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# STANDARDIZING CPUE OF ALBACORE TUNA (*Thunnus alalunga* Bonnaterre, 1788) ON TUNA LONGLINE FISHERY IN EASTERN INDIAN OCEAN

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**ABSTRACT**

Albacore (Thunnus alalunga) is the third dominant catch of Indonesian tuna longline fishery operating in the eastern Indian Ocean. The percentage production of albacore catch was reaching up 6% of the total catch of tuna groups in Indonesia. Thi study aims to examine a relative abundance indices using standardized catch per unit of effort (CPUE) of longliner based on albacore tuna. This information will give a valuable input and information to support stock assessment particularly in the regional basis. In this study, we use Generalized Linear Model (GLM) with Tweedie distribution to standardize the CPUE and to estimate relative abundance indices based on the Indonesian longline dataset time series. Data were collected from January 2006 to October 2015 (106 trip observer and 8.989 fishing days) by conducting direct onboard observation on tuna longline vessels operating in the Indian Ocean. The result show that year, area,hooks between floats, year*season, year*area and year* hooks between floats significantly influenced the nominal CPUE of albacore. The highest value of Standardized CPUE appeared in 2014 and probably related to the large number of foreign fishing vessels with a high capacity (over 60 GT) targeting frozen tuna including albacore. In 2015, standardized CPUE value was sharply decreased due to the ban of foreign vessels in Indonesia.

**Keywords: Standardization; albacore; generalized linear model; Indian Ocean**

## INTRODUCTION

A CPUE reveals as the quantity of fish (in numbers or in weight) by given amount of fishing effort. Generally, CPUE is used as an index of fish abundance in the water. Its mean that proporsional change in CPUE is expected to the proporsional change in the stock size (Riswanto, 2012; Chen & Chiu, 2009; Bordalo-Machado, 2006; Maunder & Punt, 2004; Ortega-Garcia *et al.*, 2003). The abundance index of fish is mostly based on CPUE index especially on industrial tuna longline fishery (Maunder & Punt, 2004; Maunder *et al*., 2006a; Maunder *et al*., 2006b; Ward & Hindmarsh, 2007). The abundance index based on nominal CPUE on tuna longline fleets did not taken into account confounding factors such as fishing strategy and water environment condition, which can separate indication of abundance based on hook rate (Bach *et al.,* 2000; Hampton *et al*., 1998). Therefore, the relative abundance index based on nominal CPUE data can lead to mistakes and unable to reflect the actual condition of fish resource (Maunder & Punt, 2004; Walters, 2003).

Albacore (ALB) (*Thunnus alalunga*) is the third dominant catch after yellowfin tuna (*Thunnus albacares*) and bigeye tuna (*Thunnus obesus*) with the percentage of production reached up 6 % of the total catch of tuna groups of 1.297.062 ton (DGCF, 2014). However, based on the distribution of hook rate tuna in the Indian Ocean, ALB has the highest average catches of tuna longline vessels (Bahtiar *et al*., 2014). ALB resource spread widely in tropical and subtropical water in Pacific, Indian and Atlantic Ocean (ISSF, 2014). ALB is caught by Indonesian longline fleets which operated in Eastern Indian Ocean is frozen product and exported to Sweden (53,4 %), Italy (18,7%), Poland (17,8%) dan Japan (10 %) (Davis & Andamari, 2003). ALB catches intensity is high, so we need a sustainable management to avoid overfishing which causes the decreasing population of ALB in the Indian Ocean. CPUE data are important to know as one of valuable input for fish resource management study.

A CPUE standardization is one of the general analysis which used to predict fish abundance index

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and fish resource utilization rate by including confounding factors such as catch operational (Maunder & Punt, 2004; Bigelow & Hampton, 2007; Maunder *et al*., 2006a). Several methods have been developed to standardize CPUE in fisheries data such as generalized linear model (GLM), generalised additive model (GAM), generalised linear mixed model (GLMM) dan *delta* approachment (Dowling & Campbell, 2001; Maunder *et al*., 2006a; Maunder and Punt, 2004). Su *et al.* (2008) was used GLM, GAM and *delta* approachment to analysis bigeye tuna CPUE standardization for Taiwan tuna longline fisheries. Sadiyah *et al.* (2012) applied the GLM method to develop recommendation of CPUE standardization based on Indonesian tuna longline observer data.

The aims of this study are to analysis ALB CPUE standardization model and comparison between nominal and standardized CPUE. The result is expected to support ALB management study in Eastern Indian Ocean and update the information which was previously reported by Sadiyah *et al.* (2012).

## MATERIALS AND METHODS

### Data Collection

Data were collected through a scientific onboard observer program on tuna longline fleets based in Muara Baru fishing port (Jakarta), Palabuhanratu (West Java), Cilacap (Central Java) and Benoa (Bali) that operated in the eastern Indian Ocean. Data were collected from January 2006 to October 2015 (106 trips observer and 8.989 fishing days). From 106 trips observer, Benoa station dominated the trips (97 trips) followed by Palabuhanratu (4 trips), Cilacap (3 trips) and Muara Baru (2 trips). The data collection consist of total catch, specifications of fishing gear, vessel size, operational aspects and fishing area.

### Nominal Catch per Unit of Effort (CPUE)

Catches data and the number of hooks per trip was used to calculate hook rate and nominal CPUE. Nominal CPUE or hook rate value was the number of ALB catches in 100 hooks. Nominal CPUE was calculated using equation of De Metrio & Megalofonou (1998):

$$HR = \frac{jI}{JP} XA \quad \text{....................................................} \quad (1)$$

where:
HR = *hook rate* ;
JI = the number of ALB catches;
JP = the number of hook;
A = 100 hooks.

To determine whether there were any difference of the average annual nominal CPUE based on different period of the season (west monsoon and east monsoon) and fishing sub-area, the *t-test* was used on the average of two independent samples with Microsoft Excel. Hypothesis to be test for different in season was $H_0$: the average CPUE in west monsoon was equal with the average CPUE in east monsoon and $H_1$ : the average CPUE in west monsoon was not equal with the average CPUE in east monsoon. Hypothesis for different fishing sub-area was $H_0$: the average of CPUE area one (1) was equal with the average of CPUE area two (2) and $H_1$: the average of CPUE area one (1) was not equal with the average CPUE area two (2). If value of *t-test* was greater than *t-table*, then $H_0$ rejected which mean there were any differences in the average value of CPUE.

### Confounding Factors

Confounding factors on determining fishing effort were fishing tactics and strategies are applied by Indonesian tuna longliner to catch tuna fish. Fishing tactic and strategy often different from longliner althought they have similar target of fish. This different practice and strategy are followed by the different result of catch and catchability. This phenomena would be affected the nominal trend of its CPUE trend. The confounding factors which taken into account in GLM model are :

**a. Year**

Year is the period of onboard observation. Data divided into 11 categories ranged from 2006-2015.

**b. Season**

Fishing season is divided into two (2) categorical data. There were west monsoon (December to May) and east monsoon (June to November).

**c. Fishing Area**

Fishing position was recorded based on latitude and longitude for each setting throughout trips of onboard observation. Fishing area is divides into two (2) sub-area which were operated in Eastern Indian Ocean, there were an area inside the Indonesian Exclusive Economic Zone (IEEZ) and outside the Indonesian Exclusive Economic Zone (Figure 1). Fishing sub-area were grouped in 5°x5°.

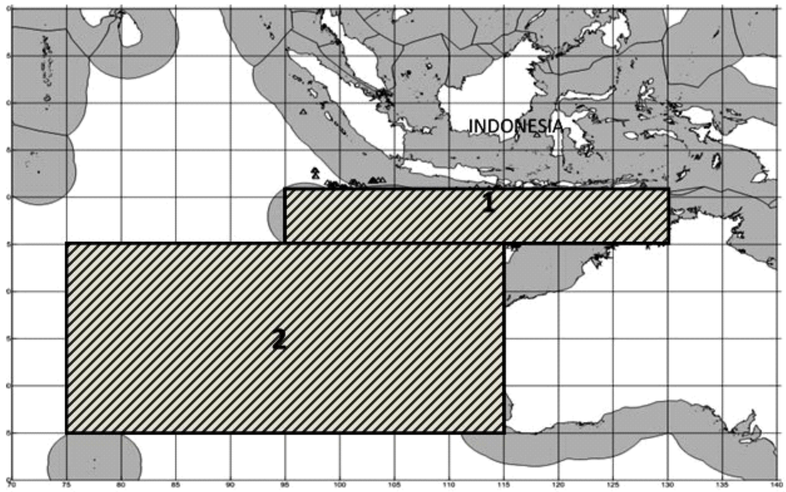


Figure 1. 2. Categorical sub-area used for CPUE standardization based on 2006-2015 onboard observation (*Remarks: sub-area 1 is inside IEEZ and sub-area 2 is outside IEEZ).*

**d. Hook Between Floats (HBF)**

The information on the number of hooks between floats (HBF) recorded based on setting data greatly varies with 4-21 HBF. Confounding factors of HBF was devided as 2 categorical i.e HBF$\leq$12 hooks and HBF > 12 hooks, which will use for Generalized Linear Model (GLM) analysis. HBF 12 hooks is a limit between deep and mid-longline. Tuna longliner based in Benoa is divided into 3 types, there are surface longline, mid longline and deep longline (Barata *et al*., 2011a). According to Irianto *et al*. (2013), the surface longline type consisted of 5 hooks among buoy which was operated at depth of 100 to 175 m, the mid longline type consist of 12 hooks among buoy which operated at depth of 125 to 350 m, and the deep longline type consist of 18 hooks or more among buoy which operated at depth of 150 to 450 m. In this analysis we use 12 hooks as limiting factor between medium and depth longline.

**Catch per Unit Effort (CPUE) Standardization on GLM**

The CPUE standardization enclosed confounding factor as covariate variable was used in GLM analysis. The result from Sadiyah *et al.* (2012) suggested that some significant confounding factor for CPUE standardization with GLM model were year, fishing area, and HBF. In this study, we added another confounding factor i. e the period of season (west monsoon and east monsoon). GLM is flexible general model on linear regression in which respond variables have error distribution in addition of normal distribution. The equation model of GLM used in CPUE standardization as follows (Candy, 2004, Basson & Farley, 2005):

$$CPUE = c + \beta 1jYear_{ij} + \beta 2jseason_{ij} + \beta 3jarea\_ij + offset(\log(effort)) + ei \quad \text{..............................(2)}$$

We used open source R software program to input and analysis GLM fit model. (Table 1) show the whole information of confounding factor which were used in this analysis.

Table 1. Confounding factor is (factor and covariate) used in GLM analysis

| **Factor** | **Level** | **Category** | **Type** |
|---|---|---|---|
| Year | 1 to 11 | 2006- 2015 | Categorical |
| Season | 1 | West Monsoon (December – May) | Categorical |
| | 2 | East Monsoon (June – November) | |
| Fishing Area | 1 | $5^0$-$14.9^0$ S; $95^0$-$130^0$ E | Categorical |
| | 2 | $15^0$-$35^0$ S; $75^0$-$115^0$ E | |
| HBF | 1 | ≤ 12 hooks | Categorical |
| | 2 | >12 hooks | |

The first step of the GLM analysis was used to determine normality of data using normality test (Kolmogorov-Smirnov and Shapiro-Wilk). If the significant value was greater than $á_{0.05}$, its mean that the data was normaly distributed but if significant value was lower than $á_{0.05}$ its mean that the data was not normalt distributed. The next step was to determine the fit distribution in GLM analysis. We used Tweedie distribution and log link function as a fit distribution because the distribution has a power variance function with the power parameter (k) range between 1.1 and 1.9, which is suitable for zero CPUE in observation (Appendix 2) (Bason & Farley, 2005; Candy, 2004).

AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) were used as criterion of model selection in fish population dynamic. AIC has a tendency to over estimate the number of parameters even in a large sample and BIC has to address the problem of over estimation in large samples. To avoid a problem of overfitting because the sample is greater that 1,000 sample based on several pre-test model, the best model used in this analysis based on stepwise AIC and BIC (Shono, 2005).

## RESULTS AND DISCUSSION

### Results

#### *Nominal CPUE*

The ALB nominal CPUE of longline catches throughout the onboard observation 2006-2015 fluctuated. Nominal CPUE ranged from 0.117-0.519 with an average of 0.253 (Figure 2). The highest nominal CPUE in 2012 and the lowest nominal CPUE in 2009. In 2007, 2008, 2010, 2012, and 2014 nominal CPUE were in above the average CPUE and in 2006, 2009 and 2015 were in under the average CPUE threshold. Nominal CPUE regarding with different season shows the CPUE range along east monsoon was 0.075-0.716 and the CPUE range along west monsoon was 0.070-0.516 (Figure 3). Nominal CPUE based on the different fishing sub-area shows CPUE range in area one (1) was 0.026-0.289 and CPUE range in area two (2) was 0.032-0.973 (Figure 4).

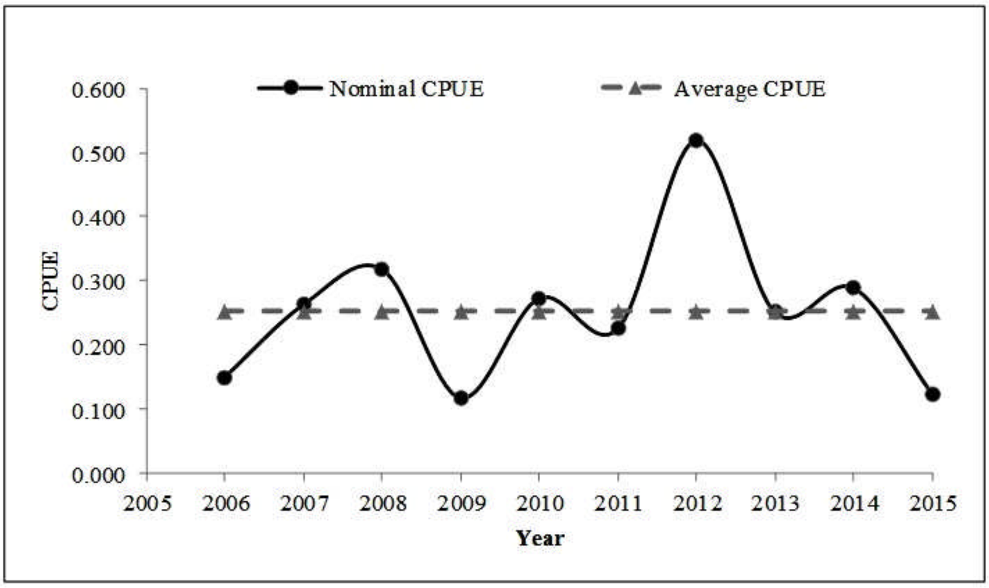


Figure 2. Nominal CPUE of ALB time series based on onboard observation during 2006-2015.

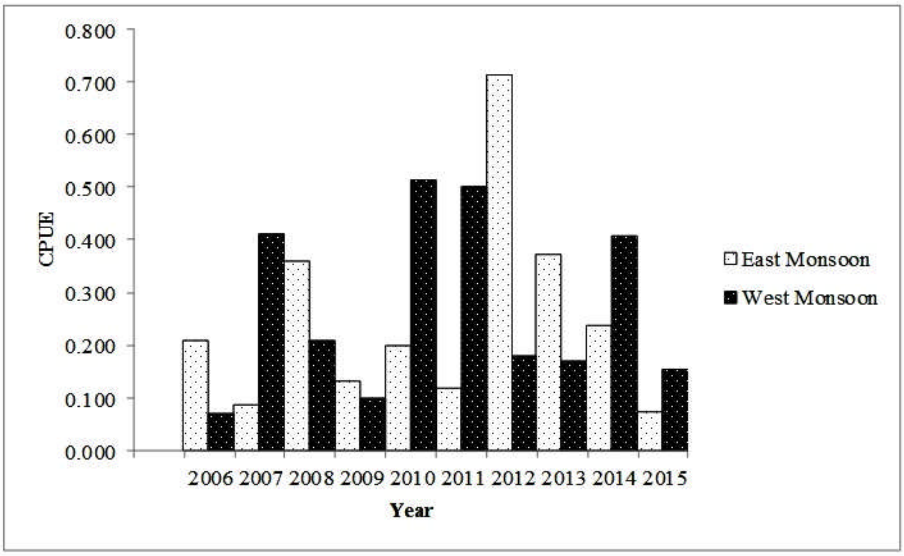


Figure 3. Nominal CPUE of ALB based on season (east monsoon and west monsoon) throughout the onboard observation ranged from 2006- 2015.

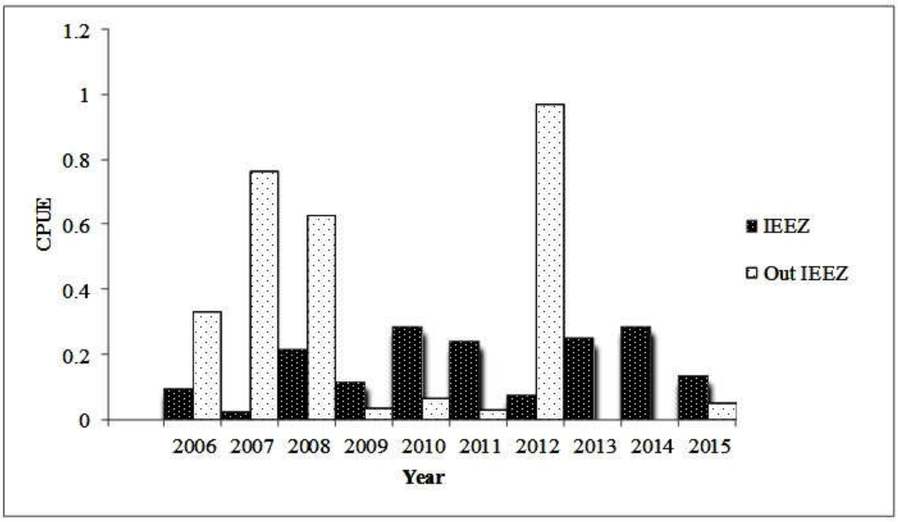


Figure 4. Nominal CPUE of ALB based on fishing area (sub-area 1 in IEEZ) dan (sub-area 2 OutIEEZ) throughout the onboard observation ranged from 2006 - 2015.

Nominal CPUE based on different season shows that the average nominal CPUE in east monsoon was 0.230 and the average nominal CPUE in west monsoon was 0.272.

**Standardized CPUE**

The best model option for ALB standardization according to AIC and BIC criterion are presented in (Table 2).

Table 2. List of model option for ALB according to AIC and BIC Value

| No | Model Option | AIC | BIC | Probability Distribution | Link Function |
|---|---|---|---|---|---|
| 1 | CPUE=Year | 3685.715 | 3665.715 | tweedie | Log |
| 2 | CPUE=Year+Season | 3686.119 | 3664.119 | tweedie | Log |
| 3 | CPUE=Year+Season+Area | 3407.499 | 3383.499 | tweedie | Log |
| 4 | CPUE=Year+Season+Area+HBF | 3043.441 | 2957.441 | tweedie | Log |
| 5 | CPUE=Year+Season+Area+HBF+ (Year*Season)+(Year*Area)+(Year*HBF) | 3039.373 | 2959.373 | tweedie | Log |

The best model that has smallest AIC and BIC is used to predict the CPUE standardization (Figure 5). In ALB GLM analysis, year, season and area were highly significant (p-value<0.05). The results of significant level of each confounding factors were summarized in Table 3 and the predicted value of CPUE standardization and standard error (SE) were given in Table 4. The randomized quantile residual diagnostic for the best model was given in Appendix1.

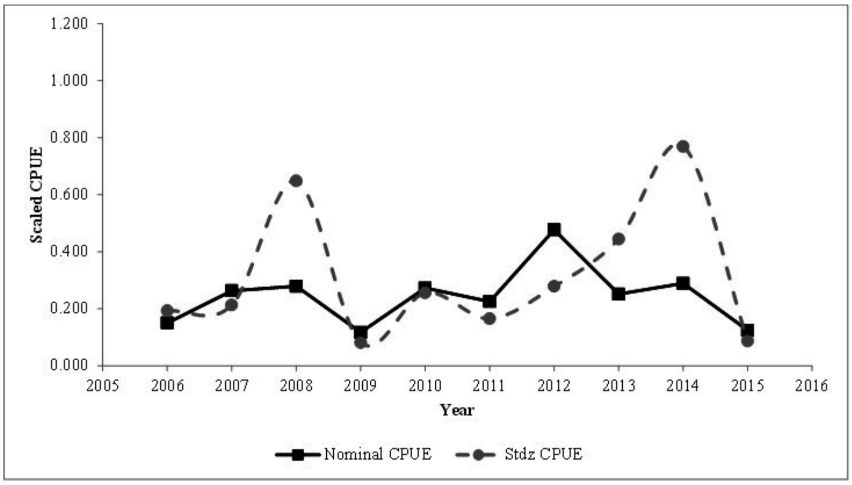


Figure 5. Nominal and standardization ALB CPUE as a time series between 2006-2015 based on RITF onboard observer program in Eastern Indian Ocean.

Table 3. Summary of significant level of each confounding factor in ALB CPUE standardization

| | DF | Deviance Residual | DF Residual | Dev. | F | | PR(>F) |
|---|---|---|---|---|---|---|---|
| NULL | | | 2380 | 3495.0 | | | |
| Year | 9 | 185.48 | 2371 | 3309.5 | 17.6273 | < 2.2e-16 | *** |
| Area | 1 | 339.40 | 2370 | 2970.1 | 290.2987 | < 2.2e-16 | *** |
| HBF | 1 | 33.91 | 2369 | 2936.2 | 29.0047 | < 7.94e-08 | *** |
| Season | 1 | 0.83 | 2368 | 2935.4 | 0.7131 | > 0.3985 | |
| Year : Season | 9 | 185.57 | 2359 | 2749.8 | 17.6261 | < 2.2e-16 | *** |
| Year : Area | 7 | 138.64 | 2352 | 2611.1 | 16.9411 | < 2.2e-16 | *** |
| Year : HBF | 8 | 112.08 | 2344 | 2499.1 | 11.9835 | < 2.2e-16 | *** |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 4. Predicted value of standardized CPUE of ALB and its standard error (upper and lower)

| Year | STDZ. CPUE Index | SE | Resid. Scale |
|---|---|---|---|
| 2006 | 0.193 | 0.041 | 1.081 |
| 2007 | 0.213 | 0.049 | 1.081 |
| 2008 | 0.649 | 0.130 | 1.081 |
| 2009 | 0.081 | 0.049 | 1.081 |
| 2010 | 0.256 | 0.092 | 1.081 |
| 2011 | 0.165 | 0.059 | 1.081 |
| 2012 | 0.278 | 0.053 | 1.081 |
| 2013 | 0.445 | 0.115 | 1.081 |
| 2014 | 0.769 | 0.230 | 1.081 |
| 2015 | 0.087 | 0.063 | 1.081 |

The characteristic of standardized CPUE was any smooth extreme peaks and troughs in nominal CPUE time series (Figure 5).

**Discussion**

Temporal trends of nominal CPUEs were much influenced by different factors which associated with fishing practice and environmental condition (Sadiyah *et al.*, 2012). The different factor such as time of fishing (year), season, fishing area and hook between float (HBF) can cause an extreme value in nominal CPUE time series. It is also alligned with other researches (Song & Wu, 2011; Sadiyah *et al.*, 2012). It seems that all variables used in this GLM are analysis are sufficiently representative for all confounding factor and the abundance and also described as real variables.

In this study, there were several types of model including interaction models between all of confounding factor in GLM analysis but only few that have significant relationship (Table 3). Its means that a closed relationship and strong interaction always appear in standardized CPUE using GLM analysis (Maunder & Punt, 2004). Maunder & Punt, (2004) also stated that simple interpretation cannot be used as a basis information regarding to develop an abundance Index of ALB fish.

The data from onboard observer program are long time data series (2006-2015), it means that we could find any phenomena regarding with fishing practice and environmental condition including temporal and seasonal abundance pattern. Temporal and seasonal pattern were clearly defined in GLM analysis and would give some indication which would confounding factors may significantly influenced in nominal CPUE time series.

The construction of the number of hooks between floats (HBF) in the longline sets appears to be one of the most significant confounding factor in CPUE and catches of ALB. This is supported by previous research conducted by Sadiyah *et al*. (2012); Ijima *et al*. (2015) that confirmed number of hooks contribute a significant factors on predicting CPUE. The model with HBF as covariate did not in out perform and can be search for the relationship between HBF and CPUE using simple linear regression model.

The determination of predictable fishing area also has an effect of ALB catch because ALB is temperate tuna (Rochman *et al*., 2016b; IOTC, 2014; Chen *et al*., 2005). The distribution of ALB (mature and immature) are strongly influenced by Oceanographic condition (IOTC, 2014) such as sea surface temperature (SST), temperature at depth of 100 m (Temp_100), salinity at depth of 0 m (Sal_0) and dissolved Oxygen at 200 m depth (OXY_200). Sea surface temperature (SST) was the most significant for immature, spawning and non-spawning stage of ALB (Chen *et al*., 2005). Therefore, an area is one of the most significant covariate on GLM analysis. Each of fishing area (area 1; inside IEEZ; <15°S or 200 nm south off Java island) and (area 2; outside IEEZ; >15°S or over 200 nm south of Java island) has the variation in the number and size of ALB catches. ALB caught in area two (2) has a smaller size than in area one (1) but with a higher number of catches or nominal CPUE. The average size and nominal CPUE of ALB caught in area one was (98.49 cmFL and 0.167) , while in the area two was (96.49 cmFL and 0.583).

From the GLM analysis, the season independently was insignificantly to influence the GLM model but if we interact with year as interaction covariate it will be significantly proved. This is probably due to migration pattern of ALB in Indian Ocean rely on seasonal factor, whether mature or immature ALB. According to Chen *et al*. (2005), in west monsoon (May to July) the higher CPUE of immature ALB contained in south of 30°S and will be move to north of 25°S to 15°S in the east monsoon (August to November). The immature ALB will be back again to 30°S in west monsoon (February to May). Chen *et al*. (2005) also stated that mature ALB tend to stay in 25°S in west monsoon (May) and 15°S in east monsoon (August). At the end of east monsoon (November) the higher CPUE of mature ALB occured in 10°S to 25°S.

The peak of standardized CPUE value occurred 2014 and may be related to a large number of foreign fishing vessels with a large capacity (over 60 GT) targeting frozen tuna including ALB. Those vessels were fishing in distant waters (10 to 30°S) which are mostly beyond EEZ jurisdiction where ALB widely captured. It's supported by (Rochman *et al*., 2016a) which stated that the total number of tuna vessels (local and foreign vessels) in 2014 was 915 units and reduced to 760 units in 2015 and particularly fishing in EEZ waters. This shifting fishing groud was probably related to the implementation of the Minesterial Decree No. 56 in 2014 and No. 10 in 2015 concerning moratorium for fishing and transhipment. Generally, as an effect of that regulation, a frozen product including ALB was decreased in 2015 to at about 338,317 tons compared with 2014 430,2 tons (Sulistyaningsih, 2014 ; Jatmiko, 2015). One should be taken into account that standardization of ALB CPUE index in 2015 can not be used as a reference points in determining abundance of ALB stock in all East Indian Ocean waters.

## CONCLUSION

This study showed that the confounding factors, namely year, area, HBF, interaction between year*area, year*season, and year* HBF have effect to CPUE. The season has insignificant influence of standardizing CPUE but if interact with year as interaction covariate, it will be significantly proved. Temporal and seasonal pattern of ALB catch were clearly defined in GLM analysis and would give some indication which would confounding factors may significantly influence the nominal CPUE time series.

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**REFERENCES**

Bach, P., Dagorn, L. & Misselis, C. (2000). The role of bait type on pelagic longline efficiency. *ICES Annual Science Conference Theme Session J: Efficiency, Selectivity and impacts of passive gears*, Brugge, Belgium, CM 2000/J: 01.

Bahtiar, A., A. Barata. & B. Nugraha. (2014). Swimming layer and feeding periodicity of Albacore (Thunnus alalunga) In the Indian Ocean South off Java. *BAWAL*. Vol. 6 (2) August 2014: 89-94. In Indonesian.

Barata, A., Novianto, D. & Bahtiar, A. (2011a).(In Indonesian). The distribution of tunas based on temperature and depth in Indian Ocean. *Ilmu Kelautan*. 16(3):165-170 doi: 10.14710/ ik.ijms.16.3. 165-170

Basson, M. & Farley, J. (2005). Commercial spotting in the Australian surface fishery, updated to include the 2004/5 fishing season. *CCSBT 6th Meeting of the Stock Assessment Group and 10th Meeting of the Extended Scientific Committee*, Taipe, Taiwan, 29 August - 3 September, and 5-8 September 2005. CCSBT-ESC/0509/23.

Bigelow, K. A., Hampton, M. N. (2007). Does habitat or depth influence catch rates of pelagic species? *Canadian Journal of Fisheries and Aquatic Science*. 64: 1581-1594.

Bordalo-Machado, P. (2006). Fishing effort analysis and its potential to evaluate stock size. *Review in Fisheries Science* 14 (4); ProQuest. 369p

Candy, S. G. (2004). Modelling catch and effort data using generalised linear models, the Tweedie distribution, random vessel effects and random stratum-by-year effects. *CCAMLR Science.* 11: 59-80.

Chen I. C., Lee P. F. & Tzeng, N. W. (2005). Distribution of Albacore (*Thunnus alalunga*) in The Indian Ocean and Its Relation to Environmental Factor. *Fish Oceanography.* 14 (1), 71-80.

Chen, C.-S., and T.-S. Chiu. (2009). Standardising the CPUE for the Illex argentinus fishery in the Southwest Atlantic. *Fish. Sci*. 75:265–272.

Davis, T. L. O. & R. Andamari. (2003). Analysis of 2001 dinas export packing list data by species, product and destination. *CCSBT Indonesian Catch Monitoring Review*, Queenstown, New Zealand, 10-11 April 2003. CCSBT-ICM/0304/7 .

De Metrio, G. & Megalofonou, P. (1998). Catch and Size Distribution , Growth and Sex Ratio of Swordfish (Xiphias gladius L.) in Gulf of Taranto. *FAO Fisheries Report* No. 394.

DGCF (Directorate General of Capture Fisheries). (2014). (In Indonesian). *Statistics of Marine Capture Fisheries 2012*. Directorate General of Capture Fisheries, MMAF. Jakarta.

Dowling, N. & Campbell, R. (2001). Assessment of the Japanese longline fishery off Western Australia: 1980-1996. *1st meeting of the Stock Assessment Group for the Southern and Western Tuna and Billfish Fishery*, Fremantle, Western Australia, 26-28 February 2001.

Hampton, J., Bigelow, K. & Labelle, M. (1998). A summary of current information on the biology, fisheries and stock assessment of bigeye tuna (*Thunnus obesus*) in the Pacific Ocean, with recommendation for data requirements and future research. *Ocean Fisheries Programme Technical Report No. 36. Noumea, New Caledonia*, Secretariat of the Pacific Community. 1-46 pp

Ijima, H., Ochi, D., Nishida, T., Okamoto, H. (2015). Standardization of CPUE for stripe marlin (*Tetrapturus audax*) of Japanese longline fishery in Indian Ocean. Paper presented on 13th *Working Party on Billfish,* Olhao, Portugal, 1-5 September 2015. IOTC-2015-WPB13-17.16pp.

IOTC. (2014). *Executive summary of the status of the albacore tuna resource* (p. 14). IOTC–2014–SC17–ES01Rev_1.

Irianto, H.E., Wudianto, Satria, F. & Nugraha, B., (2013). Tropical tuna fisheries in the Indian Ocean of Indonesia. *Scientific Committee Meeting*, *IOTC-2013-WPTT15-20* 14p

ISSF. (2014). Status of the World Fisheries for Tuna: Management of Tuna Stocks and Fisheries, 2014. *ISSF Technical Report* 2014-05. International Seafood Sustainability Foundation, Washington, D.C., USA.

Jatmiko, I., (2015). Enumeration Report of Tuna Fishery 2014. Research Institute for Tuna Fisheries. 28 p

Maunder, M. N. & Punt, A. E. (2004). Standardizing catch and effort data: a review of recent approaches. *Fisheries Research*. 70:141-159.

Maunder, M. N., Hinton, M. G., Bigelow, K. A. & Langley, A. D. (2006a). Developing indices of abundance using habitat data in statistical framework. *Bulletin of Marine Science*. 79:545-559.

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P. & Harley, S. J. (2006b). Interpreting catch per unit effort data to assess the status of individual stocks and communities. *ICES J. Mar*. SCi.63: 1373-1385.

Ortega-Garcia, S., Lluch-Belda, D. & Fuentes, P. A. (2003). Spatial, seasonal, and annual fluctuations in relative abundance of yellowfin tuna in the eastern Pacific Ocean during 1984-1990 based on fishery CPUE analysis**.** *Bulletin of Marine Science*.72:613-628.

Riswanto, S. (2012). (In Indonesian). *The status of bigeye tunar (Thunnus obesus, Lowe 1839) in Indian Ocean south off Palabuhanratu, Sukabumi*. Mathematic Faculty and Natural Science, Study Program Master of Marine Science Indonesian University p.126.

Rochman, F., Setyadji, B. & Jatmiko, I. (2016a). (In Indonesian). Impact of the moratorium enforcement on the fishing effort and production of industrial scale longline tuna fisheries based in Benoa port-Bali. *Jurnal Penelitian Perikanan Indonesia* Vol. 22 (3) September 2016: 181-188.

Rochman, F., W. Pranowo, & I. Jatmiko. (2016b). The influence of swimming layer and sub-surface oceanographic variables on catch of albacore (Thunnus alalunga) in Eastern Indian Ocean. *Indonesian Fisheries Research Journ*al Vol. 22 (2) December 2016: 69-76.

Sadiyah, L., N. Dowling, & B. I. Prisantoso. (2012). Developing recommendations for undertaking CPUE standardization using observer program data. *Indonesian Fisheries Research Journal* Vol. 18 (1). June 2012: 19-33.

Shono, H. (2005). Is model selection using Akaike's information criterion appropriate for catch per unit effort standardization in large samples? *Fisheries Science* 2005; 71: 978-986.

Song, L. M. & Wu, Y. P. (2011). Standardizing CPUE of yellowfin tuna (*Thunnus albacares*) longline fishery in the tropical waters of the northwestern Indian Ocean using a deterministic habitat-based model. *Journal of Oceanography*. October 2011, 67: 541.

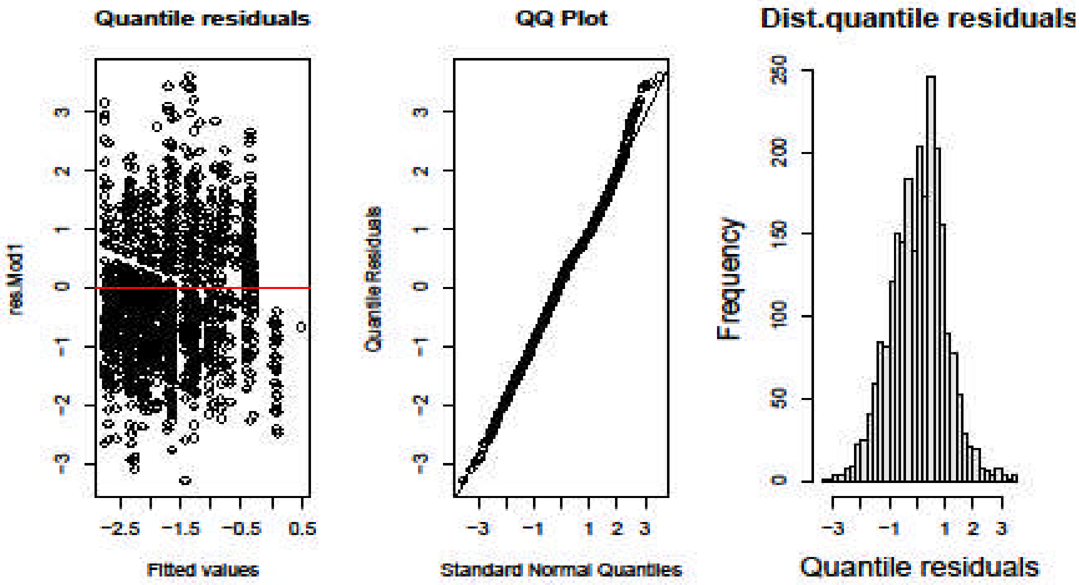
Su, N. J., Yeh, S. Z., Sun, C. L., Punt, A. E., Chen, Y. & Wang, S. P. (2008). Standardizing catch and effort data of the Taiwanese distant-water longline fishery in the Western and Central Pacific Ocean for bigeye tuna, *Thunnus obesus*. *Fisheries Research.* 90: 235-246.

Sulistyaningsih, R., K., 2014. (In Indonesia). Enumeration Report of Tuna Fishery 2014. Research Institute for Tuna Fisheries. 25 p

Walters, C. (2003). Folly and fantasy in the analysis of spatial catch rate data. *Canadian Journal of Fisheries and aquatic Science.* 60: 1433-1436.

Ward, P. & Hindmarsh, S. (2007). An overview of historical changes in the fishing gear and practices of pelagic longliners, with particular reference to Japan's Pacific fleets. *Reviews in Fish Biology and Fisheries*. 17: 501-516.

Appendix 1. Randomised quantile residual diagnostic of ALB GLMs




Appendix 2. Power parameter (k) with 95% confidential interval in GLM analysis in Tweedie distribution