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. This 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 December 2018 (2,811 data sets) by conducting direct onboard observation on tuna longline vessels operating in the Indian Ocean. The result show that year, area, hooks between floats significantly influenced the nominal CPUE of albacore. CPUE standardization of ALB in the periods of 2006 to 2014 was tend to be stable and increase from year to year but in 2015 to 2018 the CPUE standardization tend to be unstable and fluctuate due to changes in fishing patterns and changes in the area of onboard observer program.

KEYWORDS: *Standardization; albacore; Generalized Linear Model; Indian Ocean*

INTRODUCTION

Management of fish resource using catch rate approach or **catch per unit of effort (CPUE)** normatively is one of the model that can be used to recognize the utilization status of fish in the water. Catch rate is also ilustrated the ability of fishing gear catch per unit of effort and fish abundance index in a water (Riswanto, 2012; Chen & Chiu, 2009; Maunder & Punt, 2004; Ortega-Garcia *et al.*, 2003; Hilborn & Walter, 1991). 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). CPUE of tuna exploitation can serve as an effective index of fish abundance as long as different source of the catch-effort data are comparable (Maunder & Punt, 2004). The abundance index based on nominal CPUE on tuna longline fleets did not include 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). The fish 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, 2012). 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 is 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 of a sustainable management to avoid overfishing which is causes the decresing population of ALB in Indian Ocean. CPUE data is important to know as one of valuable input for fish resource management study.

CPUE standardization is one of the general analysis which is uses to predict fish abundance index and fish resource utilization rate by including confounding factors such as catch operational (Maunder & Punt, 2004; Bigelow & Maunder, 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) was applied the GLM method to develop recommendation of CPUE standardization based on Indonesian tuna longline observer data.

The aim 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 the Eastern Indian Ocean.

MATERIAL AND METHODS

Data Collection

Research material was ALB (*Thunnus alalunga*) of tuna longline fleets based in Muara Baru fishing port (Jakarta), Palabuhanratu (West Java), Cilacap (Central Java) and Benoa (Bali). Data were collected from January 2006 to December 2018 (2,811 data sets) by conducting direct onboard observation on tuna longline vessels operating in the Indian

Ocean. The data collection was includes the total catch, the data specifications of fishing gear, vessel size, operational information 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 and Megalofonou (1998):

$$HR = \frac{JI}{JP} \, X \, A \quad \ldots\ldots \quad 1$$

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 were fishing practices and strategy which were used by Indonesian tuna longliner to catch tuna fish. Fishing practices and strategy often different from longliner althought they have similar target of fish. This different practice and strategy followed by the different result and catchability. This phenomena would be affected the nominal CPUE trend of tuna longline fisheries. The confounding factor which would used in GLM model are :

a. Year

Year is the time of onboard observation which devided into 11 categorical data ranged from 2006-2018.

b. Season

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

c. Fishing Area

Fishing position recorded based on latitude and longitude for each setting throughout trips of onboard observation. Fishing area devide into two (2) sub-area which were operated in Eastern Indian Ocean, there were an area inside the Indonesian Exclusive Economical Zone (IEEZ) and outside the the Indonesian Exclusive Economical Zone (Figure 1). Fishing sub-area were grouped in 5^0x5^0.

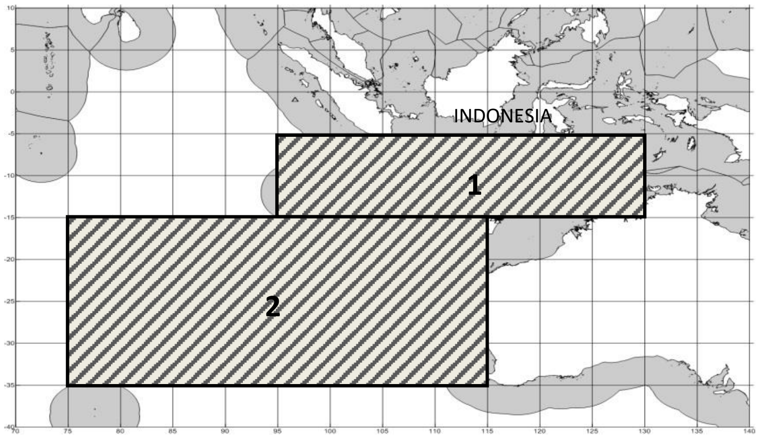

Figure 1. Fishing sub area of the onboard observation and 2 categorical sub-area used for CPUE standardization.

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 devided as 2 categorical i.e HBF $\leq$ 12 hooks dan HBF > 12 hooks, which will used on Generalized Linear Model (GLM) analysis.

Catch per Unit Effort (CPUE) Standardization on GLM

The calculation of CPUE standardization was enclosed confounding factor as covariate variable used in GLM analysis. The result of 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 were 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) :

$$CPUE = c + \beta 1j\, Year_{ij} + \beta 2j\, season_{ij} + \beta 3j\, area\_ij + \beta 1j\, HBF\_ij + offset\,(log(effort)) + ei \text{..............................} 2$$

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 (factor and covariate) used in GLM analysis

Factor	Level	Category	Type
Year	1 to 13	2006- 2018	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 to determine normality of data using normality test (Kolmogorov-Smirnov and Shapiro-Wilk). If the significant value was greater than $\alpha_{0.05}$, its mean that the data was in normal distribution but if significant value was lower than $\alpha_{0.05}$ its mean that the data was not in normal distribution. The next step was to determine the fit distribution in GLM analysis. We used Tweedie distribution and log link function as 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).

The best model used in this analysis based on stepwise AIC (Akaike Information Criterion). We used AIC to avoid a problem of overfitting because the sample is greater that 1,000 sample (Shono, 2005). The best model is a model which has lowest in AIC. value.

RESULT AND DISCUSSION

RESULT

Nominal CPUE

The ALB nominal CPUE of longline catches throughout the onboard observation 2006-2018 were fluctuated. Nominal CPUE ranged from 0.10 to 0.40 with an average of 0.27 (Figure 2). The highest nominal CPUE in 2012 and the lowest nominal CPUE in 2017. In 2007, 2008, 2010,2011, 2012,2014, 2016 nominal CPUE were in above the average CPUE and in 2006, 2009, 2015 and 2017 were in under the average CPUE threshold. Nominal CPUE regarding with different season shows the CPUE range along east monsoon was 0.07-0.51 and the CPUE range along west monsoon was 0.04-0.76 (Figure 3). Nominal CPUE based on the different fishing sub-area shows CPUE range in area one (1) was 0.03-0.35 and CPUE range in area two (2) was 0.04-0.72 (Figure 4).

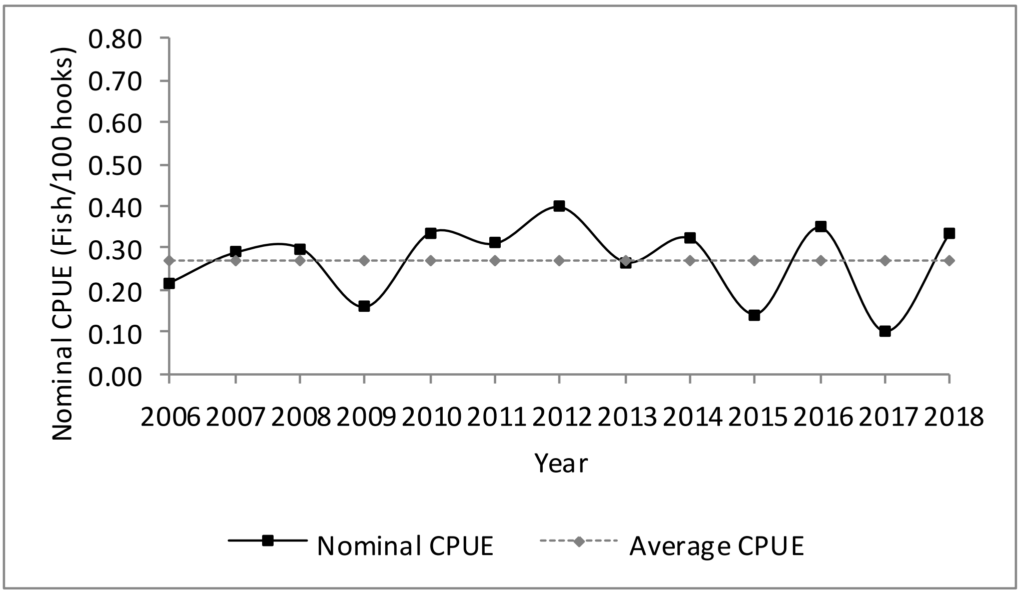

Figure 2. Nominal CPUE of ALB time series along this onboard observation ranged from 2006-2018

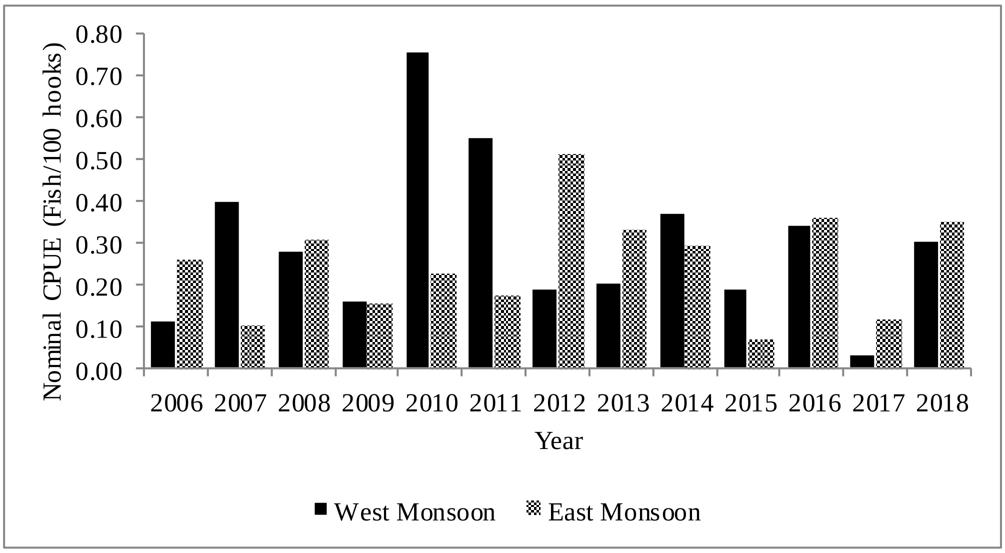

Figure 3. Nominal CPUE of ALB based on season (east monsoon and west monsoon) throughout the onboard observation ranged from 2006- 2018

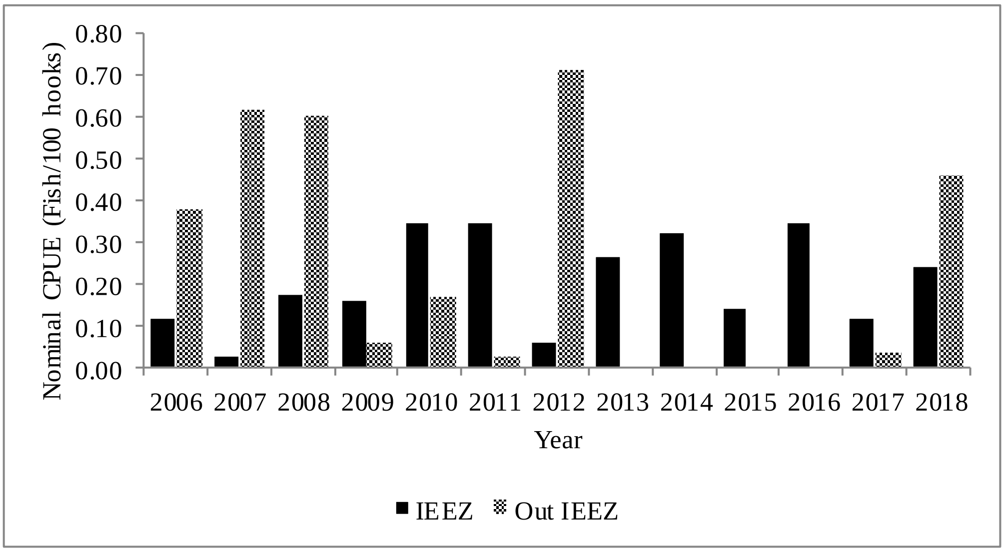

Figure 4. Nominal CPUE of ALB based on fishing area (sub-area 1 in IEEZ) dan (sub-area 2 OutIEEZ) throughout the onboard observation ranged from 2006 - 2018

Nominal CPUE based on different season shows that the average nominal CPUE in east monsoon is 0.25 and the average nominal CPUE in west monsoon is 0.30.

Standardized CPUE

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

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

No	Model Option	AIC	Probability Distribution	Link Function
1	Model 1: Catch ~ 1 + offset(log(No.Hooks))	13272.03	tweedie	Log
2	Model 2: Catch ~ Year + offset(log(No.Hooks))	13120.93	tweedie	Log
3	Model 3: Catch ~ Year + Season + offset(log(No.Hooks))	13122.57	tweedie	Log
4	Model 4: Catch ~ Year + Season + Area + offset(log(No.Hooks))	12784.68	tweedie	Log
5	Model 5: Catch ~ Year + Season + Area + HBF + offset(log(No.Hooks))	12775.73	tweedie	Log

The best model that has smallest AIC was used to predict the CPUE standardization (Figure 5). In ALB GLM analysis, year, area and HBF (hooks between Floats) were highly significant (p-value<0.05). The result of significant level of each confounding factors were summarized in Table 3 and the predicted value of CPUE standardization, UCL (Upper Control Limit) and LCL (Lower Control Limit) were given in Table 4. The randomized quantile residual diagnostic for the best model was given in Appendix1.

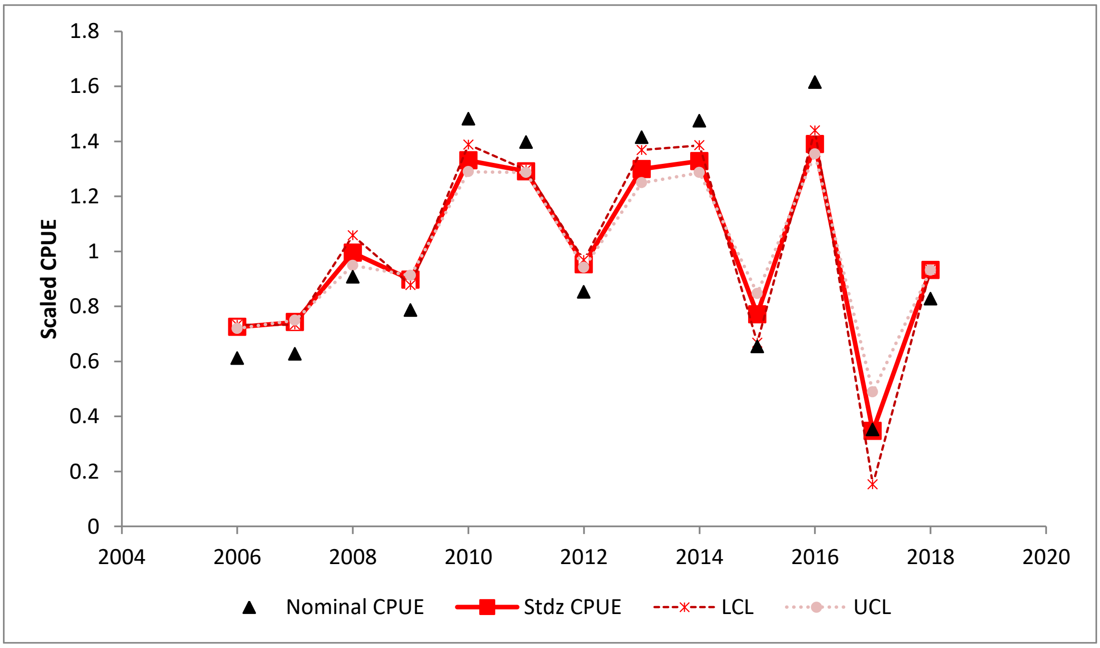

Figure 5. Nominal and standardization ALB CPUE as a time series between 2006-2018 based on RITF onboard observer program in Eastern Indian Ocean

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

	Df	Deviance Residual	DF Residual	DEV	Pr(>Chi)	PR(>F)
NULL			2810	13082		
Year	12	636.25	2798	12445.8	<0.000000	***
Season	1	1.32	2797	12444.4	0.55095	
Area	1	1188.73	2796	11255.7	<0.000000	***
HBF	1	37.31	2795	11218.4	0.00151	**

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	Nom.CPUE	Std CPUE	LCL	UCL
2006	0.612	0.725	0.733	0.719
2007	0.628	0.743	0.733	0.750
2008	0.907	0.995	1.058	0.949
2009	0.786	0.897	0.877	0.912
2010	1.481	1.331	1.388	1.289
2011	1.397	1.291	1.296	1.286
2012	0.852	0.952	0.968	0.941
2013	1.414	1.299	1.368	1.249
2014	1.475	1.328	1.385	1.286
2015	0.654	0.771	0.668	0.846
2016	1.615	1.390	1.439	1.354
2017	0.352	0.347	0.153	0.488
2018	0.827	0.932	0.933	0.931

The characteristic of standardized CPUE was any smooth extreme peaks and troughs in nominal CPUE time series. The spike and troughs in nominal CPUE for ALB were smoothed by standardization in 2006-2018 (Figure 5).

DISCUSSION

Temporal trend 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 exstreme peaks and troughs in nominal CPUE time series. The standardization of CPUE used in this study can cause extreme peaks and troughs in nominal CPUE become more smoothed and refined. It was also supported by research conducted by (Song & Wu, 2011; Sadiyah *et al*., 2012). It's seem that all variables used in this GLM analysis sufficiently representative for all confounding factor and the abundance and also described as real variables.

In this study, there were several type of models but only few that have significant relationship (Table 3). Its mean 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.

The data from onboard observer program is long time data series (2006-2018), its mean 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 define 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). 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 fishing area also has an effect of ALB catch because ALB is temperate tuna and will be moved in accordance with the environment and behaviour (Rochman *et al*., 2016; 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 area is one of the most significant covariate on GLM analysis. Each of fishing area (area 1; inside IEEZ; <15°S) and (area 2; outside IEEZ; >15°S) 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).

CONCLUSION

This study showed that confounding factors i.e year, area, and HBF significantly influenced the nominal CPUE. Standardizing CPUE by those confounding factors is a must to recognize an actual CPUE index and condition of ALB resource. Temporal and seasonal pattern of ALB catch were clearly define in GLM analysis and would give some indication which would confounding factors may significantly influenced in nominal CPUE time series.

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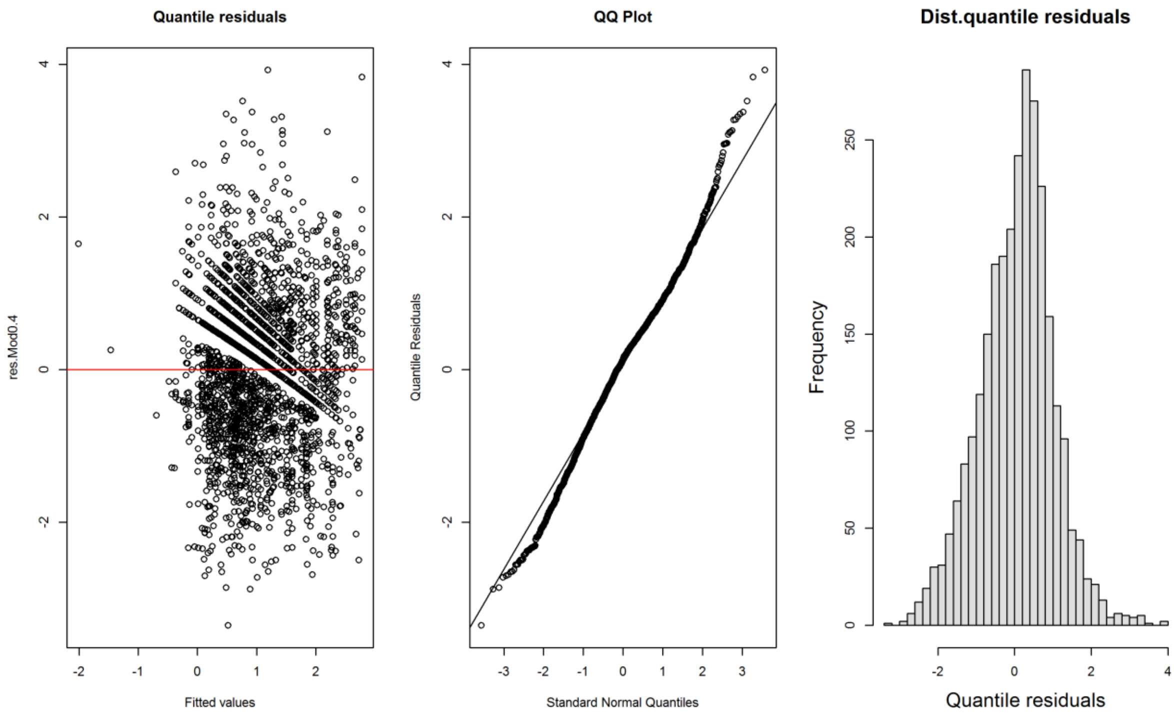
Appendix 1. Randomised quantile residual diagnostic of ALB GLMs



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