Turk. J. Fish.& Aquat. Sci. 19(2), 119-129
http://doi.org/10.4194/1303-2712-v19_2_04

RESEARCH PAPER

Turkish Journal of FISHERIES and AQUATIC SCIENCES

Standardization of Catch Per Unit Effort with High Proportion of Zero Catches: an Application to Black Marlin *Istiompax indica* (Cuvier, 1832) Caught by the Indonesian Tuna Longline Fleet in the Eastern Indian Ocean

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Article History
Received 24 May 2017
Accepted 12 March 2018
First Online 16 March 2018

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Keywords
Relative abundance
By-catch
Stock assessment
Generalized Linear Model

Abstract

Black marlin (*Istiompax indica*) is a bycatch species in the Indonesian tuna longline fishery operating in the eastern Indian Ocean. Approximately 18% (~2,500 tons) of black marlin caught in the Indian Ocean are landed in Indonesia. However, its population status in the Eastern Indian Ocean is still little known. In this present study, a Generalized Linear Model (GLM) was used to standardize the catch per unit effort (CPUE) and to estimate relative abundance indices based on the Indonesian longline dataset. Data was collected by scientific observers from August 2005 to December 2014. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the best models among all those evaluated. If using the AIC, negative binomial (NB) and zero-inflated negative binomial (ZINB) models were selected, but if using BIC, the NB model was the best option. Time trends of standardized CPUE, as calculated using NB and ZINB models, were similar from 2008 onward. However, the trends were conflictive in the early stages of the series (2005-2007). A principal outcome is that there was no strong motivation to choose one of the two models, NB or ZINB), over the other. Sensitivity analyses are recommended as the alternative when running stock assessment models using such time series.

Introduction

Black marlin (*Istiompax indica,* hereafter BLM) are an apex predator, a highly migratory species, which reach high commercial values in the tropical and subtropical Indian and Pacific Oceans (Nakamura, 1985). In the Indian Ocean, it has been caught between 20^{o} N and 45^{o} S, with highest catches off western coast of India and in area off Beira and Barazuto Archipelago in the Mozambique Channel (Benkenstein, 2013; Indian Ocean Tuna Commission [IOTC], 2015). In recent years, most of BLM were caught by gillnet fleets (59%), followed by longlines fleets (19%), while the remaining catches were recorded under troll and hand lines (IOTC, 2015). Indonesian fleet caught approximately 18% (~2,500 tons yearly) of total BLM in the Indian Ocean in the recent years, which ranked fourth after Iran, Sri Lanka and India (IOTC, 2015). In spite of the relatively high catches, BLM is considered as a bycatch of the commercial Indonesian tuna longline fishery (Setyadji, Jumariadi, & Nugraha, 2012).

By-catch is an important management issue in the tuna longline fishery. It is a growing concern for most Regional Fisheries Management Organizations (RFMOs) regarding of its impact (King & McFarlane, 2003). Most of the bycatch in the tuna fisheries, especially billfishes have barely been studied, partly due to the limited data concerning catch, biology and population dynamics. The first attempt on stock assessment of BLM in Indian Ocean was analyzed using Stock Reduction Analysis (SRA), which indicated that the stock was not overfished but has been subject to overfishing (IOTC, 2015). But, conflictive result appeared when more robust assessment used (conventional and Bayesian production models). It was stated that the stock was subject to overfishing in the recent years, and currently overfished (Andrade, 2016). Hence there was a large uncertainty about the reliability of available estimations of catches and of relative abundance indices.

Estimations of relative abundance indices (e.g. standardized CPUE) convey important information concerning the status of fisheries stocks. Furthermore,

Published by Central Fisheries Research Institute (SUMAE) Trabzon, Turkey in cooperation with Japan International Cooperation Agency (JICA), Japan

those indices are necessary to run simple models and they are also used as auxiliary data in more detailed stock assessment models (Rodriguez-Marin, 2003; Maunder & Punt, 2004). The first who attempted to estimate standardized CPUE for BLM was Uozumi (1998) based on Japanese longline fishery statistics for 1967-1997 time span. However, lack of detailed data has hampered the calculation of standardized CPUE in the recent decades caught by other fleets or in areas where Japanese longline fleet have not operated in (e.g. eastern Indian Ocean). Therefore, this paper provides new information on relative abundance trend of BLM in the east of Indian Ocean based Indonesian tuna longline fleets. We believe the results are valuable in term of fill the research gap and contribute as an auxiliary information to assess the status of BLM in the Indian Ocean.

Materials and Methods

Data and Variables

In this paper, we have analyzed the data gathered by the scientific observers onboard Indonesian commercial tuna longline vessels, which are mainly based in Benoa Fishing Port, Bali. The observer program started in 2005 as an Indonesia-Australia collaboration (Project FIS/2002/074 of Australian Centre for International Agricultural Research), and since 2010 it has been conducted by the Research Institute for Tuna Fisheries (Indonesia). Database contained information about 92 fishing trips and 2,287 longline fishing sets from August 2005 to December 2014. Longline fishing trips last for three weeks to three months. Main fishing grounds cover from west to southern part of Indonesian waters, stretched from 75 $^{\circ}$E to 35 $^{\circ}$S (Figure 1). It also informed concerning the number of fish caught by species, total number of hooks, number of hooks between floats (HBF), start time of the set, start time of haul, soak time, and geographic position where the longlines were deployed into the water. The response variable in the models was the catch of black marlin in number of fish. Year and quarter were used as categorical (factor) explanatory variables. Additional information was used as explanatory variables as follows:

a. Fishing area (AreaTree)

Area stratification method was applied using GLM-tree approach proposed by Ichinokawa and Brodziak (2010);

b. Number of hooks between floats (HBF)

Number of hooks between floats was set as a categorical variable in the model. It was assigned as 1 if HBF <10 hooks (surface longline), and 2 if HBF $\geq$10 hooks (deep longline) following Sadiyah, Dowling, and Prisantoso (2012);

c. Start time of the set

Start time of the set was treated as quantitative variable, the values were rounded to the nearest integer;

d. Soak time

Soak time was calculated as the time elapsed between the start of the fishing setting and the start of hauling of the longline. Soak time in the model was treated as continuous variable, thus the values were rounded to the nearest integer;

e. Moon phase

Moon phase (29.5 days) were categorized into two periods, as light and dark, and assumed the demilunes (first/last quarters), waxing and waning gibbous and full moon as light period, while new moon, waxing and waning crescent considered as dark period (Akyol, 2013).

Models

Six Generalized Linear Model (GLM) models were considered in this present study. Whereas nominal catch (number of fish) acted as response variable while effort (total hooks) was included in the models as an offset caught. These models are Poisson and negative binomial (NB), which we refer to as the standard models, zero-inflated Poisson (ZIP), zero-inflated NB (ZINB), Poisson hurdle (PH), and NB hurdle (NBH) models. The summary of probability function of all models is derived from Rose, Martin, Wannemuehler, and Plikaytis (2006), Saffari, Adnan, and Greene (2012), and Walsh and Brodziak (2014) which is provided in Table 1.

Black marlin is a bycatch species in the longline fisheries and the datasets contained a high proportion of zero catches (~89.4%). Hence Poisson distribution may not be suitable to model catch data, while negative binomial model can account for large number of zeros and over-dispersion since a dispersion parameter is estimated. However, if the number of zeros is excessive, even the negative binomial distribution may not be suitable to model the catch data. Zero-inflated and hurdle models are alternatives to cope with the large number of zero catches. If the zero-inflation models separate the zeros into “true” and “extra” categories, hurdle models model the zeros and non-zeros as two separate processes. Details on conventional GLMs and on zero-inflated and hurdle models can be found in Mullahy (1986), McCullagh and Nelder (1989), Lambert (1992), Colin and Trivedi (1998) and Dobson and Barnett (2008).

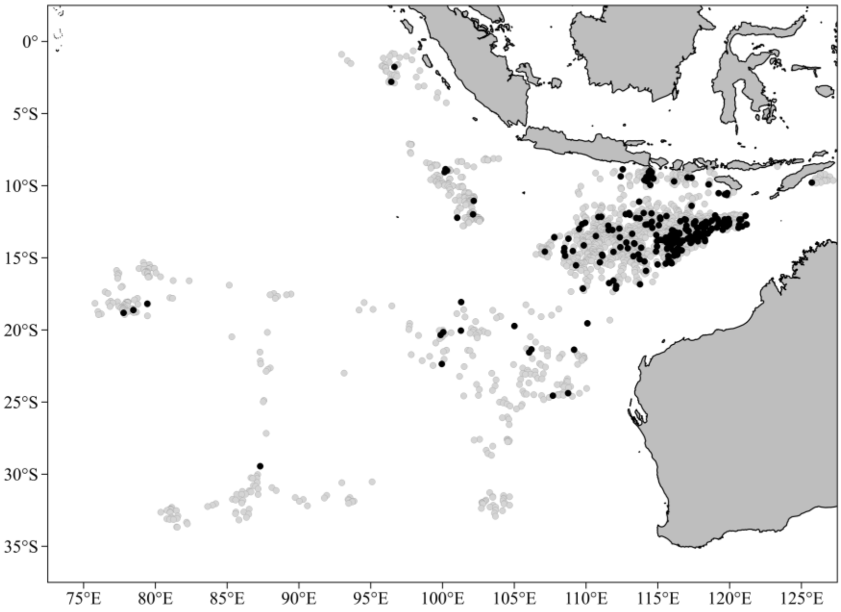

Figure 1. Distribution of Indonesian tuna longline sets from 2005-2014. Black dots represent positive sets, and grey dots represent zero-catch per set.

Table 1. Probability models and hypotheses about the capture probability of catch (C) for CPUE standardization, including the probability mass or density function for catch, and the hypothesis about nominal catches, for the Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, and delta-gamma distributions, where π is the probability of an extra zero catch per set, p is the probability of a positive catch per set, μ, k and λ are parameters.

Probability model	Probability function	Hypothesis
Poisson	$P(Y=y) = \frac{e^{-\mu}.\mu^{y}}{y!}$	Nominal catches are neither over dispersed or under dispersed
Negative Binomial	$P(Y=y) = \frac{\Gamma(y+1/\alpha)}{\Gamma(y+1)\Gamma(1/\alpha)} \cdot \frac{(\alpha\mu)^{y}}{(1+\alpha\mu)^{y+1/\alpha}}$	Nominal catches are over dispersed
Zero-inflated Poisson	$P(Y=y) = \begin{cases} P+(1-p)e^{-\mu} & y=0 \\ (1-p)\frac{e^{-\mu}.\mu^{y}}{y!} & y>0 \end{cases}$	Nominal catches are over dispersed with excess of zeros
Zero-inflated Negative Binomial	$P(Y=y) = \begin{cases} P+(1-p)\frac{1}{(1+\alpha\mu)^{\frac{1}{\alpha}}} & y=0 \\ (1-p)\frac{\Gamma\left(y+\frac{1}{\alpha}\right)}{\Gamma(y+1)\Gamma\left(\frac{1}{\alpha}\right)} \cdot \frac{\alpha\mu^{y}}{(1+\alpha\mu)^{y+\frac{1}{\alpha}}} & y>0 \end{cases}$	Nominal catches are over dispersed with excess of zeros
Hurdle Poisson	$P(Y=y) = \begin{cases} P & y=0 \\ (1-p)\frac{e^{-\mu}.\mu^{y}}{\Gamma(1-e^{-\mu})y!} & y>0 \end{cases}$	Nominal catches are over dispersed with excess of zeros
Hurdle Negative Binomial	$P(Y=y) = \begin{cases} P & y=0 \\ (1-p)\frac{\Gamma(y+\alpha^{-1})}{\Gamma(y+1)\Gamma(\alpha^{-1})y!} \cdot \frac{(1+\alpha\mu)^{-\alpha^{-1}-y}.\alpha\mu}{1-(1+\alpha\mu)^{-\alpha^{-1}}} & y>0 \end{cases}$	Nominal catches are over dispersed with excess of zeros

We have used a forward approach to select the explanatory variables and the order they were included in the full model. The first step was to fit simple models with one variable at a time. The variable included in the model with lowest residual deviance was selected first. As second step the model with the selected variable then received other variables one at a time, and the model with lowest residual deviance was again selected. This procedure continued until residual deviance did not decrease as new variables were added to the previous selected model. Finally, all main effects were considered and a backward procedure based on Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978) were used to select the final models. We also rely in AIC and BIC to compare these models. Interaction was not included in the model to avoid overfitting.

The qualities of the fittings were assessed by comparing the observed frequency distributions of the number of fish caught to the predicted frequency distribution, as calculated using the selected models. Kolmogorov-Smirnov test was used to assess if the difference of the two distributions (observed and predicted) were significant. Pearson residual was calculated for the selected models as model validation. Maps were produced using QGIS version 2.12 (QGIS Developer Team, 2009) and the statistical analyses were carried out using R software (R Core Team, 2016), particularly the package *pscl* (Zeileis, Kleiber & Jackman, 2008) and *lsmeans* (Lenth, 2016) to calculate the standardized CPUE value.

Results

Descriptive Catch Statistics

Research Institute for Tuna Fisheries (RITF) observers recorded catch and operational data at sea during 92 trips with 2,287 sets from commercial longline vessels that deployed over 3 million hooks in 2005–2014 (Table 2).

The definition of area separation based on GLM-tree was presented in Figure 2. It was divided into four areas which constructed by 5x5 degree blocks, each area was assigned with different tone of color. The nominal time series and proportion of zero catch per set of the BLM CPUE is presented in Figure 3. In general, the series was highly variable, with peaks in 2012, and lower values in the remaining years. The percentage of fishing sets with zero catches of BLM in the fishery was high, with average 89.4% of the fishing sets, varying annually between a minimum of 81.9% in 2011 and a maximum of 93.8% in 2008.

CPUE standardizations

The number of parameters (k), AIC, BIC, logarithm of the likelihood (logLik), number of predicted zero catches, and *p* values of Kolmogorov-Smirnov test as calculated using six model structures (P, NB, ZIP, ZINB,

Table 2. Summary of observed fishing effort from Indonesian tuna longline fishery during 2005–2014. Results are pooled and also presented by year of observation. Operational parameters are means (upper entries) and standard deviations (lower parenthetical entries)

Year	Trips	Sets	Total hooks	Hooks per set	Hooks per float	Mean start set	Mean soak time
2005	9	108	157,065	1,454.3 (151.8)	18.6 (1.5)	8.2 (1.8)	8.5 (0.7)
2006	13	401	577,243	1,439.5 (214.9)	11.2 (3.9)	7.4 (3.2)	11.8 (2.0)
2007	13	265	406,135	1,532.6 (326.5)	14.0 (4.4)	8.4 (2.4)	10.1 (2.0)
2008	15	370	483,662	1,307.2 (385.9)	13.0 (4.5)	8.5 (2.9)	10.3 (1.8)
2009	13	283	323,042	1,141.5 (234.7)	12.1 (4.9)	8.8 (4.2)	10.5 (1.4)
2010	6	165	220,394	1,335.7 (457.5)	13.6 (5.2)	7.9 (2.8)	11.2 (2.2)
2011	3	105	110,384	1,051.3 (173.9)	12.0 (0.0)	6.8 (0.9)	10.9 (0.6)
2012	8	198	290,265	1,466.0 (559.1)	14.1 (2.3)	7.7 (3.0)	12.0 (3.0)
2013	7	225	252,919	1,124.1 (210.4)	12.7 (2.1)	7.3 (2.3)	11.2 (1.6)
2014	5	167	193,740	1,160.1 (176.9)	15.0 (2.0)	7.6 (2.0)	12.1 (1.2)

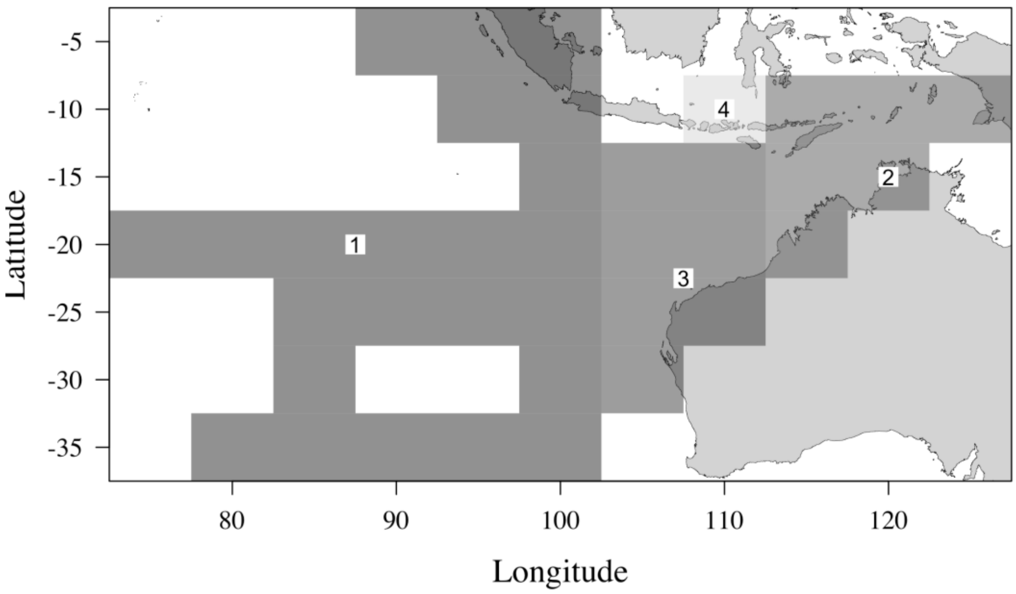

Figure 2. Spatial area stratification based on GLM-tree for the BLM CPUE caught by the Indonesian longline fleet in the eastern Indian Ocean.

HP and HNB are shown in Table 3. Overall the logarithm of likelihood of zero-inflated and particularly hurdle models were high but they are more complex with large number of parameters. The number of zero catches in the database was 2044.

If we relied on AIC, ZINB models was selected as the best among the models we have evaluated. However, if we rely on BIC, NB is selected as the best model. Hence NB and ZINB models were used to calculate standardized catch rate indices for BLM as there was no evidence they were biased, and because they were the models with lower values of AIC or BIC. ZINB model was better in term of predicting the zero catch compared to previous three models (P, NB and ZIP respectively). As hurdle models always give the correct prediction of zero catch, because of its structure.

Deviance analyses of selected NB and ZINB models are in Tables 4 and 5, respectively. Start set was dropped because AIC and BIC values increase if they are included in the models. If we rely in AIC and BIC, five categorical and one quantitative explanatory variables were included in the NB model, though estimations of parameters for the levels of factors were not significantly different from zero. ZINB model contained the same categorical and quantitative explanatory variables as NB, but the number of parameters is larger because it includes two sets of estimations, one for the binomial and one for the negative binomial part of the model.

Estimations of standardized catch rates are shown

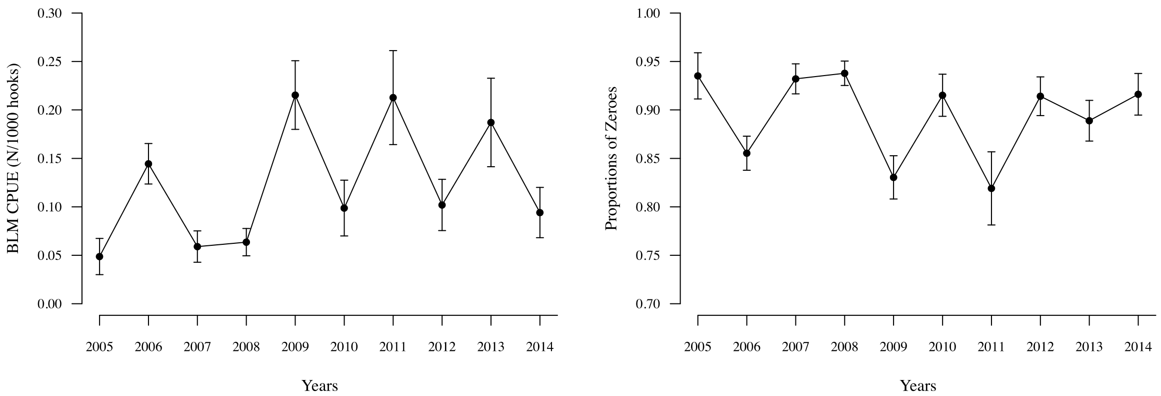

Figure 3. Nominal CPUE series (N/1000 hooks) for BLM between 2005 and 2014. The error bars refer to the standard errors (left panel); Proportion of zero catch per set for BLM between 2005 and 2014. The error bars refer to the standard errors (right panel).

Table 3. 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.

	Model structure					
	P	NB	ZIP	ZINB	HP	HNB
K	20	19	38	38	40	38
AIC	1899	1815	1821	1810	1831	1830
BIC	2014	1930	2038	2028	2060	2048
logLik	-929	-888	-872	-866	-875	-876
Zero	2008	2025	2041	2045	2044	2044
p value	~1	1	1	1	1	1

Table 4. Deviance table for NB Model.

	Df	Deviance Resid.	Df. Resid.	Deviance	Pr(>Chi)	
NULL			2286	1083.35		
AreaTree	3	152.774	2283	930.58	0.000	***
Year	9	20.143	2274	910.43	0.017	*
Quarter	3	15.849	2271	894.59	0.001	**
Soak_Time	1	14.733	2270	879.85	0.000	***
HBF2	1	6.61	2269	873.24	0.010	*
Moon3	1	3.84	2268	869.4	0.050	.

in Figure 4. Time trends of standardized CPUE, as calculated using NB and ZINB models, were similar from 2008 onwards. However, estimations of early stages of the time series were conflictive (2005-2007). Standardized catch rate calculated using the NB model increased from 2005 to 2008, but decreased during the same period if we rely on ZINB model. As there is no strong reason to select one of these two standardized time series for stock assessment purposes, a sensitivity analysis is an alternative.

On overall, nominal CPUE and scaled standardized CPUE from NB model showed similar time trends, except in the beginning and in the end of the series (Figure 5a). In addition, the scaled standardized CPUE series was smoother than the nominal CPUE. Although the Pearson residual tends to be larger when predicted values are lower (Figure 5b), the variation of the Pearson residual per each variable was relatively small, except for hooks between float and moon phase (Figure 5d & 5g). Therefore, this model is considered relatively well estimated. As for scaled standardized CPUE from ZINB model showed a strong incline trend over the years, it relatively similar compared to the scaled nominal CPUE, except for the end of the series. It also created a smoother trend compared to NB model. Even though, the Pearson residual tends to be larger when predicted values are lower (Figure 6b), the variation of the Pearson residual per each variable was relatively small, except for hooks between float (Figure 6d). Therefore, this model is considered well estimated.

Discussions

Model with negative binomial distribution is likely provide better fit for datasets with a lot of zero-valued observations, such as presented in this study. In particular, NB and ZINB model was outperformed P, ZIP, HP and HNB in term of trading off between the bias and the variance. NB model was chosen since BIC tend to choose a simpler model (Prado & West, 2010), than, as for AIC was the opposite, therefore, ZINB model was chosen. However, we found lots of problem when fitting the models because the lack of balance in the crossing levels of factors. It also became the main issue when the chosen models could only explain about 20% of the variables. Perhaps, conducting more sophisticated model like adding random effect, such as: vessel or 5x5 grid area using General Linear Mixed Model (GLMM) (Ijima, 2017), delta-lognormal GLM (Wang, 2017) or zero-inflated negative binomial regression model with smoothing (Minami, Lennert-Cody, Gao & Román-Verdesoto, 2007) could be beneficial for more robust result. The inclusion of environmental variables in the models such as sea surface temperature (SST), sea surface height (SSH), surface winds, and sea surface chlorophyll also important in order to explain more about the catch of BLM in eastern Indian Ocean (Setiawati, Sambah, Miura, Tanaka & As-Syakur, 2014; Lumban-Gaol *et al*., 2015).

Since the dataset were gathered from scientific observers, a lot of data could be incorporated into the model, but not all of them were fit into the model. Area

Table 5. Deviance table for ZINB Model.

	Df	AIC	BIC	Deviance	Chisq	Prob	
NULL		1946.046	1957.516	1940.046	109.961	0.000	***
Moon3	1	1945.589	1968.529	1935.589	4.457	0.108	.
Soak_Time	1	1935.571	1958.511	1925.571	14.475	0.001	***
HBF2	1	1927.897	1950.837	1917.897	22.149	0.000	***
Quarter	3	1924.722	1970.602	1906.722	33.324	0.000	***
Year	9	1924.171	2038.871	1882.171	57.875	0.000	***
AreaTree	3	1848.085	1893.965	1830.085	109.961	0.000	***

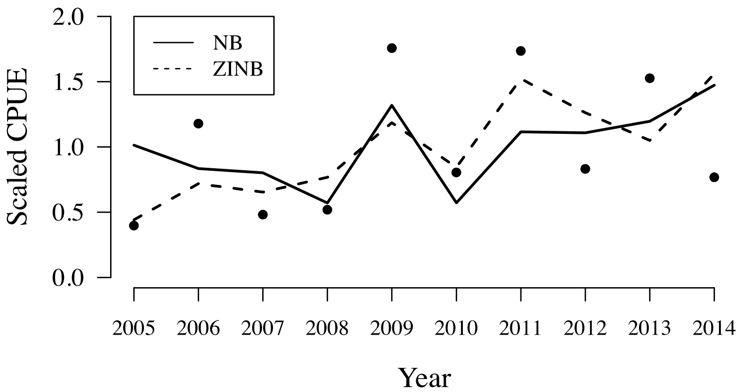

Figure 4. Standardized catch per unit effort (CPUE) of BLM calculated using Negative Binomial (NB) and Zero-inflated Negative Binomial (ZINB) models. Values were scaled by dividing them by their means. Remark: black dots represent nominal CPUE.

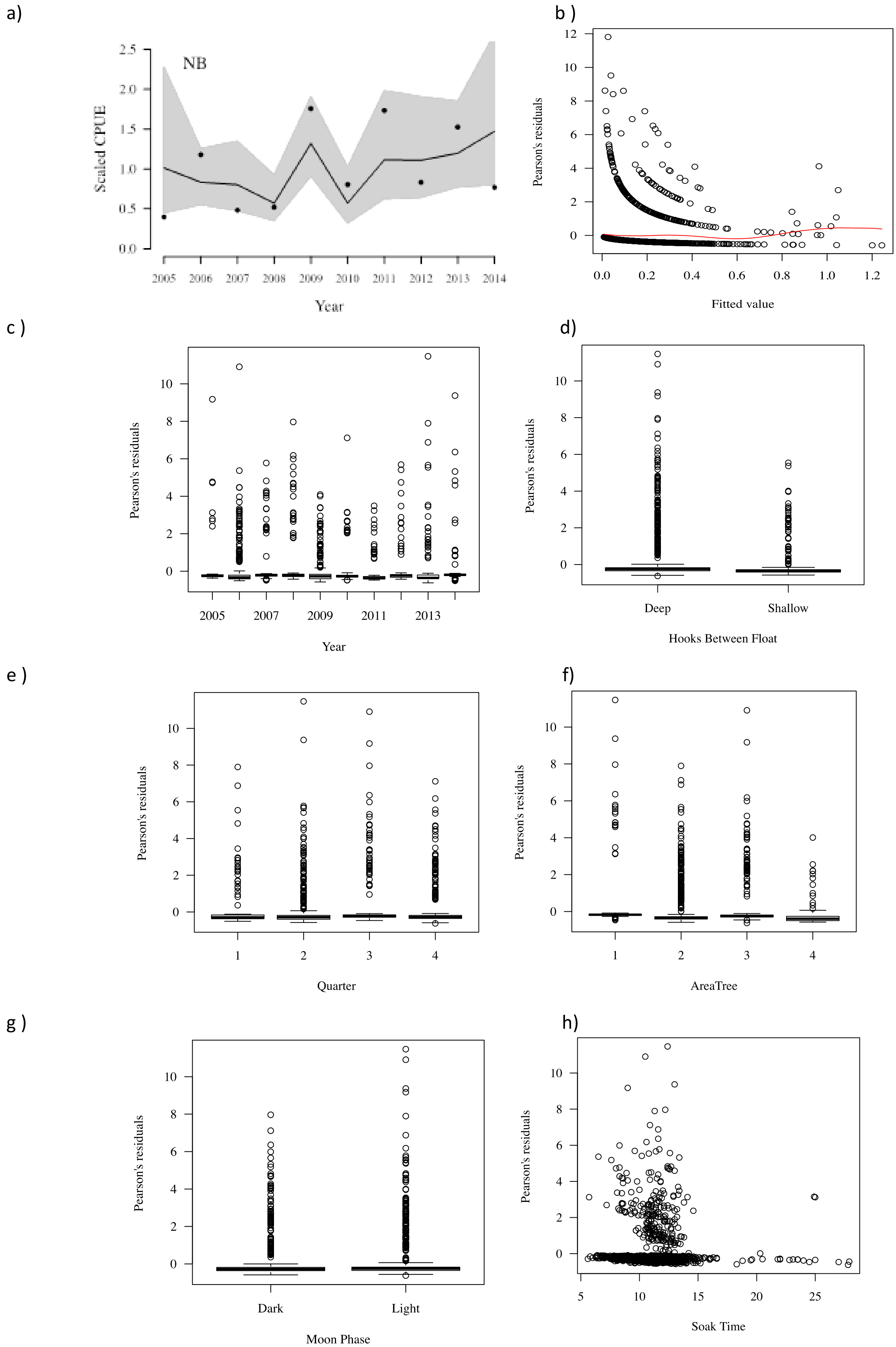

Figure 5. Standardized CPUE of eastern Indian Ocean BLM by Indonesian tuna longline fishery (2005-2014) from NB model. a) The comparison between nominal and standardized CPUE (lines denote standardized CPUE, Points denote nominal CPUE and filled areas denote 95% confidence interval of standardized CPUE); (b-g) The plots of the Pearson residual trend for each variable.

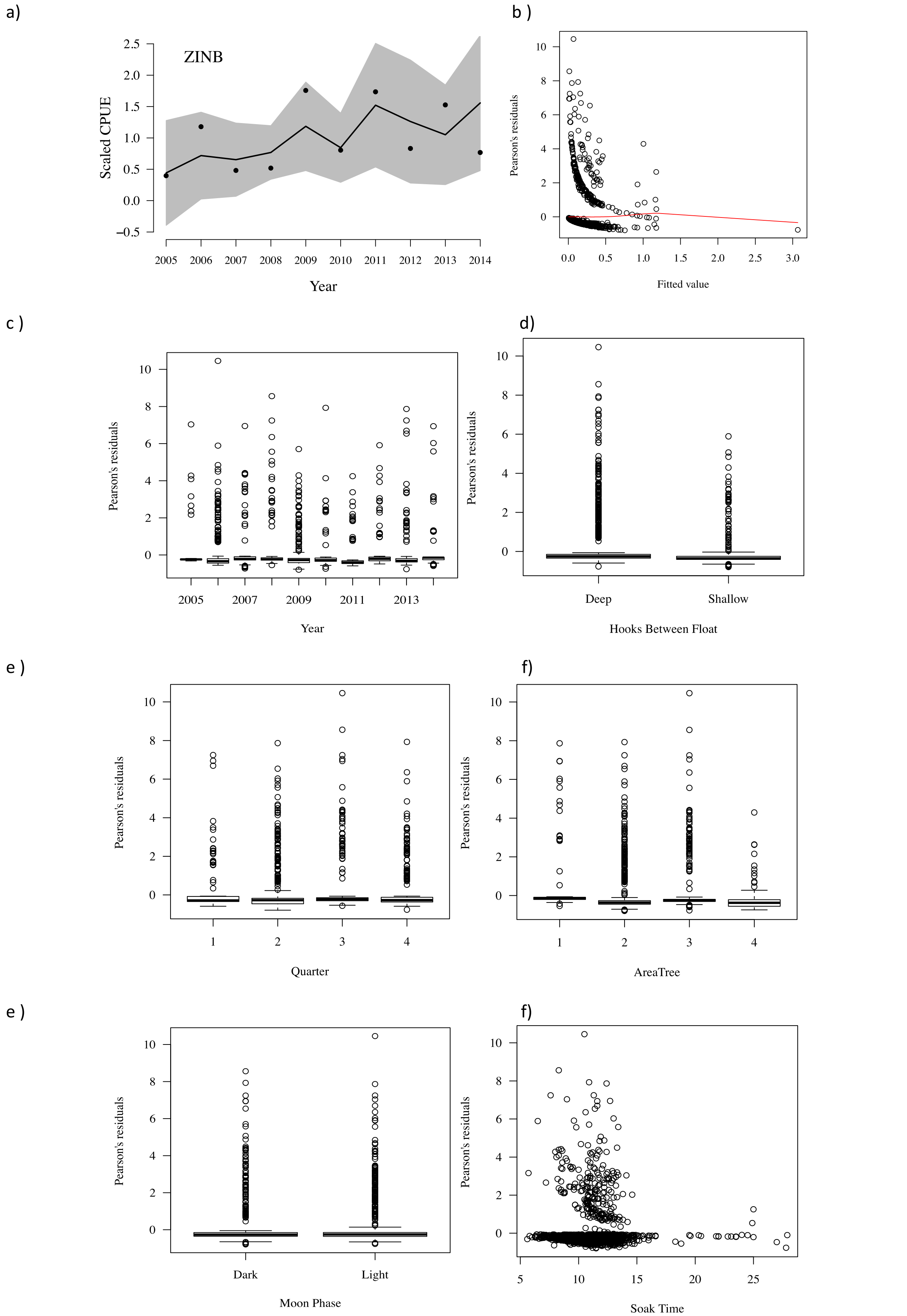

Figure 6. Standardized CPUE of eastern Indian Ocean BLM by Indonesian tuna longline fishery (2005-2014) from ZINB model. a) The comparison between nominal and standardized CPUE (lines denote standardized CPUE, Points denote nominal CPUE and filled areas denote 95% confidence interval of standardized CPUE); (b-g) The plots of the Pearson residual trend for each variable.

Tree variable was likely the most influential factor defining the catch of BLM. It is understood that most of BLM caught in the area 2, near the border between Indonesia and Australia. Those area are also known as the spawning ground of bluefin tuna (*Thunnus maccoyii*) (Farley, Eveson, Davis, Andamari, & Proctor, 2014). The HBF variable also essential in term of describing the target fishery as suggested previously in other studies on billfish (Sadiyah *et al*., 2012; Ijima, Ochi, Nishida & Okamoto, 2015). Models with HBF as a factor did not outperform the model with HBF as a covariate, and therefore simple linear models represent the relationship between HBF and CPUE of BLM. In some CPUE standardization study conducted by several authors (e.g. Chen, Song, Li, Xu & Li, 2012; Unwin *et al*., 2005), Start_Set of set and Soak_Time were considered as important covariates. In this study, however, Start_Set was dropped for all models with negative binomial distribution (i.e. P, ZIP and HP). Start_Set and Soak_Time were relatively similar in most of the fishing sets (~80% of setting was commenced at day with soaking time mostly done less than 15 hours), hence there is no contrast. Therefore, the results suggesting that these variables are not important to explain the variability of CPUE of BLM might be carefully considered.

Currently there is no consensus about the relationship between moon phase and CPUE of species caught by tuna pelagic longline, and it is likely to be species dependent. In this study, the relationship between BLM catches and moon phase was weak ($P>0.05$), which is in agreement with Ponce-Díaz, Ortega-García and Hernández-Vázquez (2003) who reported no significant differences in catches of striped marlin across the four moon phases. On the other hand, Poisson, Gaertner, Taquet, Durbec and Bigelow (2010) found the yields of the albacore tuna (*Thunnus alalunga*) and swordfish (*Xiphias gladius*) caught by the Réunion Island longline fleets targeting swordfish were significantly influenced by the phases of the moon. Jatmiko, Setyadji and Ekawati (2016) also found that moon phase had significant effect on the CPUE of bigeye tuna (*Thunnus obesus*), in particular during full moon. The effect of moon phase in CPUE and catches depends on species behavior, including nocturnal movements, and on the time of the day the longlines are set. The Indonesian tuna longlines were most often set during early morning (daylight) and hauled during late afternoon or early evening. The effect of moon phase may be stronger when longlines remain into the water during the night.

Overall, both standardized CPUE series showed a slight increasing trend across the ten-year period for which data was available. If we assume these calculations are valid indicators, there is no clear evidence that abundance of the stock of black marlin in the eastern Indian Ocean has decreased in the recent years. If we rely in the estimations calculated using the simplest NB model, the standardized CPUE of black marlin showed a slight increasing trend during recent years, similarly to CPUE time trend of blue marlin as calculated by Wang, Lin and Nishida (2012). On the other hand, standardized CPUEs of striped marlin (*T. audax*) (Wang, 2015; Ijima *et al.* 2015), Indo-Pacific Sailfish (*Istiophorus platypterus*) (Andrade, 2015) and swordfish (*X. gladius*) (Nishida & Wang, 2014) are decreased over recent years. Therefore, populations of billfish species in the Indian Ocean are probably experiencing very different fishery mortalities, in spite some of the species are caught by the same fleets. This remain as a remind that specific regulations are necessary to manage billfish stocks.

Acknowledgments

The Authors would like to thank to all scientific observers of Research Institute for Tuna Fisheries (RITF) for their contribution in collecting data throughout the years. We also would like to extend our gratitude to various organization, namely, Commonwealth Scientific and Industrial Research Organization (CSIRO), the Australian Centre for International Agricultural Research (ACIAR) and the Research Institute for Capture Fisheries (RCCF) for their funding support through research collaboration in the project FIS/2002/074: Capacity Development to Monitor, Analyze and Report on Indonesian Tuna Fisheries. The authors would also like to thank Dr. Shen Ping-Wang and Dr. Hirotaka Ijima for their valuable comments on the manuscript.

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