STANDARDIZED CPUE OF SILKY SHARK (*Carcharhinus falciformis*) CAUGHT BY INDONESIAN LONGLINE FLEET IN THE EASTERN INDIAN OCEAN

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ABSTRACT

Relative abundance indices as calculated based on commercial catches are the input data to run stock assessment models to gather useful information for decision making in fishery management. In this paper a Generalized Linear Model (GLM) was used to calculate relative abundance indices and effect of longline fishing gear configuration. Data were collected by a scientific observer program from 2006 to 2017. Most of the boats monitored were based in Benoa Port, Bali. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the best models among all those evaluated. Poisson model had the lowest AIC (504.23) and BIC (581.80) value. Trends of standardized CPUE as calculated using Poisson (P) model was fluctuated from 2006 to 2009. The trends showed that the P model increased from 2010 and reached the peak in 2015. Catches are often equal to zero because silky shark is a bycatch for Indonesian longline fleets. Therefore, a hurdle model was used. The low proportional decrease of deviance indicates that most of the variability of catch rates of silky shark caught by Indonesian longline boats are not related to year, quarter, number of hooks between floats and the length of branch lines. Other variables and information, like the daytime when the longlines are deployed in the water (day or night), type of bait, size and type of hooks, are necessary to better understand the catch rate, and improve the estimations of the relative abundance indices.

Key Words: Silky shark, standardized CPUE, GLM.

INTRODUCTION

Silky shark is one of the species of shark that exists in the ocean. Therefore, these fish stocks and their utilization are carried out by various countries. In the Indian Ocean, managing fish is carried out in countries that are members of the Indian Ocean Tuna Commission on these fish (IOTC, 2017). One of the method used is to use a relative abundance index. Assuming that the fishing effort per unit (CPUE) is calculated based on commercial data it is assumed to be proportional to abundance but also follows the capture power (Quinn & Deriso, 1999).

Therefore, nominal changes in CPUE over several years can reflect changes in abundance and capture rate. This happens because of several factors, namely changes in fishing technology and fishing grounds. If there is information about the factors that affect the catch, a statistical model can be used to calculate a standard CPUE value that reflects changes in abundance. This CPUE standard can be used to evaluate fish supply status, or as input data in estimating fish stocks (Squires & Vestergaard, 2015).

In GLM, the response variable is assumed to follow the probability distribution of the exponential family. Normal and gamma are often become the alternatives to continuous variables (catches or CPUE in weight), whereas Poisson and binomial are negative often as alternatives to discrete variables (catches or CPUE in numbers). Some distributions are not suitable for modeling catches (or CPUE) equal to zero (gamma) (Vaz *et al*., 2008). But zero catches are often found in longline tuna fisheries data. When the number of zeros is very large, most of the probability distributions are not sufficient to model catches. Therefore, zero-inflated models, mixtures and obstacles (sometimes also in the delta model) are alternatives to overcoming the zero catch excess (Hall, 2000).

In this paper the GLM are used to calculate the standard CPUE of the silky shark captured by the Indonesian longline fleet in the East Indian Ocean (McCullagh & Nelder, 1989). There are three alternative factors that need to be considered: area, year, quarter, start set time, soak time and moon light. To overcome the excess zero it is used the obstacle model. The results are useful for assessing the stock status of silky sharks, which are important fisheries resources in the Indian Ocean.

MATERIAL AND METHODS

Data and Exploratory Analysis

Tuna long line in Indonesia have gross tonnage between 14 - 149 GT with specifications consisting of main line, branch line, float line, hook, float, radio buoy and others. The material used for the main strap and branch rope is generally monofilament with a diameter of 3 mm and 2 mm. In addition to monofilament, some of the materials used for main and branch ropes are nylon, kuralon, polyamide, polyethylene, kuralon, skyama and longyarn and a combination of these materials. The fishing line used in general is No. 4

In general, longline tuna fishing operations consist of setting and hauling. Between the stocking and drawing of the fishing line there is a time lag usually called the soaking time. The activities of tuna longline fishing based in Benoa Port are generally carried out in the morning at 5:00 a.m. - 10:00 p.m. with a soaking time of about 3-7 hours and fishing hauling activities for 7-13 hours.

The data collection includes the number of captured silky sharks, the number of hooks and the location of the fishing collection, obtained by the Global Positioning System (GPS) device. In addition, scientific observers also noted long line characteristics such as the number of hooks between buoys, the length of the buoy line, the length of the branch line, and the length between the branch lines. Catches per unit of effort are calculated as $U = (C / f) \times 100$, where C is the number of fish captured in the fishing set, f is the number of hooks, and U is CPUE in the number of fish caught per 100 hooks (Klawe, 1980).

The number of fishing rods is mapped in an ordinary grid to evaluate the spatial distribution of fishing operations. A summary of basic statistics regarding central trends and dispersion is calculated for all variables. Contingency tables and mosaic plots are used to evaluate the balance of database entries at the level of intersection of factors (eg year x quarter). Histograms and dispersion diagrams are used to assess the relationship between variables. Correlation coefficients between continuous variables are also calculated to identify redundant variables.

Models

Generalized linear models (GLM) can be written in matrix notation as the realization vector of the response variable; E is hope, g is a link function, is a parameter vector and is a design matrix of explanatory variables. The probability distribution for, and link functions must be pre-selected to calculate parameter estimates, which represent the effects of explanatory variables (e.g. years) (McCullagh & Nelder, 1989).

The explanatory variables considered in the model for standardizing CPUE are fishing area (AreaTree) (Ichinokawa and Brodziak, 2010), number of hooks between floats (HBF) (Sadiyah *et al*., 2012), start set time, soak time and moon light. These variables are chosen as factors that influence the catchability level in the longline fleet. There is no separation between the Exclusive Economic Zone (EEZ) inside and outside Indonesia because fishing areas are still in the same area in the East Indian Ocean.

Akaike Information Criterion (AIC) (Akaike, 1974) is used to compare and select models that are calculated using different density distributions (gamma and gaussian) and link functions (eg logarithms and identities). When comparing models for different response variables (level of capture and logarithm of the catch level), the variable is placed in a proportional reduction of the deviation (pseudo-R2). The standard diagnostic plot is used to assess the installation of the selected model. All analyzes are carried out using the R software function.

RESULTS AND DISCUSSION

Based on the results of recording, the catchment area of Indonesian tuna raw vessels is at coordinates 00 ° 37 '- 33 ° 54' LS and 78 ° 51 '- 133 ° 40' BT with the highest fishing line density at coordinates 13 ° - 15 ° LS and 110 ° - 121 ° East. The average number of hooks between floats tends to be stagnant from year to year with an average range of 12-17 hooks. The highest average occurred in 2005 of 18 hooks, while the lowest was in 2006, 2009 and 2011 with an average of 12 hooks. While the average number of total hooks used in one fishing operation ranges from 1,300-1,600 hooks. The highest average number occurred in 2012 with almost 2,000 hooks for one arrest operation. After that it dropped to 2,200 hooks until 2017 (Table 1).

Nominal CPUE (N/1,000 hooks) showed very low number with the highest value only less than 0.3/1,000 hooks in 2015 (Figure 2). On the other hand, the proportion of zero catch showed high value from around 0.8 to almost 1.0 (Figure 3). The low number of silky shark caught by Indonesian tuna longline vessels showed that this species is bycatch from targeted tuna (Jatmiko *et al*., 2015).

The number of parameters (k), AIC, BIC, the logarithm of the probability (logLik), the predicted zero catch number, and the p value of the Kolmogorov-Smirnov test calculated using the six model structures (P, NB, ZIP, ZINB, HP and HNB). The Poisson (P) model chosen for the proportional positive set due to the lowest value of Akaike Information Criterion (AIC=504.23) (Akaike, 1974) and Bayesian Information Criterion (BIC=581.80) (Schwarz, 1978) (Table 2). From the parameter estimation of Poisson model showed that variables of start set time, soak time, hook between float and moon light (Table 3) were not significantly different ($p<0.05$) to affect the catch of silky shark. Most (86.5%) of Indonesian tuna longline vessels start the fishing operation in the morning from 5:00-9:00 AM (Jatmiko *et al*., 2016)

Estimates of the coefficients of the models suitable for the proportion of positive sets are shown in Table 2. Most estimates are significantly different from zero. Because the scope of this paper is CPUE standardization, only the estimated coefficients for the year are explored here. Estimates of the coefficients for 2006, 2007, 2009, 2010 did not differ significantly from zero, so the expected proportion of positive sets for the years was close to expectations for 2006, which is the reference level. However, estimates for 2008, 2011 and 2012 are negative and significant. This result shows that the proportion of positive sets in these three years is lower than in 2006 (reference year).

Gamma distribution and identity link functions are selected to model positive catch rates. Calculations of deviations from the model attached to positive data are shown in Table 3. Almost all explanatory variables result in significant deviation reduction. Exceptions are the main effect of the quarter. However it is stored in the model because in interactions that prove important if it depends on the AIC. The overall reduction in proportional deviation is low, which means that only a portion of the variability of the positive catch rate is explained by the variables of the year, quarter, length of the branch line and the number of hooks between buoys. What then is a more important explanatory variable.

Silky sharks are known to inhabit layers of sea level, especially at night (Compagno, 1984; White *et al*., 2006). Therefore a negative relationship was found between the proportion of positive sets and branch line lengths, the proportion of positive sets and the number of hooks between buoys, and also between CPUE in the positive set and the number of hooks between buoys, all of which were normal results.

Although Indonesian boats eventually voyage long distances in the Indian Ocean, most fishing groups were concentrated in the southeastern Indian Ocean, southwestern Indonesia and northwestern Australia. Therefore, the analyzed datasets cover a portion of the Indian Ocean stock and the standard catch can be interpreted as a local proxy. However, the analysis of calculations presented in this paper and all previous calculations based on other databases of fleets operating in other locations in the Indian Ocean could help for better understanding of the stock status of silky sharks.

Finally, it is important to highlight that the results collected after adjusting to the general linear model indicate that more information is needed to increase our knowledge of the variation in the level of silky shark fishing from the Indonesian longline fisheries. The model does not meet every time we try to adjust it using more parameters regarding the interaction between years and other variables. The lack of convergence often arises when the model is more than a parameter, when the data does not convey sufficient information to allow estimation of all parameters (McCullagh & Nelder, 1989).

The low decrease in proportional deviation shows that most of the variability in the rate of catch of silk sharks caught by Indonesian longline vessels is not related to year, quarter, number of links between buoys and length of branch lines. Variables and other information, such as during the day when a longline is deployed in water (day or night), type of bait, size and type of hook, and if fishermen use light sticks to attract fish, it is necessary to better understand catch levels, and increase relative abundance index estimates . Therefore, Indonesian onboard observers are encouraged to collect more detailed data, which is very important for assessing the status of fisheries in the southeast, and the stock of Indian silky sharks.

ACKNOWLEDGEMENT

This research is funded in cooperation between Research Centre for Fisheries Management and Conservation and Australian Centre for International Agricultural Research (2005-2009). Research fund was from Research Institute for Marine Fisheries (2010-2011), continued by a research fund from Research Institute for Tuna Fisheries (2012-2017). Authors would like to thank Dr. Humber Agrelli Andrade from University of Pernambuco, Brazil, Dr. Rui Coelho from IPMA, Portugal and Dr. Philippe Sabarros from IRD, France for the several CPUE script analysis. We also would like to thank the scientific observer from Research Institute for Tuna Fisheries for their contribution on data collection.

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Table 1. Summary of observed fishing effort from Indonesian tuna longline fishery during 2006–2017. Results are pooled and also presented by year of observation. Operational parameters are means (upper entries) and standard deviations (lower parenthetical entries).

Row Labels	Trips	Sets	Total hooks	Hooks per set	Hooks per float	Mean Lat (°S)	Mean Lon (°E)
2006	14	201	301,473	1,500	12	21.9	109.2
2007	13	216	350,418	1,622	15	19.2	100.8
2008	16	163	227,441	1,395	15	14.9	102.9
2009	6	51	66,380	1,302	12	12.5	112.9
2010	5	67	103,471	1,544	16	12.9	111.0
2011	4	4	5,260	1,315	12	18.2	110.7
2012	6	99	185,467	1,873	14	24.6	95.9
2013	5	32	36,354	1,136	15	11.1	104.2
2014	6	48	57,335	1,194	16	11.2	102.9
2015	5	96	107,828	1,123	15	10.8	100.7
2016	8	215	276,483	1,286	13	11.4	108.4
2017	15	249	319,100	1,282	17	11.9	99.3

Table 2. Summary of indicators as calculated using six model structures: Poisson (P), Negative Binomial (NB), Zero-inflated with Poisson (ZIP), Zero-inflated with Negative Binomial (ZINB), Hurdle with Poisson (HP), and Hurdle with Negative Binomial (HNB). The terms in the column at left indicate: number of parameters (k), Akaike (AIC) and Bayesian (BIC) Information Criteria, logarithm of the likelihood (logLik), number of predicted zero catches (zero), and *p* values as calculated using a Kolmogorov-Smirnov test.

Parameters	Model structure					
	poisson	negbin	zinp	zinb	hp	hnb
k	16	11	32	32	32	32
AIC	504.23	599.44	458.84	464.53	506.80	508.36
BIC	581.80	658.83	617.24	622.92	665.20	666.76
logLIk	-236.12	-287.72	-197.42	-199.26	-221.40	-221.18
zero	856	969	871	871	863	863
p.value	1.00	1.00	1.00	1.00	1.00	1.00

Table 3. Summary of parameter estimations of Poisson model. Terms: SE – standard error, p – p values as calculated using Z test to assess difference from zero.

```
              Estimate Std. Error z value Pr(>|z|)    
(Intercept) -12.06349    1.50522  -8.014 1.11e-15 ***
AreaTree2     2.77188    0.49837   5.562 2.67e-08 ***
AreaTree3     1.33830    0.35938   3.724 0.000196 ***
Year2007     -0.98397    0.49286  -1.996 0.045887 *  
Year2008     -1.71591    0.74736  -2.296 0.021678 *  
Year2009      0.81633    0.42219   1.934 0.053169 .  
Year2010      0.55315    0.39199   1.411 0.158199    
Year2015      0.68701    0.37811   1.817 0.069223 .  
Year2017     -0.87796    0.80402  -1.092 0.274851    
Quarter2      2.30668    1.02116   2.259 0.023891 *  
```

```
Quarter3      1.20315    1.05565   1.140 0.254401
Quarter4      0.49066    1.08496   0.452 0.651100
Start_Set    -0.03615    0.03460  -1.045 0.296163
Soak_Time     0.06537    0.05880   1.112 0.266289
HBF           0.00444    0.04065   0.109 0.913017
Moon2Light    0.24076    0.22134   1.088 0.276708
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
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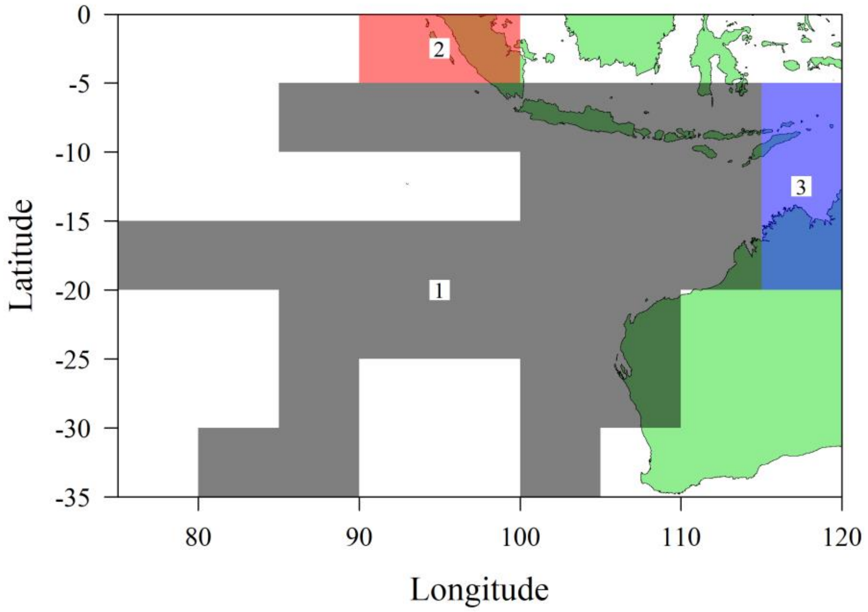

Figure 1. Area stratification used in the analysis based on GLM tree algorithm.

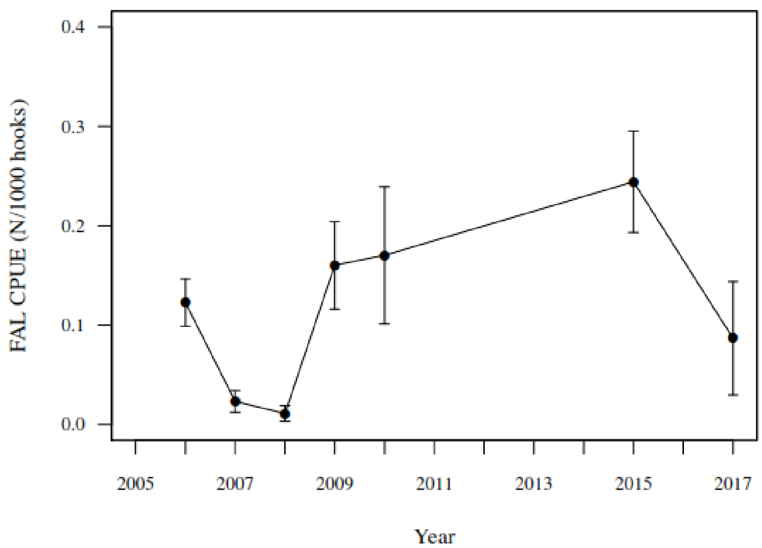

Figure 2. Nominal CPUE series (N/1000 hooks) for FAL from 2005 to 2017. The error bars refer to the standard errors.

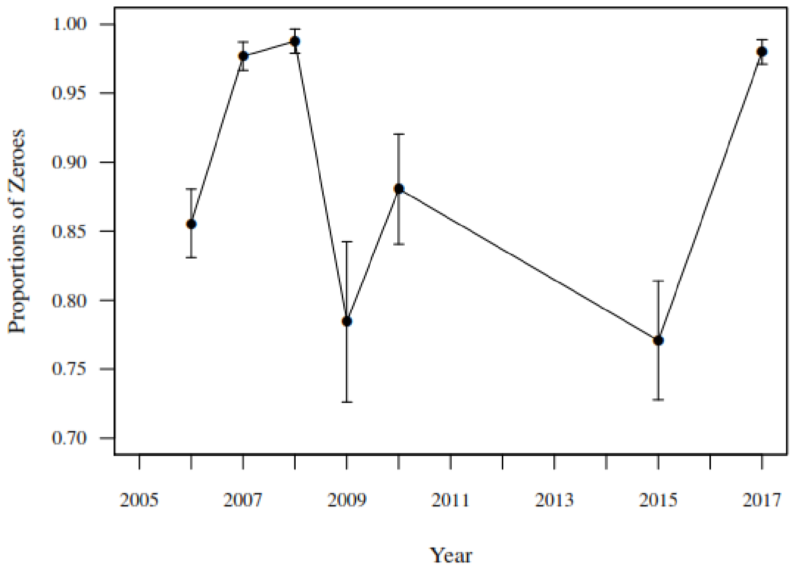

Figure 3. Proportion of zero FAL catches from 2006 to 2017. The error bars refer to the standard errors.

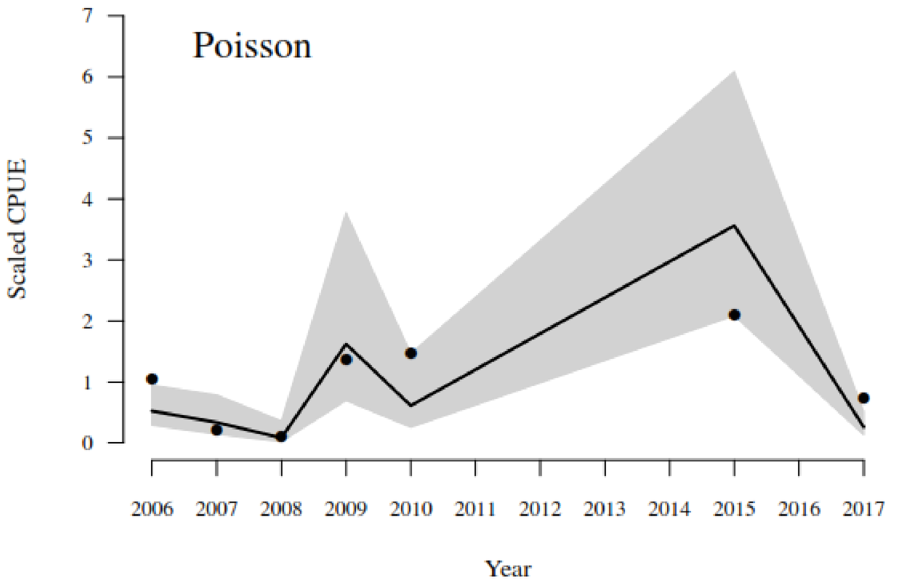

Figure 4. Standardize catch per unit effort (CPUE) calculated using Poisson model. Values were scaled by dividing them by their means.