Relative abundance of skipjack tuna (*Katsuwonus pelamis* L.) in waters around Sorong and Fak-Fak, West Papua, Indonesia

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Abstract. This study aims to estimate relative abundance of skipjack tuna (*Katsuwonus pelamis* L.) in the waters around Sorong and Fak-Fak, West Papua, Indonesia by using catch and fishing effort data of commercial pole-and-line fishery. General linear model (GLM) was used for analyzing catch per unit of effort (CPUE) data (as representation of relative abundance) to accommodate the variables and factors affecting the catch. From the results of this study it was revealed that CPUE varied according to year, month, live bait, fishing day, and engine size. In addition, fish aggregating devices (FADs) affected the CPUE. Relative abundance of skipjack tuna in the waters around Sorong and Fak-Fak decreased from 1985 to 2000 after the FADs were introduced.
Key Words: skipjack, CPUE, relative abundance, pole-and-line, Sorong and Fak-Fak, general linear model.

Introduction. Catch and effort data from commercial fisheries are often used in the analysis of fish stocks, and to assess the impact of fishing on stock abundance (Stanley 1992; Campbell 1998; McDonald et al 2001). Time series of catch per unit of effort (CPUE) can be obtained relatively easily from these fishery dependent data which are less expensive to collect than through a fishery independent survey using fishery research vessels. However, to use CPUE data generated from commercial fisheries to derive an index of stock abundance requires standardization to account for variability in the data caused by factors rather than variability in fish abundance (Kleiber & Bartoo 1998). Variability in CPUE may be due to factors affecting catchability of the target species such as inter annual and sesonal variations in oceanographical conditions, fishing areas and CPUE of other species in the catch, and factors affecting fishing power including vessel size and fishermen skills (Hilborn & Walter 1992; Pascoe & Robinson 1996). In addition, McDonald et al (2001) state factors such as fishing methods, productive inputs and frequency of zero-catch may also distort CPUE as index of fish abundance. The standardization of CPUE data, especially targeting pelagic fish which show schooling behavior such as tuna is important to reduce the risk that the trend of CPUE does not represent the trend of the fish stock. For example, the CPUE can remain stable while the stock is decreasing which is known as hyperstability (Hilborn & Walter 1992). After the standardization process, the fishing effort is expected to be proportional to fishing mortality and therefore the CPUE can be used as an index of abundance (Watters & Deriso 2000). The standardization method was used to estimate trend of index of abundance of skipjack tuna (*Katsuwonus pelamis* Linnaeus, 1758) taken by skipjack tuna in water around Sorong and Fak-Fak, Indonesia.

The skipjack tuna fishery in Indonesia uses a variety of fishing gears but is dominated by pole-and-line and purse-seine vessels with various level of fishing technology and productive inputs (e.g. size of vessels). In spite of recognition of this variation, there has not been any effort to standardize CPUE for the Indonesian skipjack tuna fishery. The most recent study on the status of skipjack tuna in Western and Central Pacific Ocean (WPCO) (Langley et al 2004) estimated the CPUE for Indonesian skipjack tuna fishery by assuming that fishing effort was proportional to the catch without considering other factors which may affect stock estimates.

In particularly in waters around Sorong and Fak-Fak and other proximity areas, such as in Manokwari and Biak, most skipjack fisheries stopped their fishing operation since periods early of 2000s until today. Those skipjack fisheries belong to fishing companies, such as PT. Usaha Mina (pole and line fishery in Sorong), PT. Inter Galaxy (purse seine fishery in Manokwari), and PT. Biak Mina Jaya (purse seine fishery in Biak). There has been no study explaining these circumstances. The present study aims to estimate the relative abundace of skipjack tuna stock from CPUE data of pole and line fishing around Sorong and Fak-Fak water during periods 1976 to 2000. It is expected that it would provide some explanations about the condition of skipjack stock which might have affected the collapse of many skipjack companies in the areas.

Material and Method. Data used for the analysis of CPUE were taken from commercial pole-and-line fishing vessels based in Sorong. These vessels fish in waters around Sorong (01^oN–02^oS and 129^o–132^oE) and waters around Fak-Fak (02^o–05^oS and 129^o–135^oE) (Figure 1). However, data available were not recorded separately for the two areas. Data from individual pole-and-line fishing vessels in Sorong were recorded monthly by fishing companies and available from 1976 to 2000. Data consisted of catch data and vessel attributes, i.e. gross registered tonnage (GRT), horse power (HP), number of fishing days (including steaming and searching time), vessel age (year) and number of live bait used (measured in number of buckets). Number of fishing vessels operated during the time period varied every month and every year. Hence, the data are unbalanced. Numbers of observations including data with zero-catch (zero-catch indicates unsuccessful fishing operation since there was a fishing operation but no catch) are 2576 and 6610 for period 1977–1984 and 1985-2000, respectively (data before 1985 consisted of catch and effort of vessels that fished on free schooling and after 1985 till today most of the fishing have been taken place around FADs).

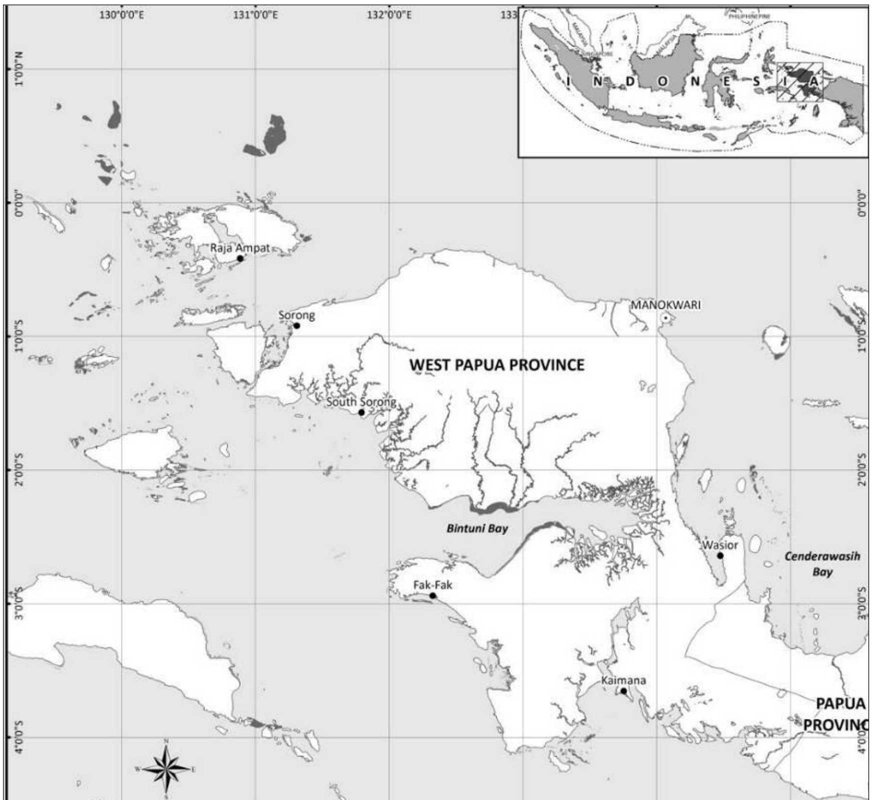


Figure 1. Study location in water around Sorong and Fak-Fak, West Papua.

Accounting for the FAD's effect. To test for the effect of the introduction of fish aggregating devices (FADs) in 1985 to the fishing grounds in water around Sorong and Fak-Fak on CPUE, catch was standardised by comparing the catch rate before and after the introduction of FADs. The standardization of catch data was done by firstly identifying vessels with the same characteristics (in terms of GRT and HP) operating in year 1984 (non FADs) and 1985 (with FADs). Vessels with 30 GRT and 200 HP were chosen. Secondly, catch rate was calculated for each individual vessel by dividing skipjack catch by the number of fishing days and the amount of bait consumed, and then calculating the yearly mean of the catch rate. The means for the two years data are 0.00171±0.00037 (n = 267) (t/day.bucket) and 0.00223±0.00018 (n = 263) (t/day.bucket) for 1984 and 1985 respectively. These figures show a 30.5% increase in catch rate with the introduction of FADs and this figure was used to calibrate the FAD effect by reducing catch after the introduction of FADs by this amount. This method is valid if several assumptions are met, i.e. 1) the nominal catch rate is sufficiently represented by the amount of catch per fishing day and amount of bait used and no other vessel characteristics affected the catch rate; 2) the number of pole and line and other skipjack tuna fishing gears on each vessel is similar for the two years; and 3) there was no significant difference in environmental factors between the two years that may influence the stock availability and recruitment.

By doing so, the data before the adoption of FADs (1977-1985) and after the use of FADs can be included in one General Linear Model (GLM) framework. While we believe that the first two assumptions were met, we do not have sufficient information to determine whether environmental factors which may affect fishing were similar in both years. Therefore we included several levels of FAD effects: 0%, 5%, 15% and 30% in GLMs which are treated as offsets. Several scenarios were tested by varying these FAD effects.

Standardization models. The purpose of CPUE standardization is to acquire CPUE that represents a relative abundance of fish (Stanley 1992; McDonald et al 2001; Soto et al 2009). The standardization of CPUE here was done by using GLMs based on a multiplicative model proposed by Robson (1966) and developed further by Gavaris (1980). GLMs were chosen due to its ability to accommodate many factors in the same model in which the data can be in form of both continuous and categorical/discrete variables (Hilborn & Walter 1992). The GLMs have used in many studies on standardization of relative fish abundance (e.g. Soto et al 2009; Mateo & Hanselman 2014; Sun et al 2014).

The basic idea of inferring index of stock abundance from CPUE data is based on a relationship that CPUE is assumed to be linearly proportional to the stock size (Hilborn & Walter 1992; King 1995):

$$U = qN \qquad (1)$$

where *U* is CPUE, *q* is the catchability coefficient, *N* is stock abundance. Since the catchability coefficient as well as fishing power of vessels is not constant (Pascoe & Robinson 1996; Marchal et al 2001), it is necessary to identify affecting factors. Those factors will then be used in the GLMs for the standardization.

The following factors that affect fishing power and catchability were included in the standardization of skipjack tuna CPUE data taken by pole-and-line fishery: amount of live bait, vessel size (GRT), engine power, number of crew, crew/skipper experience, age of vessel, and FADs. 1) *live bait*. Live bait is essential to the success of pole-and-line fishing as it attracts tuna close to the fishing vessel. Pole-and-line fishermen in Indonesia commonly use *Stolephorus* spp. as a live bait since this fish can be kept alive for about 7 days and when those fish are thrown into the water, they remain close to the fishing vessel. The amount of live bait determines the length of fishing time per day; 2) *vessel tonnage*. The size of vessel can affect fishing power in several ways. Firstly, the larger size of vessel will carry more live bait, fuel and crew. Secondly, a large vessel will be able to travel further to fishing grounds where fish are probably more abundant; 3) *vessel main power*. The need for a large engine power may not be essential in the pole-and-line in the period after the use of FAD since the vessel does not need to hunt the free fish school. However, a sufficient engine power is still important in order to reach fishing ground faster and to cruise from fishing ground to live bait locations and *vice versa*; 4) *number of crew*. Since the fishing operation by using pole-and-line is to catch fish "one by one" by each crew, the more crew in each vessel may enable the vessel to catch more fish. However, when each vessel carries almost the same number of crew, this variable may not affect the variety of fishing power; 5) *crews' experience*. Fishing power of a pole-and-liner may be affected by the experience of crews since experienced crews will do the fishing well and do not cause any hooked fish to release to the water. In addition, an experienced skipper or captain will enable to determine fishing ground that fish are abundant. Nevertheless, in the case of pole-and-line fishery in Indonesia that has been developed for years, it may be possible to assume that the skipper' as well as other crews' experience has been well developed, thereby different skipper may not impact on CPUE variance; 6) *age of vessel*. The age of vessel may influence the ability of the vessel. A vessel may experience a decrease in efficiency as its age increases; and 7) *FADs.* The use of FADs to aggregate fish has made the fishing operation easier since the fishermen are no longer hunting fish school.

Factors that possibly affect catchability of skipjack can be identified through understanding the definition of the catchability. Catchability (q) is the proportion of stock taken by one unit of effort (Wilberg et al 2010) and can be written in mathematic form based on formula (2) as follows:

$$q = \frac{Catch}{Effort\ x\ Fish\ Stock} = \frac{CPUE}{Fish\ Stock} \qquad (2)$$

Those factors are 1) *Stock size*. Proportion of stock taken by one unit of effort (catchability) will be high for the larger stock size, assuming the fishing effort is constant since the increase in stock abundance can lead to a high catch rate. However, for pelagic fish which normally forms shoaling behavior even if in low abundance. This may results in high catch rate and also catchability (Cubillos et al 2002). For a constant stock size (i.e. constant or large supply of recruitment entering the fishing area to maintain the stock size), an increase in fishing power will lead to a higher catchability of the species; 2) *Distribution of fish and fishing effort.* When fish are evenly distributed in a fishing area, each fishing effort exerted on the stock in any part within the area may result in the same catchability. On the contrary, when the fish are randomly distributed, fishing in some part within the area may have a lower catchability than other parts. A similar situation may exist when fishing efforts are concentrated only in some part of the area; catchability will decrease when there is a high concentration of effort. The use of fish aggregating devices (FADs) to attract fish may cause fish tend to concentrate in some particular areas (i.e. around the FADs) and consequently lead to the more vessels to fish in that areas; 3) *Competition between vessels*. When some fishing vessels compete to catch the same stock in the same area, some vessels may catch more than others. Or, when those vessels have the same fishing power, they may have the same catchability. However, the catchability may be higher if they do not share the same stock: no competition among the vessels; and 4) *Oceanographic and seasonal variables.* Oceanographic factors (such as temperature, oxygen and salinity) have been recognized to affect the presence of skipjack in a fishing area. Hence, these factors may affect more on the stock abundance than on catchability (Kleiber & Bartoo 1998). However, seasonal variables such as weather may cause a difficulty in catching the fish; this can be detected by including month as a factor in the model.

Considering factors that may influence the stock, Marr (1951) introduced the term availability which is defined as the proportion of population available for a fishery. This availability is mainly caused by variation of oceanographic condition. When including coefficient of the availability (*r*) in the relationship between CPUE and stock, then equation (2) becomes:

$$U = qrN \qquad (3)$$

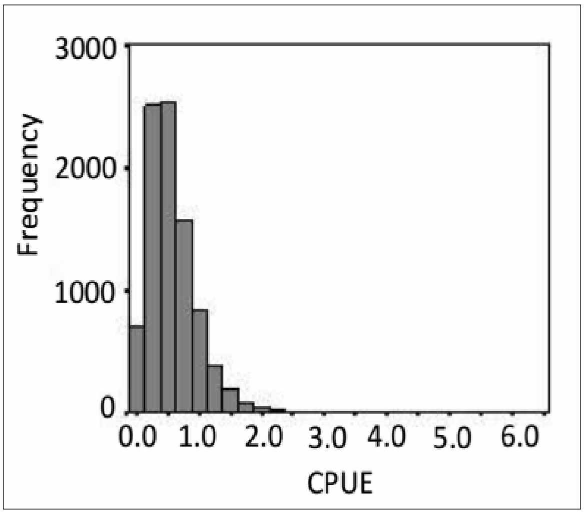
In the present study, not all of the factors were included in the standardization models due to lack of recorded data for those variables. Factors chosen to be readily examined in the GLMs were year, month, vessel size (GRT), amount of live bait, main power (HP), vessel age. Amount of live bait consumed every month of fishing operation was chosen as a part of the model because this was the most important factor affecting the successful fishing operation by using pole-and-line (Gafa & Merta 1987). The vessel age was also included in the model in order to examine the change in vessel efficiency due to increase in age. In order to eliminate bias due to variability of characteristics of each vessel, each vessel was coded and the vessel codes were included in the model as a factor. Summary of characteristics of the variable included in the GLM is shown in Table 1.

Table 1

Summary of variables included in the GLM models for standardization of pole-and-line CPUE

Variables	*Type of data*	*Value or range*
Year	Categorical	1977-2000
Month	Categorical	1, 2, 3, ..., 12
Vessel code	Categorical	1-127
Vessel size (GRT)	Continuous	30-334 (Sorong data)
Livebait (bucket)	Continuous	0-18000 (Sorong data)
Vessel age (year)	Continuous	1-17
Vessel horse power (HP)	Continuous	165-330

CPUE used in the GLMs was defined as ratio between skipjack catch (ton, ***t***) and number of fishing day (day). Number of fishing day included steaming and searching time. Distribution of nominal catch rate data (Figure 2, left side) reveals that more proportion of small figures which cause data distribution skew to the right. Logarithmic transformation improves the data distribution to become approximately normal (Punsly 1987) (Figure 2, right side). This implies models with log-normal error may appropriate.



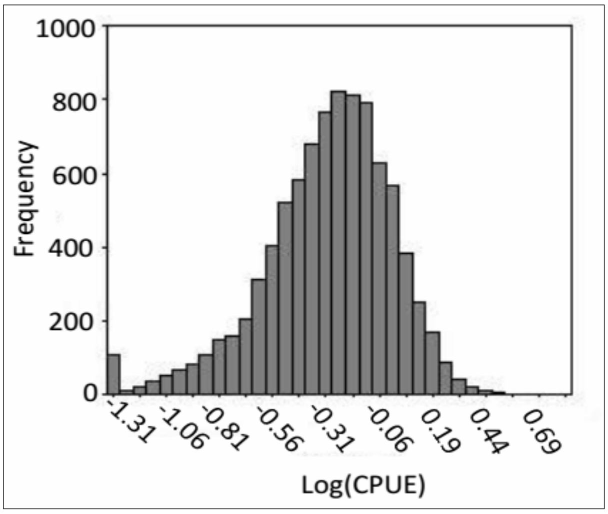


Figure 2. Distribution of CPUE and log(CPUE) of skipjack taken by Sorong pole-and-liners.

Based on data availability described above, two GLM models are proposed in this study:

$$\log(\text{CPUE}) \sim \text{Year} + \text{Month} + \text{VesselCode} + \log(livebait) + \log(GRT) + \log(HP) + \log(vesselage) + \text{Year} * \text{Month} \quad (4)$$

In order to include data with zero catch in the model, especially for the individual data, a value 0.05 was added to each observed catch rate. This figure is equivalent to about 10% of mean of catch rate and the bias caused by the adjustment would be minimized (Campbell 2004).

In assessment of the influence of factors affecting data, especially FAD effect and estimated skipjack composition, several scenarios were developed. These scenarios were only applied to Sorong data. Scenario 1 used data (1993-2000) where skipjack was recorded separately with other tuna. Therefore, it can be as reference for other four scenarios which used predicted skipjack composition for the year before 1993. The scenarios 2 to 5 was set to sense various levels of FAD effect on CPUE. The scenario details were described in the Table 2.

Table 2

The scenarios were set for standardization of Sorong pole-and-line CPUE

Scenario	*Data*
1	Period 1993-2000
2	Period 1976-2000 without FAD effect
3	Period 1976-2000 with 5% of FAD effect
4	Period 1976-2000 with 15% of FAD effect
5	Period 1976-2000 with 30% of FAD effect

The parameters of the models were estimated by fitting the models to the data using GLM procedure in GENSTAT (GENSTAT Eighth Edition, Lawest Agricultural Trust). The fitting process assumed that data were normally distributed. The choice of variable(s) included in the model was done by using forward stepwise regression: variable(s) that are not significant contributing to the log(CPUE) variation ($p < 0.05$), were eliminated from the model. However, the nature of the study is also put into consideration in order to avoid any misspecification; only variables which give biological and ecological meaning to explain the CPUE were included in the models. The year effect was maintained since it refers to relative abundance (Hilborn & Walter 1992).

Inclusion of year-month interaction in model was based on Akaike's Information Criterion (AIC) (Akaike 1974): AIC = (-2) log (maximum likelihood) + 2*k*, where *k* is number of parameters. The model which fits better to the data gives lower AIC value. The choice of AIC in selecting the models is because it performs better than dimension-consistent criteria (e.g. Bayesian Information Criterion, BIC) for the sample size less than 100.000 (Burnham & Anderson 2002).

Calculations of abundance indices. Extraction of year effect as an abundance index from the models was done by considering year.month interaction, since it was suspected that CPUE may vary for the same month, at different year. The method used for generating index of abundance when year interaction is significant follows Campbell (2004) which is based on Aitken et al (1989):

$$\begin{aligned} E(CPUE_{ij}) &= \exp(\mu + \sigma^2/2) \\ &= \exp(\mu_o + year_j + month_i + year*month)\exp(\sigma^2/2) \end{aligned} \tag{5}$$

where $E(CPUE_{ij})$ is a standardized CPUE for month i year j, μ_o denotes reference for year and month. Year 1993 was taken as reference in order to enable comparison among the model results, especially to accommodate the scenarios set above (Table 2), while December was set as a reference because Sorong data of in 1976 started from April. σ^2 denotes variance. When year*month interaction exists in the model, that is statistically significant, formula (5) results in monthly standardized CPUE. The annual standardized CPUE which refers to annual indices of abundance were got by taking average of the estimated monthly standardized CPUE for each year. For model fitted with data which include zero catch, the E(CPUE) must be deducted by the amount of small value (δ) added to the catch rate data Campbell (2004) ($\delta = 0.05$ used in the present study).

Results and Discussion

Fitting models to data. Fitting GLM model to Sorong data for various scenarios by assuming normal distribution of errors showed that for scenario 1 which was used data 1993-2000, covariates log(HP), log(GRT) and log(vessel age) were not significantly (p >

0.05) influenced variation of the pole-and-line CPUE (Table 3). However, for other four scenarios (scenarios 2-5) which used series data from 1976 to 2000, the only insignificant variable ($p > 0.05$) affected the CPUE is log (GRT). The results of variance analyses of the scenario 2 to 5 are shown in Tables 4-7. It was detected that there was a collinearity between log(GRT) and log(HP). Therefore, inclusion of only log(HP) in the models to represent vessel characteristics may be justified.

Table 3
Analysis of variance of Sorong pole-and-line data using scenario 1. Factors or covariates with $p > 0.05$ are excluded from the final model

Fitted terms	*d.f.*	*Sum of squares*	*Mean square*	*Variance ratio*	*p*
+ year	7	88.1813	12.5973	52.87	< 0.001
+ month	11	93.8213	8.5292	35.80	< 0.001
+ vessel code	79	289.4629	3.6641	15.38	< 0.001
+ log (livebait)	1	309.4097	309.4097	1298.58	< 0.001
+ log (HP)	1	0.0393	0.0393	0.17	0.685
+ log (GRT)	1	0.0698	0.0698	0.29	0.588
+ log (day fished)	1	10.0564	10.0564	42.21	< 0.001
+ log (vessel age)	1	0.1275	0.1275	0.54	0.465
+ year*month	77	219.4855	2.8505	11.96	< 0.001
Residual	3367	802.2483	0.2383		
Total	3546	1812.9020	0.5113		

Table 4
Analysis of variance of Sorong pole-and-line data using scenario 2. Factors or covariates with $p > 0.05$ are excluded from the final model

Fitted terms	*d.f.*	*Sum of squares*	*Mean square*	*Variance ratio*	*p*
+ year	24	637.9316	26.5805	112.18	< 0.001
+ month	11	180.6967	16.4270	69.33	< 0.001
+ vessel code	126	726.7095	5.7675	24.34	< 0.001
+ log (livebait)	1	973.4343	973.4343	4108.37	< 0.001
+ log (HP)	1	3.1682	3.1682	13.37	< 0.001
+ log (GRT)	1	0.1899	0.1899	0.80	0.371
+ log (day fished)	1	5.3477	5.3477	22.57	< 0.001
+ log (vessel age)	1	1.2853	1.2853	5.42	0.020
+ year*month	261	652.4770	2.4999	10.55	< 0.001
Residual	8623	2043.1294	0.2369		
Total	9050	5224.3696	0.5773		

Table 5
Analysis of variance of Sorong pole-and-line data using scenario 3. Factors or covariates with $p > 0.05$ are excluded from the final model

Fitted terms	*d.f.*	*Sum of squares*	*Mean square*	*Variance ratio*	*p*
+ year	24	561.5282	23.3970	98.75	< 0.001
+ month	11	180.6967	16.4270	69.33	< 0.001
+ vessel code	126	726.7095	5.7675	24.34	< 0.001
+ log (livebait)	1	973.4343	973.4343	4108.37	< 0.001
+ log (HP)	1	3.1682	3.1682	13.37	< 0.001
+ log (GRT)	1	0.1899	0.1899	0.80	0.371
+ log (day fished)	1	5.3477	5.3477	22.57	< 0.001
+ log (vessel age)	1	1.2853	1.2853	5.42	0.020
+ year*month	261	652.4770	2.4999	10.55	< 0.001
Residual	8623	2043.1294	0.2369		
Total	9050	5147.9662	0.5688		

Table 6

Analysis of variance of Sorong pole-and-line data using scenario 4. Factors or covariates with $p > 0.05$ are excluded from the final model

Fitted terms	*d.f.*	*Sum of squares*	*Mean square*	*Variance ratio*	*p*
+ year	24	442.5007	18.4375	77.82	< 0.001
+ month	11	180.6967	16.4270	69.33	< 0.001
+ vessel code	126	726.7095	5.7675	24.34	< 0.001
+ log (livebait)	1	973.4343	973.4343	4108.37	< 0.001
+ log (HP)	1	3.1682	3.1682	13.37	< 0.001
+ log (GRT)	1	0.1899	0.1899	0.80	0.371
+ log (day fished)	1	5.3477	5.3477	22.57	< 0.001
+ log (vessel age)	1	1.2853	1.2853	5.42	0.020
+ year*month	261	652.4770	2.4999	10.55	< 0.001
Residual	8623	2043.1294	0.2369		
Total	9050	5028.9387	0.5557		

Table 7

Analysis of variance of Sorong pole-and-line data using scenario 5. Factors or covariates with $p > 0.05$ are excluded from the final model

Fitted terms	*d.f.*	*Sum of squares*	*Mean square*	*Variance ratio*	*p*
+ year	24	330.3423	13.7643	58.09	< 0.001
+ month	11	180.6967	16.4270	69.33	< 0.001
+ vessel code	126	726.7095	5.7675	24.34	< 0.001
+ log (livebait)	1	973.4343	973.4343	4108.37	< 0.001
+ log (HP)	1	3.1682	3.1682	13.37	< 0.001
+ log (GRT)	1	0.1899	0.1899	0.80	0.371
+ log (day fished)	1	5.3477	5.3477	22.57	< 0.001
+ log (vessel age)	1	1.2853	1.2853	5.42	0.020
+ year*month	261	652.4770	2.4999	10.55	< 0.001
Residual	8623	2043.1294	0.2369		
Total	9050	4916.7803	0.5433		

Based on the variance analyses, variables that were insignificant affected the CPUE were not included in the final models. Therefore, for scenario 1, only year, month, vessel code, log(livebait), log(day fished), and year.month were chosen to be included in the GLM model for standardization of CPUE period 1993-2000. For scenarios 2-5, the variables included in the standardization models were year, month, vessel code, log(HP), log(livebait), log(day fished), log(vessel age) and year*month.

In order to justify the inclusion of year*month interaction in the models, the AIC value for each model was presented in Table 8. The AIC values for model with the interaction show considerable lower than that for models without the interaction. The difference of AIC values for the model using scenario 1 was 702. AIC values for the models with year*month interaction by using scenarios 2-5 was 1986 lower than without the interaction. Consequently, year*month interaction was included in the final models for CPUE standardization of Sorong data by using the scenario 1-5.

Table 8

Comparison of AIC values for CPUE standardization models of Sorong pole-and-line fishery data for scenario 1 using model with and without year*month interaction and for scenarios 2-5 using model with and without year*month interaction. Model with lower AIC value was considered better fit to the data

Scenario	*Model*	*AIC*
1	year + month + vesselcode + log(live bait) + log(day fished) + year*month	24075
	year + month + vesselcode + log(live bait) + log(day fished)	24779
2 - 5	year+month+vesselcode+log(live bait)+log(HP)+log(day fished)+log(vessel age)+year*month	69844
	year+month+vesselcode+ log(live bait)+log(HP)+log(day fished)+log(vessel age)	71830

Standardization of CPUE was a method in analyzing catch and effort data in order to eliminate factors other than fish abundance which affected variation of CPUE (Hinton & Maunder 2003); thereby the standardized CPUE can be used as index of abundance (Maunder & Punt 2004). Factors influencing CPUE are very complex as stated by (Maunder & Langley 2004): "*These include environmental factors (e.g. temperature), fishing methods (e.g. trawl versus longline), fishing equipment (e.g. the use of sonar), fisher behavior (e.g. experience), management (e.g. the introduction of a quota management system), and economic factors (e.g. the price of fuel).*"

In the present study, I have used GLMs to identify factors that influenced variation of CPUE of Sorong pole-and-line. Due to data limitation, not all influencing factors described above enable to be included in the standardization models. Factors that were identified to affect Sorong pole-and-line CPUE included year, month, live bait, fishing day, engine power (HP) and vessel age. Surprisingly, the vessel size (GRT) was not significantly affected CPUE, as vessel with larger GRT can provide larger capacity for live bait and crews. Moreover, it can enable to reach further fishing ground. However, it was not the case for Sorong pole-and-line. A larger vessel did not always carry a larger amount of live bait, since it depended on availability of live bait caught by live bait fishery. Also, a larger vessel size did not always carry significantly larger crew number, as shown by Sala (1999) by using 1997 data; crew number was 23-26. Furthermore, since the fishing grounds of the pole-and-line were only confined inside the Indonesian territorial waters and had to be closed to fishing grounds of live bait, all the pole-and-line vessels which were size larger than 30 GRT were capable to reach the skipjack fishing grounds.

However, neither GRT, HP, nor vessel age statistically explained the variation of CPUE when using data 1993-2000 (scenario 1). This may be due to nature of data during that period in which vessel size and main power became unimportant factors in determining the success in fishing with pole-and-line in that area. This needs further investigation for its explanation. Insignificance of vessel age effect may be because the pole-and-liners during the period were mostly dominated by vessels that were at ages between 1 and 15 years old, which were still within their technical efficiency ages, 7 to 15 years (McElroy & Uktolseja 1992). This was in contrast to 1976-2000 data where some of vessels were at ages 16-17 years old.

The existence of year*month interaction in models explained that seasonal (monthly) variation of CPUE in one year differed from another year; it would be hard to expect that fishing season of skipjack would be the same from year to year. This could be caused by inconsistency in the recruitment season/spawning season or other factors. However, there was not enough information available to explain this phenomenon.

From the variance analyses for all models, it was clearly shown that live bait was a very important factor in determining a success in pole-and-line fishery. This of course has to be also considered in the management of skipjack fishery if pole-and-line fishery is maintain to exist; management development of pole-and-line fishery has to be together with the development of livebait fishery.

Evaluations of model assumptions were done by examining model residuals, as presented in Figure 3. I only presented residuals plots for scenario 5 which used 30% level of FAD effect since residuals plots for other scenarios followed the same patterns. In general, the two figures suggested that the models sufficiently described the data. Histogram plots of residuals [Figure 3(A)] showed normal pattern even though normality plots showed curvature [Figure 3(C)]. This may due to the log-transformed CPUE data were slightly skew (Figure 2). However, the curvature of the normality was not severe, so the normal assumption of the models was still satisfied. Finally, there was no evidence that the model variance was not constant [(Figure 3(B)].

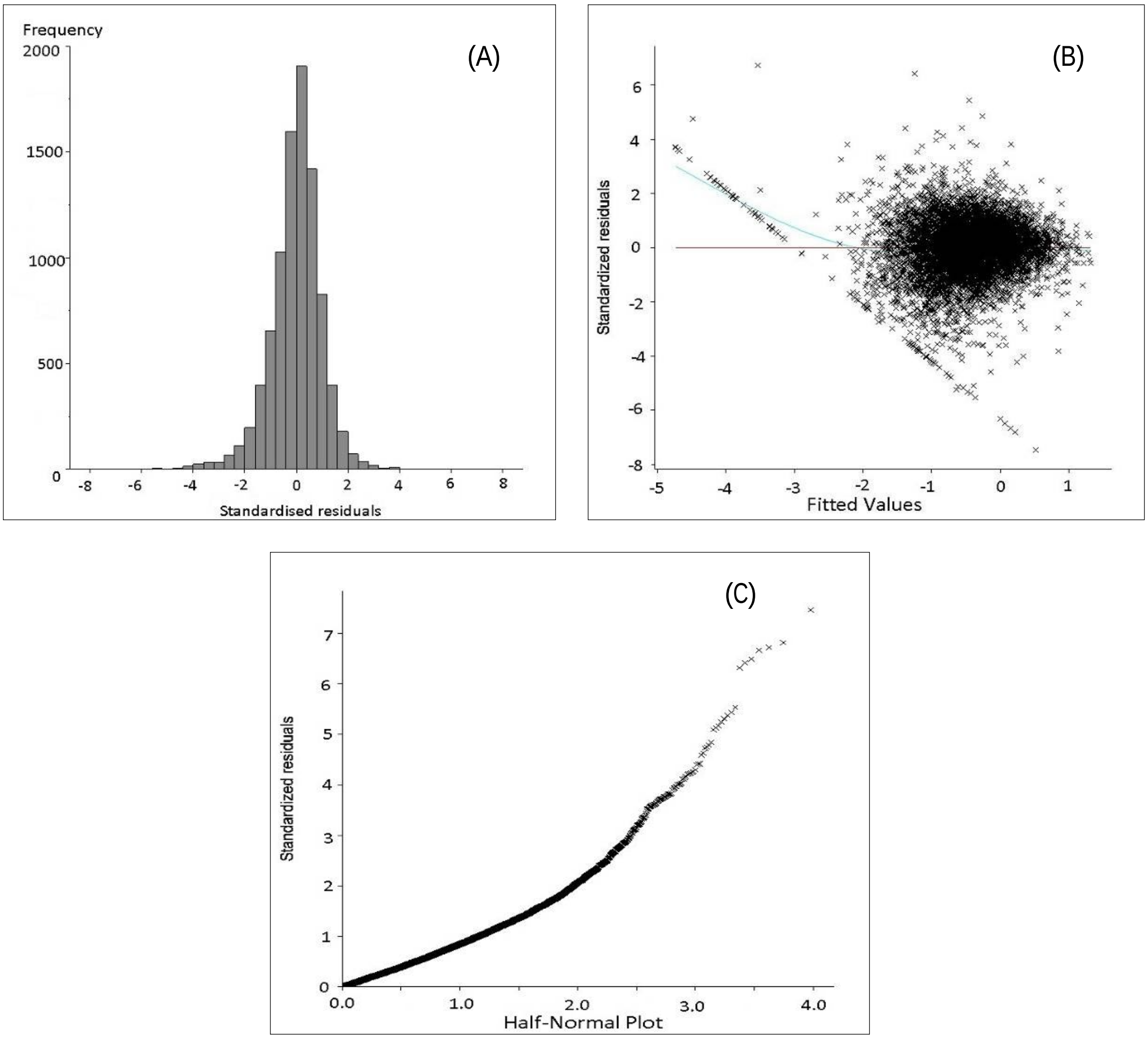


Figure 3. Standardised residuals of general linear model (normal distribution) of Sorong pole-and-line data (scenario 5). (A) normal distribution of residuals; (B) no pattern of plot of standardized residuals against predicted log(CPUE); and (C) normality plot.

Standardized CPUE. Process of fitting GLM models to catch and effort data of Sorong pole-and-line fishery by using some chosen variables as previous explained, had resulted in the estimates of standardized CPUE that were assumed proportional to relative of abundance of skipjack. Parameters of GLMs estimated through some fitting process of the models to the data of catch and effort of Sorong pole-and-line then were used as inputs for estimation of standardized CPUE by using formula (5). The results of CPUE standardization for 5 scenarios of Sorong pole-and-line catch and effort data were shown in Figure 4. For scenario 1, the data started from 1993 to 2000, the standardized CPUE showed a decreasing trend relative to 1993. Even though there was slightly increased in

the CPUE in 1995 and 1996 compared to 1994, it still continued to go down afterwards; the CPUE in 2000 was only 46% of CPUE in 1993.
The estimates of standardized CPUE for scenarios 2 to 5 fluctuated in a similar pattern [Figure 4(b) – Figure 4(e)]; the CPUE during period 1976-1985 (i.e. period before the use of FADs) in average showed no clear trend of increase or decrease. Nevertheless, the trend of decrease was obvious after 1985 (i.e. period where FADs were used).

Standardized CPUE generated by using GLMs models described above showed interesting patterns. This particularly occurred for Sorong pole-and-line CPUE. Since data for the pole-and-line covered data periods before the use of FADs and after the use of FADs, it was possible to study how FADs may affect the CPUE by using various scenarios representing levels of FAD effect. The higher level of FAD effect led to higher standardized CPUE during periods before FADs were used. However, there was no supporting information available that can be used to estimate accurately the level of FADs effect. Also, there was no estimate of skipjack abundance available for the study area by using fishery independent data which can be used as a comparison. Therefore, when using the standardized CPUE estimated through the present study as index of abundance, one needs to consider the assumed level of FADs effect. Another finding, there was a constant decrease in standardized CPUE during period 1985-2000 (i.e. the period when FADs were used). If the standardized CPUE was proportional to relative index of abundance, it indicated that skipjack abundance in the fishing grounds of Sorong pole-and-line fishery was decreasing. Further investigation by using more recent data is needed to detect whether this trend continues to happen. Also, management of the fishery is required in order to sustain the skipjack stock.

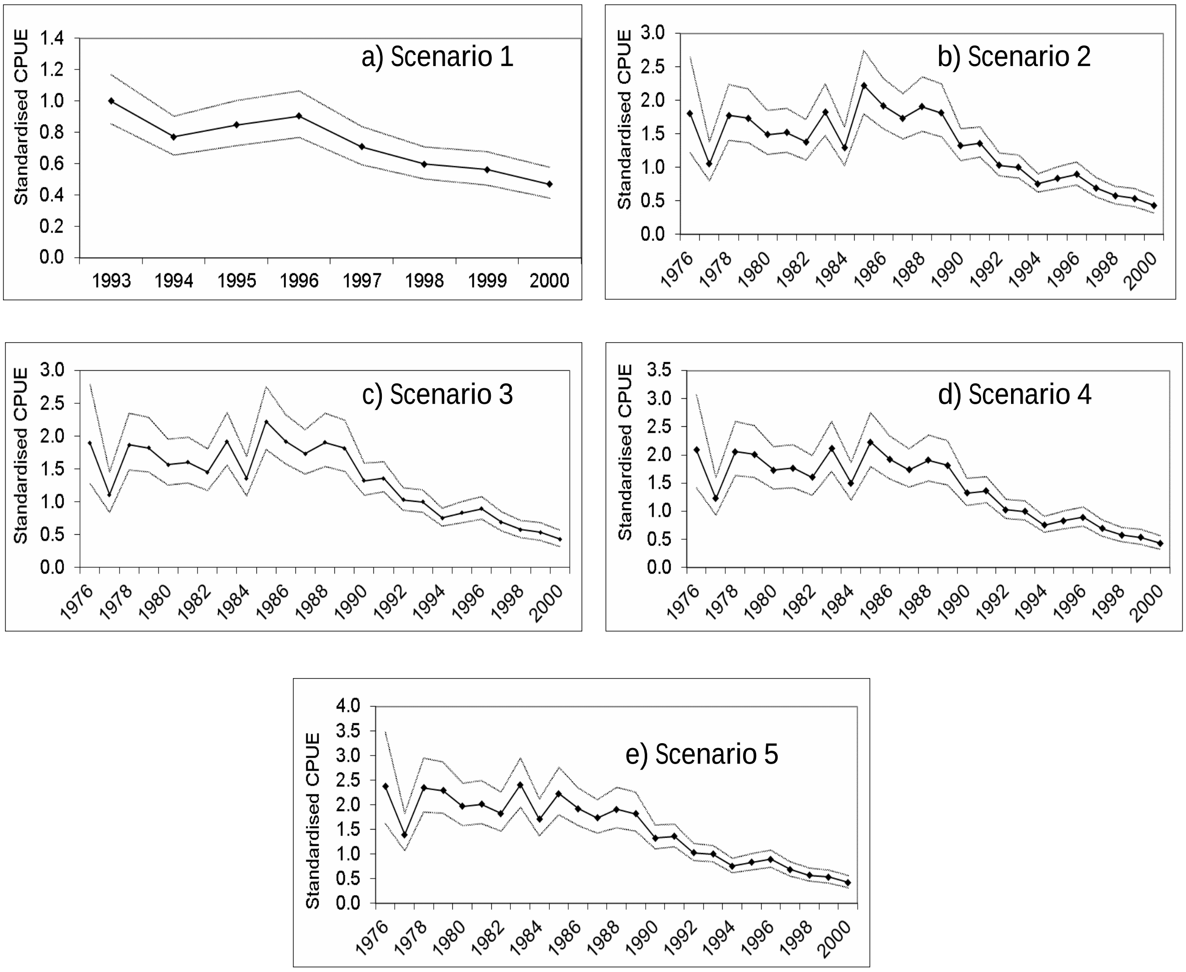


Figure 4. Standardized CPUE with 95% confidence intervals for Sorong pole-and-line fishery estimated based on 5 scenarios. The CPUE in 1993 was set to 1 in order to enable comparison among the scenarios.

I have used robust method to analyze catch and effort data in order to generate standardized CPUE as index of abundance. Hyperstability (i.e. condition where CPUE remains high even fish abundance decreases) may be reduced through the standardization, especially for the analyses of Sorong data, as there was a decreasing trend of the standardized CPUE even though the un-strandardized (nominal) CPUE remained stable. However, the present study can still be improved in several ways when the following data and information are made available. Firstly, records of fishing activity including catch and effort which are recorded separately between fishing fish shoals around FADs and fishing free swimming fish shoals. This can be very useful for getting better estimates of FADs effect on catch or CPUE. Secondly, records of geographical locations of fishing activity. When such data are available, it is possible to stratify data into small areas; thereby random distribution of catch and effort data would be more likely met and hyperstability could be reduced (Hilborn & Walter 1992). Finally, records of crew (including fishing master) characteristics (such as age, experiences, etc.) if made available and incorporated into the standardization models would enable to capture fishing efficiency due to fisherman skills.

Conclusions. The results of series analyses in order to construct standardized CPUE that is assumed proportional to skipjack abundance reveals that the variation of CPUE of pole-and-line fishery were influenced by year, month, live bait and fishing day. Vessel characteristics, main engine power (HP) also contributed to the CPUE variation.

Scenarios of various level of FAD effect on CPUE of Sorong pole-and-line showed that the higher level of FAD effect led to higher standardized CPUE for a period before the use of FADs. Furthermore, there was a trend of continuous decrease in standardized CPUE during period where FADs used in 1985 to early of 2000. This implied that there was tendency of decrease in skipjack abundance in the area. At last, further study by using finer spatial scale and more data and information is still needed in order to improve the results of the present study.

Acknowledgements. I would like to thank to the owners and staff of PT. Usaha Mina Sorong, PT. Ramoi, and PT. Karya Teknik Utama for allowing the author to have access to part or whole data and information available at the companies. Thanks also to pole-and-liners' crews for providing data and information during the survey. Lastly, I appreciate support and help from local governments (*Dinas Kelautan dan Perikanan Kabupaten*) of Sorong during the survey.

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Received: 08 April 2017. Accepted: 05 June 2017. Published online: 10 June 2017.
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How to cite this article:
Sala R., 2017 Relative abundance of skipjack tuna (*Katsuwonus pelamis* L.) in waters around Sorong and Fak-Fak, West Papua, Indonesia. AACL Bioflux 10(3):551-564.