SPATIOTEMPORAL DYNAMIC OF BLUE SHARK (*PRIONACE GLAUCA*) ASSOCIATED WITH LONGLINE FISHERY IN THE EASTERN INDIAN OCEAN

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ABSTRACT

Fish stock management worldwide is based on stock assessment models. The relative abundance index of the species of interest is one of the most critical inputs in most stock assessment models. The main problem in determining the abundance index occurs in a dependence survey, where the catchability covariates are highly influential on the species abundance index to cover the actual reality in nature. This study used the Vector Autoregressive Spatiotemporal Model (VAST) for blue shark species associated with Indonesian longline tuna fisheries in the Eastern Indian Ocean. The results indicated that the resulting abundance index was better with low residuals, excluded catchability, and included habitat covariates, making the results better than those of the conventional GLM model. The population density is well illustrated in the VAST model, where the VAST model can impute the population density in unfished areas to obtain a weighted area index. This is a distinct advantage, considering the many unfished areas in our research survey. This information is expected to benefit stakeholders in their decision making in the field.

Keywords: Blue shark, Longline fisheries, Eastern Indian Ocean, Spatiotemporal, VAST Model, Indonesian tuna fisheries.

This paper should be cited as: Rochman, F. 2022. *Spatiotemporal dynamic of blue shark (Prionace glauca) associated with longline fishery in the Eastern Indian Ocean*. GRÓ Fisheries Training Programme under the auspices of UNESCO, Iceland. Final project. https://www.grocentre.is/static/gro/publication/1802/document/Rochman21prf.pdf

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1 INTRODUCTION

1.1 Indonesian tuna longline fishery

Indonesia is one of the main participants in tuna fisheries in the Eastern Indian Ocean. The total landings in 2019 were 190,319 tons, accounting for 17.24% of the total tuna production in the Indian Ocean (CCSBT 2021; Fahmi et al. 2020; IOTC 2020). The target species are yellowfin (*Thunnus albacares*), bigeye (*Thunnus obesus*), albacore (*Thunnus alalunga*), skipjack (*Katsuwonus pelamis*), and southern bluefin tuna (*Thunnus maccoyii*). Vessels in Indonesian tuna fisheries use a variety of fishing gear, including gill nets, lines, longlines, and purse seines. In 2019, vessels using longlines landed 15,298 tons of tuna, corresponding to 8% of the total longline catch in the Indian Ocean (Fahmi et al., 2020).

The Indonesian longline tuna fleet is primarily based at four ports in the Indian Ocean: Bungus (Sumatra), Palabuhanratu (West Java), Cilacap (Central Java), and Benoa (Bali), where vessels based at the port of Benoa contribute to more than 60% of longline tuna caught in the Eastern Indian Ocean (Rochman et al., 2016). In 2019, there were 283 vessels registered with the Indian Ocean Tuna Commission (IOTC), with gross tonnage (GT) ranging between 90 and 200 (Fahmi et al., 2020). The fishing grounds of the longline fleet in the Indian Ocean cover an extensive area, from 5°to 35°S latitude and 70°E to 125°E longitude. Landings of non-schooling tuna (bigeye tuna, yellowfin tuna, southern bluefin tuna, and albacore) are primarily destined for export in the form of fresh products. Approximately 77% of catches were carried out outside Indonesia's exclusive economic zone (Rochman, 2019; Setyadji et al., 2016).

1.2 Blue shark associated with tuna longline fisheries

A pelagic longline fishery targeting large tuna and billfish species typically has a high incidental catch of sharks that are landed in an incomplete form (fins and cutlets) (Clarke, Francis, & Griggs, 2013) or discharged onboard (Campana, 2016; Jordaan, G. L., Santos, J. & Groeneveld, 2020). Characterising shark bycatch in tuna fisheries can be challenging because its capture is not included in the fisher's logbook. Therefore, their abundance, species composition, and fishing mortality are poorly understood (Jordaan G. L., Santos,. & Groeneveld, 2020) and are usually not included in population assessments.

The blue shark (*Prionace glauca*) is closely associated with longline tuna fisheries and is captured as bycatch. The swimming depth of the blue shark ranges from 75 m to 600 m (Hideki, N. & Stevans, 2009) but is caught chiefly at surface depths and the thermocline area at 75 - 300 m (Barata, A., Novianto, D. & Bahtiar, 2012; Rochman et al., 2021). Previous research has shown that fishing strategy and selection of fishing areas by tuna fleets affect the number of blue sharks captured as bycatch. The use of deep longlines contributes significantly to the increase in the number of captured blue sharks. The abundance index for blue sharks showed that abundance was higher on the high seas between Indonesia and northwest Australia than the area around the Indonesian islands of Sumatra, Java, Bali, and Nusa Tenggara (Rochman, F., Wujdi, A., Arnenda, G. L. & Kurniawan, 2021).

In the North Pacific, the abundance of blue sharks is influenced by seasons, geographical regions, and fishing strategy (Hiraoka, Kanaiwa, Ohshimo, Takahashi, Kai, and Yokawa, 2016). The blue shark CPUE is higher during the spring and summer (April and June) and within an area between 35°N and 45°N. Research on the abundance index of blue sharks in the Eastern Indian Ocean showed that the abundance index of blue sharks was high in high seas areas (>200 NM) close to northwest Australia (Rochman, F., Wujdi, A., Arnenda, G. L. & Kurniawan, 2021). The study found that the use of deep longlines significantly affected the increase in the abundance index.

1.3 Blue Shark Status

The Blue shark is the most abundant pelagic shark, and many are caught by world fisheries, primarily as bycatch in longlines and gill nets. Blue sharks are categorised as near-threatened version 3.1 by the International Union for Conservation of Nature (IUCN) (Rigby et al., 2019). This species has the highest population growth rate among pelagic sharks and reaches sexual maturity at a relatively young age.

Blue shark populations are closely related to commercial and small-scale pelagic longlines, purse seines, and gillnet fisheries. Only fins are generally utilised; however, more recently, meat has been widely used. The blue shark population decline was the highest in the North and South Atlantic waters, followed by the Indian Ocean, with a median population decline of 7.3% to 20% over the last 30 years. However, owing to the uncertainty in some regional forecast trends, experts estimate a population decline of 20–29% over three generations, and the blue shark is rated as near threatened (Rigby et al., 2019).

Population trend estimates are available for the Atlantic, Pacific, and Indian Oceans (Rigby et al., 2019). Although the assessment had some uncertainty, the North and South Atlantic regions estimated that the stock was unlikely to be overfished and was not subject to overfishing. The average population reduction rate ranges from 1.5-2.3% per year, with an estimated median reduction of 38.2-53% over three generations (30 years) (ICCAT, 2015). The Pacific Stock Assessment is considered a work in progress. Trend analysis of the Southwest Pacific spawning biomass for 1999-2014 (21 years) revealed an annual rate of increase of 0.2%, with a median of 5.7% over three generations (31.5 years) (WCPFC, 2016). The Indian Ocean stock assessment showed that the stock was not overfished, but may be experiencing overfishing. The trend in biomass (1949-2020) (72 years) revealed an annual reduction of 8.4%–20% (maximum < 20%) (IOTC, 2020b).

1.4 Blue shark biology

The blue shark (*Prionace glauca*, Carcharhinidae) is a marine species found worldwide in temperate and tropical waters, characterised by a slender body, long pectoral fins, indigo blue back, metallic blue sides, and sudden white undersides. This species is a large species of up to 383 cm TL with an average length of 220 cm TL and a similar growth pattern between males and females.

Age and growth studies of blue sharks in the North Pacific and South Atlantic have shown that 50% of male blue sharks reach sexual maturity at 218 cm in length (total length), although some blue sharks can reach a lower maturity level of approximately 182 cm. Females appear to approach a lower mean asymptotic maximum length and grow more rapidly than males (Hideki, N. & Stevans, 2009). The blue shark reproduction mode is placental viviparity with a gestation period of 9-12 months and an average production of 30 new individuals per year, where reproduction occurs in spring and summer and reaches sexual maturity after six years (Hazin, F. H.V., Kihara, K., Otsuka, K., Boeckman, C. E. & Leal, 1994).

The main prey of blue sharks is small pelagic fish and cephalopods, especially squids, pelagic crustaceans, small sharks, cetaceans, and sea birds (Henderson, A. C., Flannery, K. & Dunne, 2001). Blue sharks are known to feed for 24 hours but are reported to be active at night and more active in the early evening.

Blue sharks are widely distributed throughout tropical and temperate oceans, between 60ºN and 50ºS. The blue shark is an oceanic species but can also be found close to the narrow continental shelf, usually around 150–1,000 m. Blue sharks prefer temperatures of 12–220 °C, and are found at greater depths in tropical waters. The general relative abundance is the lowest in equatorial waters and increases with latitude (Hideki, N. & Stevans, 2009).

1.5 Standardization of abundance indices

Data from fishery-dependent and fishery-independent sources are inputs for stock assessment models that provide the information needed for fisheries management (Methot Jr., R. D.,& Wetzel, 2013). A fundamental requirement of these models is a relative abundance index that can provide information regarding trends in population size. In many cases, catch-per-unit-effort (CPUE) is used in stock assessment models as a relative abundance index, particularly when data comes from commercial fisheries (Francis, 2011). In longline fisheries, the CPUE is usually expressed as the number or weight of fish caught per hook.

The use of CPUE as a relative abundance index assumes a constant and proportional relationship between CPUE and density of the target species (Maunder, M. N. & Punt, 2004). Nevertheless, the relationship between CPUE and density may not be constant and may change in space and time because of differences in vessel power, fishing strategy, environmental conditions, and other factors. This effect is substantial, especially in fishery-dependent data because vessel skippers know the target species well and can identify areas of high abundance. In this situation, the standardised abundance index values do not adequately reflect the actual abundance of the target species. Therefore, raw CPUE values cannot be used directly as indices of abundance, and they need to be standardised to account (at least partially) for these factors. A well-standardized CPUE value is expected to be proportional to the population abundance value (Maunder, 2001; Rochman, F., Setyadji, B. & Wujdi, 2017; Sadiyah, L., Dowling, N. & Prisantoso, 2012).

Several approaches have been used to standardise the CPUE values (Maunder and Punt, 2004). The most common approach is to use generalised linear models (GLMs). However, other methods exist, including generalised additive models (GAMs) and generalised linear mixed models (GLMMs). Recently, standardisation using Vector Autoregressive Spatiotemporal (VAST**)** models has been proposed as an alternative approach. VAST is a spatiotemporal model that can explicitly account for changes in population densities over time and at multiple locations (Thorson, J. T. & Barnett, 2017; Xu, H., Lennert-Cody, C. E., Maunder, M. N., Minte-Vera, 2019).

1.6 Objective

This study aimed to model the abundance index of blue sharks in the Indonesian longline tuna fishery using a VAST model and perform a comparative analysis with the nominal index and standardised index using GLM.

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2 MATERIALS AND METHODS

The CPUE dataset was aggregated by year and month with a spatial resolution of 1°×1° and covered the Eastern Indian Ocean between 0 and 35°S and 75 – 125°E from 2006 to 2018. CPUE was defined as the catch of blue sharks in a number of fish per 100 hooks, with a spatial CPUE value of 1,542 observations.

2.1 Data Collection

This study used fishery-dependent data from the Indonesian tuna longline fishery collected by the Research Institute for Tuna Fisheries (RITF) scientific onboard observer program. The data include tuna longline fishing operations in the Eastern Indian Ocean, both in Indonesian and international waters (high seas) between Australia and Indonesia. The locations of the catches ranged from to 0-35°S to and 70-135°E.

The data for this study consisted of 2,951 longline sets deployed during the period 2006-2018. The information from each set included vessel (trip), operational (setting and hauling), time, coordinates, species, size (length or weight), catch number, catch per unit effort, depth of catch, fishing strategy, and environmental data. Catch per unit of effort (CPUE) was calculated using the number of fish per 100 hooks (Rochman, F., Setyadji, B. & Wujdi, 2017).

2.2 Nominal index and standardized index using GLM

Nominal CPUE, also called raw CPUE, is simply the total catch divided by an observable measure of effort (Maunder, Sibert, Fonteneau, Hampton, Kleiber & Harley, 2006). In this study, the CPUE was computed as the number of fish per 100 hooks. In studies using CPUE as an abundance index, this is referred to as nominal index (I_{nominal}): $I_{nominal} = \frac{\sum_{i=1} C_i(t)}{\sum_{i=1} E_i(t)}$ (1)

Where *I* is the index, *Ci* is the number of catches at time *t* and E_i is the effort at time *t*. The nominal index does not account for any factor that influences the relationship between CPUE and abundance (e.g. fishing strategy and environmental covariates).

Most methods used to standardise CPUE data estimate the annual effect on the catch on which an abundance index can be based (Maunder & Punt, 2004). The most common method uses generalised linear models (GLM**)** to identify trends in the abundance of target species by adjusting for confounding effects of other covariates. Here, we use GLMs to standardise the CPUE. The CPUE dataset was aggregated by year and month, with a spatial resolution of 1°×1° and covered the Eastern Indian Ocean. The GLM model applied to the data is as follows:

$$\mathrm{C}(s,t) = \sim Year(t) + cell(s) + \sum_{j=1}^{nj} \gamma j x j(s,t) + \sum_{k=1}^{nk} \lambda(k) Q(k) + \log(\mathrm{sett}(\mathrm{s},\mathrm{t})) \tag{2}$$

Where *C*(*s*,*t*) is the prediction of blue shark catch (in numbers) in cell *s* and year *t*, *year* (*t*) is the fixed effect for each year *t*, *cell*(*s*) is the fixed effect for each cell *s*, γ_j represents the effect of covariate *j* (i.e. the linear impact of SST, n_j=1) with value x_j(s,t) on the catch for cell *s*, and Year *t*,

λ_k is the coefficient for catchability covariate $Q(k)$ (i.e. fleet, $nk = 1$), and *sett* is the fishing effort (setting) as a log offset in cell *s* and Year *t* . The results of this analysis will be used as a baseline to compare the outputs of the VAST model described next.

GLMs include several variables that affect the number of fish caught in each longline. The covariates included in the analysis were year, quarter, season, month, longline type, vessel, fish depth, sea surface temperature, chlorophyll, sea depth, and distance to the 1000 m isobath. A preliminary evaluation was carried out using ANOVA, and CPUE modelling was the effect of these covariates. Only covariates that significantly affected CPUE (chi-square <0.05) were included in the GLM.

GLMs were built using a Tweedie distribution and log-link function. Tweedie distributions are a family of probability distributions whose shape is defined by a power parameter, k. The Tweedie distributions include several well-known distributions, including normal (k=0), Poisson (k=1), gamma (k=2), and inverse Gaussian (k=3) distributions. K between 1 and 2 defines a compound Poisson-gamma distribution (Rochman, F., Setyadji, B. & Wujdi, 2017; Rochman, F., Wujdi, A., Arnenda, G. L. & Kurniawan, 2021; Sadiyah, L., Dowling, N. & Prisantoso, 2012). The Tweedie distribution is applicable to catch data that is not normal (negative skewness) with zero catch data, as in the case of blue sharks caught in the longline tuna fishery. To select the optimal value for the power parameter, a maximum likelihood estimation was performed, testing values for k between 1 and 2. A GLM was fitted with the selected parameters to a set of candidate models with standard quantile selection (residual, QQ plot, and residual histogram). The selection of the GLM index model was based on the Akaike Information Criterion (AIC) using the "statmod" (Giner and Smyth, 2016) and "Tweedie" (Dunn, 2021) packages in the R statistical software (R-Development-Core-Team, 2021). Model evaluation was performed by examining diagnostic plots. The model with the smallest AIC value was chosen as a reference and was expected to provide an optimal value for the final model.

2.3 Standardised index using VAST (Vector-Autoregressive Spatio-Temporal) model

In recent years, more advanced methods have been developed to standardise CPUE using spatio-temporal models that can provide more precise estimates of abundance because they account for spatial and temporal correlation, which is the trend that CPUE observations that occur closer in space and time are more likely to be similar. This study used the Vector-Autoregressive Spatio-Temporal (VAST) model. We used the R package, VAST (https://github.com/James-Thorson-NOAA/VAST) (Thorson, 2019). VAST uses a Gaussian random field to model the auto-spatial correlation with anisotropy (i.e. the autocorrelation relationship at velocity is not the same in all directions) and an interactive relationship between space and time (i.e. spatiotemporal correlation). Gaussian random fields were defined using the Matern covariance function (Thorson, 2019).

VAST is a delta-generalised linear mixed model, where the distribution of the catch data is decomposed into two components: a) the probability of encounter (binomial model) and b) the expected catch rate given that the species is encountered. The predicted logarithm of the blue shark abundance *p(s,t)* in knots *s* and year *t,* is predicted as follows:

$$p(s,t) = \beta(t) + \omega(s) + \varepsilon(s,t) + \sum_{j=1}^{nj} \gamma j x j(s,t) + \sum_{k=1}^{nk} \lambda(k) Q(k) \qquad (3)$$

where, $\beta(t)$ is the intercept for each year t as a fixed effect, $\omega(s)$ is the time-invariant spatial autocorrelated variation for knot s, and $\varepsilon(s,t)$ is a time-varying spatial-temporal autocorrelated variation for knot s and in Year t. γj represents the impact of covariate j with value $xj(s,t)$ on density for knot s and year t, and λ is the coefficient for the catchability covariates $Q(k)$ (i.e., fleet, nk=1).

VAST requires the definition of a network of points or knots, where the correlation between spatial and spatiotemporal effects is estimated. Each observation in the dataset was then connected to the closest node using k-means clustering. In this study, we used a total of 3480 nodes (Figure 1, upper two figures), based on a regular grid with an input of 500 knots (Figure 1, red dots) and a resolution of 50 km, bounded by a concave hull surrounding the locations of the longlines in the data (Figure 1).

Two VAST models were fitted. The first model modelled the blue shark abundance only as a function of space and time, with no covariates. The second model included fish depth, sea surface temperature, chlorophyll, sea depth, and distance to the 1000 m isobath as covariates.

Residual histograms were used to assess the normality of GLM and VAST and quantile-quantile normal probability plots (Normal Q-Q plots) for both.

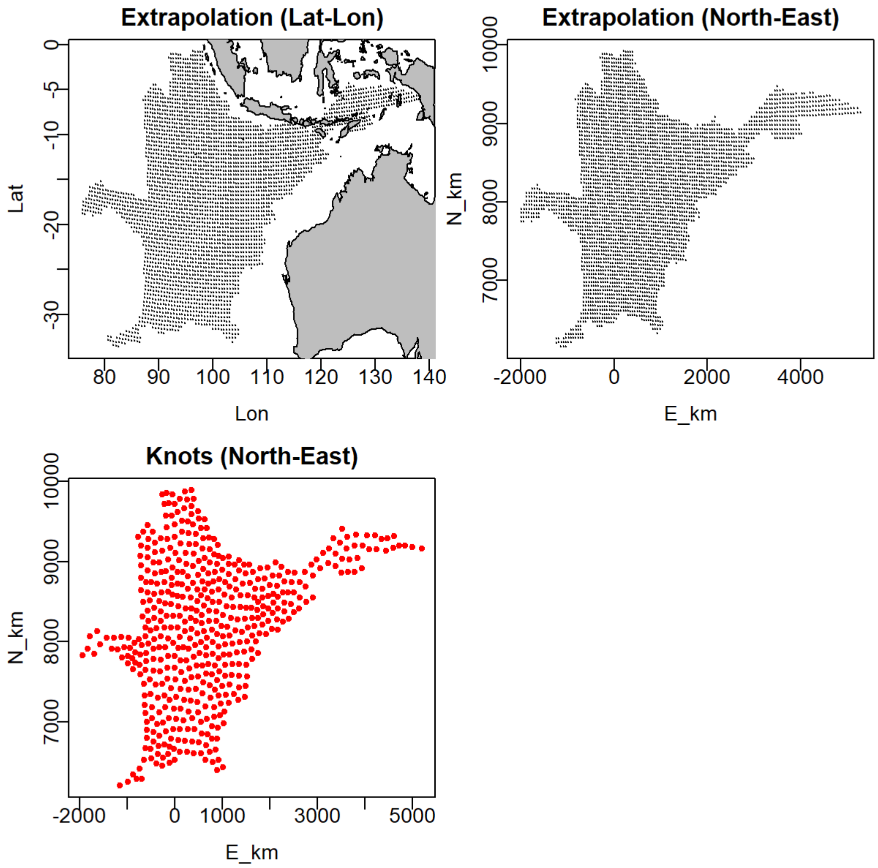

Figure 1. A grid comprising 3480 nodes marks the spatial coverage of the data and the surrounding bounds (upper figures) that were used to fit the VAST models. Five hundred knots were specified, which the model places geographically to minimise the distance between the data and knots over the study area (lower figure).

3 RESULTS

3.1 Distribution of fishing effort

The overall distribution of longlines sampled by the Indonesian Scientific Observer Program is shown in Figure 2. The fishing areas included the Eastern Indian Ocean, West of Sumatra, South of Java-Bali-Nusa Tenggara, Northwest-West Australia, and the Banda Sea.

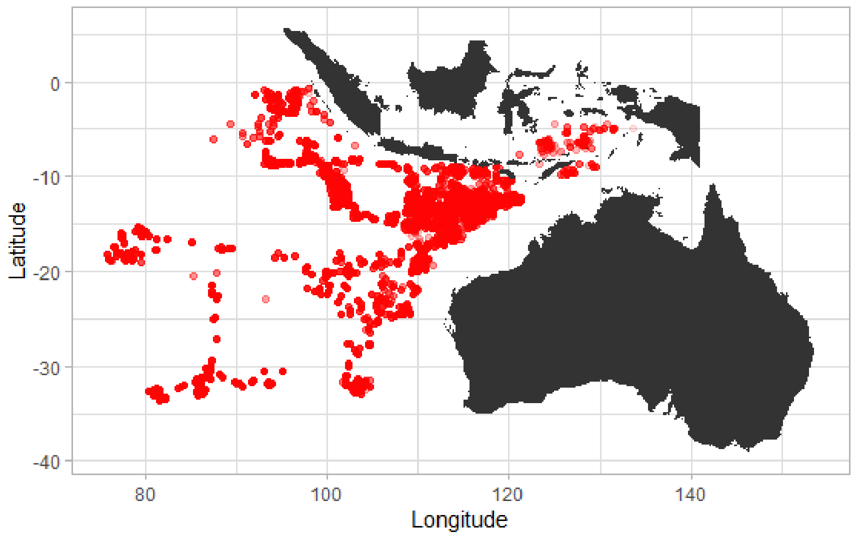

Figure 2. The study area of the Indonesian tuna longlines scientific observer program in the Eastern Indian Ocean 2006-2018.

The spatial distribution of longlines varies throughout the year (Figure 3). During the first quarter (January–March), the dominant fishing grounds were near the west coast of Sumatra, Southern Java-Bali-Nusa Tenggara, and parts of the Banda Sea (0-15°S and 90-130°E). However, some fishing locations were far from the coast, off Western Australia (15-35°S and 75-110°E). In the second quarter (April–June), the main fishing grounds were in the waters between South Java-Bali-Nusa Tenggara and the waters around Northwest Australia (5-25°S and 95-125°E), with a small number of fishing locations in the high seas off Western Australia (20-35°S and 80-90°E). During the third quarter (July–September), fishing grounds showed similarities with quarter two, but fishing locations off Western Australia were farther north and more widespread (15-30°S and 75-110°E). The fishing locations were widely and evenly distributed in the fourth quarter (October–December), with locations south of Java-Bali-Nusa Tenggara, Northwest Australia, Western Australia, and the high seas.

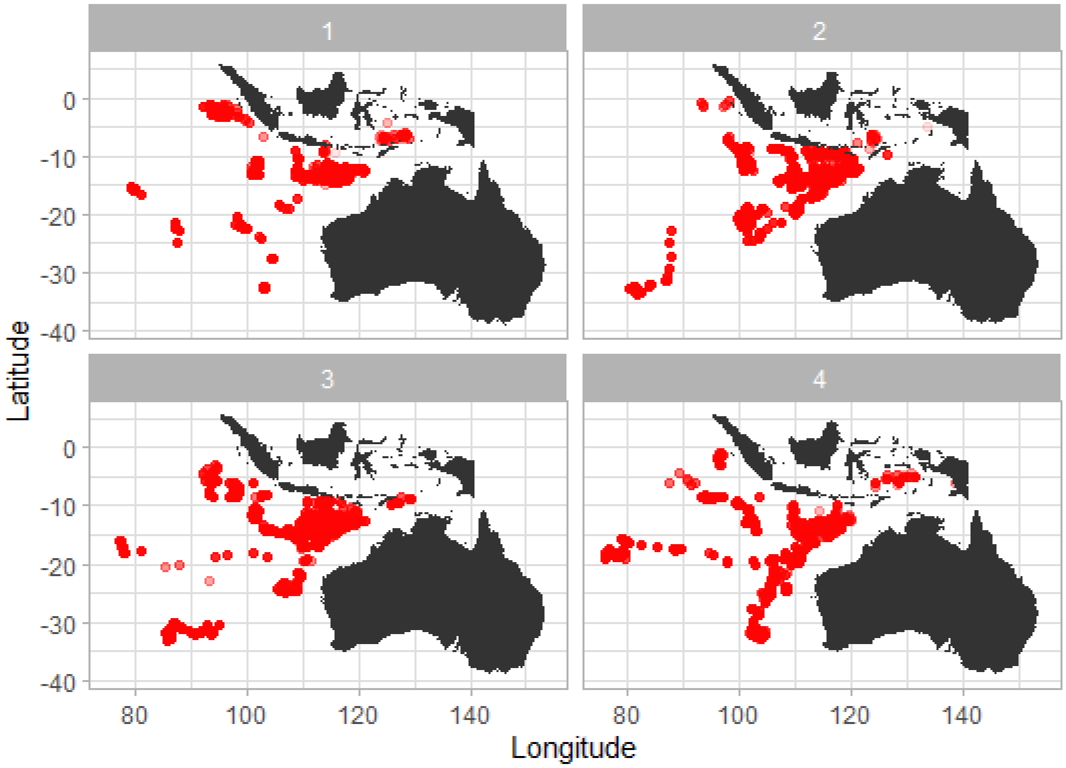

Figure 3. The geographic distribution of the study area, aggregated for 2006-2018 by quarter (1. January-March, 2. April-June, 3. July-September, 4. October-December).

In general, fishing efforts ranged from 500 to 2,500 hooks per set, with most sets between 1,000-1,500 hooks per set (Figure 4). However, the effort was greater in fishing areas far from the Indonesian coastline. The effort was higher (~1500-2500 hooks per set) in sets by the deep-sea tuna longline fishing off Western Australia (15-30°S and 75-110°E). Examination of the quarterly distribution shows that fishing effort was higher in the high seas area than in areas closer to the shoreline, especially off Northwest and Western Australia (10-30°S and 75-110°E) (Figure 5).

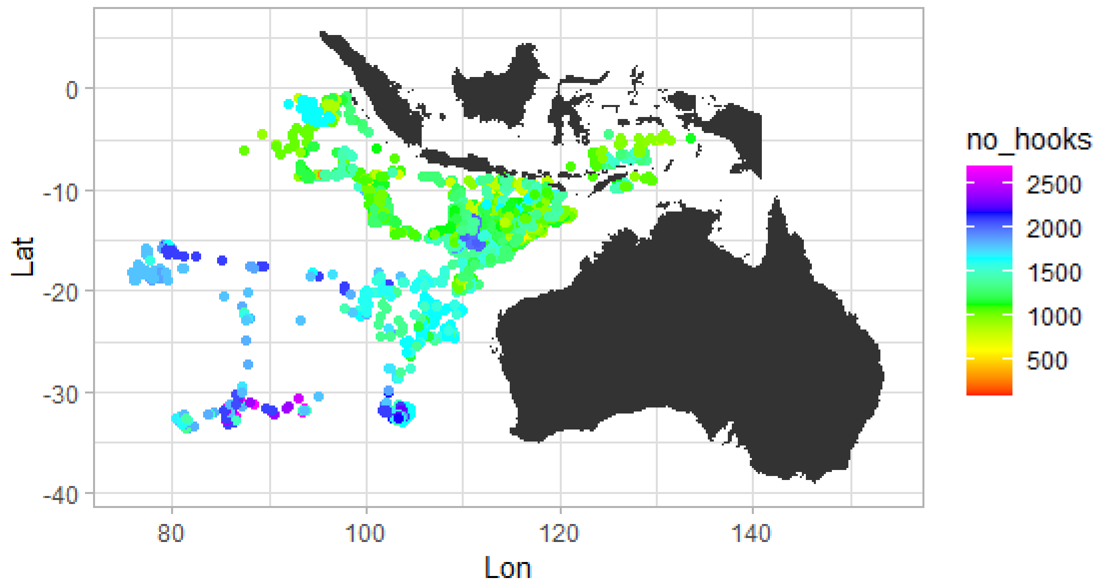

Figure 4. Spatial distribution of fishing effort defined as the mean number of hooks used per set per 1°x1° grid cell from 2006 to 2018.

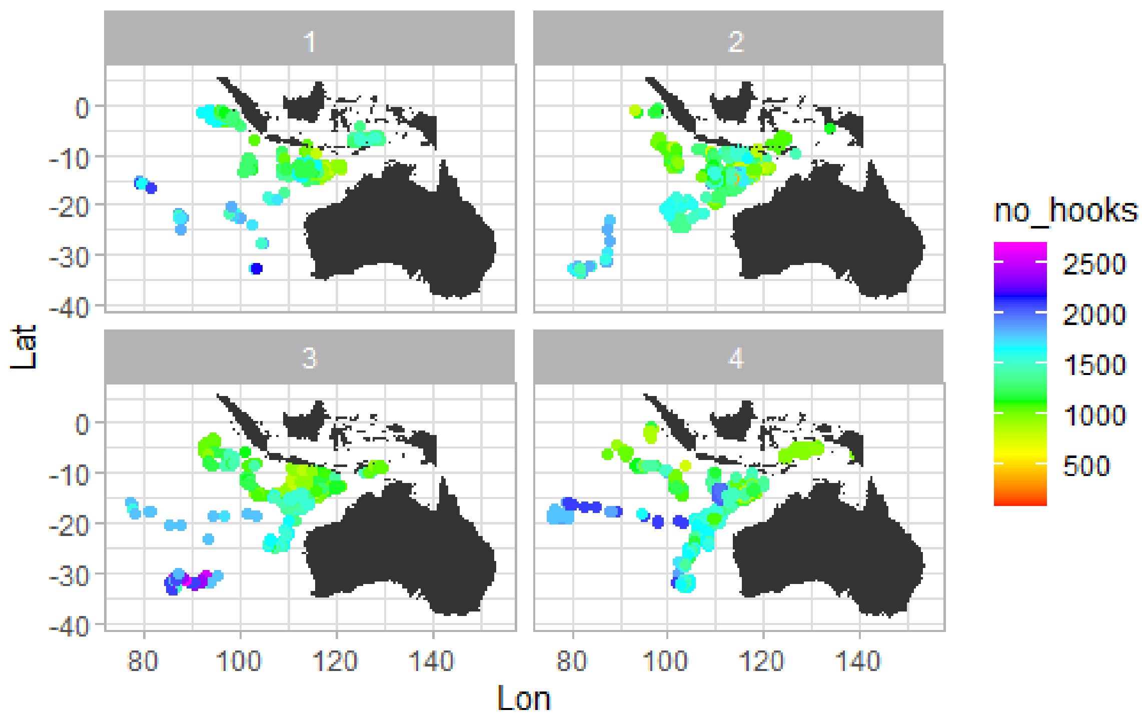

Figure 5. Spatial distribution of fishing effort by quarter year, 2006-2018. Effort is defined as the mean number of hooks per set per 1° × 1°.

3.2 Nominal index and generalized linear model (GLM) index

The nominal abundance index and the index standardised using generalised linear models were computed as a time-series dataset, that is, they did not explicitly consider the spatial location of the catches.

As a preliminary analysis before estimating the standardised GLM index, we determined the significance of several covariates that affect blue shark catches using analysis of variance (ANOVA; Chi-Square). (Table 1). The results indicated that variables related to catch time (year, quarter, season, and month) and technical characteristics, Trip_id, which identifies individual vessels and the type of longline, were strongly significant. In addition, the depth of fishing and distance to the 1000m isobath were marginally significant.

A series of GLM models were built using strongly significant covariates, marked with gray in Table 1. The first three models were used as predictor years, and one of the covariates indicating the time of year (quarter, season, and month). Models were compared using AIC values, with year and month having the lowest AIC (Model 3). Next, we fitted three additional models, expanding Model 3 with permutations of Trip_id and longline type. The best model was Model 5, which included year, month, and Trip_id as the predictors. Diagnostic plots, including randomised quantile residuals, QQ Plots, and the distribution of quantile residuals, are shown in Figure 6.

Table 1. Summary of the significant covariates in GLM fitted from the dataset (2006-2018).

	Df	Deviance Resid.	Df Resid.	Dev	Pr(>Chi)	sig.
NULL			1888	66.796		
Year	12	28.8387	1876	37.957	<2.2e-16	***
Quarter	3	5.5787	1873	32.378	<2.2e-16	***
Season	1	0.2612	1872	32.117	4.31E-10	***
Month	7	0.6618	1865	31.455	<2.2e-16	***
Type_LL	2	0.2342	1863	31.221	2.59E-08	***
Trip_id	65	21.3687	1798	9.853	<2.2e-16	***
Depth_fish	1	0.0262	1797	9.826	0.04816	*
sst	1	0.0024	1796	9.824	0.55225	
chl	1	0.0119	1795	9.812	0.18187	
depth	1	0.0046	1794	9.807	0.40903	
dist1000	1	0.033	1793	9.774	0.02653	*
Signif. Codes	0 '***'		0.001 '**'		0.01 '*'	
	0.05 '.'		0.1 '	'		1

Covariates included in GLM model with smallest AIC

Table 2. List of model option GLM standardized index according to AIC value

No	Model Options	AIC
1	CPUE~Year+Quarter	-12,442
2	CPUE~Year+Season	-12,109
3	CPUE~Year+Month	-12,503
4	Model 3+ Type_LL	-12,519
5	Model 3+ Trip_id	-14,845
6	Model 3+ Type_LL+ Trip_id	-14,842

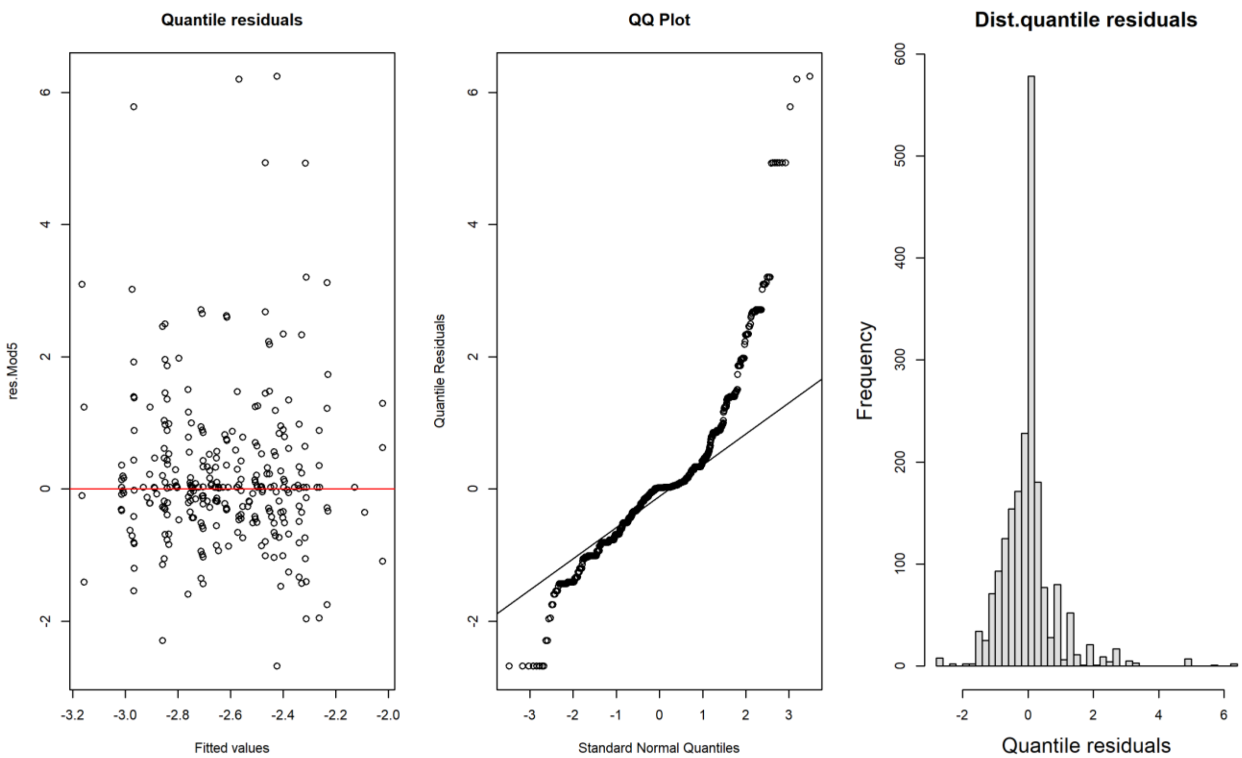

Figure 6. Residual plot of GLM standardised index of blue shark associated with tuna longline fisheries in the Eastern Indian Ocean.

The covariate effect was included in the standardised GLM index by comparing it to the nominal index. During the study period (2006-2018), the average nominal index of blue shark abundance was 0.767. A minimum abundance index of 0.0595 was achieved in 2012, with a maximum of 0.09375 in 2011 (Figure 7).

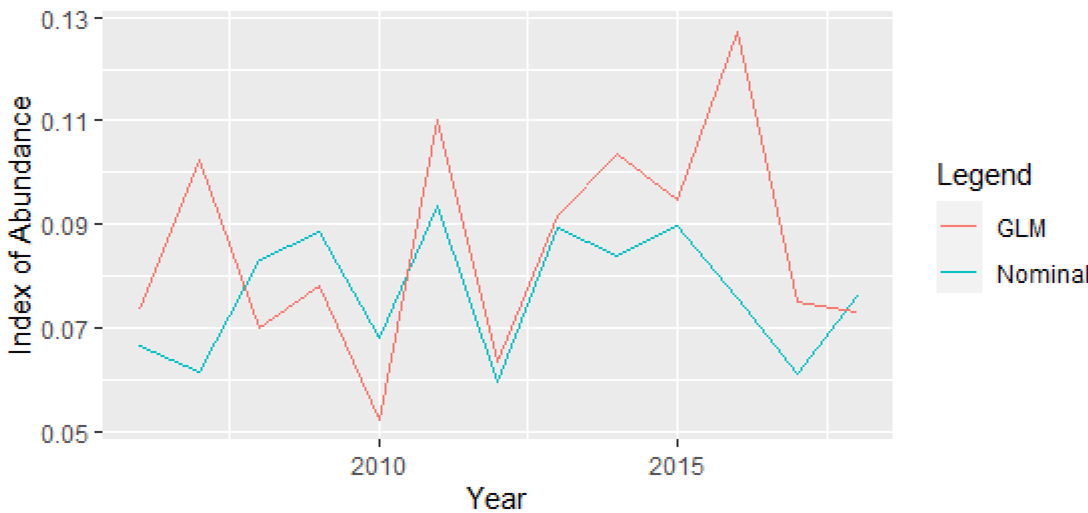

Figure 7. Nominal and GLM standardised abundance index of blue shark associated with tuna longline fisheries in the Eastern Indian Ocean (2006-2018).

3.3 The VAST model standardised index

Preliminary research evaluated the VAST model by examining the resulting, observational, and predictive residuals. We used the non-covariate model as a reference material to develop the next VAST model (Figure 9). The VAST model without covariates showed that the observed and expected values were positively related to the normal distribution of the residuals, indicating that the VAST model could be used to assess the abundance index.

In addition, we also ran the VAST model, including depth of fish, sea surface temperature (sst), chlorophyll concentration (chl-a), bottom depth, and distance to a 1000 m isobath as habitat explanatory covariates, resulting in an excellent fit (Figure 10). The abundance index of the VAST model with and without covariates is shown in Figure 8. The predicted density values of the VAST model are presented in Figure 11 and 12.

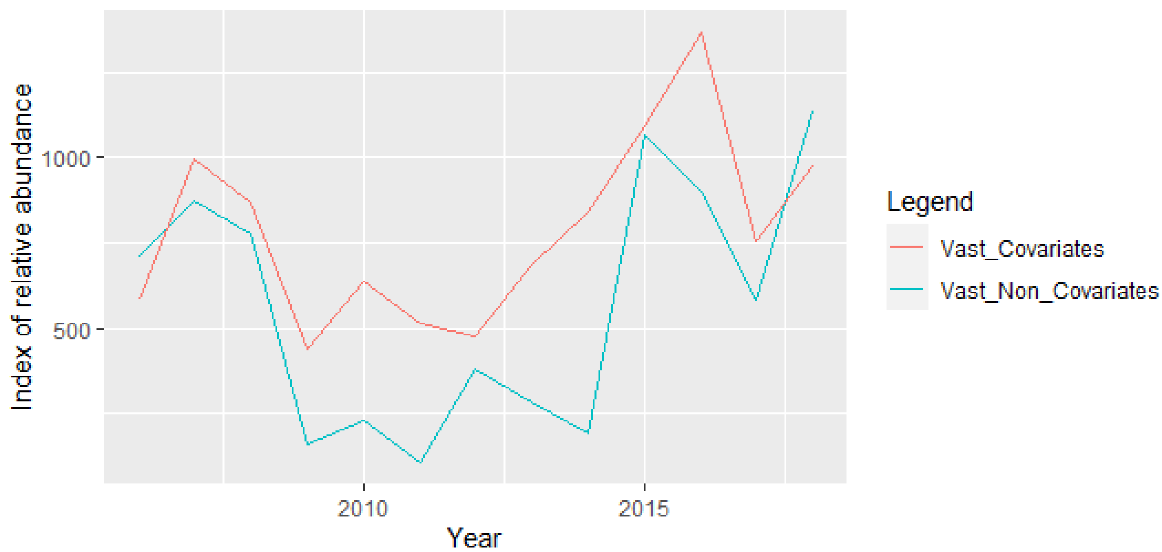

Figure 8. The abundance index of blue sharks associated with tuna longline fisheries using the VAST model with and without habitat covariates.

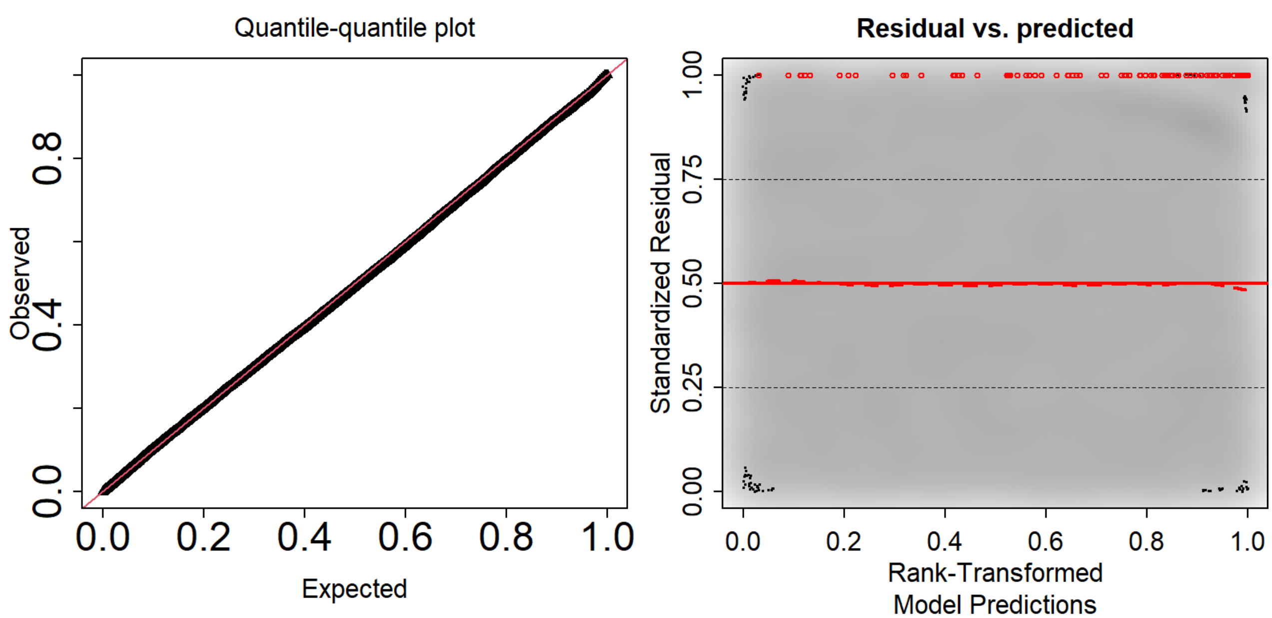

Figure 9. Plot of the residual model of VAST without covariates for blue sharks associated with longline tuna fisheries in the Eastern Indian Ocean.

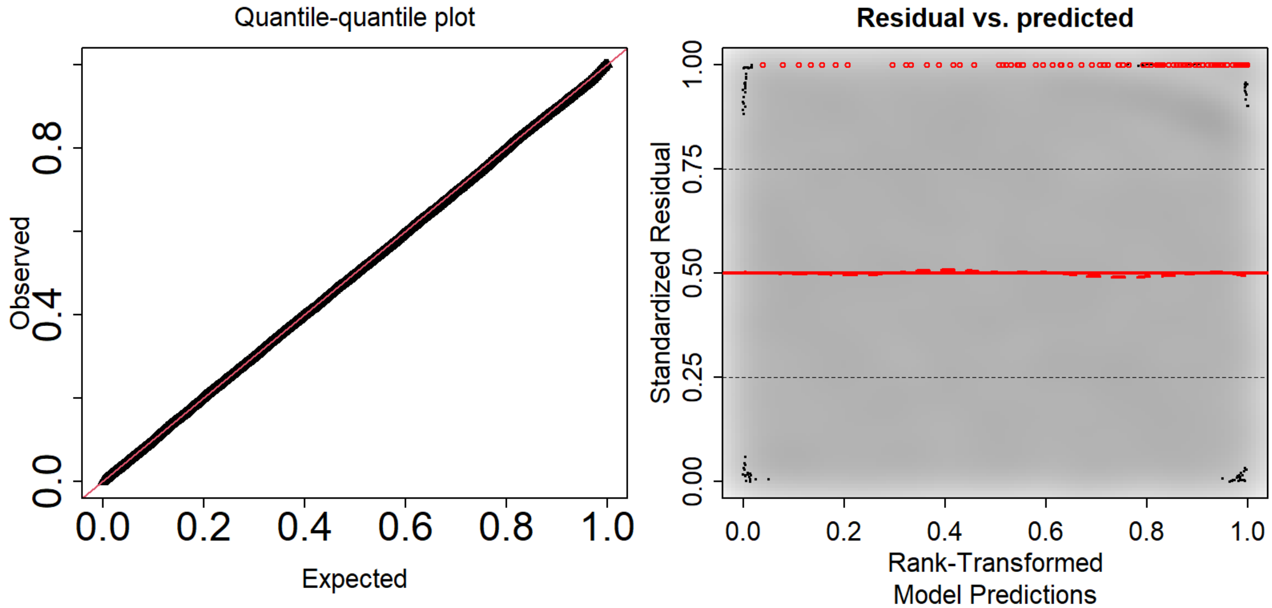

Figure 10. Plot of the residual model of VAST with habitat covariates for blue sharks associated with longline tuna fisheries in the Eastern Indian Ocean.

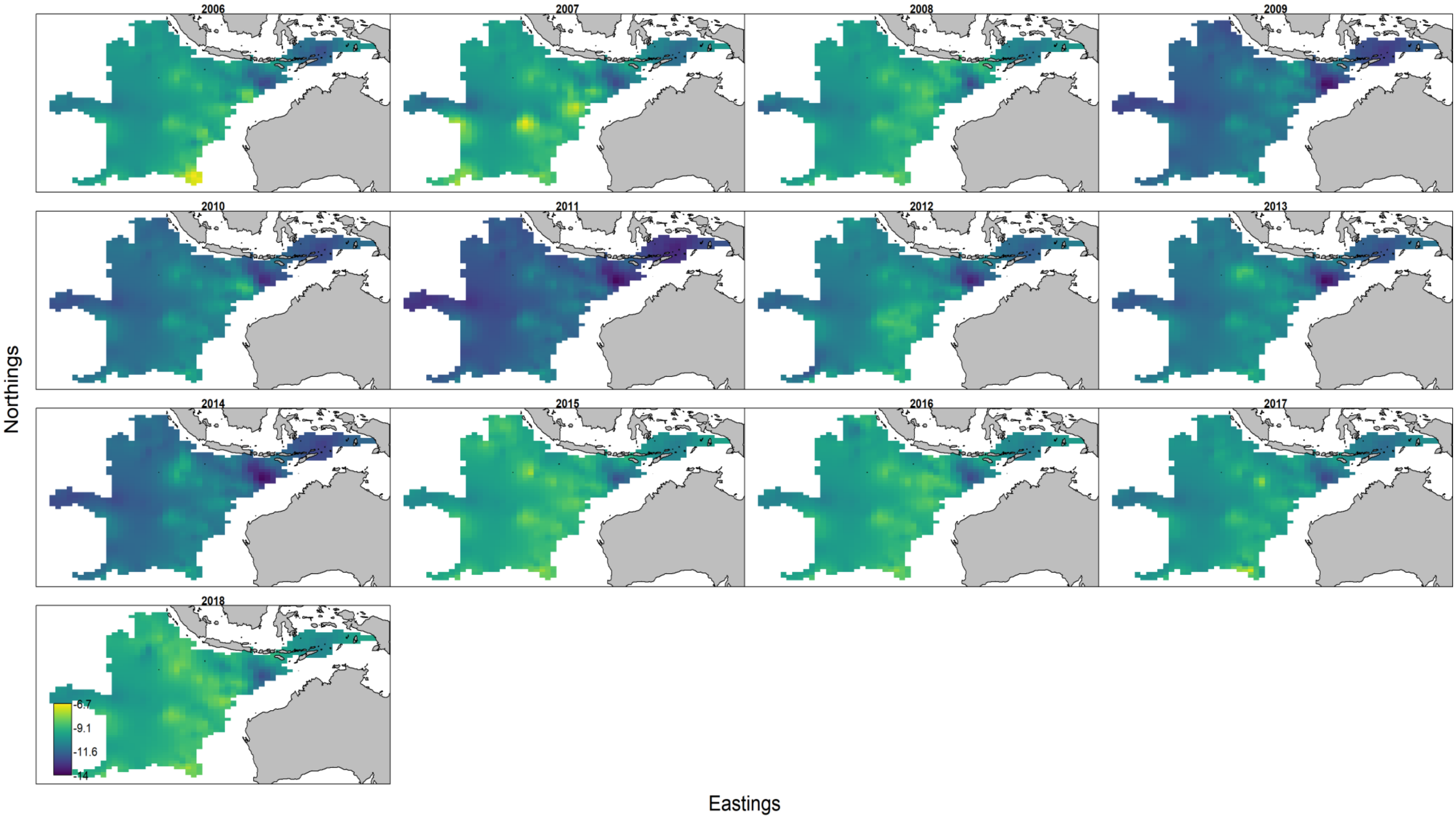

Figure 11. Spatiotemporal distribution of predicted log density of blue sharks associated with tuna longline in the Eastern Indian Ocean 2006-2018 using the VAST model without covariates (dark green: high density, yellow: low density).

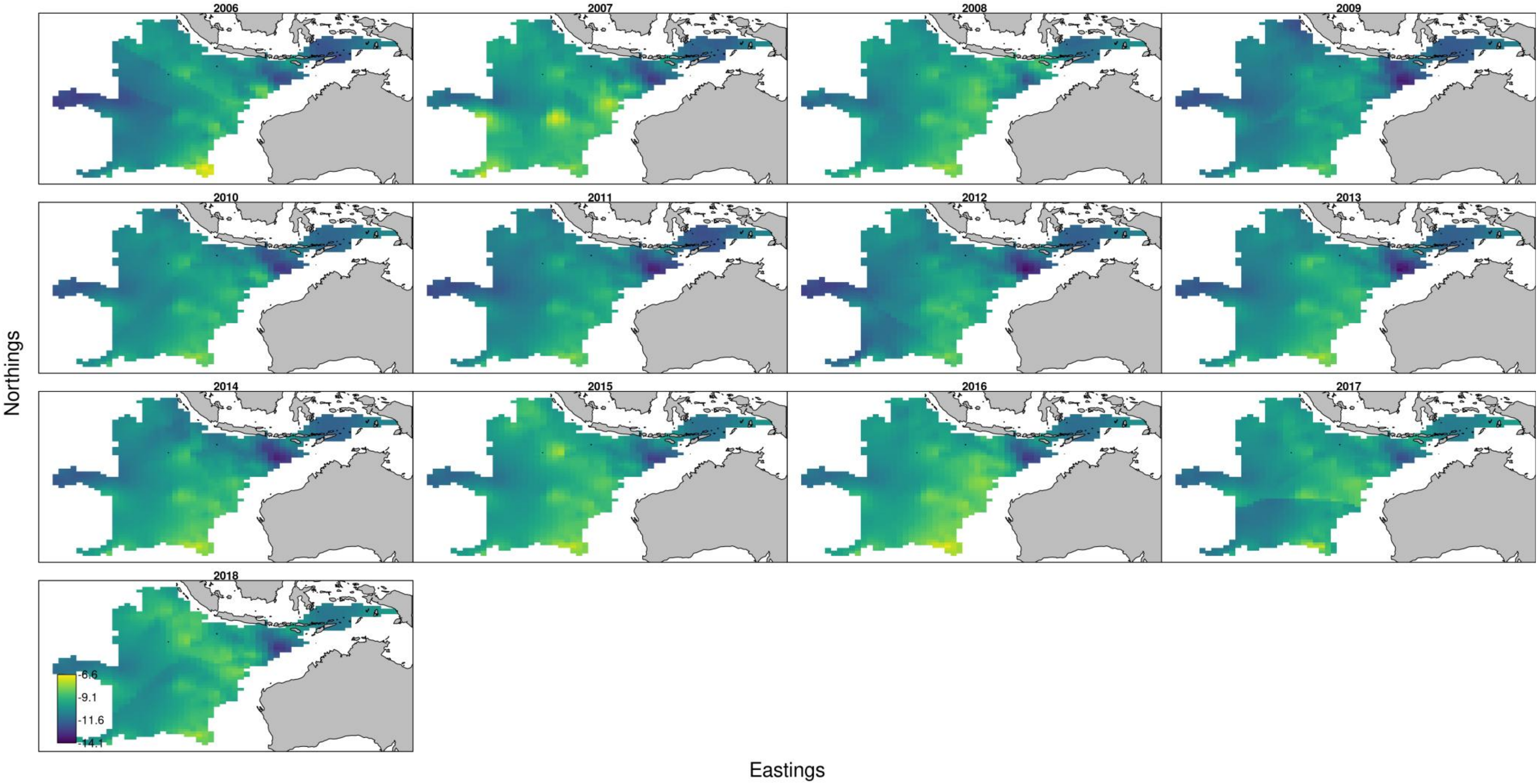

Figure 12. Spatiotemporal distribution of predicted log density of blue sharks associated with tuna longline in the Eastern Indian Ocean 2006-2018 using the VAST model with environmental variables as covariates (dark green: high density, yellow: low density).

At this initial stage, it was concluded that the VAST model could be implemented in the 2006-2018 onboard observer program data. The residual graph indicates an excellent fit between the observations and predictions. The results showed that the addition of habitat covariates to the model produced a smoother index.

3.4 Comparison between nominal, GLM, and VAST indices

To make a comparative analysis between the nominal, GLM standardised index, and VAST models, we must know each model's diagnostic quantile residual value. Quantile residual diagnostics suggested that the VAST spatiotemporal model has a good fit for the number of catch and effort data in the longline tuna fisheries dataset (Figure 10). Meanwhile, the quantile residuals for the standardised GLM model indicated underestimation at the beginning and overestimation at the end of the study period (Figure 6). The VAST model appears to be a better reference than the conventional GLM model.

For comparison, we used four models, namely the nominal index, GLM index, VAST index without covariates, and VAST index with a combination of five habitat covariates (depth of fish, sea surface temperature, bottom depth, chlorophyll-a, and distance at 1000 m isobath). Considerable variation was observed in the abundance indices from 2006 to 2018 (Figure 13). These results show a similar pattern between the GLM, VAST, and nominal indices. The GLM and VAST indices increase in 2006-2007 and decreased until 2011. Then there was an increase from 2011-to 2018. We did not find fluctuations in the nominal abundance index, which tended to be flat with a scaled index between 0.75 and 1.25. However, using the GLM index, we found an unusual pattern, especially in 2011, which had a significant increase in the index, but was profoundly corrected in 2012. We did not find this pattern in two of the VAST indices.

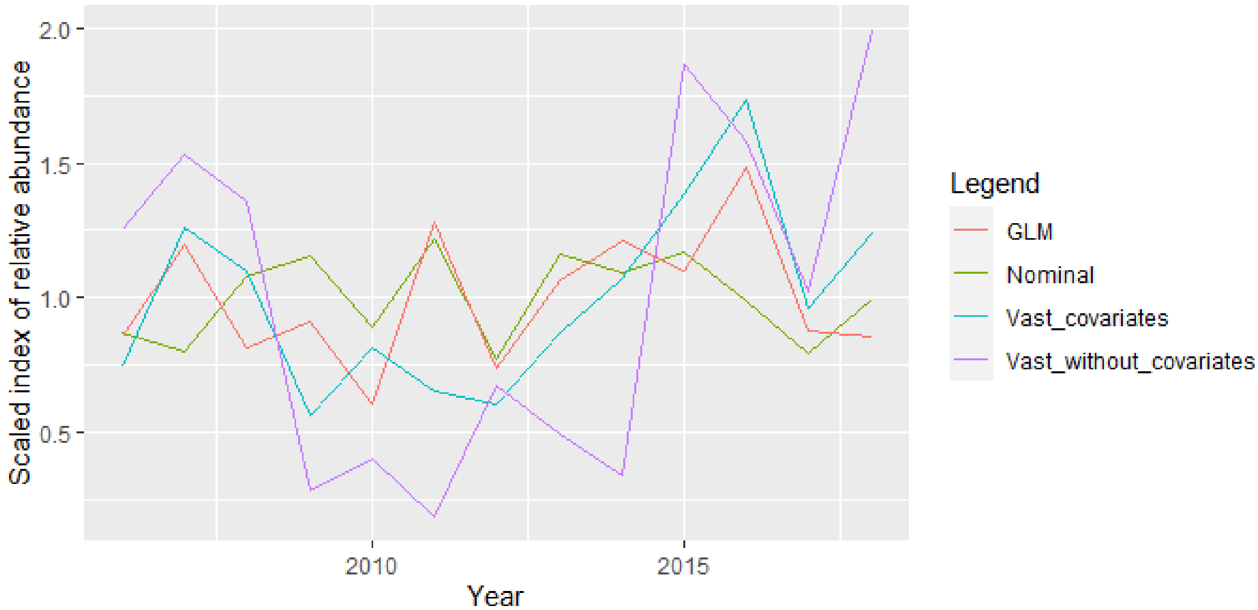

Figure 13. Comparison of three scaled relative abundance indexes of blue shark associated with the tuna longline fisheries in the Eastern Indian Ocean

Other advantages were obtained from the VAST spatiotemporal model compared to the conventional GLM model. The VAST model can estimate the population density for the species at multiple locations and times, explicitly including associations with environmental variables and changes in space and time. The VAST model is a state-space model that incorporates variability and measurement error in the fisheries model but is further expanded to consider geographical aspects. Geographically, there is a tendency for the calculation error process to occur in locations that are close together compared with locations that are very far away. This function is called the "common currency" model, which brings together different stock, ecosystem, and climate assessment approaches (Thorson, 2019).

The predicted density of the blue shark population using the VAST model by year is presented in Figure 11, and the quarterly data are presented in Figure 12. The blue shark population density trend varies annually and undergoes several changes. From the log density population generated by the VAST model, several areas have a very high level of population density compared to other areas, especially the area around the southern coast of the island of Bali-Nusa-Tenggara, the Banda Sea, and the high seas area West of Australia at latitudes of 75 °–100°E. From the prediction of population density using the VAST model, it was found that the general population trend increased from 2006 to 2014; moreover, there was a slight decrease in population density from 2015 to 2018 during the research survey process.

4. DISCUSSION

4.1 The advantage of the VAST model index

The VAST spatiotemporal model successfully fit 24,483 catch and effort data on blue sharks associated with Indonesian longline tuna fisheries in the Eastern Indian Ocean. The conclusions of this study are as follows.

- The diagnostic quantile residual obtained from the VAST model was better than that obtained from the GLM model, with a low residual level between the observed and predicted values. This proves that the VAST model is feasible and can be developed for fisheries modelling and stock assessment. We also found good residual levels in previous studies using the VAST model, including research on yellowfin tuna in purse seine fisheries in the Eastern Pacific Ocean 1975-2016 (Xu, H., Lennert-Cody, C. E., Maunder, M. N., Minte-Vera, 2019), pacific blue marlin in Taiwan tuna longline fisheries in the Pacific Ocean 1971-2019 (Hsu, J. & Chang, 2020) and the on-going investigation of Japanese longline CPUE of yellowfin tuna in the Indian Ocean 1975-2020 (Satoh, K., Matsumoto, T., Yokoi, H. & Kitakado, 2021). The conventional GLM index includes catchability covariates in the model, such as fishing strategy, and operational variables such as time, type of longline, hook between float, the vessel, which are positively correlated with the catch rate and the resulting index of abundance. This result was an underestimated value at the beginning and an overestimation at the end of the study period, as shown in the diagnostic quantile residual (Figure 6). Underestimation and overestimation of residual conditions have also been found in previous studies on swordfish fisheries using tuna longline fishing gear in Hawaii (Sculley & Brodziak, 2020). This study shows that replacing the conventional GLM model with the VAST model can increase the value of the log-likelihood of the assessment model, which is consistent with other inputs in the model, similar to the yellowfin tuna study in the Eastern Pacific Ocean (Xu, H., Lennert-Cody, C. E., Maunder, M. N., Minte-Vera, 2019).
- The VAST model predicted density and both spatial and temporal variations across the fishing area in the Eastern Indian Ocean. The predicted log density in the VAST model uses habitat preferences to spatiotemporally calculate population density. Meanwhile, catchability preference is not used in model fitting, so that the index and population density generated by the VAST model are pure without underestimating or overestimating residuals. The VAST model automatically predicts unfished areas not included in the survey via imputation and implements an area-weighting scheme by referring to the nearest node. In addition, the VAST model can predict population density based on habitat covariates and the accompanying spatiotemporal random effect. Furthermore, these covariates provide the random effect value in the VAST model. The VAST model can substantially improve population density predictions by conditioning the model based on a previously known residual pattern using geostatistical methods using kriging (Thorson, 2019).

- The VAST model's abundance index does not have an initial underestimation or overestimation at the end and has less noise due to catchability covariates. This study is crucial for identifying the best methods for estimating the abundance of fish resources correctly and precisely, without bias due to catchability factors, fishing tactics, fishing strategy, and technology. The assessment of fish stocks can be performed accurately and reliably.

4.2 Application of the VAST model in Indonesia tuna longline fisheries

The Indonesian longline tuna fishery, operating in the Eastern Indian Ocean, has experienced ups and downs in the last decade. Political issues, economics, and the availability of fishery resources always accompany the fishery business. In 2014 and 2015, there were government policies to tackle IUU (illegal, unregulated, and unreported) fishing in Indonesia by prohibiting foreign fishing vessels from operating in Indonesia, resulting in a massive reduction in the number of ships operating and landing at Indonesian ports (Rochman, F., Setyadji, B. & Jatmiko, 2016). In recent years, the number of longline tuna fleets registered with the Indian Ocean Tuna Commission (IOTC) has ranged from 217 to 283 units in 2016-2021 from the previous 1,227 to 1,282 units in 2012-2015 (MMAF Indonesia, 2021).

Fuel prices are an economic issue that is closely related to longline tuna fisheries. The fuel prices increase the longline tuna fishery's production and operational costs, especially if the operating area is far from the coastline and high seas area. A sharp increase in fuel prices occurred in 2005, which caused the largest tuna fishing company in Indonesia, namely *Perikanan Samudera Besar Ltd.*, to collapse (Rochman & Nugraha, 2014).

The issue of fishery resources occurred because of a decrease in CPUE and stocks of essential tuna commodities in the Indian Ocean, such as a decrease in yellowfin tuna stock (IOTC, 2021) which resulted in the displacement of fishing gear from longline tuna to other fishing gear, particularly purse seines. However, this has resulted in the emergence of another issue, where the purse seine fishery uses a fish aggregating device (FAD) which is not friendly to small tuna and interferes with the tuna migration process (Rochman, Jatmiko, & Fahmi, 2019).

Research on longline tuna fisheries in the Eastern Indian Ocean in the 2006-2018 period was conducted by participating in tuna longline fishing activities in several fishing ports in Sumatra, Java, Bali, and Nusa Tenggara. The weakness of the dependent survey is that it cannot determine the research area and departure time by itself, so the results of the study contain unfished areas (un-surveyed) and some empty observation times. The use of fishing strategy and technology (catchability) by fishing masters has proliferated over the past decade. An increase in catch could offset the decline in abundance index. Therefore, the abundance index tends to be biased and cannot correctly describe the actual fishery conditions.

The VAST model can answer all these problems well by reducing bias and error by excluding catchability covariates and including only habitat covariates as model predictors. In addition, the system contained in the VAST model allows for a weighting area for unfished areas with various accompanying systems (Thorson, 2019). The VAST model generated extrapolated density logs or density populations in our traditional fishing grounds in the Eastern Indian Ocean annually and quarterly. It is hoped that the modelling results using the VAST model can be used as a reference for making decisions regarding the management of tuna longline fisheries in Indonesia and simultaneously provide valuable information and inputs for longliners in the context of effective and efficient fishing operations.

5. CONCLUSION AND FUTURE RESEARCH

The spatiotemporal VAST model provides a better abundance index than previous nominal and conventional GLM indices. The VAST model can estimate the population density of species in fishing areas annually and quarterly and has a suitable mechanism for population weighting, especially in areas that are not surveyed or unfished. This is compatible with the results of dependent survey research. In the future, we will refine the research results by filling the unfished area with research surveys and implementing them for target species in the longline tuna fishery.

ACKNOWLEDGEMENTS

Gratitude and praise for the presence of Allah God Almighty and His abundance of grace and gifts so that the author could complete the GRO FTP Project 2021/2022. Sincere appreciation and gratitude to the supervisors who guided me, Julian Mariano Burgos Ph.D. and Magnús Thorlacius Ph.D. I would also like to thank the GRÓ FTP directors and staff (Mary Frances Davidson, Stefan Úlfarsson, Tumi Tómasson, Thor Heiðar Asgeirsson, Agnes Eydal, and Julie Ingham) for the opportunity given to attend training and the assistance during my studies in Iceland.

I also express my deep gratitude to the project coordinator (Jonas P. Jonasson) and the teaching staff at GRÓ FTP (who I cannot mention individually). Additionally, I would like to thank the fellows in the stock assessment specialist line for the cooperation and joy shared, my dear colleagues Aisyah, Angela Kwapena, Sidi Ahmed Hemed, Kamarel Ba, Diana Barohana, and Amidu Mansaray.

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