The index of abundance and density prediction of albacore (*Thunnus alalunga*) in the eastern Indian ocean using dependence survey

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ABSTRACT

Worldwide, the management of fish stocks is based on stock assessment models. One of the most critical inputs in most stock assessment models is a relative abundance index of the species of interest. The main problem in determining the abundance index occurs in a dependence survey where the catchability covariates are very influential on a species abundance index to cover the actual reality in nature. This study uses the Vector Autoregressive Spatiotemporal Model (VAST) on Albacore species in the Indonesian longline tuna fisheries in the Eastern Indian Ocean. The results indicate that the resulting abundance index is better with low residuals, excluded catchability, and included habitat covariates make the results better than 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. It is a distinct advantage considering many unfished areas in our research survey. This information is expected to benefit stakeholders in decision-making in the field.

Keywords: **Index of Abundance, Albacore, Density, Longline, Indian Ocean**

INTRODUCTION

Indonesia plays a significant role in tuna fisheries, especially in fishing areas in the Eastern Indian Ocean. Indonesia's total production is 17.24% of the total production of tuna fisheries in the Indian Ocean, with an estimated landing of 190,319 tonnes (CCSBT, 2021; Fahmi, Z., Hikmayani, Y., Yunanda, T., Yudiarso, P., Wudianto & Setyadji, 2020; MMAF Indonesia, 2021). Vessels in the Indonesian tuna fisheries use a variety of fishing gears, including gill nets, lines, longlines, purse seines, and others. In 2019, vessels using longlines landed 15,298 tonnes of tuna, corresponding to 8% of the total longline catch in the Indian Ocean (Fahmi, Z., Hikmayani, Y., Yunanda, T., Yudiarso, P., Wudianto & Setyadji, 2020).

In 2019, there were 283 vessels registered with the Indian Ocean Tuna Commission (IOTC), with gross tonnages (GT) ranging between 90 and 200 (Fahmi, Z., Hikmayani, Y., Yunanda, T., Yudiarso, P., Wudianto & Setyadji, 2020). The fishing grounds of the longline fleet in the Indian Ocean cover an extensive area, from 5 to 35°S latitude and from 70 to 125°E longitude. Landings of non-schooling tuna (bigeye tuna, yellowfin tuna, southern bluefin tuna, and albacore) are mainly destined to the export market in fresh products. Approximately 77% of catches were carried out outside Indonesia's exclusive economic zone (Setyadji, B. & Jatmiko, 2016).

Total albacore production in the Indian Ocean in 2020 was 38,100 tonnes, a decrease of 4% from 2019, and most of the catch is carried out by the longline tuna fishery (ISSF, 2022). Indonesia's albacore tuna fishery production is 5,850 tonnes, or about 15.35% of the total albacore catch in the Indian Ocean (MMAF Indonesia, 2021). The Indian Ocean albacore is estimated not to be overfished but is subject to overfishing. However, there is also some uncertainty related to the latest stock developments by IOTC (Indian Ocean Tuna Commission) (IOTC, 2021; ISSF, 2022).

Data and information related to Indonesian albacore tuna fisheries are sourced from fishery-dependent survey data (Indonesian onboard observer program) in the Eastern Indian Ocean. In the dependent survey, there are several weaknesses, including the very high bias value associated with the catchability covariates and many unfished areas in the survey area. An alternative method is needed to calculate the albacore abundance index in our survey area. The standardized abundance index values do not adequately reflect the actual abundance of the targeted species. Therefore, raw CPUE values cannot be used directly as indices of abundance, and they need to be standardized to account (at least partially) for these factors. A well-standardized CPUE value is expected to be proportional to the population abundance value (Maunder, M. N. & Punt, 2004; Rochman, F., Setyadji, B. & Wujdi, 2017; Sadiyah, L., Dowling, N. & Prisantoso, 2012). Several approaches standardize CPUE values (Maunder, M. N. & Punt, 2004). The most common approach is to use generalized linear models (GLMs), but other methods exist, including the use of generalized additive models (GAMs) and generalized linear mixed models (GLMMs). In recent years, standardization using VAST (Vector Autoregressive Spatiotemporal**)** models has been proposed as an alternative approach. VAST is a Spatio-temporal model that can explicitly account for changes in population densities over time and multiple locations (Thorson, J. T. & Barnett, 2017; Thorson, 2019b; Xu, H., Lennert-Cody, C. E., Maunder, M. N., Minte-Vera, 2019).

This study aims to model the abundance index of albacore in the Indonesian longline tuna fishery using a VAST model and perform a density prediction of albacore in the Eastern Indian Ocean.

MATERIALS AND METHODS

Data Collection

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

The data for this study consists of 2,951 longline sets deployed in the period 2006-2018. The information from each set includes 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)

Standardized Index Using VAST (Vector-Auto Regressive Spatio-Temporal) model

This study used the Vector-Autoregressive Spatio-Temporal (VAST) model. We used the R package VAST (https://github.com/James-Thorson-NOAA/VAST)(Thorson, 2019b). VAST uses a Gaussian random field to model the auto-spatial correlation with anisotropy (i.e., the auto-correlation relationship at velocity is not the same in all directions) and an interactive relationship between space and time (i.e., Spatio-temporal correlation). The Gaussian random fields are defined by the Matern covariance function (Thorson, 2019a).

VAST is a delta-generalized 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 is given that the species is encountered. The predicted logarithm of the albacore abundance *p(s,t)*, in knots *s* and year *t*, is predicted as:

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

Where, $\beta(t)$ is the intercept for each year t as a fixed effect, $\omega(s)$ is time-invariant spatial autocorrelated variations 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, *s* where the correlation of spatial and Spatio-temporal effects are estimated. Each observation in the data set is then connected to the closest node using k-means. In this study, we used a total of 3480 nodes (Figure 1, upper two figures), based on a regular grid with an input of 100 knots (Figure 1, red dots) and a resolution of 50 km and bounded by a concave hull surrounding the locations of the longlines in the data (Figure 1).

The 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 normality for GLM and VAST and quantile-quantile standard probability plots (Normal Q-Q plots) for both.

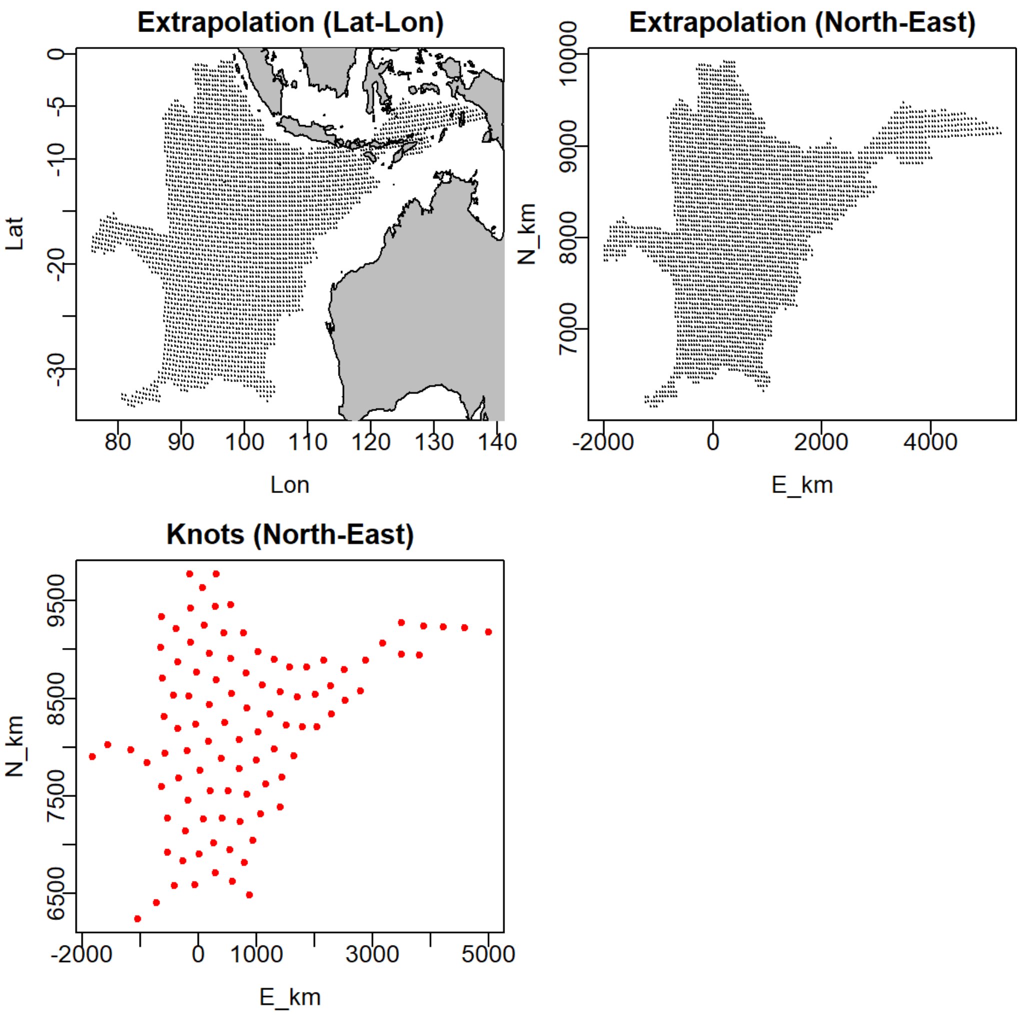

Figure 1. A grid comprising 3480 nodes marks the spatial coverage of the data and the surrounding bounds (upper figures) that were used to fit the VAST models. One hundred knots were specified, which the model places geographically to minimize the distance between data and knots over the study area (lower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

RESULT AND DISCUSSION

Distribution of Fishing Efforts

The overall distribution of longlines sampled by the Indonesian scientific observer program is shown in Figure 2. Fishing areas include the Eastern Indian Ocean, West of Sumatra, South of Java-Bali-Nusa Tenggara, Northwest-West Australia, and the Banda Sea.

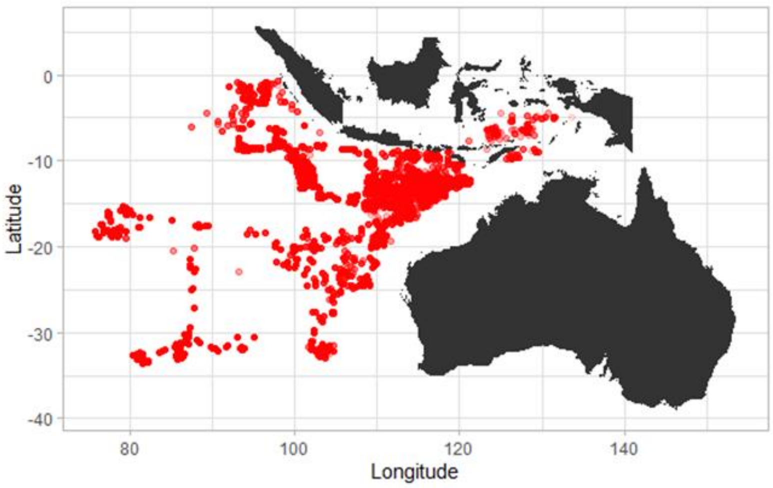

Figure 2. The study area of the Indonesian tuna longlines scientific observer program in the Eastern Indian Ocean 2006-2018.

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 3). However, the effort was higher 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).

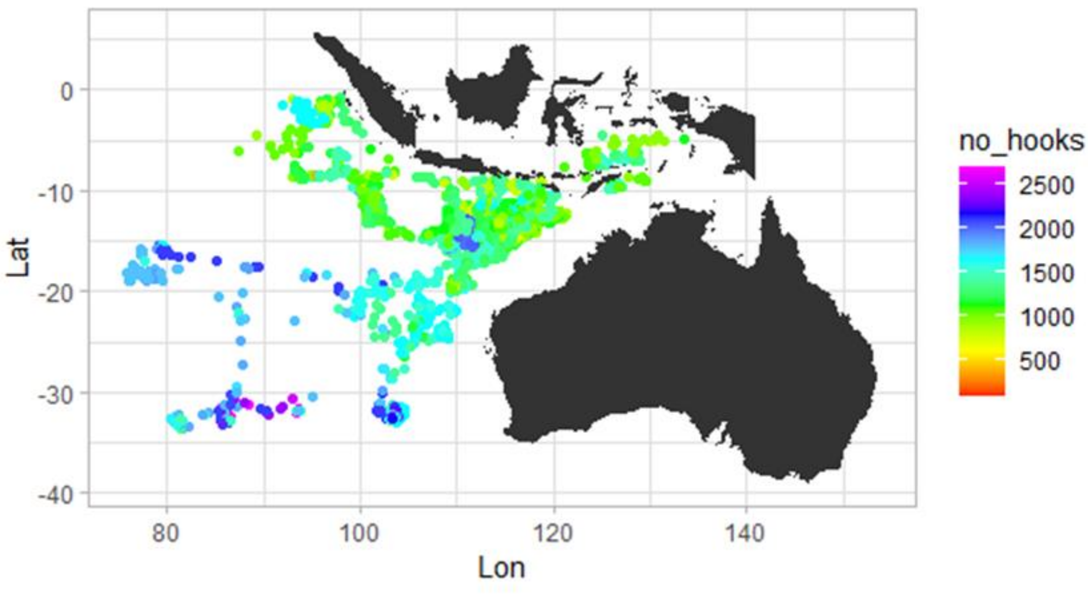

Figure 3. Spatial distribution of fishing effort defined as the mean number of hooks used per set per 1°x1° grid cell during 2006-2018.

Standardized Index Using VAST (Vector-Auto Regressive Spatio-Temporal) model

The Vast model uses several covariates as explanatory variables in determining the abundance index and predicting the density of albacore in the Longline Fishery Indian Ocean. This study used several habitat covariates, including fish depth, sea surface temperature, chlorophyll-a, sea depth, and distance to 1000 m isobath. VAST models the resulting residuals, both observational and predictive residuals, and looks an excellent fit (Figure 4). The abundance index of the VAST model is presented in Figure 5, and density prediction is presented in Figure 6.

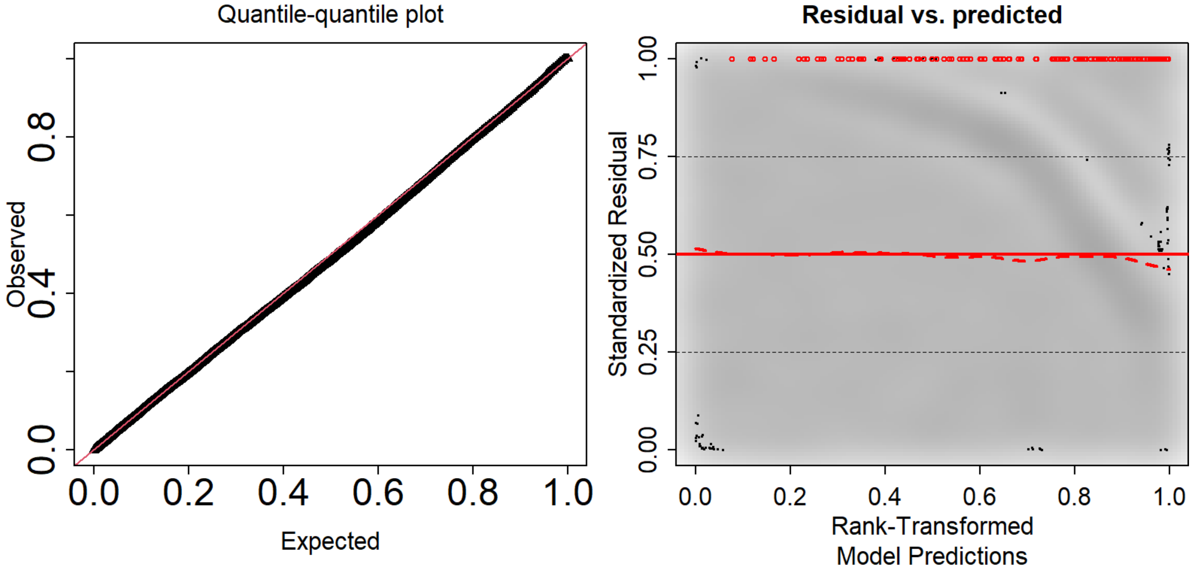

Figure 4. A plot of the residual model of VAST with habitat covariates on albacore in longline tuna fisheries in the Eastern Indian Ocean

Quantile residual diagnostic suggested that the VAST spatiotemporal model has well fitted for the number of catch and effort data in the longline tuna fisheries data set (Figure 14). Meanwhile, previous research using conventional GLM obtained that the quantile residuals for the standardized GLM model indicate underestimation at the beginning and overestimation at the end of the study periods (Rochman, F., Setyadji, B. & Wujdi, 2017; Sadiyah, L., Dowling, N. & Prisantoso, 2012). The conventional GLM index includes catchability covariates in the model such as fishing strategy and operational variables such as time, type longline, hook between float, the vessel, which are positively correlated with the catch rate and the resulting index of abundance. The result was an under-estimated value at the beginning and an over-estimate at the end of the study period, as shown in the diagnostic quantile residual. The VAST model seems to be a better reference than the conventional GLM model. 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).

Other advantages are obtained from the VAST spatiotemporal model compared to the conventional GLM model. The VAST model can estimate the population density for the species for multiple locations and multiple times, explicitly including association with environmental variables and changes in space and time (Figure 6). 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 tends to occur in locations that are close together compared to locations that are very far away. This function is called the "common currency" model, bringing together the different stock, ecosystem, and climate assessment approaches (Thorson, 2019).

From the log density population generated by the VAST model, several areas have a very high population density compared to other areas, especially the area around the West coast of Sumatera, the Banda Sea, and the high seas area West of Australia at latitude 75- 100°E. The population density prediction showed that the general population trend decreased from 2006 to 2008 and slightly increased from 2009 to 2011. In 2012 the population slightly decreased and began increasing from 2013 to 2016; moreover, a slight decrease in 2017 to 2018 (Figure 6).

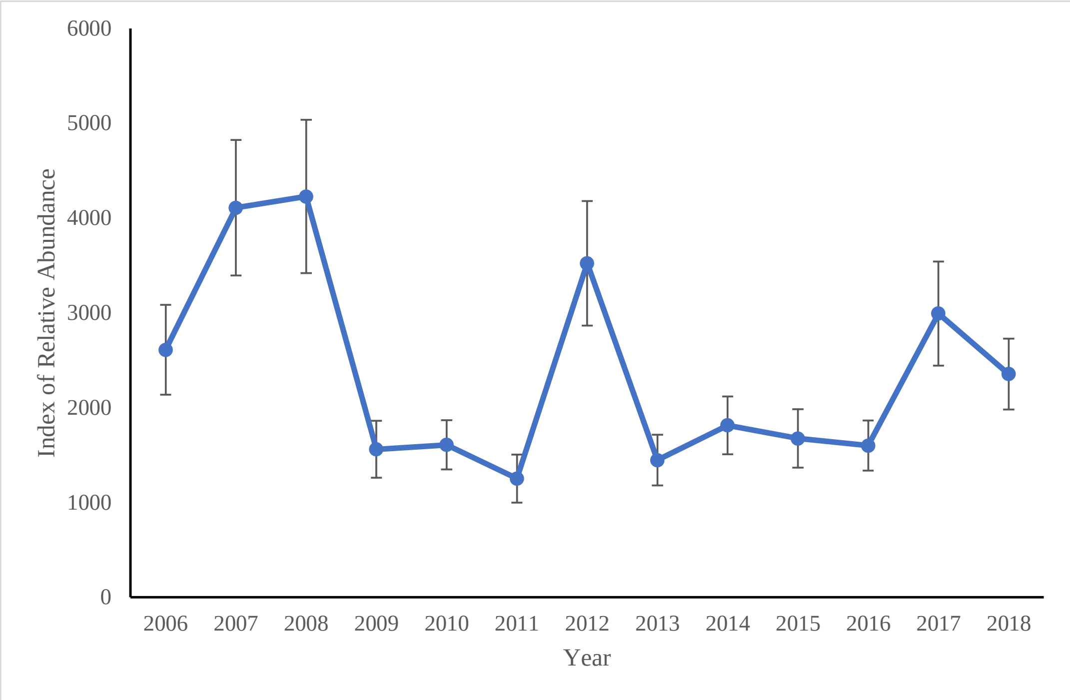

Figure 5. The abundance index of albacore in tuna longline fisheries using the VAST model with habitats covariates.

The VAST model has predicted density, both spatial and temporal variation across the fishing area in the Eastern Indian Ocean. The predicted log density in the VAST model uses habitat preferences to calculate population density spatiotemporally. Meanwhile, catchability preference is not used in model fitting so that the index and population density generated by the VAST model is pure without underestimating or overestimating residuals. The VAST model will automatically predict unfished areas not included in the survey via imputation and implement the area weighting scheme by referring to the nearest node. Besides that, the VAST model can predict population density based on habitat covariates and the accompanying spatial-spatiotemporal random effect. Furthermore, these covariates inform the random effect's value in the VAST model. The VAST model can substantially improve the population density predictions by conditioning the model based on the previously known residual pattern using geostatistical methods through kriging (Thorson, 2019).

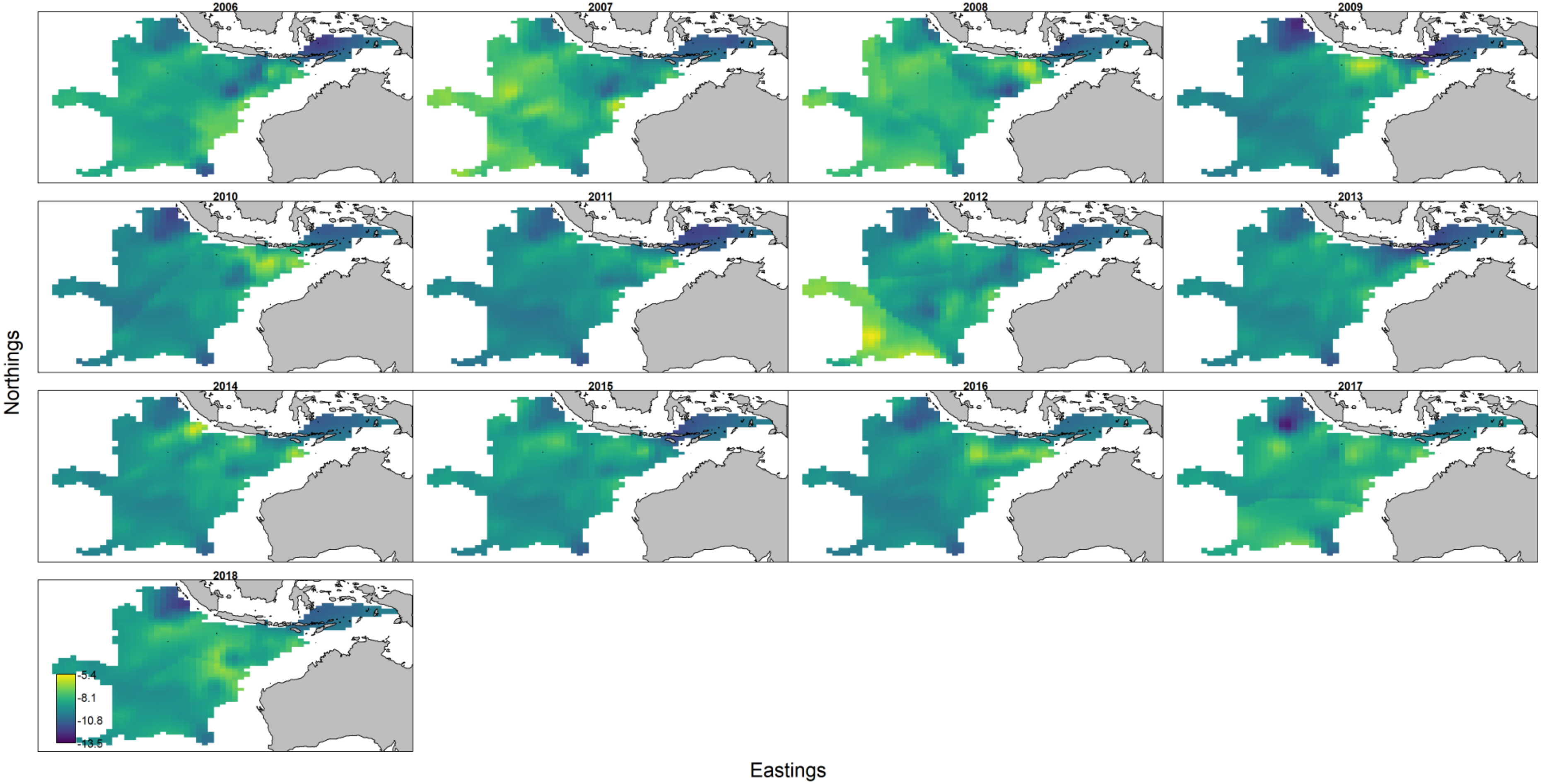

Figure 6. Spatiotemporal distribution of predicted log density of albacore in tuna longline fishery in the Eastern Indian Ocean 2006-2018 using the VAST model (dark green: high density, yellow: low density).

The VAST model's abundance index does not have the initial underestimation, the 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 obtained correctly and reliably.

CONCLUSION

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

REFERENCE

CCSBT. (2021). *Commission for the Conservation of Southern Bluefin Tuna Report of the Twenty Eighth Annual Meeting of the Commission*. https://www.ccsbt.org/sites/default/files/userfiles/file/docs_english/meetings/meeting_reports/ccsbt_28/report_of_CCSBT28.pdf

Fahmi, Z., Hikmayani, Y., Yunanda, T., Yudiarso, P., Wudianto & Setyadji, B. (2020). Indonesia National Report to The Scientific Committee of The Indian Ocean Tuna Commission. In *IOTC-2020-SC23* (Issue IOTC). https://iotc.org/documents/SC/23/NR07

Hsu, J. & Chang, Y. J. (2020). Cpue Standardization of Blue Marlin (Makaira Nigricans) for the Taiwanese Longline Fishery in the Atlantic Ocean. In *Collect. Vol. Sci. Pap.* (Vol. 20, Issue 3).

IOTC. (2021). Report of the 24th Session of the IOTC Scientific Committee. In *Iotc–2021–Sc24-R[E]* (Issue December). http://www.iotc.org/meetings/search?s=&field_meeting_tid_i18n=68&field_meeting_year_tid=All

ISSF. (2022). Status of the World Fisheries for Tuna. Mar 2021. In *ISSF Technical Report 2022-04* (Issue March).

Maunder, M. N. & Punt, A. E. (2004). Standardizing catch and effort data: A review of recent approaches. *Fisheries Research*, *70*(2-3 SPEC. ISS.), 141–159. https://doi.org/10.1016/j.fishres.2004.08.002

MMAF Indonesia. (2021). Indonesia National Report to The Scientific Committee of The Indian Ocean Tuna Commission. In *Iotc-2021-Sc24* (Issue IOTC). https://iotc.org/documents/SC/23/NR07

Rochman, F., Setyadji, B. & Wujdi, A. (2017). Standardizing CPUE of Albacore Tuna (Thunnus alalunga Bonnaterre, 1788) on Tuna Longline fishery in Eastern Indian Ocean. *Indonesian Fisheries Research Journal*, *23*(1), 29–38. https://doi.org/10.15578/ifrj.23.1.2017.29-38

Sadiyah, L., Dowling, N. & Prisantoso, B. I. (2012). Developing Recommendations for Undertaking Cpue Standardisation Using Observer Program Data. *Indonesian Fisheries Research Journal*, *18*(1), 19. https://doi.org/10.15578/ifrj.18.1.2012.19-33

Satoh, K., Matsumoto, T., Yokoi, H. & Kitakado, T. (2021). *On-going investigation of Japanese longline CPUE for yellowfin tuna in the Indian Ocean standardized by vector-autoregressive spatiotemporal model* (Vol. 23).

Setyadji, B. & Jatmiko, I. (2016). Comparison of Indonesian Tuna Longline Fishing Performance Within and Outside Indonesia Exclusive Economic Zone (EEZ). *Indonesian Fisheries Research Journal*, *23*(1), 1–6. https://doi.org/10.15578/ifrj.23.1.2017.1-6

Thorson, J. T. & Barnett, L. A. K. (2017). Comparing estimates of abundance trends and distribution shifts using single- and multispecies models of fishes and biogenic habitat. *ICES Journal of Marine Science*, *74*(5), 1311–1321. https://doi.org/10.1093/icesjms/fsw193

Thorson, J. T. (2019a). Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments. *Fisheries Research*, *210*(October 2018), 143–161. https://doi.org/10.1016/j.fishres.2018.10.013

Thorson, J. T. (2019b). *VAST model structure and user interface*. 1–19.

Xu, H., Lennert-Cody, C. E., Maunder, M. N., Minte-Vera, C. V. (2019). Spatiotemporal dynamics of the dolphin-associated purse-seine fishery for yellowfin tuna (Thunnus albacares) in the eastern Pacific Ocean. *Fisheries Research*, *213*(September 2018), 121–131. https://doi.org/10.1016/j.fishres.2019.01.013