Habitat Model Development of Bigeye tuna (*Thunnus obesus*) during Southeast Monsoon in the Eastern Indian Ocean using Satellite Remotely Sensed Data

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**Abstract.** Bigeye tuna (*Thunnus obesus*) is one of the commercially important fish in the eastern Indian Ocean and is a highly migratory species. A modeling approach and remotely sensed data were used to develop an appropriate prediction model and to understand the contribution of oceanographic factors in the distribution of Bigeye tuna in 2 different depths. The daily data of sub-surface chlorophyll-a (SSC), sub-surface temperature (SST) and sub-surface salinity (SSS) were downloaded from infrastructure development of space oceanography (INDES0) project website, meanwhile fishing vessel for Bigeye tuna were obtained from vessel monitoring system (VMS) from April through September 2015 - 2016. The daily VMS data and environmental factors were used for maximum entropy model construction. The predictive model performance was then assessed using a threshold-independent metric, the area under the curve (AUC) metric of the receiver operating characteristic (ROC). Maximum entropy model results based on AUC (more than 0.80) indicated its potential to deduce the spatial distribution of Bigeye tuna. At a depth of 155 m, SSC (37.9%) is the most effective variable in the Bigeye tuna distribution, followed by SST (32.7 %) and SSS (29.4%), meanwhile at a depth of 222 m, SSS (46.8%) is the most important variable followed by SST (31.3%) and SSC (21.9%). Combination of a modelling approach and multi-sensor remote sensing data offers an innovative way to determine the potential fishing zone of the Bigeye tuna in the eastern Indian Ocean.

**Keywords:** Bigeye tuna, different depths, eastern Indian Ocean, maximum entropy model, potential fishing zones.
1. Introduction

Bigeye tuna (*Thunnus obesus*) is one of the tuna species that mostly caught in the eastern Indian Ocean (EIO). This species is a highly migratory pelagic species. They were distributed in sub-tropical and all tropical waters of the world’s ocean, but not in the southwestern of the Atlantic [1]. Bigeye tuna prefers to stay near and below the thermocline layer [2]. Several studies showed that it was mostly found at the depth around 150 m [3,4] and around 209 – 259 m [5]. Besides, the optimum water temperature at hook depths ranges between isotherm 10° – 15°C which is below the thermocline depth [1,2]. This condition indicated that sub-surface could influence the distribution of tuna.

In term of an ecology, analysis of the association between a species and its environment is essential. In general, marine species are correlated with specific physical or biological habitats; therefore, it creates curiosity in understanding the role of environmental conditions in directing distribution patterns and abundance [6]. The familiar approach to assess the actual or potential geographical distribution of a species is to understand the environmental characteristics that are appropriate for the species and then identify where the favorable environment is spatially distributed [7].

The species distribution model is an empirical model that connects field observation to environmental predictor variables based on the response surface derived statistically or theory [8]. Species distribution model theory states that the model can expect the potential spatial occurrence of various species, by connecting the occurrence points with predictor variables [9]. Habitat modeling techniques assume that, for each species, there is a set of ideal environmental variables that make the occurrence of a species more likely.

The data generally exist in a presence-only form, which presents another challenge for predicting events, ranges, and niches of species offshore. Presence-only data and biophysical variables can be used to predict precisely 'niche-based models' using many methods. The presence-only model produces spatially explicit suitability surfaces that represent habitat suitability [10]. One of the habitat modeling techniques that widely used is maximum entropy [11,12]. Therefore, it is interesting to understand how potential fishing zones of Bigeye tuna in the EIO at a different depth influenced by sub-surface oceanographic factors by using a maximum entropy model.

2. Methods

Figure 1 shows the study area in the eastern Indian Ocean (104° – 120°E and 6° – 16°S) with some oceanic currents and waves exist. The complexity currents and waves system in this region generate interest region to figure out the PFZ of Bigeye tuna as the impact of oceanographic parameters.
2.1. Detection of the fishing vessel from vessel monitoring system data

The daily vessel monitoring system (VMS) data were provided and distributed by the Ministry of Maritime Affairs and Fisheries Indonesia (http://integrasidjp.dkp.go.id). We collected 387 data for southeast monsoon (April through September) 2015 and 2016 (Table 1). The period was chosen for analysis since it corresponds with the main fishing season of Bigeye tuna and the available data in the marine research and observation agency (Balai Riset dan Observasi Laut/BROL), Bali. The speed and fishing gear type of vessels were used as an indicator to determine the fishing vessel for Bigeye tuna. Barata et al. and Syamsuddin et al. reported that longline is a standard fishing gear to catch the Bigeye tuna in the EIO [19,20]. Besides, the speed of vessels less than 3 knots was considered conducting fishing activities while vessels velocities more than 3 knots were assumed not to be conducting fishing activities. Therefore, in this study, we selected vessels equipped with longline tuna fishing gear and speed of vessels less than 3 knots as the location of the fishing vessels for Bigeye tuna in the EIO. The hot spot of the fishing boats was then believed to reflect the Bigeye tuna fishing position in the EIO.

Table 1. Number of fishing vessels from the Vessel Monitoring System for the period April - September 2015 and 2016.

| Year | Apr | Mei | Jun | Jul | Aug | Sep |
|------|-----|-----|-----|-----|-----|-----|
| 2015 | 27  | 31  | 21  | 19  | 11  | 29  |
| 2016 | 31  | 51  | 54  | 26  | 41  | 46  |

2.2. Satellite-derived environment variable

In the maximum entropy models, we used sub-surface chlorophyll-a (SSC), sub-surface temperature (SST), and sub-surface salinity (SSS) data at a depth of 155 meters and 222 meters for period April – September 2015 and 2016 as environmental variables. Daily SSC, SST and SSS data with nine spatial resolutions were downloaded from Infrastructure Development of Space Oceanography website (www.indeso.web.id.). To construct the appropriate habitat model, ArcGIS 10.2.2 was used to convert the daily data and then compiled in a monthly database. The grid function of the software package Generic Mapping Tools, vers. GMT 4.5.7 (http://gmt.soest.hawaii.edu/) was then used to reprocess the data into Esri ASCII grid format (Esri, Redlands, CA).

2.3. Construction of a maximum entropy model

The software program Maxent, vers. 3.3.3k was used to develop a habitat suitability model at a depth of 155 m and 222 m with a maximum entropy approach. The default values for maximum iteration (5000), a regulation parameter (1), and automatic feature class selection were used to construct the habitat suitability model. To evaluate the performance of the models, a cross-validation procedure was used in this study. The data were randomly split into two groups for each depth habitat suitability model: group one (75%) for training data and group two (25%) for testing data.

2.4. Evaluation and validation of the model

The area under the curve (AUC) of the receiver operating characteristic (ROC) were used to evaluate model fit [12]. Heuristic estimate of variable importance was used to examine the relative contribution of individual environmental variables. To obtain the affirmative condition for PFZ, response curves were examined. The habitat suitability models were employed to design habitat suitability indices (HSIs). Spatial HSI maps were produced and overlain with fishing position generated from VMS for period southeast monsoon 2015 and 2016.
3. Results

3.1. Spatiotemporal distribution of fishing locations
The distribution variation of fishing vessels for Bigeye tuna for during southeast monsoon 2015 and 2016 is shown in Figure 2. The figure showed that there were two hot spots location fishing activities of Bigeye tuna in EIO, i.e., south of Java Islands and south of Bali – West Nusa Tenggara waters. However, it can be clearly seen that the south water of Bali – Nusa Tenggara archipelago was preferable than south of Java Islands for fishing areas for Bigeye tuna.

Figure 2. Spatial distribution of fishing locations for Bigeye tuna (*Thunnus obesus*) (red dot) during southeast monsoon 2015 and 2016, and two hot spots of fishing locations.

3.2. Model performance and potential fishing zones
Maximum entropy model showed an excellent performance with the AUC value of 0.808 (155 m) and 0.812 (222 m), respectively. These results indicate the high predictive success of the habitat suitability model [12]. Furthermore, the relative contribution of each parameter is shown in Table 2. The models’ results revealed that the most crucial factor in the distribution of Bigeye tuna, both in the depth of 155 m and 222 m were SSC and SSS, respectively, followed by SST.

Table 2. The relative percent contribution of environmental variables to the model. The higher environmental variables contribution is presented in bold.

| Depth (m) | SSC (mg/m³) | SST (°C) | SSS (psu) |
|-----------|-------------|----------|-----------|
| 155       | 37.9        | 32.7     | 29.4      |
| 222       | 21.9        | 31.3     | 46.8      |

Figure 3 shows the model-acquire favor ranges for each environmental variable. The plots in the figure showed the contribution and performance of each environmental data to model fit. Based on the figure, the high probability of Bigeye tuna presence both in the two depth was noticed in the low SSC concentration (0.01 mg/m³), SSS of 34.55 – 34.85 PSU, and SST of 18 °C (155 m) and 12 °C (222 m), respectively.
Figure 3. Response curves from the model for (A and D) sub-surface chlorophyll-a (SSC), (B and E) sub-surface temperature (SST), and (C and F) sub-surface salinity (SSS) At a depth of 155 m (Upper panel) and at a depth of 222 m (Lower panel) in the eastern Indian Ocean.
3.3. Prediction and validation of occurrence

The predicted HSI maps during southeast monsoon at a depth of 155 and 222 m are shown in Figure 4.

**Figure 4.** The spatial distribution of fishing locations (black dots) for Bigeye tuna (*Thunnus obesus*) from the vessel monitoring system, overlain on maps of habitat suitability predicted at a depth of 155 m (A) and depth of 222 m (B). The suitability is illustrated as Habitat Suitability Index (HSI) score ranging from 0 to 1, characterizing “poor” to “good” habitat quality, respectively.

During this period, the predicted probability of presence of Bigeye tuna has high value of HSI (≥ 0.6) both at a depth of 155 m and 222 m especially at 113° – 120° E and 9° – 13°S. However, it was clearly seen that at a depth of 222 m, high value of HSI was broader compared with a depth of 555 m. At a depth of 222 m, high potential fishing zones occurred offshore areas of Bali–West Nusa Tenggara (113° - 120°E and 9° - 13°S), the total fishing position at a high value of HSI (>0.5) At a depth of 222 m was higher than at a depth of 155 m (Figure 5).

**Figure 5.** The Frequency of Habitat Suitability Index (HSI) at a depth of 155 m (blue bar) and 222 m (red bar).

4. Discussion

Fishing locations of Bigeye tuna are relatively difficult to find in Indonesian fisheries. This is due to competition between ships; accordingly, this is the reason of the fishing location data is confidential and difficult to find [21]. In this study, a fishing vessel monitoring system (VMS) were used to identify the location of a fishing vessel for Bigeye tuna in the eastern Indian Ocean. The vessel monitoring system is a radar satellite-based ship monitoring system. This system can be used to generate the position of a fishing vessel for Bigeye tuna. Analyses of VMS data provide us to detect fishing vessel position across space and time. Where fishing vessels were identified, we considered a Bigeye tuna location. Based on the obtained fishing vessel positions, we can predict the temporal and spatial distribution of Bigeye tuna potential fishing zones.
Fishing locations for Bigeye tuna and oceanographic variables at a depth of 155 m and 222 m with maximum entropy models were used to predict the potential fishing zones for Bigeye tuna in the EIO. The predicted distribution of Bigeye tuna showed areas of high probability of presence off Bali – West Nusa Tenggara Islands (Fig. 4). This pattern coincided with the fishing vessel for Bigeye tuna, especially at a depth of 222 m. Fanani reported that most of Bigeye tuna caught at a depth of 209 – 259 m [5]. The maximum entropy model performance at two different depths indicates that the model performed well to predict potential fishing zones for Bigeye tuna. However, the performance of the model at a depth of 222 m had a value of AUC (0.812) higher than at a depth of 155 m (0.808). Furthermore, the results showed that the distribution of Bigeye tuna significantly influenced by an oceanographic condition. Migration and productivity of fish are influenced by an oceanographic condition such as salinity, currents, temperature, and wind fields are believed to influence the productivity and fish distribution [22, 23]. In this research, among the set of oceanographic variables analyzed at two both depth, SSC (depth of 155 m) and SSS (depth of 222 m) showed the highest contribution (Table 2), respectively. Our results demonstrate that Bigeye tuna presence mostly occurred in low SSC concentration, 0.010 – 0.015 mg/m³ (Figure 3A and 3D). This result was supported by Syamsuddin et al. who reported that chl-a was essential parameters in the distribution of Bigeye tuna in the EIO with relatively low-to-moderate chl-a values [20].

Unlike at the depth of 155 m, at a depth of 222 m parameters, SSS showed the highest contribution in Bigeye tuna distribution. This indicates that oceanographic parameters at different locations and depths will have different effects on marine species distribution. Bigeye tuna is epipelagic and mesopelagic fish, fast swimmers and highly migratory species. Salinity is very influential on physiology (osmotic pressure) of marine species including tunas. Faizah reported that the distribution of Bigeye tuna is influenced by various oceanographic factors including salinity [24]. Our study showed that most Bigeye tuna fishing sets were located in SSS value of 34.55 – 34.85 psu (Figure 3C and 3F). The result was supported by Novianto and Susilo, who reported that Bigeye tuna mostly distributed in salinity value around 34 psu and high salinity will delay the migration of Bigeye tuna [25].

Another interesting part of this study was the SST parameters. In this study, SST always ranks second as a parameter that affects the distribution of Bigeye tuna in the EIO. This indicates that Bigeye tuna distribution is influenced by SST [4, 26]. Syamsuddin et al. reported that SST is the most significant variable for Bigeye tuna catches in the EIO [20]. They also reported that Bigeye tuna catches declined at temperatures of >27.5°C but elevated in areas with relatively low temperatures (24–27.5°C). Our results indicate that at a depth of 155 m, Bigeye tuna mostly appeared in SST of 18 °C (Figure 3B). These results supported by Sukresno et al. who reported that Bigeye tuna were mostly located at a depth around 150 m with SST of 16° – 21 °C [4]. However, at a depth of 222 m, our results showed that Bigeye tuna mostly appeared in SST of 12°C (Figure 3E). Fanani reported that most of Bigeye tuna caught at a depth of 209 – 259 m with temperature of 12.38° – 14.06 °C [5]. In addition, Ffield et al. and Gordon et al. reported that remote pressure from the Pacific Ocean has a significant impact on hook rate during an El Niño since the degradation in heat transferred from the Pacific to the Indian Ocean by the ITF during El Niño events [17,27].

5. Conclusion
During southeast monsoon, the fishing vessel for Bigeye tuna mostly appeared around south of Bali – West Nusa Tenggara Island. High potential fishing zones for Bigeye tuna at a depth of 222 m was wider compared with a depth of 155 m. Sub-surface chlorophyll-a (depth of 155m) and sub-surface salinity (depth of 222 m) showed the highest contribution to the habitat suitability model, respectively, followed by sub-surface temperature.

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References

[1] E. Hanamoto, “Effect of oceanographic environment on Bigeye tuna distribution”, *Bull. Jap. Soc. Sci. Fish. Oceanogr.*, 3, 203–216, 1987.

[2] M. Mohri, E. Hanamoto, and S. Takeuchi, “Optimum water temperatures for Bigeye tuna (*Thunnus obesus*) in the Indian ocean as seen from tuna longline catches,” *Bulletin of the Japanese Society of Scientific Fisheries* (Japan), 62, 761-764, 1996.

[3] A. Hartoko, “Spatial distribution of Thunnus. sp, vertical and horizontal sub-surface multilayer temperature profiles of in-situ agro float data in Indian Ocean,” *J. Coastal Development*, 14, 61-74, 2010.

[4] B. Sukresno, A. Hartoko, B. Sulistyo, and Subiyanto, “Empirical cumulative distribution function (ECDF) analysis of Thunnus.sp using ARGO Float sub-surface multilayer temperature data in Indian Ocean South of Java,” *Procedia Environmental Sciences*, 23, 358 – 367, 2015.

[5] Fanani, "Distribusi vertikal tuna berdasarkan kedalaman mata pancing rawai tuna dan suhu air hasil pengukuran minilog-TD," *Skripsi*. Fakultas Perikanan dan Ilmu Kelautan, 1999.

[6] J. Elith, S. J. Phillips, T. Hastie, M. Dudik, Y. E. Chee, and C. J. Yates, “A statistical explanation of MaxEnt for ecologists,” *Drivers Distrib.*, 17, 43–57, 2011.

[7] R. G. Pearson, C. J. Raxworthy, M. Nakamura, and A. T. Peterson, “Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar,” *J. Biogeogr.*, 34, 102–117, 2007.

[8] A. Guisan, and W. Thuiller, “Predicting species distribution: offering more than simple habitat models,” *Ecol Lett* 8, 993–1009, 2005.

[9] J. Franklin, “Mapping species distributions: spatial inference and prediction,” *Cambridge University Press*, Cambridge, UK. 2009.

[10] J. Elith, C. H. Graham, R. P. Anderson, M. Dudik, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, J. Li, L. G. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. McC, Overton, A. T. Peterson, S. J. Phillips, K. Richardson, R. Scachetti-Pereira, R. E. J. Schapire, Soberón, S. Williams, M. S. Wisz, and N. E. Zimmerman, "Novel methods improve prediction of species’ distributions from occurrence data," *Ecography*, 29,129–151, 2006.

[11] S. M. C. Edren, M. S. Wisz, J. Teilmann, R. Dietz, and J. Soderkvist, “Modelling spatial patterns in harbour porpoise satellite satellite telemetry data using maximum entropy,” *Ecography*, 33, 698–708, 2010.

[12] S. J. Phillips, R. P. Anderson, and R. E. Schapire, “Maximum entropy modeling of species geographic distributions,” *Ecol. Model*, 190, 231–259, 2006.

[13] J. Sprintall, S. E. Wijffels, R. Molcard, and I. Jaya, “Direct estimates of the Indonesian Throughflow entering the Indian Ocean: 2004–2006,” *J. Geophys. Res.* (C Oceans) 114, 1–19, 2009.

[14] L. Zhou, R. Murtugudde, and M. Jochum, “Dynamics of the intra seasonal oscillations in the Indian Ocean South Equatorial Current,” *J. Phys. Oceanogr.*, 38, 121–132, 2008.

[15] A. L. Gordon, "Oceanography of the Indonesian seas and their throughflow," *Oceanography*, 18(4), 13–26, 2005.

[16] R. Molcard, M. Fieux, and F. Syamsudin, "The throughflow within Ombai Strait. *DeepSea Res. (I Oceanogr. Res. Pap.).* 48, 1237–1253, 2001.

[17] A. Gordon, J. Sprintall, V. H. M. Aken, R. D. Susanto, S. Wijffels, R. Molcard, A. Ffield, W. Pranowo, and S.Wirasantosa, "The Indonesian throughflow during 2004–2006 as observed by the INSTANT program," *Dyn. Atmos. Oceans*, 50, 115–128, 2010.
[18] F. Syamsudin, A. Kaneko, and D. B. Haidvogel, "Numerical and observational estimates of Indian Ocean Kelvin wave intrusion into Lombok Strait," Geophys. Res. Lett. 31:L24307, 2004. doi:10.1029/2004GL02 1227.

[19] A. Barata, A. Bahtiar, and H. Hartati, "Pengaruh perbedaan umpan dan waktu setting rawai tuna terhadap hasil tangkapan tuna di Samudera Hindia," Jurnal Penelitian Perikanan Indonesia, 17 (2), 133-138, 2011.

[20] M. L. Syamsudin, S.I. Saitoh, T. Hirawake, S. Bachri, A. B. Harto, "Effects of El Niño-Southern Oscillation events on catches of Bigeye tuna (Thunnus obesus) in the eastern Indian Ocean off Java," Fishery Bulletin, 111 (2), 175-188, 2013. doi: http://dx.doi. org/10.7755/FB.111.2.5.

[21] T. A. Wibawa, "Pemanfaatan data satelit oseanografi untuk prediksi daerah potensial penangkapan tuna mata besar (Thunnus obesus) di Samudra Hindia selatan Jawa-Bali," Jurnal Segara, 7, 1 – 12, 2011.

[22] A. J. Southward, G. T. Boalch, and L. Maddock, "Fluctuations in the herring and pilchard fisheries of Devon and Cornwall linked to change in climate since the 16th century," J Mar Biol Assoc UK, 68, 423–445, 1988.

[23] J. Alheit, and E. Hagen, "Long-term climate forcing of European herring and sardine populations," Fish Oceanogr. 6, 130–139, 1997.

[24] R. Faizah, "Biologi reproduksi ikan tuna mata besar (Thunnus obesus) di Perairan Samudera Hindia," Tesis. Institut Pertanian Bogor, 2010.

[25] D. Novianto, and E. Susilo, "Role of sub surface temperature, salinity and chlorophyll to Albacore Tuna abundance in Indian Ocean. Indonesian Fisheries Research Journal 22(1), 17-26, 2016.

[26] R. W. Brill, K. A. Bigelow, M. K. Musyl, K. A. Fritsches, and E. J. Warrant, "Bigeye tuna (Thunnus obesus) behavior and physiology and their relevance to stock assessments and fishery biology," Col. Vol. Sci. Pap. ICCAT, 57(2), 142–161, 2005.

[27] A. Ffield, K. Vranes, A. L. Gordon, R. D. Susanto, and S. L. Garzoli, "Temperature variability within Makassar Strait," Geophys. Res. Lett., 27, 237–240, 2000.