Application of remotely sensed data and maximum entropy model in detecting potential fishing zones of Yellowfin tuna (*Thunnus albacares*) in the eastern Indian Ocean off Sumatera

Achmad Fachruddin Syah*, Emma Suri Yanti Siregar, Vincetius P Siregar, Syamsul B Agus

*University of Trunojoyo Madura, Jl. Raya Telang PO BOX 2 Kamal, Bangkalan, Madura
2Sekolah Tinggi Perikanan dan Kelautan Matauli, Jl. Ki Hajar Dewantara No. 1, Pandan, Tapanuli Tengah – Sumatera Utara
3IPB University, Jl. Raya Dramaga, Babakan, Dramaga, Bogor, West Java 16680

*e-mail: fachrudin@trunojoyo.ac.id

Abstract. Yellowfin tuna (*Thunnus obesus*) is one of the most important and most caught fish in the eastern Indian Ocean off west Sumatera and has extensive migration. To develop an appropriate prediction model and to understand the contribution of oceanographic parameters in the potential habitat of Yellowfin tuna, remotely sensed data and habitat modeling were used. Daily data of sea-surface temperature (SST), sea-surface salinity (SSS) and sea-surface height (SSH) were downloaded from the marine copernicus website, meanwhile fishing vessel position for Yellowfin tuna were obtained from fishing port Samudera, Bungus, west Sumatera, from January through December 2015. Daily fishing vessel position and environmental parameters were used for maximum entropy model construction. The model predictive performance was then evaluated using a threshold-independent metric, the area under the curve (AUC) metric of the receiver operating characteristic (ROC). Maximum entropy model results (AUC > 0.90) indicated its potential to figure out the spatial distribution of Yellowfin tuna. In general, SST (50.5%) is the most affective variable in the Yellowfin tuna distribution, followed by SSS (37%) and SSH (12.5%). This study showed that integration multi remotely sensed data and a modeling approach provide an innovative way to decide the potential fishing zones of the Yellowfin tuna in the eastern Indian Ocean off west Sumatera.

Keywords: Eastern Indian Ocean, maximum entropy model, potential fishing zones, remotely sensed data, Yellowfin tuna.

1. Introduction
Yellowfin tuna (*Thunnus albacares*) is one of the commercially important pelagic species in the eastern Indian Ocean. Indian Ocean Tuna Commission (IOTC) reported that Indonesia is the fourth leading tuna-fishing nations in the Indian Ocean after Spain, Sri Lanka, and Maldives [1]. One of the tuna species in Indonesia especially in the eastern Indian Ocean off Sumatera is Yellowfin tuna. The production value of Yellowfin tunas in this area could reach Rp 89,676,784 in 2012 and only 21,842,583 in 2016 [2]. The fluctuation condition of tuna catches were believed affected by oceanographic condition ([3]; [4]; [5]).
The number, size and location of fishing ground for Yellowfin tuna are significantly affected by oceanographic condition. The distribution and migratory patterns of Yellowfin tuna have been correlated with chlorophyll-a concentration, sea-surface temperature (SST), salinity, and sea surface height ([6]; [7]; [8]). Sea-surface height can be used to infer physical oceanographic features, such as fronts, eddies, and convergences [9]. In addition, sea-surface height can be used to indicate water mass movements and the flow of heat and nutrients, which will subsequently influence productivity [10]. [11] has been used SST to investigate productive frontal zones which can be used to indicate potential tuna fishing grounds.

Analysis of the relationship between a species and its environment is always important in an ecology. Marine species often associate with specific physical or biological habitats, thus building interest in understanding the role of environmental conditions in directing patterns of distribution and abundance [12]. The most common strategy for estimating the actual or potential geographic distribution of a species is to understand the environmental characteristics that are suitable for the species and then identify where the suitable environment is distributed spatially [13].

Distribution species models are empirical models that connect field observation to environmental predictor variables based on response surfaces derived statistically or in theory [14]. The species distribution models theory states that the model can predict the potential spatial distribution of a species range, by connecting emergence points to predictor variables [15]. The habitat modeling techniques are based on the assumption that, for each species, there is an ideal set of environmental variables (signatures) that make the emergence of a species more likely. The study potential distribution of Yellowfin tuna using generalized additive model (GAM) has been made by [16]. However, the result showed that GAM only could explain 56.9% of the hook rate. Therefore, to increase the prediction of Yellowfin tuna distribution in the eastern Indian Ocean off Sumatera, maximum entropy model will be employed. The maximum entropy model [17] was one of the most extensively used machine-learning algorithms for deducing species distributions. In recent studies, the method of maximum entropy has been covered to both terrestrial [18] and marine ecosystems ([19]; [20]). The objective of this study is to understand the influence of oceanographic factors and the formation of potential areas for Yellowfin tuna by using oceanographic data derived from remote sensing data integrated with the maximum entropy model.

2. Material and methods

Study area

The study area was located in the EIO, west of West Sumatera, spanning between 0.5°N – 9.7°S and 89°E – 103°E. This area has been known as one of the fishing areas for Yellowfin tuna (Thunnus albacares).
Fisheries data sets
Catch data for Yellowfin tuna were obtained from longline fishing logbooks provided by Pelabuhan Perikanan Samudera (PPS) Bungus, West Sumatera. Data included fishing position (latitude and longitude), operational days, fish weight (in kilograms), vessel number, number of hooks, and the number of fish caught per month during 2015. The truth of this data has been validated by Kesyahbandaran Pelabuhan, as the holder of the fisheries database at PPS Bungus. Table 1 shows the number of fishing vessels for Yellowfin tuna.

Table 1. The number of fishing for Yellowfin tuna (Thunnus albacares) from Pelabuhan Perikanan Samudera (PPS) Bungus, West Sumatera, from January through December 2015.

| JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | NOV | DEC |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 23  | 33  | 79  | 49  | 19  | 9   | 85  | 99  | 46  | 63  | 40  | 70  |

Analysis of tuna catches
Fish abundance analysis was stated in tuna longline hook rate, namely the number of tuna caught by 100 fishing rods operated [21].

\[
HR = \frac{E}{P} \times 100
\]

where: \( HR = \) hook rate
\( E = \) the number of tuna caught
\( P = \) the number of hooks

The catch rate is a stock density index, used to determine the level of exploitation of fisheries resources. The hook rate value was then being described using a graph based on the fishing season.

Satellite-derived environment variable
Unlike [16], in this study, we did not use chlorophyll-\(a\) concentration (chl-\(a\)) in constructing the habitat suitability model. [22] reported that chl-\(a\) showed the lowest contribution to the model prediction. The quite weak impact of chl-\(a\) on hook rate was believed because the lag time in food chain processes. Therefore in this study, we used sea-surface salinity (SSS), sea-surface temperature (SST), and sea-surface height (SSH) data for period January – December 2015 as environmental factors in the maximum entropy models. Daily SSS, SST and SSH data with 4 km spatial resolutions were downloaded from marine copernicus website (http://marine.copernicus.eu/). To construct the habitat suitability model, the daily data were reprocessed with Ferret v6.96 and SeaWiFS Data Analysis Sistem (SEADAS) 7.3.2 software. The data were then compiled in a monthly database. We converted to Esri ASCII grid format (Esri, Redlands, CA) or to comma-separated values (CSV) format with the grid function of the software package Generic Mapping Tools, vers. GMT 4.5.7 (http://gmt.soest.hawaii.edu/). This format was required by the software program Maxent.

3. Results and discussions
3.1 Spatio temporal distribution of fishing location and hook rate
Figure 2 shows the variation distribution of fishing location from January through December 2015. In January – March most of fishing vessel appear around Siberu – North Pagai Islands (Fig. 2A). During this period, some of fishing vessels also appear in offshore areas. In April – June, the fishing vessels still appear around Siberu – North Pagai Islands (Fig. 2B). However, during this period the number of fishing vessel slightly decrease and there was no fishing vessels in offshore area. In July – September, the number of fishing vessels increase (Fig. 2C). Based on the number of fishing vessel, this period
was considered as the peak of fishing season of Yellowfin tuna in the EIO off Sumatera. In the last three months, the number of fishing vessels slightly decrease and some of fishing vessels appear in offshore areas (Fig 2D).

Figure 2. Spatial distribution of fishing locations for Yellowfin tuna (*Thunnus albacares*) in the eastern Indian Ocean off Sumatera pooled during (A) January - March, (B) April - June, (C) July - September, and (D) October - December, for the period 2005.

Tuna catch data collected from 43 tuna longline vessels during 2015 varied for weight and hook rate per month. Figure 3 shows the fluctuation of hook rate and tuna catches during January – December 2015. The lowest catches occurred in June with total weight of 749 kg. In contrast, the highest catch occurred in December with total weight of 8,859 kg and hook rate of 0.85. During this month, the increase of hook rate in line with the increasing of number of catches.

Figure 3. Hook rate tuna longline and catches data in 2015
3.2 Spatial distribution of SST, SSS and SSH

Figure 4 shows the snapshots of SST, SSS and SSH, each displaying the means of value from January through December 2015. During this period high SST occurred in north side of study areas. This condition is thought to be caused by the north side close to the equator. During this period SST has value of 28.5 – 30 °C. On the hand, high value of SSS occurred in the off shore areas. During 2015 SSS has value of 33 – 34.5 psu. In the same period, high value of SSH also occurred in the north side. Low SSH occurred in areas around 6 – 9 °S and 90 – 97 °E. During this period, SSH has value of 0.5 – 1 cm.

![Image of SST, SSS, and SSH snapshots]

Figure 4. Images of mean values during 2015 obtained from remotely sensed data for (A) sea-surface temperature (°C), (B) sea-surface salinity (psu) and (C) sea-surface height (cm) in the eastern Indian Ocean off Sumatera.

3.3 Model performance and potential fishing zones

The AUC value of > 0.9 showed the excellent performance of the model. This result indicates that the model have high predictive success [23]. In addition, the relative percent contribution of each parameter was shown in Table 2. The results showed that most essential factor in distribution of Yellowfin tuna was SST followed by salinity and sea surface height.

| Parameter | Relative Percent Contribution |
|-----------|-------------------------------|
| SST (°C)  | 50.5                          |
| SSS (psu) | 37                            |
| SSH (cm)  | 12.5                          |

Table 2. Heuristic estimates of the relative percent contribution of environmental variables to models

The model-derived preferred ranges for each oceanographic factor were shown in Fig. 5. The plot in the figure pointed out the performance and contribution of the oceanographic data to model fit. High probability of Yellowfin tuna presence looked in SST value of 29.5°C, salinity of 33.7 psu and SSH of 0.89 – 0.92 cm.
Productivity and fish distribution are influenced by changes in the environment condition from the variations in temperature, currents, salinity, wind fields, thermocline depth and sea surface height ([24]; [25]; [26]). In this study, SST variable showed as the most important variables in distribution for Yellowfin tuna in EIO off Sumatera. Water temperature greatly affects growth, activity and mobility, migration and distribution of fish. Changes in the waters temperature below optimal temperatures cause a decrease in movement and eating activities and inhibit the process of spawning [27]. Our study showed that the preferred habitat for Yellowfin tuna in SST values of 29.5 to 29.7°C (Fig. 5A). [28] stated that Yellowfin tuna (Thunnus albacares) prefers temperatures range from 17°C - 31°C. In addition, [29] reported that Yellowfin tuna prefer to stay around the thermocline layer with a range water temperature 18°C - 31°C.

Salinity was the second-most important factor for Yellowfin tuna distribution in the EIO off Sumatera. Salinity is defined as the amount of salt dissolved in one kilogram of sea water [30]. Salinity is a dissolved substance in water that plays an important role in an ecosystem. Salinity will affect the nature of seawater and organisms and biota. Fish tend to choose areas with salinity that are in accordance with the body's osmotic pressure, such as Yellowfin tuna. Yellowfin tuna are rarely found in low salinity, generally tuna can be caught in the range of salinity between 32-35 psu [31]. In this study, the preferred habitat for Yellowfin tuna in salinity values of 33.7 psu (Fig. 5B).

Among the 3 oceanographic parameters assimilated in the model, SSH exhibited the lowest contribution to the model prediction. SSH was used to understand oceanic variability, such as divergences, convergences, eddies, and current dynamics, which could be used as proxies for the potential location of tuna catches [9]. Our study showed that the preferred habitat for Yellowfin tuna was in the range of SSH values of 0.89 to 0.92 cm (Fig. 5C). This finding indicates that Yellowfin tuna forage in areas of low SSH values. The presence of a strong gradient of SSH in the region of

![Response curves from the monthly base model for (A) sea-surface temperature (°C), (B) salinity (psu) and (C) sea-surface height (cm) in the eastern Indian Ocean off Sumatera.](image-url)
Palmyra Atoll during the 1997–98 El Niño, coinciding with an increase in the geostrophic (subsurface) flow that may increase shoaling of longline sets [32].

Predicted HSI map for January – December 2015 are shown in Figure 6. During January – March, the predicted probability of presence of Yellowfin tuna was very small (Fig. 6A) and slightly increase during April – June, especially south of South Pagai island (Fig. 6B). For the next three months, July – September, the high probability areas (HSI ≥ 0.5) increase significantly especially in areas of 99° – 103°E and 1° – 9°S (Fig. 6C). During this period, the predicted probability of presence of Yellowfin tuna also occurred in offshore areas although with small value of HSI. In the next three months, October – December (Fig. 6D), the high probability areas (HSI ≥ 0.5) shifted to the north in areas of 97° – 100°E and 1° – 5°S.

Figure 6. The spatial distribution of fishing locations (red dots) for Yellowfin tuna (Thunnus albacares) for the period (A) January – March, (B) April – June, (C) July – September (D) October - December 2015, overlain on maps of habitat suitability predicted with base models. The suitability is depicted as an Habitat Suitability Index (HSI) score ranging from 0 to 1, representing “poor” to “good” habitat quality, respectively.

4. Conclusions

Maximum entropy model showed out performance in detecting potential distribution for Yellowfin tuna in the eastern Indian Ocean off Sumatera. Yellowfin tuna mostly found in SST value of 29.5°C, salinity of 33.7 psu and SSH of 0.89 – 0.92 cm. High potential fishing zones mostly occurred from July – December and appeared around Siberu – South Pagai Island.
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