., 2006). The peak of standardized CPUE values in 2015-2016 appeared in simple effect adding environment variables. It may be related to a strong El Niño phenomenon in this area. In the Indian Ocean high peak of IOD in the second semester of 2015 coinciding with El Nino, the IOD escalate cold anomaly to higher primary productivity and record low peak in 1st semester of 2016 increased warm anomaly to higher tuna forage (micronekton) productivity (Lehodey, 2016).

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# Figures



**Figure 1**. Histograms of the range of values for the environmental variables (top plots) and GAM plots with the non-linear effects of the environmental variables on the BSH nominal CPUEs (bottom plots).



**Figure 2**. Distribution of the Indonesia observer data used in this BSH CPUE standardization. The effort is represented in 2\*2 degree grids with darker and lighter colors representing respectively to areas with more and less effort in number of hooks.



**Figure 3**. Results from the GLM tree method for area definitions (4 areas) using the Indonesia data for the BSH CPUE standardization.



**Figure 4**. Nominal CPUE series (N/1000 hooks) for BSH in the Indonesia data, between 2005 and 2016. The error bars refer to the standard errors.



**Figure 5**. Proportion of zero BSH catches by set and per year, in the Indonesia data, between 2005 and 2016. The error bars refer to the standard errors.



**Figure 6**: Distribution of the nominal BSH CPUE from the Indonesia data in non-transformed (top) and log-transformed (bottom) scales.



#### **BSH CPUE index Indonesia - Model sensitivities**

**Figure 7**. Sensitivity analysis to the various models built for the analysis, specifically a simple effects model with operational variable only, a simple effects model adding environmental variables, and the final model with added interactions.



**Figure 8**. Residual analysis for the final BSH CPUE standardization model for the Indonesia data, between 2005 and 2016. In the plot it is presented the histogram of the distribution of the residuals (right), the QQPlot (middle) and the residuals along the fitted values on the log scale (left).

**BSH CPUE index Indonesia - Final model** 



**Figure 9**. Standardized CPUE series for BSH from Indonesia data using a tweedie model, between 2005 and 2016. 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.

## Tables

**Table 1**. Deviance table of the parameters used for the BSH CPUE standardizations if the Indonesia data, using a Tweedie GLM with link=log. For each parameter it is indicated the degrees of freedom (Df), the deviance (Dev), the residual degrees of freedom (Resid Df), the residual deviance (Resid. Dev), the F-test statistic and the significance (*p*-value).

Parameter	Df	Dev	Resid. Df	Resid. Dev.	F-stat.	p-value
(Intersept only)			2543	5020.4		
Year	11	717.2	2532	4303.2	28.06	< 0.001
Quarter	3	67.0	2529	4236.2	9.60	< 0.001
NHBF	1	129.6	2528	4106.6	55.77	< 0.001
length_between_branchline	1	39.4	2527	4067.2	16.95	< 0.001
NSharkline	1	54.7	2526	4012.5	23.56	< 0.001
Area	3	796.0	2523	3216.5	114.18	< 0.001
SST	1	136.3	2522	3080.2	58.64	< 0.001
SLA	1	13.0	2521	3067.2	5.59	0.018
Quarter : NHBF	3	64.7	2518	3002.6	9.28	< 0.001
NHBF : length_between_branchline	1	41.06	2517	2961.5	17.67	< 0.001
NHBF : Area	3	24.09	2514	2937.4	3.46	0.016

**Table 2**. Nominal and standardized CPUEs (N/1000 hooks) for BSH using the Indonesia data in the Indian Ocean. The point estimates, 95% confidence intervals and the coefficient of variation (CV, %) of the standardized index are presented, as well as the nominal CPUE values.

	Nominal – CPUE	Standardized CPUE index (N/1000 Hooks)							
Year		Stdz CPUE	CV (%)	Lower CI (95%)	Upper CI (95%)				
2005	0.35	0.25	7.03	0.14	0.44				
2006	0.82	0.33	10.92	0.20	0.53				
2007	1.07	0.61	6.38	0.43	0.87				
2008	0.40	0.37	9.18	0.25	0.55				
2009	0.15	0.19	9.10	0.12	0.31				
2010	0.35	0.64	6.75	0.41	1.01				
2011	0.02	0.03	17.29	0.01	0.12				
2012	1.06	0.66	6.96	0.43	1.02				
2013	0.17	0.28	8.49	0.17	0.47				
2014	0.29	0.19	7.12	0.12	0.30				
2015	0.87	0.75	5.40	0.52	1.10				
2016	0.61	0.93	5.15	0.63	1.37				