Spatial Modeling of Yellowfin Tuna in the Banda Sea Based on Oceanographic Factors Using MaxEnt

Sunarwan Asuhadi[1]*, Mukti Zainuddin[2], Safruddin Safruddin[2], Musbir Musbir[2]

[1]National Research and Innovation Agency
Gedung B.J Habibie Jl. M.H Thamrin Nomor 8, Jakarta Pusat 10340 Indonesia
[2]Faculty of Marine Sciences and Fisheries, Hasanuddin University
Jl. Perintis Kemerdekaan Km. 10 Tamalanrea, Makassar Sulawesi Selatan 90245 Indonesia
Email: suna032@brin.go.id

Abstract

This study models the spatial distribution of yellowfin tuna (YFT) in the Banda Sea using the MaxEnt approach, addressing critical questions about its predictive capability, the influence of environmental variables such as sea surface temperature (SST) and chlorophyll-a concentration, and temporal patterns. MaxEnt was chosen for its ability to predict potential distribution areas based on presence data and environmental factors. Data utilized include fish catch records obtained from the fishing logbook of the Ministry of Marine Affairs and Fisheries of the Republic of Indonesia, chlorophyll-a concentration, and SST data sourced from ocean color satellite observations. Model performance was evaluated using the Area Under the Curve (AUC) metric. Study results reveal that significant spatial and temporal variations in YFT distribution are influenced by oceanographic factors, with the model performing best in July (AUC 0.72) and lowest in April, September, and December (AUC ~0.60). SST was the dominant variable in November (82.35%), while chlorophyll-a had the highest contribution in April (83.02%). These findings highlight the dynamic link between tuna distribution and environmental conditions. The spatial maps offer insights for optimizing fishing practices, reducing pressure on overexploited stocks, and supporting sustainable fisheries management through data-driven approaches like MaxEnt. However, the MaxEnt model has limitations such as sensitivity to multicollinearity, overfitting, and low transferability. Future research could enhance accuracy and robustness by using advanced methods like Spatial Maxent, Monte Carlo Variable Selection, or ensemble modeling to support adaptive fisheries management.

Keywords: *MaxEnt, Spatial distribution, Yellowfin tuna, Banda Sea, SST, Chlorophyll-a*

Introduction

Modeling the spatial distribution of yellowfin tuna (*Thunnus albacares*) is crucial for understanding the environmental factors influencing its habitat. One widely used method in species distribution modeling is Maximum Entropy (MaxEnt) due to its ability to predict potential distribution areas based on the presence of data and relevant environmental variables (Anand *et al*., 2021; Lin *et al*., 2023). MaxEnt has been extensively applied in various marine ecological studies, particularly for modeling the distribution of large pelagic fish like tuna (Sharifian *et al*., 2023).

The yellowfin tuna (YFT) is a species with high economic value and is widely distributed in tropical and subtropical waters (Nimit *et al*., 2020). Research on the spatial distribution of this fish is crucial within the context of sustainable fisheries, particularly in climate change and increasingly intensive fishing activities (Sambah *et al*., 2023). Modeling with MaxEnt enables the integration of various environmental variables, such as sea surface temperature (SST), salinity, and chlorophyll content, which play a significant role in determining the habitat of yellowfin tuna (Siregar *et al*., 2019). Moreover, oceanographic factors like temperature, oxygen concentration, and sea surface height influence this fish's vertical movement and distribution in its habitat (Rohner *et al*., 2023). Regarding fishing, the application of remote sensing data and the MaxEnt model has proven effective in identifying potential fishing zones for yellowfin tuna in the Eastern Indian Ocean (Syah *et al*., 2020).

The MaxEnt method enables the development of distribution models based on presence-only data, often the only available information in marine studies (Anand *et al*., 2021). Therefore, this method is particularly suitable for predicting the distribution of yellowfin tuna in vast ocean areas that are often difficult to access for comprehensive data collection (Anand *et al*., 2021; Lin *et al*., 2023). This model also addresses sample bias issues, which frequently occur in modeling the distribution of marine species (Sharifian *et al*., 2023).

*) Corresponding author

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Previous studies have demonstrated that MaxEnt can predict potential fishing areas accurately, especially when combined with satellite data on oceanographic conditions (Anand *et al*., 2021; Sharifian *et al*., 2023). For instance, the application of MaxEnt in the waters of Aceh successfully identified ideal tuna fishing locations, showing excellent model accuracy with high AUC (Area Under the Curve) values (Siregar *et al*., 2019).

With the increasing pressure on yellowfin tuna stocks due to overfishing, distribution modeling using MaxEnt is expected to provide important information to support more effective and sustainable fisheries management. This approach not only helps to understand the spatial distribution patterns of yellowfin tuna in the waters of the Banda Sea but also has the potential to be used to identify new strategic fishing areas (Siregar *et al*., 2019). This is important to reduce fishing pressure on yellowfin tuna populations in specific locations, thereby supporting the sustainability of fish stocks in the area and improving the efficiency of fishery activities. Thus, the results of this study can contribute to a more adaptive and conservative data-based fisheries management (Haruna *et al*., 2019).

This study aims to answer several important questions related to the spatial distribution of yellowfin tuna in the Banda Sea. How can the MaxEnt model be used to predict the spatial distribution of yellowfin tuna, the extent to which environmental variables such as chlorophyll-a concentration and SST affect the prediction results, and whether there is a significant temporal pattern in the accuracy of distribution prediction? In addition, this study also seeks to explore how the prediction results can be used to improve the effectiveness of fishing while supporting more sustainable fisheries management in the region.

Materials and Methods

As shown in Figure 1, the research location is in Fisheries Management Area (FMA) 714, which covers the waters of the Banda Sea and its surroundings. This area is known for its rich biodiversity, particularly as a habitat for tuna species, and plays a critical role in Indonesia's fisheries sector (Romdon *et al*., 2019).

Collecting and processing data

The initial stage of this research involves setting up the working environment in R Studio by loading packages such as `dplyr` for data manipulation, `lubridate` for date processing, and `sf` and `sp` for spatial analysis. This is followed by raster and `dismo`, which support species distribution modeling, enabling the analysis to be conducted effectively and comprehensively (Doser *et al*., 2022). This study utilizes fish catch data, chlorophyll concentration, and SST. Fish catch data in the form of a location of arrest as presence data, a total of 13,371 rows, is sourced from logbooks collected and managed by the Directorate of Fishery Resources Management under the Ministry of Marine Affairs and Fisheries, covering the period from 2014 to 2022. Meanwhile, chlorophyll-a concentration data, a total of 2,994,105 rows, and SST data, a total of 3,234,156 rows focusing on the Banda Sea and its surroundings, were obtained via Aqua MODIS with a spatial resolution of 4 km (Sean, 2023) and then processed using the Ocean Data View (ODV) software. All data collected through this research were subsequently cleaned, further processed, and visualized using R Studio version 4.4.0, utilizing appropriate libraries and executing necessary functions for analysis.

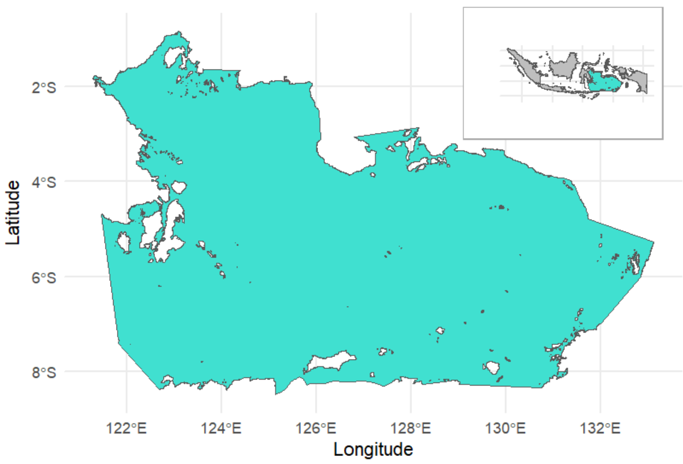

Figure 1. Research location in the Banda Sea region

The assumption of the selection of chlorophyll-a and SST variables in the MaxEnt model is that both significantly affect the distribution of fish. Chlorophyll-a, as a primary productivity indicator, indicates high food availability, so areas with optimal chlorophyll-a concentrations are often potential fishing zones (Nursan *et al*., 2022). SST affects the thermal habitat of fish and the distribution of their prey, making it the dominant variable in predicting fish habitat spatially-temporal (Siregar *et al*., 2019). This combination of variables allows MaxEnt to generate accurate predictions of fish distribution under various environmental conditions (Kamaruzzaman *et al*., 2021).

Geographical transformations and projections

The data coordinates were converted into the appropriate format and aligned with a consistent geographic projection using the WGS84 coordinate system. This step ensures that all data have a uniform spatial projection for subsequent analysis (Liu *et al*., 2020).

Utilizing MaxEnt for modeling

The maxent() function from the dismo package was used to build the MaxEnt model predicting the spatial distribution of fish in FMA 714, utilizing the presence data of yellowfin tuna and environmental variables such as chlorophyll-a and SST. This model is highly effective in generating accurate distribution maps, particularly when available data is limited or computational constraints exist, and it can identify potential habitats based on environmental variables (Baines & Weir, 2020; Kaky *et al*., 2020).

Model validation

The developed model was evaluated using performance metrics such as ROC (Receiver Operating Characteristic) and AUC. AUC indicates the model's accuracy in predicting species distribution and is a reliable metric, particularly when dealing with imbalanced data or when studying species with rare or sparse occurrences (Hallman & Robinson, 2020). Furthermore, AUC is valuable for evaluating model performance when predictions are extended to broader geographical areas (Sofaer *et al*., 2019). AUC is a performance measure of a classification model based on two main components: True Positive Rate (TPR) and False Positive Rate (FPR).

Prediction and visualization of spatial distribution

The spatial distribution of yellowfin tuna is predicted monthly using the MaxEnt model and visualized with plotting functions in R Studio for further analysis. This approach effectively identifies potential fishing areas by considering oceanographic parameters such as sea surface temperature and chlorophyll-a concentration obtained from satellite data. Additionally, this method allows for real-time habitat forecasting, which can enhance the efficiency of fishing activities and support sustainable fisheries management (Syah *et al*., 2023; Wu *et al*., 2023).

Measuring the contribution of environmental variables

Each environmental variable in the model is evaluated using "contribution score" and "permutation importance" metrics to understand its role and influence on the spatial distribution predictions of yellowfin tuna. This method helps identify the most significant variables influencing the prediction outcomes. MaxEnt models widely apply this approach to assess the importance of variables such as SST and chlorophyll-a in estimating potential habitats for yellowfin tuna in the Indian and Pacific Oceans (Vayghan & Lee, 2022).

Analysis of environmental variable responses

The model's response to each environmental variable is analyzed to understand how each affects the spatial distribution of yellowfin tuna in the study area. This analysis utilizes response curves generated through the response () function from the `demo` package. The application of this approach in modeling the habitat distribution of yellowfin tuna shows significant variations in the response of environmental variables, such as SST and chlorophyll-a, to the spatial distribution of the species.

Result and Discussion

Model validation

The performance of the MaxEnt model in predicting the spatial distribution of yellowfin tuna in the Banda Sea and its surrounding waters was evaluated using the ROC curve, AUC metric, the number of presences (n presences), absences (n absences) of the species for each month, predictive correlation (cor), and the maximum value of TPR+TNR (max_TPR+TNR_at). The MaxEnt model metrics for various months are presented in Table 1 and the AUC values are visualized in Figure 2.

The metrics presented in Table 1 comprise the counts of presences (n_presences) and absences (n_absences) in the dataset, the AUC, correlation, and max_TPR+TNR_at. AUC is the main metric to assess how well the model differentiates between presence and absence locations. An AUC value close to 1 reflects high predictive accuracy, where as a value

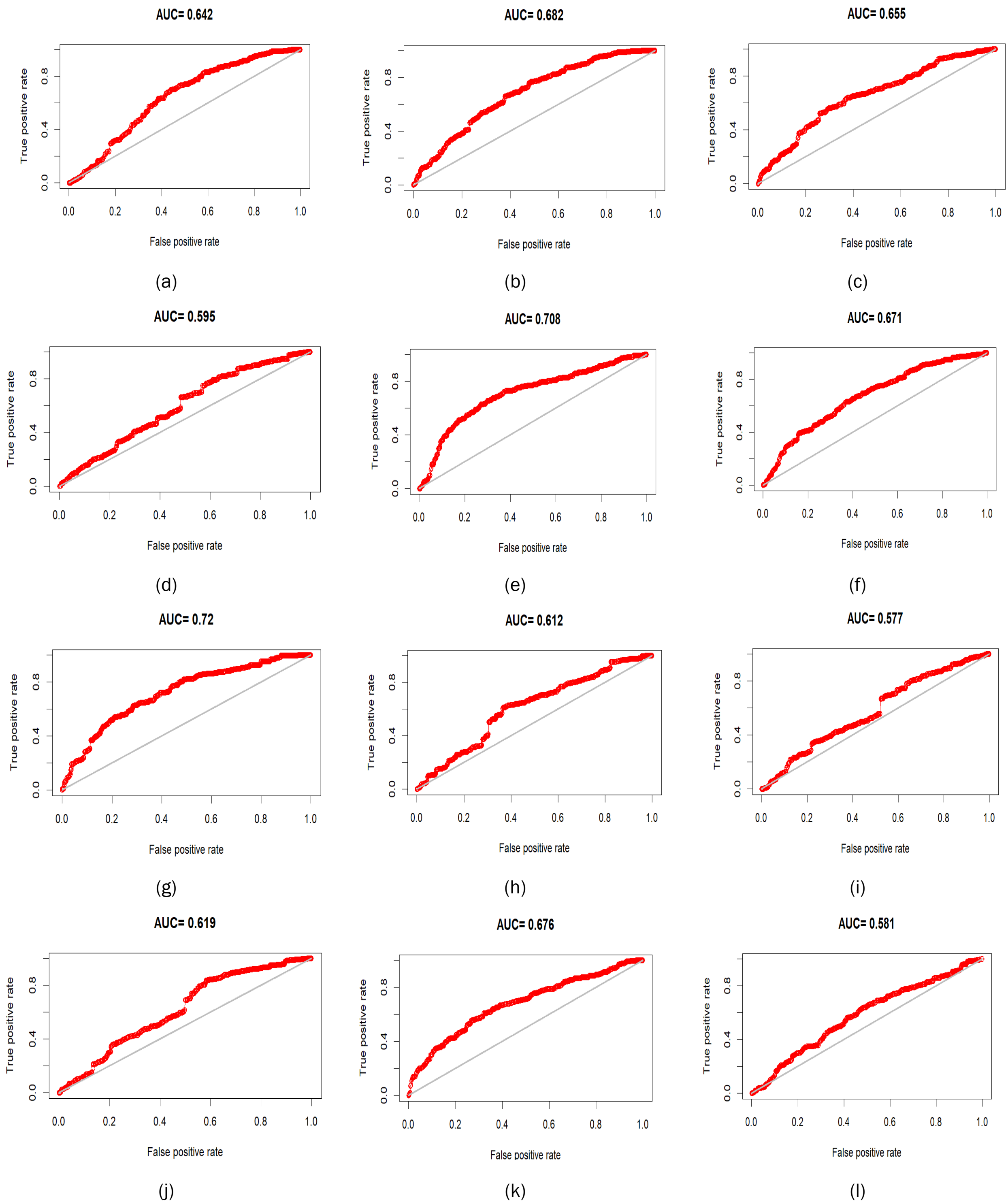

Figure 2. Visualization of AUC values for the spatial distribution of yellowfin tuna: (a) January; (b) February; (c) March; (d) April; (e) May; (f) June; (g) July; (h) August; (i) September; (j) October; (k) November; and (l) December

nearing 0.5 implies predictions are essentially random. A higher AUC score, such as 0.72, observed in July, indicates strong model performance. The correlation reflects the linear association between model predictions and observed values, where greater values demonstrate a better fit. The metric max_TPR+TNR_at represents a combination of the TPR and TNR, aiming to identify the optimal prediction threshold; the peak values recorded in May and August (0.64) suggest an ideal balance in detecting both the presence and absence of the species.

Table 1. Performance evaluation of the MaxEnt model for the spatial distribution of yellowfin tuna

Month	n_presences	n_absences	Cor	max_TPR+TNR_at
January	1,156	1000	0.28	0.60
February	1,281	1000	0.30	0.60
March	1,681	1000	0.20	0.61
April	1,097	1000	0.18	0.61
May	701	1000	0.36	0.64
June	749	1000	0.31	0.60
July	793	1000	0.37	0.52
August	694	1000	0.20	0.64
September	1,110	1000	0.17	0.61
October	1,527	1000	0.26	0.62
November	1,389	1000	0.30	0.67
December	1,157	1000	0.16	0.62

Visualizing and predicting spatial data distributions

This study utilized the MaxEnt model to predict the monthly spatial distribution of yellowfin tuna from 2014 to 2022, as shown in Figure 3. The resulting distribution maps outline the potential areas of yellowfin tuna presence in the Banda Sea and surrounding waters, considering environmental factors such as chlorophyll-a concentration and SST. A monthly distribution pattern analysis was conducted to identify yellowfin tuna's seasonal variations and distribution trends. Areas with a high probability of yellowfin tuna presence were successfully identified, demonstrating the model's ability to capture ecological patterns influenced by environmental conditions.

From January to December, the spatial distribution predictions of yellowfin tuna in the Banda Sea and its surrounding regions, using the MaxEnt model, reveal variations in the probability of presence across different areas, with fluctuating values throughout the year. In January, areas with a high probability (0.7) are predominantly found in the northern part, slightly increasing in February, with the highest probability reaching around 0.8 in the northwest. The probability distribution becomes more uniform between March and April, with peak values ranging from 0.6 to 0.7. During May to July, areas with high probability are more fragmented and scattered, dominated by light green and pink colors (0.2-0.4), indicating a low likelihood of yellowfin tuna presence across most regions. From August to October, the probability of presence increases again, reaching values around 0.6 to 0.7 in certain areas. In November, the probability distribution becomes more uniform, with values ranging from 0.2 to 0.7, while in December, there is an increase in areas with high probability, particularly in the northwest and central regions, reaching up to 0.8, indicating a higher concentration of yellowfin tuna presence towards the end of the year.

Temporal dynamics of environmental factors and fish spatial distribution

The temporal variability in environmental conditions and fish distribution is evident from January to December, with significant changes in chlorophyll-a concentration and SST. In January, the chlorophyll-a concentration ranges from 0.11-8.29 mg.m^{-3} and SST from 27.73-31.24°C; in February, chlorophyll-a ranges from 0.099-1.48 mg.m^{-3} and SST from 27.56-32.41°C; in March, chlorophyll-a is 0.10-4.39 mg.m^{-3} with SST ranging from 28.05-32.13°C; April shows chlorophyll-a between 0.073-2.10 mg.m^{-3} and SST from 28.78-31.21°C; in May, chlorophyll-a is 0.10-1.79 mg.m^{-3} and SST 28.87-32.26°C; in June, the chlorophyll-a concentration is 0.010-4.71 mg.m^{-3} with SST ranging from 28.25-31.75°C; July shows chlorophyll-a at 0.11-1.43 mg.m^{-3} and SST from 26.03-30.68°C; in August, chlorophyll-a is 0.11-1.92 mg.m^{-3} and SST ranges from 26.16-29.59°C; while in September, chlorophyll-a reaches its highest value of 0.086-6.93 mg.m^{-3} with SST between 26.82-31.65°C; October records chlorophyll-a at 0.10-2.02 mg.m^{-3} and SST from 28.60-32.95°C; in November, chlorophyll-a is 0.067-1.39 mg.m^{-3} with SST ranging from 27.99-32.17°C; and in December, the chlorophyll-a concentration is 0.085-2.27 mg.m^{-3} with SST from 28.39-32.52°C. These variations reflect the dynamic changes in marine environmental conditions throughout the year, with peaks in chlorophyll-a concentrations in January and September and SST fluctuations following seasonal patterns that influence the distribution of yellowfin tuna.

Assessing model sensitivity to environmental factors

To gain a deeper understanding, an analysis was conducted on how the MaxEnt model responds to each environmental variable influencing the spatial distribution of yellowfin tuna. The response curves generated by the response function from the dismo package illustrate how the predicted probability of

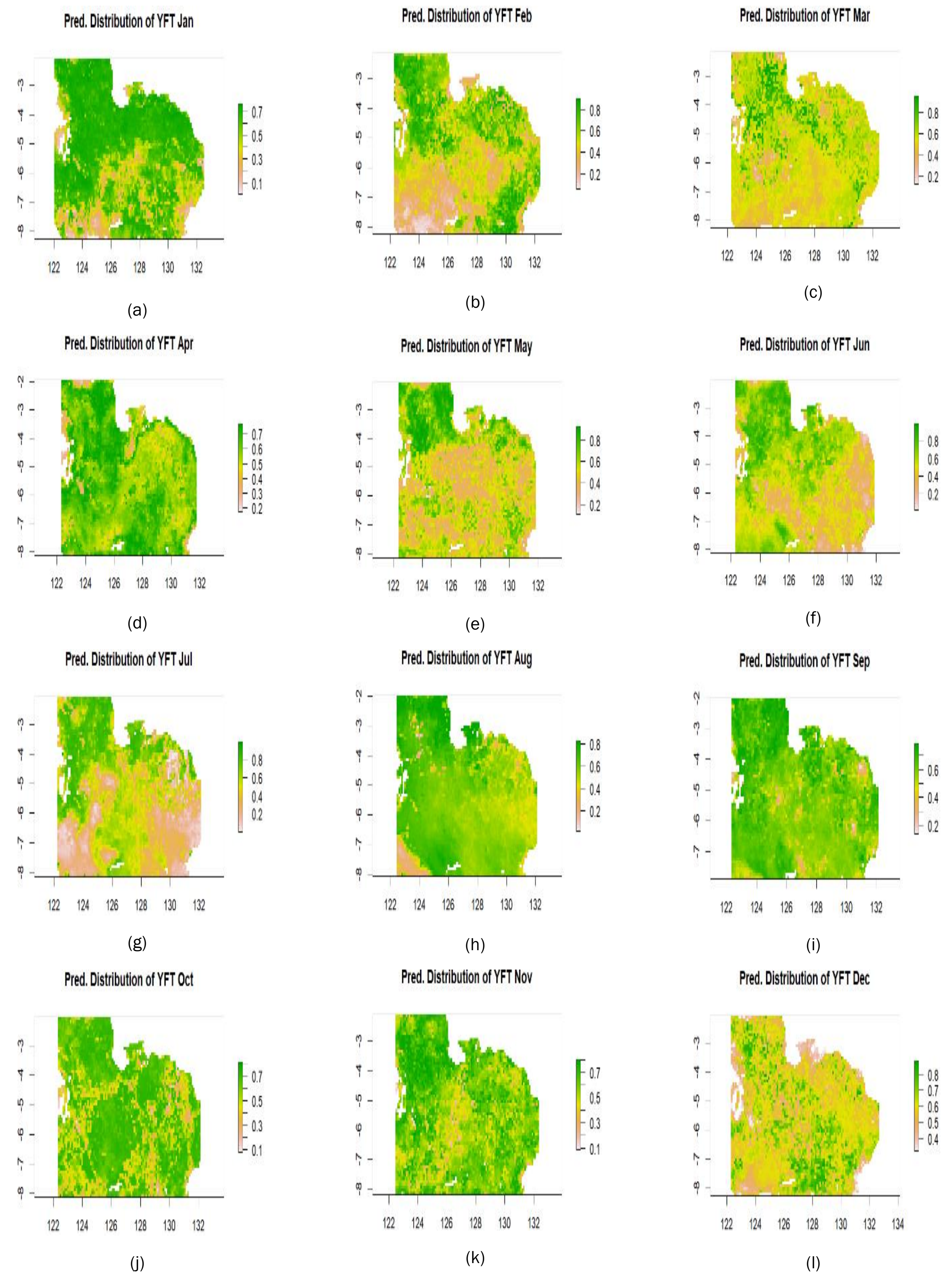

Figure 3. Predicted distribution of yellowfin tuna in the Banda Sea and its surrounding waters: (a) January; (b) February; (c) March; (d) April; (e) May; (f) June; (g) July; (h) August; (i) September; (j) October; (k) November; and (l) December

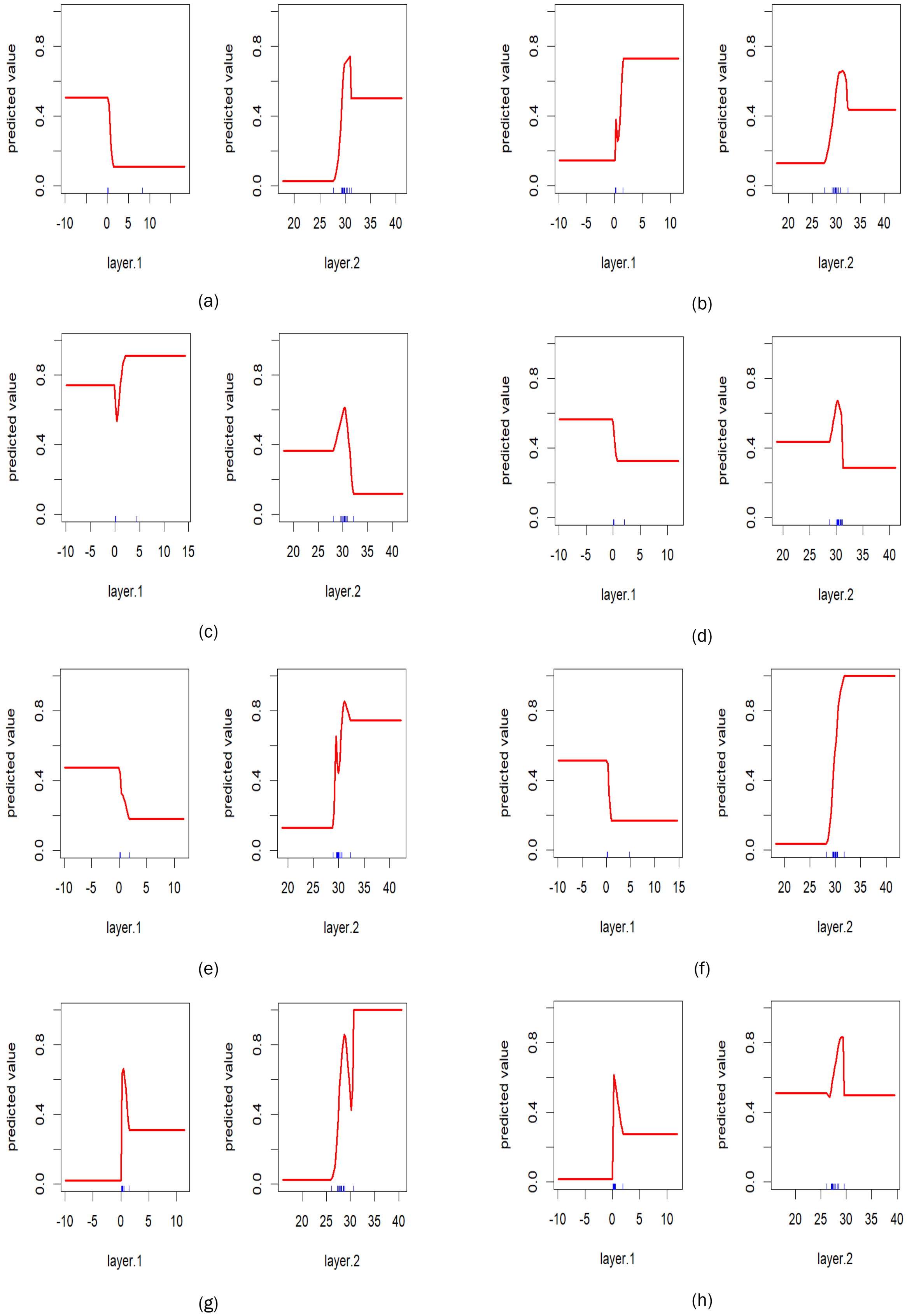

Figure 4. MaxEnt model response to each environmental variable: (a) January; (b) February; (c) March; (d) April; (e) May; (f) June; (g) July; (h) August; (i) September; (j) October; (k) November; and (l) December.

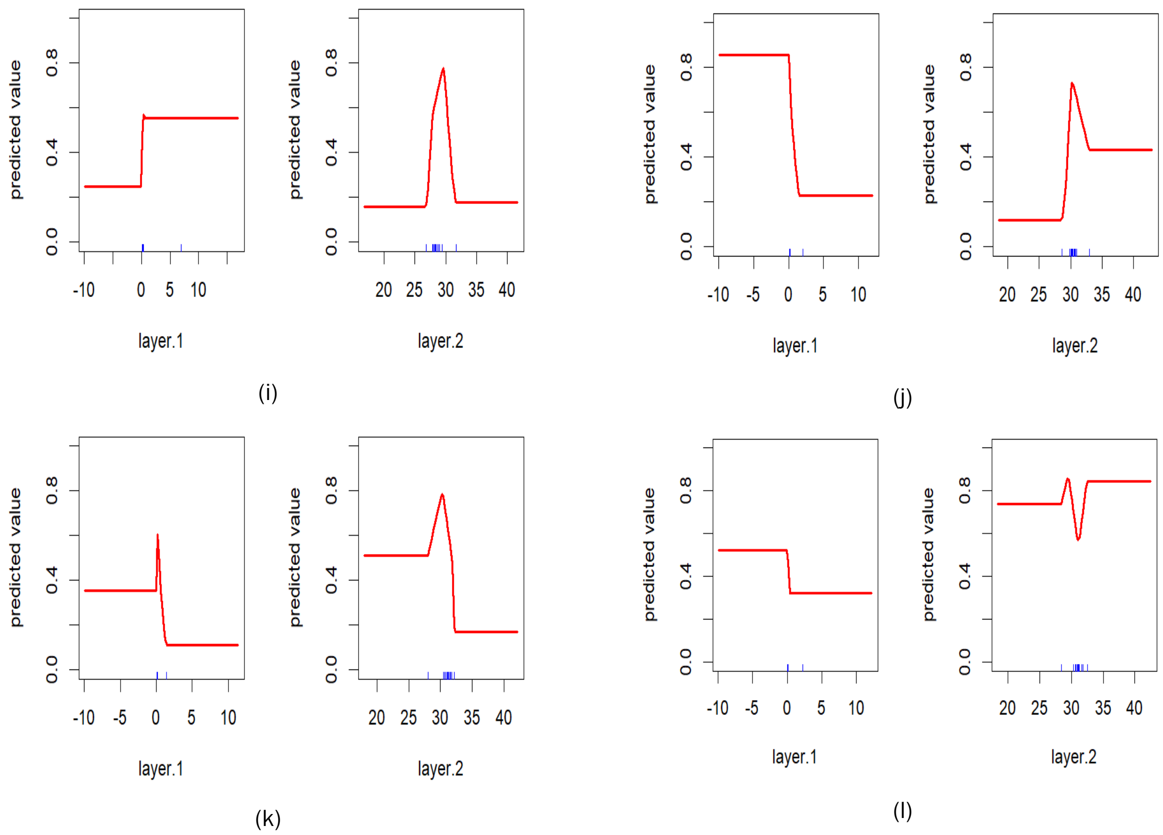

Figure 4. MaxEnt model response to each environmental variable: (a) January; (b) February; (c) March; (d) April; (e) May; (f) June; (g) July; (h) August; (i) September; (j) October; (k) November; and (l) December. (continue)

yellowfin tuna presence changes across various levels of chlorophyll-a and SST. These curves reveal threshold values and optimal ranges for each variable, where outside these ranges, the probability of tuna presence tends to decrease. The visualization of the model response is presented in Figure 4.

The graph above shows that from January to December, the MaxEnt model's response to environmental variables like chlorophyll-a (layer.1) and SST (layer.2) exhibits different patterns affecting the spatial distribution predictions of yellowfin tuna. For the chlorophyll-a variable, the model's response generally indicates an increase in predicted fish presence at values around 5 to 10, as seen in the sharp spikes in February, May, and December. Conversely, the model shows a decrease in predictions at lower chlorophyll-a concentrations (around -5 to 0), which occurs consistently throughout the year. Meanwhile, the model's response demonstrates a broader range of variations for the SST variable, with a significant increase in predicted fish presence at 30-35°C temperatures, especially in January, June, and October. On the other hand, lower temperatures around 20-25°C in July and August indicate a decrease in the predicted fish presence. This pattern shows that the concentration of chlorophyll-a and SST significantly influences the spatial distribution of yellowfin tuna throughout the year.

Assessing the significance of model predictions

The mode values for chlorophyll-a and SST were used to understand the potential presence of yellowfin tuna throughout the year. In January, the mode of chlorophyll-a is 0.14 mg.m^{-3} with an SST of 29.53°C; February shows a chlorophyll-a mode ranging from 0.10 to 0.11 mg.m^{-3} and an SST of 29.55°C; in March, the chlorophyll-a mode is 0.11 mg.m^{-3} and SST is 29.75°C; April has a chlorophyll-a mode between 0.092 and 0.095 mg.m^{-3} with an SST of 30.58°C; May indicates a chlorophyll-a mode of 0.11 mg.m^{-3} and an SST of 29.71°C; in June, the chlorophyll-a mode ranges from 0.10 to 0.13 mg.m^{-3} with an SST of 29.86°C; July shows a variation in chlorophyll-a mode from 0.18 to 0.34 mg.m^{-3} with an SST of 28.22°C; in August, the chlorophyll-a mode reaches 0.19 to 0.33 mg.m^{-3} with SST dropping to 27.25°C; September shows a chlorophyll-a mode of 0.17 mg.m^{-3} and SST between

28.12 and 28.14°C; October has a chlorophyll-a mode of 0.11 mg.m^{-3} with an SST of 30.19°C; November shows a chlorophyll-a mode between 0.078 and 0.11 mg.m^{-3} with an SST of 31.10°C; and in December, the chlorophyll-a mode is between 0.094 and 0.098 mg.m^{-3} with an SST of 31.25°C. These values indicate that the potential presence of yellowfin tuna appears higher in months with greater chlorophyll-a concentration and cooler SST, such as in July and August.

The impact of environmental variables on model performance

To assess the influence of environmental variables chlorophyll-a and SST in the MaxEnt model from January to November, the metrics Variable Contribution and Permutation Importance were used. chlorophyll-a made the highest contribution in April at 83.03%, while SST showed its greatest contribution in June at 87.11%. For Permutation Importance, chlorophyll-a peaked in February at 68.79%, whereas SST had its highest value in January at 77.35%. Both metrics are used to understand the role and impact of each variable in the model, where Variable Contribution indicates the priority of variables during the model training process. At the same time, Permutation Importance measures the influence of variables on prediction accuracy after training. These metrics are presented in Table 2.

Discussion of research findings and their implications

This study applied the MaxEnt model to predict the spatial distribution of yellowfin tuna in the Banda Sea and its surrounding waters by utilizing environmental data such as chlorophyll-a concentration and SST. The modeling results indicate significant variation in the spatial distribution of yellowfin tuna, influenced by changes in environmental conditions throughout the year.

The AUC values of the MaxEnt model for predicting the distribution of yellowfin tuna vary each month, with the highest value in July (0.72) and the lowest in April, September, and December (0.60), indicating fluctuations in model performance due to environmental variability or a lack of observational data. In comparison, a study in the Aceh waters reported an AUC of 0.96 for predicting potential fishing grounds for yellowfin tuna using the MaxEnt model (Siregar *et al*., 2019), while in the eastern Indian Ocean off Sumatra, the AUC reached more than 0.90 for the potential habitat of this species (Syah *et al*., 2020), reinforcing the reliability of the MaxEnt model in predicting fish distribution based on different oceanographic conditions. The research also indicates that SST and salinity are the dominant environmental variables influencing the predicted distribution of yellowfin tuna, particularly during the transitional and monsoon seasons. Months with SST within the optimal range of approximately 29.5°C and stable salinity around 33.7 psu show a higher probability of yellowfin tuna presence (Syah *et al*., 2020).

Based on the table "Variable Contribution and Permutation Importance," the measurement of variable contributions highlights the significant roles of both environmental variables, chlorophyll-a, and SST, in the prediction model for the distribution of yellowfin tuna. Chlorophyll-a showed the highest contribution, reaching 83.02% in April, while sea surface temperature had its largest contribution in November, at 82.35%. Conversely, months with lower variable contributions, such as June, where chlorophyll-a only contributed 12.89%, indicate that the variability of environmental parameters during certain periods can affect the accuracy of the model's predictions. For comparison, a study in the Aceh waters using the Model MaxEnt found that SST contributed the most to the prediction of yellowfin tuna fishing zones in Aceh waters, with 64.4% in March, 62.4% in April, and 60.5% in May (Siregar *et al*., 2019).

Using SST and chlorophyll-a data that tend to be more spatially distributed, MaxEnt can predict the ecological distribution of fish habitats even though fishing data is not consistently distributed throughout the year (Siregar *et al*., 2019). However, the model is susceptible to bias if the catch data reflects more human activity preferences than the actual biological distribution of fish (Dunn and Curnick, 2019). In addition, when the capture data is averaged for each pixel in an area, the model can miss important spatial-temporal dynamics of the species, so the results reflect more human activity than the natural distribution patterns of the species (Wu *et al*., 2023). Therefore, MaxEnt requires representative data integration and rigorous validation to generate more accurate predictions to minimize bias from the retrieval data structure.

The findings of this study have significant implications for fisheries management in the Banda Sea and its surrounding areas. Information on the spatial and temporal variation in the distribution of yellowfin tuna can be utilized to make more accurate decisions regarding the timing and location of fishing to improve catch yields. Furthermore, this study supports the implementation of fisheries management strategies that consider environmental dynamics to maintain the sustainability of fish resources. Understanding the periods and areas with low probabilities of fish presence can help reduce the risk of overfishing in less productive regions and protect areas with high ecological value.

Table 2. Variable Contribution and Permutation Importance

Month	Chlorophyll-a Contribution (%)	SST Contribution (%)	Chlorophyll-a Permutation Importance (%)	SST Permutation Importance (%)
January	28.54	71.46	22.65	77.35
February	65.97	34.03	68.79	31.21
March	81.05	18.95	63.77	36.23
April	83.02	16.98	83.64	16.36
May	32.94	67.06	25.86	74.14
June	12.89	87.11	17.30	82.70
July	42.54	57.46	44.59	55.41
August	45.94	54.06	32.52	67.48
September	18.13	81.87	35.15	64.85
October	54.28	45.72	47.16	52.84
November	17.66	82.34	15.42	84.58
December	39.26	60.74	47.46	52.54

Overall, this study provides insights into the impact of environmental factors on the distribution patterns of yellowfin tuna and offers a scientific basis for a more adaptive and sustainable fisheries management approach in Indonesian waters.

MaxEnt has several disadvantages, including sensitivity to the multicollinearity of environmental variables, overfitting due to suboptimal regulatory parameters, and low model transferability to other regions or times (Feng *et al*., 2019). Data resolution mismatches are also often a problem that affects prediction accuracy (Alsamadisi *et al*., 2020). To overcome this weakness, new methods such as SpatialMaxent can improve accuracy by considering the spatial structure of the data (Bald *et al*., 2023). In contrast, the Monte Carlo Variable Selection approach accelerates the selection of predictor variables from large data sets (Schnase *et al*., 2020). Additionally, ensemble modeling that combines algorithms such as Random Forest and Boosted Regression Trees with MaxEnt offers more accurate and robust results (Kaky *et al*., 2020).

Conclusion

This study successfully applied the MaxEnt model to predict the spatial distribution of yellowfin tuna in the Banda Sea by considering environmental variables such as chlorophyll-a concentration and SST. The model demonstrated good performance, with the highest AUC value reaching 0.72 in July, while the lowest values were recorded in April, September, and December, each with an AUC of ~0.60. The variation in prediction accuracy reflects significant fluctuations in environmental conditions. The study also revealed that SST had the most significant influence on the distribution prediction in November (82.35%), while chlorophyll-a was the dominant factor in April, contributing up to 83.02%. The spatial distribution maps generated from this study can be used to enhance fishing effectiveness and support more sustainable fisheries management in the region. However, the MaxEnt model has limitations, including sensitivity to multicollinearity, overfitting risks, and reduced transferability. Future studies could incorporate advanced methods like SpatialMaxent, Monte Carlo Variable Selection, or ensemble modeling to improve model accuracy and robustness, further supporting data-driven and adaptive fisheries management.

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