

Application of Fishery-independent Data as an Alternative Source for Determining Relative Abundance Indices of Blue Marlin, *Makaira nigricans* (Actinopterygii: Perciformes: Istiophoridae) in the North-eastern Indian Ocean

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Abstract

The present study aimed to determine the abundance index of blue marlin, *Makaira nigricans* (Lacepède, 1802) utilizing fishery-independent data, i.e., scientific observer, and attempted to bridge the research's gap for low coverage information in the northeastern Indian Ocean. A total of 2,984 set-by-set observer data from 2006-2018, spatially disaggregated by one-degree blocks, were obtained from the Indonesian scientific observer program following commercial longline fleets. A delta-lognormal model was chosen to fit the dataset, using catch as the response variable with seven covariates. A backward procedure based on AIC, BIC and R^2 were used to select the best model. Overall, the delta-Gamma performs better when modelling data with a high proportion of zeros than other traditional models. The blue marlin CPUE trend is relatively stable over time, despite the inter-annual fluctuations, which are likely a result of natural variation in the population as opposed to operational changes or inter-annual environmental variation. Given the low spatial coverage compared to logbook data, scientific observer data performed well and produced a robust abundance index of blue marlin in the northeastern Indian Ocean.

Introduction

Relative indices of abundance, such as catch-per-unit-effort (CPUE), are generally developed from fishery-dependent data (e.g., logbook data), which is considered to be a reliable source (Carruthers et al., 2011; Fonteneau & Richard, 2003; Maunder & Punt, 2004). However, fleet-specific behaviour and changes thereof complicates the development of abundance indices. In such cases, expert knowledge regarding changes in fleet dynamics and how such changes may influence the logbook data received by scientists is paramount to developing indices that accurately depict true fish abundance.

In the case of Indonesian tuna and tuna-like fisheries, establishing fishery-dependent data to model the relative abundance indices is still a major challenge. Although the Ministry of Marine Affairs and Fisheries (MMAF) reiterated the obligation of logbook data collection, especially for tuna longline fleets in 2010 (Sunoko & Huang, 2014), low compliance from fishers means this data has failed to capture the fisheries dynamics. Despite improvements having been made, such as the introduction of electronic form of logbook in early 2014 (Nugroho et al., 2017), the level of coverage remains below 10% (Geehan, 2018) and the data would not be adequate for analysis until it reaches the level of consistency for an extended time.

Therefore, finding an alternative data source is essential, considering the importance of Indonesian tuna and tuna-like fisheries in the northeastern Indian Ocean. In 2005 a joint research initiative between Indonesia and Australia (ACIAR Project FIS/2002/074) initiated a trial of scientific observer program for the Indonesian tuna longline fishery (Proctor et al., 2011), which the Research Institute subsequently adopted for Tuna Fisheries (RITF) in 2011. The program initially intended to provide information additional to logbook data but has become the primary source information for modelling the abundance of tuna and tuna-like species, especially for marlins species (Hartaty, Setyadji, & Fahmi, 2019; Hartaty, Setyadji, Nishida, et al., 2019; Jatmiko et al., 2019; Rochman et al., 2017; Setyadji, Andrade, et al., 2018; Setyadji & Fahmi, 2020).

Blue marlin *Makaira nigricans* (Lacépède, 1802) was chosen as the specific interest as it is considered a vital non-target species from industrial and artisanal fisheries worldwide. The total reported global catch exceeded 38,000 tons in 2013, wherein the most significant proportion (~95%) was harvested from the Pacific and Indian oceans. Less than 5% came from the Atlantic Ocean (Chen et al., 2016). In the Indian Ocean, the catch trend has steadily increased since the 1980s, with longline fisheries accounting for most catch (70%), followed by gillnet and troll/hand line (IOTC-WPB17, 2019). Previously, the contribution from the Indonesian fleet during the period 2013-2017 was thought to be around 30% (~3,900 tons) of the total catch in the Indian Ocean, ranked second after the Taiwanese fleet (IOTC-WPB16, 2018). However, these catches were revised to ~865 MT (9%) to refine the methodology to estimate catch (IOTC-WPDCS14, 2018).

Blue marlin stocks are overexploited (ICCAT, 2018; IOTC-WPB17, 2019; ISC, 2016; Pons et al., 2017). The

2019 assessment of the Indian Ocean blue marlin stock strongly indicated the stock was overfished and subject to overfishing (IOTC-WPB17 2019). Assessment predictions advised a high probability (>80%) of violating the MSY-based reference points in the following ten years if the high catch levels were maintained (IOTC-WPB17, 2019). However, uncertainty in abundance indices and nominal catches, especially in the northeastern Indian Ocean where the Indonesian longline fleet traditionally operated, was identified as a concern when evaluating the stock status based on the applied assessment approaches.

The northeastern Indian Ocean is a productive fishing area concerning blue marlin catches but is often poorly represented in their assessment due to the low coverage of catch data. This study aims to address this by producing a blue marlin abundance index for the region using fishery-independent data from the Indonesian Observer Program. Such an index would undoubtedly help assess the stock of blue marlin, which is a vital fishery resource in the Indian Ocean.

Materials and Methods

At the highest spatial resolution, a total of 2,984 shot by shot catch and effort data from January 2006 to December 2018 were obtained from the Indonesian scientific observer programme, which covers commercial tuna longline vessels. The length of fishing trips ranged from three weeks to three months. The main fishing grounds cover the western and southern part of Indonesian waters, extending from 75°E to 35°S (Figure 1). The catch rate was expressed as the number of blue marlins caught per 1000 hooks. In addition, to catch and effort information, each daily record also included temporal (year and month) and spatial

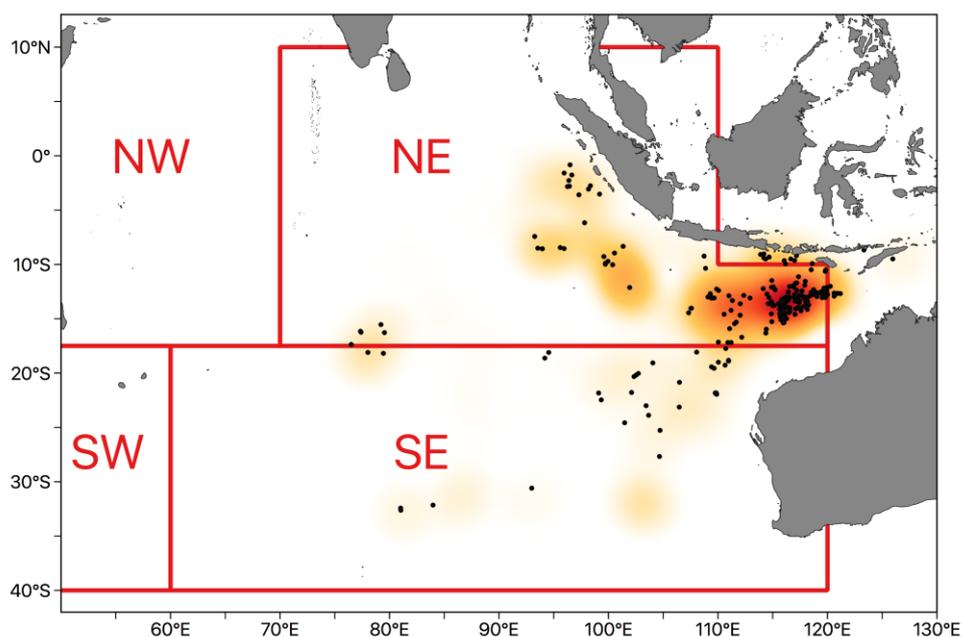


Figure 1. Map of the fishing area where the observer data were collected. After filtering the data, the northeastern (NE) area was the only area used for analysis.

information (latitude and longitude) based on where the set is commenced. The covariates included in the analyses were selected based on their likely impact on the catch-rate of blue marlin, as recorded by previous studies (Fonteneau & Richard, 2003; Yokoi et al., 2016; Zhou et al., 2019). These covariates are *Year*, *Quarter*, *Number of Hooks Between Floats (HBF)*, *Soak Time*, *Start Set*, and *Moon Phase*. Both *Year* and *Quarter* were used as categorical (factor) explanatory variables. *HBF* was set as continuous instead of categorical since both approaches resulted in similar results (Setyadji & Fahmi, 2020).

On the other hand, *Soak time* was calculated as the time elapsed between the start of the longline setting and the beginning of hauling off the longline and rounded to the nearest integer, and also set as a continuous variable. *Start Set* was included in the model to account for diurnal variation in fishing. *Moon Phase*, introduced as a daily (where the set is commenced) index of moon fraction between 0 (new moon) and 1 (full moon), was calculated using a lunar package (Lazaridis, 2014). To account for the effect of cyclic behaviour, the *Moon Phase* was defined by the following function (Sadiyah et al., 2012):

$$Moon = \sin(2\pi \times moon\ phase) + \cos(2\pi \times moon\ phase) - 1$$

Data Filtering

Catch data for billfishes from the Indonesian tuna longline fishery inherently has a high proportion of zero-catch-per-set occurrence (Setyadji, Andrade, et al., 2018). It was acknowledged that the predominance of zero catches could be driving the previous model outputs as the CPUE trends do not appear to be biologically plausible (IOTC-WPB16, 2018). Initially, the mean annual proportion of zero catches from the data was approximately 91%. In an attempt to reduce it, three filters were applied to the data:

1. Data collected in 2005 were excluded from analysis, as it was the beginning of the trial scientific observer program and therefore it might contain species misidentification;

2. Spatial coverage of the scientific observer data, from the northeastern to the southeastern Indian Ocean, ranged from 0°-33° S and 75°-129° E (Figure 1). However, the temporal coverage was not completed for the data collected in the southern areas. Moreover, the positive sets for blue marlin were concentrated in the northeastern region. Therefore, the data used for analysis was limited to the area north of 17.5° S or northeastern area (NE) according to the IOTC statistical areas applied to swordfish (Nishida & Wang, 2006) (Figure 1);
3. Data were subset only to include trips where one or more blue marlin was caught.

Modelling Approach

Previous studies suggested that although conventional model distributions such as Poisson, negative binomial, zero-inflated, and hurdle could be used for modelling zero-inflated catch data, caution should be applied when interpreting the model outputs (Jatmiko et al., 2017; Setyadji, Andrade, et al., 2018; Setyadji et al., 2017). Therefore, a generalized linear model (GLM) with an assumed delta-gamma distribution was applied to standardize the blue marlin CPUE from the Indonesian tuna longline fishery. Since it has been proven better to model by-catch species, i.e. marlins, catch data usually consist of a high proportion of zeros (Campbell et al., 2017; Wang, 2018).

The model was run with the following variables: *Year*, *Quarter*, *HBF*, *Moon*, *Soak Time* and *Start Set*. To avoid overfitting, no interactions among variables were included. Therefore, the gamma and delta components of the GLM were conducted as follows:

Gamma model for CPUE of positive catch:

$$\log(CPUE) = \mu + Year + Quarter + HBF + Moon + Soak\ Time + Start\ Set + \epsilon^{gamma} \tag{2}$$

Delta model for presence and absence of catch:

$$P/A = \mu + Year + Quarter + HBF + Moon + Soak\ Time + Start\ Set + \epsilon^{del} \tag{3}$$

Table 1. Probability models and hypotheses about the capture probability of catch (*P*) for CPUE standardization, including the probability mass or density function for the catch, and the hypothesis about nominal catches, for the negative binomial, zero-inflated negative binomial, Tweedie and delta-Gamma distributions (Rose et al., 2006; Saffari et al., 2012; Walsh & Brodziak, 2014).

Probability model	Probability function	Hypothesis
Negative Binomial	$P(Y = y) = \frac{\Gamma(y+1/a)}{\Gamma(y+1)\Gamma(1/a)} \cdot \frac{(a\mu)^y}{(1+a\mu)^{y+1/a}}$	Nominal catches are overdispersed
Zero-inflated Negative Binomial	$P(Y = y) = \begin{cases} p + (1-p) \frac{1}{(1+a\mu)^{1/a}} & y = 0 \\ (1-p) \frac{\Gamma(y+1/a)}{\Gamma(y+1)\Gamma(1/a)} \cdot \frac{\alpha\mu^y}{(1+\alpha\mu)^{y+1/a}} & y > 0 \end{cases}$	Nominal catches are overdispersed with an excess of zeros
Tweedie	$P(Y: \mu, \sigma^2, p) = a(y: \mu, \sigma^2, p) \exp\left\{-\frac{1}{2\sigma^2} d(y: \mu, p)\right\}$ $P(Y = 0) = 1 - p$	Nominal catches are overdispersed with an excess of zeros
Delta-Gamma	$P(Y = y y > 0) = p \times \left(\frac{\lambda^\alpha y^{\alpha-1} \times \exp(-\lambda y)}{\Gamma(\alpha)}\right)$	Nominal catches are either overdispersed or under dispersed

We applied a stepwise approach for model selection, starting with a null model and incorporating variables one at a time and only selecting the variable that produced the lowest model residual deviance. This approach was repeated until model residual deviance did not decrease as new variables were added. Finally, explanatory variables were selected through a backward procedure based on Akaike Information Criterion (AIC) (Akaike, 1974), Bayesian Information Criterion (BIC) (Schwarz, 1978) and the values of the coefficient of determination (R^2). Results from models with alternative error distributions, such as Tweedie, zero-inflated negative binomial, and simple negative binomial were also considered in this study for comparative purposes (Table 1).

The area-specific standardized CPUE trends were estimated based on the exponent of the year's adjusted means (least-square means) effects (Butterworth, 1996; Maunder & Punt, 2004). The standardized relative abundance index was calculated by the product of the standardized CPUE of positive catches and the standardized probability of positive catches:

$$index = e^{\log(CPUE)} \left(\frac{e^{\bar{P}}}{1 + e^{\bar{P}}} \right) \quad 4)$$

Where $CPUE$ is the adjusting means (least-square means) of the year effect of the gamma model and \bar{P} is the adjusted means (least-square means) of the year effect of the delta model.

Maps were produced using QGIS version 3.11 (QGIS Developer Team, 2020) and the statistical analyses were carried out using R software version 3.6.0 (R Core Team, 2018).

Results

Before data filtering, the initial combined dataset contained 112 trips, 2,984 sets, and almost 4 million hooks deployed. Post filtering procedures, the number of trips approximately halved. The mean observed sets deployed was 101.1 (45.8) per year or 21.4 (6.8) per trip. The total number of hooks observed was 1.6 million, with approximately 1200 hooks deployed every set using a configuration of 11 or more hooks between floats (Table 2). As a result of applying data filtering, the proportion of zero-catch-per-set decreased by 6%.

In general, the nominal catches of blue marlin from the tropical areas have been relatively stable since 2006, except in 2012 when catches were notably high (0.44 (0.09)) fish per 1000 hooks) (Figure 2). The positive

Table 2. Summary of the annual observed fishing effort from the Indonesian tuna longline fishery for 2006–2018 (post-filtering). Values represented in means and standard error showed in parenthesis.

Year	Trips	Sets	Total Hooks	Hooks per Set		Hooks per Float	
2006	8	153	220,432	1,391.6	(21.18)	11.8	(0.06)
2007	3	41	66,577	1,522.5	(35.29)	16.1	(0.04)
2008	8	155	182,583	1,389.6	(23.12)	11.6	(0.03)
2009	5	154	181,911	1,199.2	(10.22)	11.4	(0.00)
2010	6	119	151,787	1,242.0	(20.39)	12.7	(0.11)
2011	3	105	110,384	1,046.2	(18.03)	12.0	(0.00)
2012	4	69	76,008	1,263.2	(25.38)	12.8	(0.00)
2013	6	163	176,456	1,112.7	(13.36)	12.1	(0.08)
2014	5	65	74,779	1,222.6	(11.38)	14.2	(0.01)
2015	2	32	40,261	1,161.1	(15.25)	12.9	(0.25)
2016	3	88	109,064	1,222.1	(10.87)	12.7	(0.09)
2017	4	60	65,348	996.4	(15.66)	13.8	(0.03)
2018	5	110	144,764	1,308.2	(15.93)	14.8	(0.13)

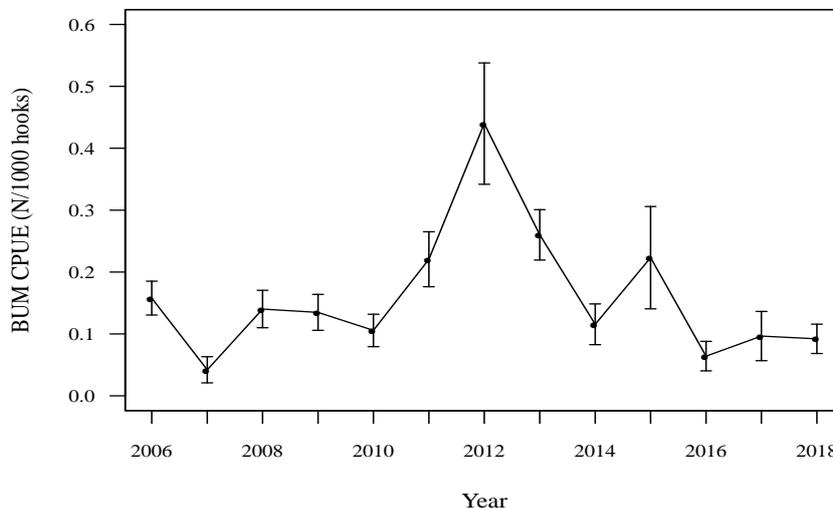


Figure 2. Nominal CPUE series (N/1000 hooks) for blue marlin caught in the Indonesian tuna longline fleet from 2006 to 2018. Vertical bars refer to the standard errors.

anomaly in that particular year is thought to result from data filtering procedures, which caused deletion on some trips without blue marlin catch. Hence the remaining data consist of fortunately high catch at relatively low effort, which caused the spike instead of changes in true abundance. The lowest CPUE recorded was in 2007 (0.042 (0.02)) with average 0.16 (0.04) per year. The proportion of zero catch sets varied annually between 71.01% in 2012 and 93.70% in 2016, with an average value of 85.24% (Figure 3).

All retained effects were statistically significant, except for *Moon Phase*. *Soak Time* was excluded from both models as it had negligible influence. The deviance tables for selected Gamma models are shown in Table 3. The results indicated that *Year* was the most influential variable when modelling the positive catch of blue marlin, followed by targeting (*HBF*), season (*Quarter*) (Table 3). *Moon Phase* and *Start Set* were shown to have

little effect on positive catches. As for the delta model, the results were quite similar, with *year* again proving to be the most crucial factor (Table 4). However, unlike the gamma model, the *start set* had considerable influence contributing to the probability of successful capture.

A comparison of standardized CPUE trends for the period 2006 - 2018, as calculated using delta-gamma (DELTA), negative binomial (NB), zero-inflated negative binomial (ZINB) and Tweedie (TWEEDIE) models, produced relatively similar outputs (Figure 4). In general, the trend is stable from 2006-2010, increases drastically after that and peaks in 2012, after which it decreases again. The DELTA model produced a smoother trend with better model performance and was chosen as it is likely to better account for the high proportion of zero catches in the data (Figure 5 and Table 5).

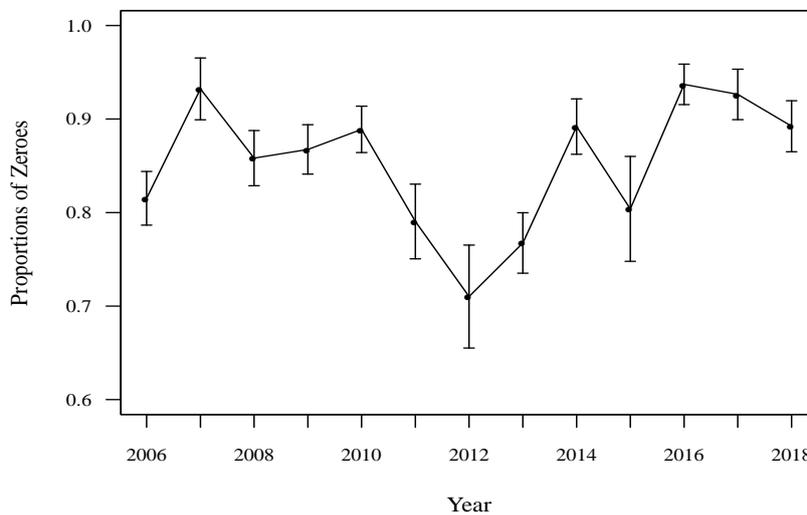


Figure 3. The proportion of zero blue marlin catches observed from the Indonesian tuna longline fleet for 2006 - 2018. Vertical bars refer to the standard errors.

Table 3. Deviance table documenting the relative importance of the explanatory variables included in the gamma model

Variable	Df	Deviance Resid.	Df. Resid.	Deviance	F	Pr(>F)
NULL			230	39.376		
Year	12	6.790	218	32.586	3.4886	0.0001018 ***
Quarter	3	1.709	215	30.877	3.5125	0.0161207 *
HBF	1	1.224	214	29.653	7.5447	0.0065364 **
Moon	1	0.467	213	29.186	2.8812	0.0910855 .
Start_Set	1	0.606	212	28.580	3.7389	0.0544919 .

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Table 4. Deviance table documenting the relative importance of the explanatory variables included in the delta model

Variable	Df	Deviance Resid.	Df. Resid.	Deviance	Pr(>F)
NULL			1571	1312.2	
Year	12	46.328	1559	1265.9	0.00006 ***
Quarter	3	8.774	1556	1257.1	0.03245 *
HBF	1	5.542	1555	1251.6	0.01857 *
Moon	1	2.247	1554	1249.3	0.13388
Start_Set	1	4.235	1553	1245.1	0.03960 *

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

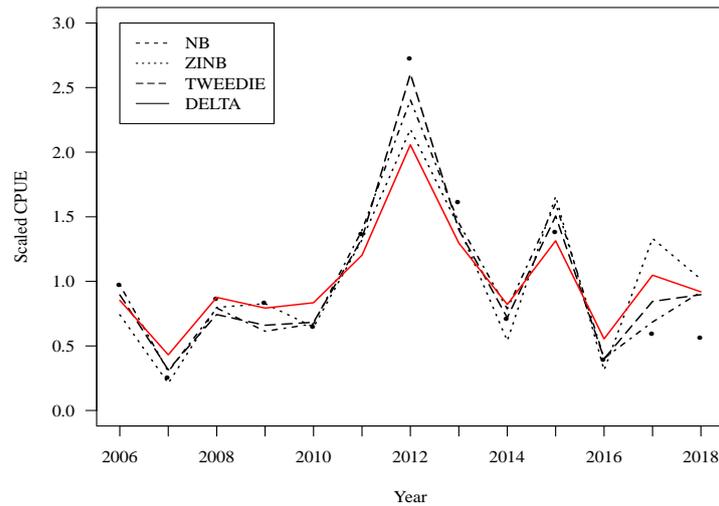


Figure 4. Standardized catch per unit effort (CPUE) of blue marlin caught in the Indonesian tuna longline fleet for 2006-2018, calculated using various models. The values were normalized by dividing by their means for comparison purposes.

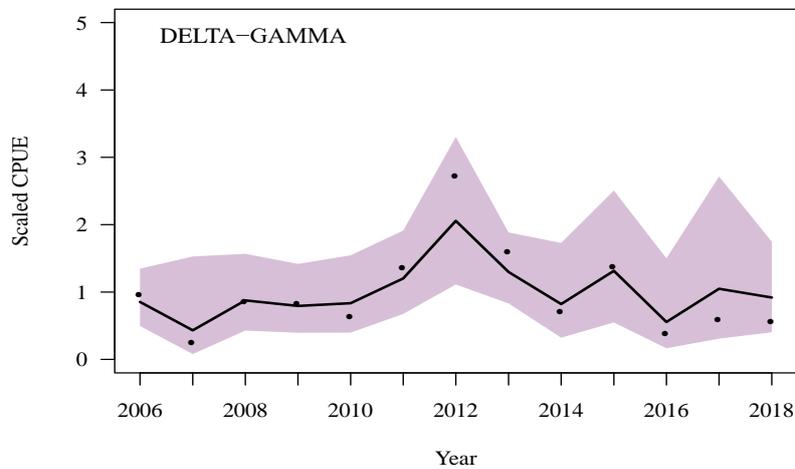


Figure 5. Final standardized catch per unit effort (CPUE) of blue marlin caught in the Indonesian tuna longline fleet for 2006 – 2018, calculated using a delta-gamma model with 95% confidence interval (greyed area). The values were normalized by dividing by their means for comparison purposes.

Table 5. Summary of indicators as calculated using four model structures: Tweedie (TWEEDIE), Negative Binomial (NB), Zero-inflated with Negative Binomial (ZINB), Delta-lognormal (DELTA). The terms in the column at left indicate Akaike (AIC), Bayesian Information Criteria (BIC), and R²

Indicators	TW	NB	ZINB	DELTA	
				Gamma	Delta
AIC	1962.38	1513.51	1529.42	200.73	1283.10
BIC	1922.38	1620.71	1722.38	269.58	1384.95
R ²	0.14	0.14	0.01	0.21	0.04

Discussion

Fisheries dependent data (e.g., logbook) is preferred information for deriving relative abundance indices for tuna and tuna-like fisheries. However, in Indonesia, constraints have limited the transmission of catch information from vessels to authorities. Low educational background and heavy reluctance from the skippers on sharing fisheries information has led to low acceptance of obligatory logbook submission in longline vessels (Geehan, 2018). Concern regarding data sharing (i.e., fishing ground) was likely the primary source

behind the refusal. Moreover, the skipper knowledge about common names or standard codes of fishes remains questionable, especially for by-catch species, leading to misidentification on some species with similar physiology (e.g., marlins).

On the other hand, scientific observer data provides more detailed information and a high level of confidence in the data since it is obtained from well-trained personal. However, it is inherently expensive, and invariably the quantity or coverage of data is much less than what is expected from logbook data, but the quality is generally much better. Therefore, It has been

extensively used to decrypt the catch and effort data from longline fisheries (Block et al., 2005; Huang & Liu, 2010; Teo & Block, 2010), especially for by-catch species which are usually not fully covered by logbook data. According to the IOTC, the minimum mandatory observer coverage for longline fleets is 5% of the total fishing effort (i.e., the total number of hooks) and does not require stratification by area, vessel or season. Therefore, each country's responsibility is to ensure that the data collected from national observer programs are sufficiently stratified to provide meaningful information. In this case, due to a strict budgeting policy, the level of Indonesian scientific observer coverage was less than 2% every year (Fahmi et al., 2020).

This study shows that, apart from the spatial limitation, the model performed well in characterizing the relative abundance of blue marlin. There was no apparent trend in catch rates, suggesting that the northeastern Indian Ocean blue marlin population has remained relatively stable for the period 2006-2018. However, this is a relatively short time series and the observed stability in the CPUE trend does not indicate a healthy population. More extended CPUE time series, such as those derived from the Japanese and Taiwanese longline fleets operating in the Indian Ocean, show an extended period of decline from 1979 until 2010 and then stabilizes (Taki et al., 2019; Wang, 2019). The most recent assessment of blue marlin in the Indian Ocean indicates that the stock is overfished and subject to overfishing. The catches of blue marlin would have to be reduced by approximately 35% (approx. 7,800 tons) to ensure sustainability (Parker et al., 2019). As mentioned earlier, the Indonesian CPUE information from this study was included in the stock and corroborated the recent stability observed in the Japanese and Taiwanese CPUE indices.

Further, the variation in abundance of blue marlin could also be driven by some oceanographic and socio-cultural phenomenon. A couple of studies found that the conditions of primary productivity strongly influence fish habitat in the southern part of Indonesian waters. Where it's strongly influenced by the sea-air interaction, significantly influenced by monsoon (Utamy et al., 2015), and the interannual ENSO and IOD (Ningsih et al., 2013; Susanto & Marra, 2005). For example, during 2006-2018, there were several coupling events between ENSO and IOD. Some of those events correlated with semi-permanent upwelling (June - October), which might influence the catch rate of billfish. However, such an assumption wasn't incorporated in this study. Hence an in-depth investigation is required for future research. In addition, the low catch rate of tuna and billfish in the southern waters of Java might be related to inadequate primary productivity Yu et al. (2015). Also, socio-cultural influence wherein particular month of the year, during the religious events the fishing activities were usually put on hold (Setyadji, Pranowo, et al., 2018).

The two-stage delta-GLM approach has been frequently used for modelling the relative abundance of

billfish species from longline fisheries (Walsh & Brodziak, 2014; Wang, 2019). It is recommended in cases where excessive zero catch occurrences are observed (Campbell et al., 2017). The first stage of the model incorporates the pattern of the event of positive catches, while the second phase models the mean size of the positive catch rates. Zero-inflated models are also expressed in two parts. Although conceptually may be more appropriate for modelling catch data of infrequently encountered species (Minami et al., 2007), the delta-Gamma model was considered more appropriate in this study than the zero-inflated and other traditional model structure (e.g., Tweedie, negative binomial). Apart from its ability to account for the high proportion of zero catches, the delta-Gamma was also better in handling the high nominal CPUE in 2012 and gave stability to the overall series without signs of overfitting, as shown in Walsh and Brodziak (2015). However, a higher level of uncertainty progressed towards the end of the data series, which remains a lingering issue. It is likely to result from low coverage of the dataset instead of the inconsistent catches. Low data coverage is a typical restraint for scientific observer data. It would take a substantial cost (approx. \$1,000,000/year) to comply with the minimum requirement (i.e., 5% coverage) from regional fisheries regulation. Improving the submission and quality of logbook data should be the main priority for Indonesian authorities while maintaining the continuity of the scientific observer program. Improving deployment stratification by common fishing ground, fleet and time of the year (e.g., quarterly) would result in a more representative dataset being obtained.

Conclusions

Overall, the Delta-gamma performs better when modelling data with a high proportion of zeros than other traditional models. The blue marlin CPUE trend is relatively stable over time, despite the inter-annual fluctuations, which are likely a result of natural variation in the population as opposed to operational changes or inter-annual environmental variation. The final model still possesses a high level of uncertainty and, therefore, can be further improved. Future research should focus on incorporating large-scale ecological data or habitat suitability information.

Ethical Statement

Not applicable.

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Author Contribution

B.S. and D.P. was contributed in sharing ideas, designed/re-designed and performed the initial statistical models, and draft the base paper. D.P. and S-P.W. were contributed in providing critical revision on the article, cross-checked the final statistical models, proofreading and providing final approval of the version to publish.

Conflict of Interest

The authors declare that they have no conflict of interest.

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