Prediction of potential fishing zones for yellowfin tuna (*Thunnus albacares*) using maxent models in Aceh province waters

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Abstract. The exploitation of tuna in the Indian Ocean is increasing due to the high demand of its resources. This research aims to predict the fishing ground of the yellowfin tuna (*Thunnus albacares*) using Maximum entropy models (MaxEnt) based on oceanographic satellite data and tuna fishing data obtained from Aceh waters, from June-August 2015. The highest MaxEnt (AUC) model in the transition season 1 occurred in May with AUC values of 0.9612, followed by March (0.8200) and April (0.6780). The high AUC value shows the potential to know the spatial distribution of tuna yellowfin tuna which can be interpreted as the level of accuracy of the model produced. Environmental parameters have a major contribution to the prediction of tuna fishing ground. In March the SST variable (64.4%) had the largest contribution, followed by SSH (8.4%) and Salinity (7.2%). Then in April the SST variable (62.4%) also had the largest contribution, followed by SSH (22.9%) and Salinity (17.6%). Similar to May SST (60.5%) had the largest contribution, followed by SSH (12.6%) and Salinity (7.0%). Based on the Maxent model, potential fishing grounds in the transition season 1 of 2015 are found in the waters of north and south of the Aceh Province.

1. Introduction

Tuna fish is economically important and high value products in the global market and a large role in the trade of seafood [1]. Tuna is a big pelagic fish is known for speed and movement. The main species of tuna fish on sale in the international market including, southern bluefin (*Thunnus maccoyii*), Atlantic bluefin (*Thunnus thynnus*), Pacific bluefin (*Thunnus orientalis*), albacore (*Thunnus alalunga*), bigeye (*Thunnus obesus*), yellowfin (*Thunnus albacares*) dan skipjack tuna (*Katsuwonus pelamis*) [2].

Yellowfin tuna or fish that is often called the yellowfin tuna is one of the leading fish resources in Aceh province and belongs to the species of fish beruaya (migrasy species) as well as whales and turtles [3]. Based on the data center's overall fishery statistics the number of yellowfin catches production from the province of Aceh in 2003 to 2010 reaching 47,631 tons with commercial value reached Rp 615,795,188 [4]. Fishery statistics data Aceh province showed a decrease in the catches of yellowfin tuna year 2003 until 2010. This indicates the possibility of regional changes of fish catching yellowfin tuna that are caused by changes to the environmental factors of the sea.

The biological resource exploration has been done a lot, which is one of the efforts to obtain information about the potential resources of the oceans and coastal areas in order to optimize the management of coastal and ocean areas is the use of remote sensing technology and geographic information systems (GIS). Satellite remote sensing for natural resources of the Sea provides an...
important contribution in exposing a variety of oceanographic phenomena as well as the potential of the sea are relatively hard to do with direct measurements. This is because the ability of remote sensing technology can monitor in the synoptic observation and range.

Things that may be released from the utilization of the data associated with the potential marine remote sensing i.e. environmental parameters that indicate the existence of an area in the sea site of interaction between organisms (biotic) and biota with environment (abiotic), so the area became a gathering place for the organisms to make the process of his life [5,6] due to various factors required for typical Oceanographic suitability of his life available to adequately. Certainty about the information in predicting regional fisheries are expected to provide information of spatial and temporal dispersion. The utilization of geographic information systems (GIS) in the fields of capture fisheries can simplify the operation of fishing and time savings in quest of fishing ground.

The methods of analysis to model the spatial distribution has been heavily developed, one of the common methods used i.e. Maximum Entropy [7-17]. The prediction of fishing ground was performed through an approach based on the principle finding the interconnectedness and the suitability of the oceanographic parameters in the presence of hordes of fish by using a MaxEnt models.

The main principle of the MaxEnt was to estimate the chances of distribution of a species distribution opportunities by searching for the subject (pixels) that has a maximum entropy and other pixel value estimates on acreage research [7]. The MaxEnt model data using only a distribution presence in its analysis, which was made into a sample of research areas including environment variables inside for a presumes the value surrounding distribution opportunities [8].

However, there is currently no regional prediction methods that develop fisheries, especially the yellowfin tuna by using model MaxEnt. The availability of satellite oceanography data which is near realtime potentially to be used as sources of data to predict areas of catching yellowfin tuna in Aceh waters.

The purpose of this research is to predict the fishing ground of yellowfin tuna and see the most excellent model in predicting the fishing ground in Aceh Province waters.

2. Material & Methodology

2.1. Tools and Materials

To performed this research, some image processing software were used. They are: Weasel (version 6.96) for visualizing the data of satellite imagery in the form of netCDF; SeaWiFS data analysis system (SEADAS 7.3.2) for extracting the parameter values of the Oceanography satellite data; and the maximum entropy Models (MaxEnt version 3.4.1) for prediction of fishing ground; as well as ArcGIS (version 10.3 ) for creating a location map and potential fishing ground. The data used includes: oceanographic satellite data in the form of sea surface temperature (SST), sea surface high (SSH) and salinity (from the site http://marine.copernicus.eu/), the catch data of yellowfin tuna.

2.2. Fishery Data

The yellowfin tuna catches data obtained from fishermen who operate in the waters of the Aceh Island, Rondo Island, Sabang, Indian Ocean and the waters of the West Aceh using fishing gear such as; purse seine and longline (figure 1). This research was conducted by following fishing vessels and ships which perform operations purse seine catching yellowfin tuna in the territorial waters of the province of Aceh. The data collected in the form of catches, catching position, and operating time catching fish. The number of catches from vessels recorded on the sample in the form of a logbook provided.

2.3. Oceanographic Data

The oceanographic parameters describe the environmental conditions in the event of the arrest of the fish. The oceanographic data retrieved from data consisting of the merger; sea level anomalies, geostrophic surface current, sea surface temperature and in-situ observations, namely the surface temperature of the sea and sea surface salinity by using satellite sensors such as; Medium Resolution Imaging Spectrometer (MERIS), Moderate Imaging Spectroradiometer (MODIS), Visible Infrared
Imaging Radiometer Suite (VIIRS) and Sea-Viewing Wide Field of View Sensor (SeaWiFS) through statistical methods. The resulting data in the form of sea surface temperature data (SST), salinity and sea surface height (SSH). Satellite data from the oceanographic parameters (SST, salinity and SSH) this is a monthly Level 4 data with spatial resolution 0.250 x 0.250, data coverage from date of 01-01-2014-2018.

The data retrieved from the http://marine.copernicus.eu/website. The data of the above parameters, each processed using software Ferret v 6.96 and SeaWiFS Data Analysis System (SEADAS) 7.3.2 which have a function to visualize satellite image data and extracting an oceanographic parameter values will then be used to predict fishing ground using software Maxent 3.4.1. The format of the data prepared for the MaxEnt model in ASCII format or comma-separated values (CSV).

**Figure 1.** Location map of research.

2.4. The Analysis of Catch

The production of yellowfin tuna data obtained during the research are used to calculate the CPUE. The formula used to compute CPUE [18]:

\[
CPUE = \frac{\text{Catch}_i}{\text{Effort}_i} = 1, 2, 3, \ldots, n
\]

Description:
CPUE = catch per unit effort
Catch\(_i\) = catches
Effort\(_i\) = fishing effort

The catch then in analysis and is described using a graph based on the season of his abduction. In addition, the catch is also used to predict fishing ground by developing a Maxent models.

2.5. Prediction of Potential Fishing Zones

Prediction of fishing ground has been done by many researchers using modeling. One of the best models with high accuracy is MaxEnt. Maxent was one of modeling a dataset that uses two data i.e. the presence of species and environment variables in a build a model prediction the distribution of species. The evaluation model of the distribution of species is needed to measure the degree of accuracy that illustrates the level of performance models [19]. As with any approach model, the accuracy of the model was tested to determine the relevance of the model [20]. In this study, the evaluation model is performed using the method of Receiver Operating Characteristic (ROC). The ROC is a method based on the sensitivity and specificity [1]. Sensitivity describes how well the model predicts the presence, whereas the specificity describes how well the model predicts the absence.
The ROC was built with methods to select the data to be used as a sample. A good model can be defined by a curve that maximize the sensitivity value of fractional positive [1]. It can be measured by calculating the *Area Under Curve* (AUC) [21]. The AUC is the ranking approach for assessing the performance of the model by specifying the location of the probability of the existence of (*presence*) that have a rating higher than the site background (*absence*) at random [20]. The performance of the model is demonstrated by the high value of the AUC, in which the value of 0.5-0.7 is considered low, 0.7-0.9 useful models and more than 0.9 indicates a high level of accuracy in measuring the *presence* dan *absence* [22].

The Predictive modeling of fishing ground in built with 10 times the Deuteronomy with type Deuteronomy subsample. Any repeat of the ROC curve analysis will yield that give information about the value of the AUC values were then averaged so obtained the average AUC value with standard deviation. Average AUC values are used to measure the performance of the model prediction area catching tuna. As has been previously stated value of AUC ranged from 0 to 1, with a value approaching 1 mean the optimal model and performance value below 0.5 means the performance model. Araujo dan Guisan [1], classifies the AUC values for assessing the performance of the classification model, and is used to assess the performance of the model prediction of fishing ground in this study. Maxent model prediction of values expressed in the *Most Probable Location* (MPL) with the standard value ranging from 0 (lowest) to 1.0 (highest).

### 3. Results and Discussion

#### 3.1. The Catch of Tuna

The catches of tuna on transition season 1 in 2015th (figure 2) shows that there was a rise from March to May. The highest catches occurred in May in effect of 3.014 kg and the lowest catches occurred in March amounted to 1.595 kg. If terms of CPUE in this season, the highest CPUE also occurred in May in effect amounted to 151 kg and the lowest CPUE trip occurred in March amounted to 123 kg/trip. Thus, it can be said that the arrest of the month best on transition season 1 occurred in May. Guardian a decrease in the number of yellowfin tuna catches on the season likely influenced by the number of arrests, travel weather conditions, as well as the dynamics of the area arrests its nature is not settled each month.

![Figure 2. CPUE and catch of tuna on transition season 1.](image)

#### 3.2. Oceanographic Parameters

##### 3.2.1. Sea Surface Temperature (SST)

The temperature in May are likely to be warmer compared to the other months in the transitional seasons I (figure 3). In March, the warm temperatures are found in the southern part of the Aceh Province, then the temperature of the waters in the area has increased so that in the southern part in domination by the warmer temperatures than previous months in May. Upon deployment, the average fish caught in the temperature range 29.6°C – 30.2°C. Rising temperatures in the transitional seasons I
is influenced by Eastern season to come. East season marked by high solar radiation and low rainfall which causes a temperature increase.

3.2.2. Sea Surface Height (SSH)

Sea surface height in March belongs to low, where low SSH is in the western part of the Aceh province. However, in April-May, SSH has increased so that the entire area of study dominated by SSH. Upon deployment, the average fish caught on the range SSH 0.87 cm – 1.03 cm.

3.2.3. Salinity

The high of salinity in March found in West from Aceh Province. Then the salinity has increased in the month of April, so salinity became higher in North, West to the South of Aceh Province. Then the salinity has decreased in May so that the salinity is lower than previous months. The highest peak of the salinity in the season reached 34.2 psu (figure 5). Upon deployment, the average fish caught on a range of salinity 33.2 psu – 34.0 psu.
3.3. Prediction of Potential Fishing Zones

3.3.1. Performance and Evaluation Model

The spatial model of probability tuna was built using Maximum Entropy (Maxent) software to predict fishing ground of yellowfin tuna and identify the environmental factors that contribute against the probability of tuna. External (output) such as Maxent, the AUC values represent the performance model, the response curve, table of percentage contribution towards environment variable spatial prediction model and prediction fishing ground of yellowfin tuna.

The accuracy or performance of models in predicting fishing ground can be viewed from one superficial Maxent IE in the form of a graph of average omission and predicted area as well as a graph of sensitivity and specificity. The graph of average omission and predicted area will show the accuracy of model whereas graph of sensitivity and specificity demonstrated the results of an evaluation of model.

The evaluation model in this study showed that the obtained probability model of the presence of yellowfin tuna was very good. According to Araujo dan Guisan [1] the performance of model is shown by high value of AUC, in which the value of 0.6-0.7 is considered low, 0.7-0.8 is considered moderate, 0.8-0.9 is considered as good, and more than 0.9 indicates a high level of accuracy in measuring the presence and absence. In this study, the value of the AUC to model the probability of the presence of yellowfin tuna showed a high level of performance with the AUC value of 0.8200 and standard deviation of 0.0442 in March, then in April the value of AUC was 0.6780 with standard deviation of 0.1366 and AUC values in May amounted to 0.9612 with standard deviation of 0.0012 (figure 6). The red line shows the average value of the AUC and the blue line shows the average value of the standard deviation. The closer the red line to the left (values approaching 1) and the smaller the standard deviation value, the better performance of the model. In addition, the graph of the average omission and predicted area in this research showed that there was a close relationship between the presence data and the prediction results. This also proved the accuracy of the resulting model (Figure 7).
3.3.2. Curves Response

The relationship between the probability of presence of yellowfin tuna with environment variables can be seen on curve of response generated by Maxent models. This curve shows how environment variables which vary greatly affect the prediction fishing ground of yellowfin tuna, as shown in the response curves of three environment variables (figure 8). In general, the response of yellowfin tuna against the environment variables that are not interconnected (nonlinear) located above the middle value (0.5).
Figure 8. Curves response of three environment variables.

Based on the response curve, every such environmental parameters provide different information against the probability of presence of yellowfin tuna. The response curve of sea surface height (SSH) in March showed that the probability of the presence of yellowfin tuna occurred on SSH with range 0.88 cm – 0.89 cm, then in April 0.87 cm – 0.91 cm and May 0.95 cm – 1.06 cm. It can be seen in figure 9 below.

Figure 9. Curves response of SSH.

The response curve of environment variable salinity is shown in figure 10. The probability of the presence of yellowfin tuna occur on the range 33.0 psu – 33.5 psu in March, then in April ranged from 31.0 psu – 33.3 psu and in May 31.4 psu – 33.3 psu.
The curve response of sea surface temperature (SST) in March showed that the probability of the presence of yellowfin tuna occurs at the SST with range 29 °C – 29.2 °C, then in April 28.4 °C - 29.7 °C and May 28.4 °C – 29.9 °C. It can be seen in Figure 11 below.

If the environment variable response curve seen above, any environment variables contribute to the probability of the presence of yellowfin tuna. But the Maxent would conduct the analysis of the overall contribution to the variable to specify the variable which contributes to the probability of the presence of yellowfin tuna.

### 3.3.3. Analysis of The Contribution of Environmental Variables

On the analysis of the contribution of environment variables, Maxent provide output regarding the environment variables that are considered important and contributes to the resulting prediction model. There are 2 output generated in analyzing the contribution of environment variables: first, environment variables based on the rankings of its contribution to the prediction model and secondly, environment variables considered important based on the results of test the jackknife.

The results of the analysis of contribution of three environment variables that are used in building the model prediction fishing ground of yellowfin tuna is presented in Table 1. In March, the highest contribution i.e. has a SST of 64.4% followed by SSH (8.4%) and Salinity (7.2%). In April the SST also has the highest i.e. contribution amounted to 62.4%, followed by SSH and Salinity i.e. respectively 22.9% and 17.6%. Later in the month of May is also the same, that the SST have highest contribution amounted to 60.5% followed SSH (12.6%) and Salinity (7.0%). Based on the analysis of the parameters is developed, it can be concluded that most parameters have the greatest contribution in regional prediction of catching tuna, namely SST, then SSH and Salinity.
Table 1. Contribution of three environmental variables.

| Models | SST (%) | SSH (%) | Salinity (%) |
|--------|---------|---------|--------------|
| March  | 64.4    | 8.4     | 7.2          |
| April  | 62.4    | 22.9    | 17.6         |
| May    | 60.5    | 12.6    | 7.0          |

The result of Jackknife test on Maxent models contained in three parts namely in training gain, test gain and AUC. The result of Jackknife of regularized training gain showed an influential environmental variable either individually or without variables. This test is done on the training data used to build the model predictions. The result of Jackknife test on training gain can be seen in figure 12.

![Figure 12. The result of Jackknife test on training gain.](image)

The Jackknife test on test gain also shows the environment variables that influence either individually or without variables. However, this test is performed on the data that is used to test model predictions. The result of Jackknife test on test gain can be seen in Figure 13.

![Figure 13. The result of Jackknife test on test gain.](image)

The results of Jackknife test on AUC showed environment variables that influence either individually or without variables. This test is done on performance model used in evaluating model predictions. The result of Jackknife test on AUC can be seen in figure 14.

![Figure 14. The result of Jackknife test on AUC.](image)
Based on the results of the jackknife test on training gain, gain test and AUC (figure 12, 13 and 14) indicates that the SST variable on March-April-May is a parameter that will give the highest rating of good in training gain, gain test and AUC. This makes SST variables on March-April-May is the effective variables in model predictions fishing ground of yellowfin tuna if using only one variable alone. But if the whole of the environment variables used in the model predictions fishing ground of yellowfin tuna then SST variable on March-April-May are ignored then the value of training gain, gain test and AUC on the model will decrease. The difference is the case if the SSH variable on March-April-May, also experienced a decrease in the value of the AUC but not as big as the decline happens if ignore SST variable on March-April-May. This makes SST variables is one of the important variables in model predictions fishing ground of yellowfin tuna if some other environment variables used in the model predictions.

3.4. The Result of Potential Fishing Zones

Based on the value of the AUC that represents performance modeling, analysis and response curve environment variable contributions against the Maxent model prediction, then it can be described in spatial prediction fishing ground of yellowfin tuna (figure 15). The spatial models of prediction fishing ground of Yellowfin tuna showed a tint, which tint has information on tuna in the waters of prediction fishing ground in Aceh Province. The Tint has a value range of predictions ranging from 0 (lowest) to 1.0 (highest), it shows the Most Probable Location (MPL) fish for yellowfin tuna. The lower the value prediction then the lower the MPL for tuna in Aceh waters. The low of MPL can representation of tuna is depicted through the blue tint with minimal value of 0 – 0.3. On the contrary, the higher the value the higher the MPL then prediction of yellowfin tuna in Aceh waters. MPL high representativeness of yellowfin tuna is depicted through a red tint with a maximum value of 1.0.

The spatial distribution of fishing ground of yellowfin tuna can be seen upon the high to the low value of the MPL. In March, the highest the MPL found in parts of North and West of Aceh Province, where its spread was quite wide. MPL high in the area in the anticipated presence of influence of environmental parameters which indicate that the area in accordance with the conditions of the parameters that are favored by fish yellowfin tuna.

![Figure 15. Spatial distribution of potential fishing zones.](image)

The most Probable Location (MPL) that those influenced by high SST, SSH and Salinity. SST in the region range from 29.6 °C – 30 °C, then with SSH 0.86 cm – 90 cm and Salinity 32.4 psu – 34.2 psu. Then in April, the highest the MPL is also found in the North, West to the South of Aceh Province, where vast areas are getting so dominated by the MPL. If review of the parameters, that this region has a temperature that ranges between 29.6°C – 30.2°C, SSH 0.90 cm – 0.92 cm and Salinity 32.2 psu – 34.2 psu. In may a high MPL is also found in the North to South Aceh. The temperature in areas with high MPL ranges between 30.6°C - 29.6 °C with MPL between 1.00 cm – 1.05 cm and Salinity 32.8 psu – 33.8 psu.
The high of MPL indicates that the area is an area of potential for catching yellowfin tuna. All of that is reinforced by the large number of arrests activity found around the waters. Based on the statement above, the fishing ground that belongs to this season's potential is found in northern and southern of Aceh waters.

4. Conclusions

The highest MaxEnt (AUC) model in the transition season 1 occurred in May with AUC values of 0.9612, followed by March (0.8200) and April (0.6780). The high AUC value shows the potential to know the spatial distribution of tuna yellowfin tuna which can be interpreted as the level of accuracy of the model produced. Environmental parameters have a major contribution to the prediction of tuna fishing ground. In March the SST variable (64.4%) had the largest contribution, followed by SSH (8.4%) and Salinity (7.2%). Then in April the SST variable (62.4%) also had the largest contribution, followed by SSH (22.9%) and Salinity (17.6%). Similar to May SST (60.5%) had the largest contribution, followed by SSH (12.6%) and Salinity (7.0%). Based on the Maxent model, potential fishing grounds in the transition season 1 of 2015 are found in the waters of north and south of the Aceh Province.

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