Egyptian Journal of Aquatic Biology & Fisheries
Zoology Department, Faculty of Science,
Ain Shams University, Cairo, Egypt.
ISSN 1110 – 6131
Vol. 29(6): 1797 – 1812 (2025)
www.ejabf.journals.ekb.eg

Multi-Algorithm Species Distribution Approach in Modeling Suitable Habitat Distribution for Skipjack Tuna *(Katsuwonus pelamis)* in FMA 713 and 714, Indonesia

Ainun Apriliyani Muhyun[1*], Gilar Budi Pratama[2], Rian Hidayat[3], Muhammad Mujahid[4], Syakirah Chuzaimah[5], Nasywa Aurellia Zamira[6], Oksto Ridho Sianturi[7]

[1]Study Program of Fishery Product Technology, Institut Teknologi Sains dan Bisnis Muhammadiyah Selayar, Indonesia
[2]Department of Fisheries, Faculty of Fisheries and Marine Science, Universitas Padjadjaran, Sumedang, Indonesia
[3]Practitioner of Data Desa Presisi, IPB University, Bogor, West Java, Indonesia
[4]Department of Fisheries and Marine, State Polytechnic of Lampung, Lampung, Indonesia
[5]Capture fisheries practitioners, West Java, Indonesia
[6]Marine Fisheries Technology Study Program, Graduate School of IPB University, Bogor, Indonesia
[7]Research Center for Oceanograpy, National Research and Innovation Agency, Jakarta, Indonesia
[*]Corresponding Author: ainunamuhyun@gmail.com

ARTICLE INFO

Article History:
Received: Aug. 30, 2025
Accepted: Nov. 15, 2025
Online: Dec. 5, 2025

Keywords:
Fishing seasons,
Fisheries management,
Oceanography,
Prediction,
Skipjack tuna

ABSTRACT

This study aims to model the potential habitat distribution of skipjack tuna (*Katsuwonus pelamis*) in Fisheries Management Areas (FMA) 713 and 714 using a multi-algorithm Species Distribution Modeling (SDM) approach. Catch logbook data from 2020–2024 were combined with key oceanographic parameters, namely sea surface temperature (SST), chlorophyll-a (CHL), salinity (SAL), sea surface height (SSH), and ocean currents (CUR). Four modeling algorithms (Generalized Additive Model (GAM), Multivariate Adaptive Regression Splines (MARS), Maximum Entropy (MAXENT), and Support Vector Machine (SVM)) were applied and evaluated using two commonly used metrics, the Area Under Curve (AUC) and True Skill Statistics (TSS). The evaluation results showed that most algorithms performed well, with average AUC values > 0.7 and TSS > 0.5, making them suitable for habitat distribution analysis. Variable importance analysis revealed that SAL and SSH were the dominant factors influencing habitat distribution. The contribution of SAL was most prominent in the MAXENT algorithm (47.47%), while SSH was dominant in MARS (34.23%). Prediction overlays generated spatial habitat suitability index (HSI) maps, with a suitability threshold of ≥ 0.6 indicating optimal habitats. The results indicated that the skipjack tuna habitats are seasonal, being most extensive and stable in the first half of the year (April–July) and at the end of the year (November–December), aligning with the skipjack fishing seasons.

INTRODUCTION

The capture fisheries sector plays a strategic role in supporting food security, the national economy, and the welfare of coastal communities in Indonesia. One of the key commodities is skipjack tuna (*Katsuwonus pelamis*), a pelagic species with high economic value, wide distribution in tropical and subtropical waters, and significant importance as an export commodity (**Santoso *et al.*, 2023**). In eastern Indonesia, Fisheries Management Area (FMA) 713 (Sulawesi Sea and surrounding waters) and FMA 714 (Banda Sea) are the primary fishing grounds for skipjack tuna, with high productivity influenced by oceanographic dynamics such as upwelling, current convergence, and sea surface temperature variation (**Fajrianti *et al.*, 2016**).

Fishing activities in these two FMAs not only sustain local communities' protein needs but also contribute to national foreign exchange through exports. However, high fishing pressure (**Amir & Mallawa, 2015**), climate change, and marine environmental variability are altering the spatial distribution and abundance of skipjack stocks (**Putri, 2021; Santoso *et al.*, 2023**). Identifying appropriate fishing grounds is therefore crucial to improve fishing efficiency while ensuring resource sustainability. Stock assessments in FMA 713 indicate that skipjack exploitation rates are relatively high, with population parameters suggesting potential stock decline if not managed sustainably (**Amir & Mallawa, 2015**). Accurate and data-driven fishing ground identification is essential to enhance fishing efficiency, reduce fuel costs, and ensure resource sustainability (**Precioso *et al.*, 2021**).

Various methods have been applied to estimate fishing grounds, ranging from traditional knowledge-based approaches, simple statistical analyses, to oceanographic and remote sensing-based modeling (**Syamsuddin *et al.*, 2020**). One widely applied method is Species Distribution Modeling (SDM), which links species occurrence data with environmental variables to map potential distributions (**Guisan & Thuiller, 2005; Elith & Leathwick, 2009**). Advances in remote sensing technology, global oceanographic databases, and modern computing have significantly improved the accuracy of SDM, including predicting the distribution of tuna and skipjack (**Precioso *et al.*, 2021; Komori *et al.*, 2023**). However, the use of a single SDM algorithm often has limitations due to sensitivity to data type, spatial scale, and model parameters (**Araújo & New, 2007**). Some models may yield biased or inconsistent predictions when applied to different regions or periods (**Dormann *et al.*, 2018**). Therefore, approaches that minimize the weaknesses of single algorithms and enhance predictive robustness are required.

Multi-algorithm approaches have been shown to improve predictive accuracy and model robustness against data variability (**Dunn *et al.*, 2021; Nguyen *et al.*, 2023**). Studies such as Tuna-AI, which utilized machine learning to estimate tuna biomass by integrating oceanographic and echosounder data, provide a strong example of successful multi-source data integration in fisheries prediction (**Precioso *et al.*, 2021**). In this study, several machine learning algorithms, including the Generalized Additive Model (GAM), Multivariate Adaptive Regression Splines (MARS), Maximum Entropy (MAXENT), and Support Vector Machine (SVM), are combined to predict skipjack tuna distribution based on optimal habitat conditions.

Modeling studies employing multiple algorithm combinations or so-called multi-algorithm approaches to model skipjack distribution in Indonesia, particularly in FMA 713 and FMA 714, remain limited, especially those utilizing the latest oceanographic data with comprehensive spatio-temporal validation. Previous studies in FMA 713 focused on analyzing peak fishing seasons and their relationship with oceanographic parameters such as sea surface temperature and chlorophyll-a (**Fajrianti *et al.*, 2016**), while in FMA 714, population studies have indicated signs of overfishing (**Santoso *et al.*, 2023**). Therefore, this study aims to develop a skipjack fishing ground prediction method using machine learning through a multi-algorithm SDM approach, integrating logbook catch data, satellite-derived oceanographic data, and spatio-temporal validation. The results are expected to support more targeted and sustainable fishing planning in these two FMAs.

MATERIALS AND METHODS

Data and data sources

This study utilized two main groups of data: skipjack tuna fishing location information as presence data, and oceanographic data as environmental variables. Fishing location information was obtained from fishing vessel logbooks compiled by the Directorate of Fish Resources Management – Directorate General of Capture Fisheries, Ministry of Marine Affairs and Fisheries (MMAF) for the period 2020–2024, covering the fisheries management areas FMA 713 (Sulawesi Sea and surrounding waters) and FMA 714 (Banda Sea). The logbook records include details of fishing positions, operation times, and catch volumes, making them the primary source for spatial fisheries analysis (**Abdi *et al.*, 2019**).

The oceanographic data were sourced from Marine Copernicus and included parameters such as sea surface temperature (SST), chlorophyll-a concentration (CHL), sea surface height (SSH), surface currents (CUR), and salinity (SAL). These variables have been widely used in studies of large pelagic fish distribution, including tuna and skipjack, due to their strong relationship with habitat conditions (**Pratama *et al.*, 2022; Yati *et al.*, 2024**). In addition to satellite data, direct field measurements were also conducted using *in-situ* water quality testing devices to obtain actual values of salinity, temperature, and ocean currents at the research sites.

Catch data validation

Validation of skipjack tuna fishing locations was carried out by comparing vessel logbook points with data from Indonesia's Vessel Monitoring System (VMS), a satellite-based system that periodically records vessel positions and movements. VMS has been proven to provide more accurate estimates of fishing area extent and activity intensity compared to manual logbook records, as demonstrated in studies showing that VMS data are more reliable in representing the spatial footprint of fishing activities (**Guillot *et al.*, 2017**).

The comparison of these two data sources enabled the detection and removal of irrelevant logbook points, such as locations outside FMA 713 and 714 or when vessels were not engaged in fishing operations, ensuring that only valid and representative presence data were used for distribution modeling. After the validation stage, the dataset was reorganized and exported into CSV format as input for subsequent analysis in R Studio, which was used to run the skipjack tuna distribution modeling process.

Oceanographic data processing

Raw oceanographic data from Marine Copernicus were downloaded and processed using SeaDAS version 7.5.3 to extract specific satellite-derived parameters. The data were then processed in ArcGIS version 10.8 through several steps, including clipping to match the research area boundaries, spatial interpolation to fill missing data, and format conversion into GeoTIFF to ensure compatibility with spatial analysis tools. All oceanographic datasets were resampled to a uniform spatial resolution of 0.083° to maintain consistency across algorithms. The final habitat suitability index (HSI) maps were generated at the same resolution, making them appropriate for regional-scale fisheries management applications. Interpolation techniques play an important role in producing consistent environmental data distributions that accurately represent actual field conditions (**Hengl *et al.*, 2009; Li & Heap, 2014**).

Multicollinearity test

Before the modeling stage, multicollinearity analysis among environmental variables was conducted using the variance inflation factor (VIF) method to ensure the absence of high correlations that could cause bias in parameter estimation. Variables with a VIF value greater than 10 were considered highly collinear and were removed from the analysis to avoid redundancy and maintain model stability (**Kutner *et al.*, 2005; O'Brien, 2007**). This approach is commonly applied in species distribution modeling to improve the reliability of predictive results.

Species distribution modeling

The skipjack tuna distribution modeling process was carried out using four algorithms commonly applied in Species Distribution Modeling (SDM): Generalized Additive Model (GAM), Multivariate Adaptive Regression Splines (MARS), Maximum Entropy (MaxEnt), and Support Vector Machine (SVM). The selection of this algorithmic combination was based on empirical evidence that each method has distinct strengths in capturing complex and non-linear relationships between environmental variables and the spatial distribution of marine species (**Guisan & Thuiller, 2005; Dunn *et al.*, 2021; Nguyen *et al.*, 2023**).

All analyses were conducted in RStudio (version 2024.12.0+467) using the ‘sdm’ package (version 1.2-55). The modeling employed a bootstrap replication procedure (n = 100) with 30% of the data reserved for independent testing. Background points were generated using a random sampling method (‘gRandom’, n = 100). Parameter tuning and cross-validation were automatically handled within the ‘sdm’ framework to optimize model performance and minimize overfitting. All R scripts and processed datasets are available from the corresponding author upon reasonable request.

The predictive outputs from each algorithm were then evaluated using two accuracy metrics: Area Under the Curve (AUC) and True Skill Statistic (TSS). AUC measures the model’s ability to distinguish suitable from unsuitable habitats, while TSS combines sensitivity and specificity to provide a balanced assessment of model accuracy (**Allouche *et al.*, 2006**). This multi-algorithm approach reduces potential bias arising from single-model dependency and enhances prediction robustness against data variability and spatial scale differences.

Mapping of modeling results

After model evaluation, the predictive outputs from GAM, MARS, MaxEnt, and SVM were combined (overlayed) to generate a habitat suitability index (HSI) map. The HSI value represents the probability of habitat suitability based on the integrated information from environmental variables and the distributional patterns detected by each algorithm. Habitat suitability classification followed a threshold: HSI < 0.6 = unsuitable habitat, and HSI ≥ 0.6 = suitable habitat. Suitability levels were further differentiated based on the number of models predicting a given area as suitable habitat. Areas predicted as suitable by all four models were categorized as highly suitable; overlapping predictions by two to three models as suitable; and predictions from a single model as moderately suitable.

This integrated multi-algorithm approach offers advantages in minimizing bias that could arise from the limitations of any single model while leveraging the strengths of each algorithm. Consequently, the final results not only reflect more accurate predictions but are also more resilient to data variability and uncertainties in marine environments. The resulting HSI maps can serve as a basis for decision-making in planning efficient and sustainable fishing grounds in FMA 713 and FMA 714.

RESULTS

Multicollinearity test

All oceanographic parameters (environmental predictor variables) used in the modeling were tested for multicollinearity. This test produces a Variance Inflation Factor (VIF) value, which indicates whether any oceanographic parameter exhibits significant multicollinearity issues (**Ghozali, 2018**). Multicollinearity problems need to be addressed by eliminating oceanographic parameters with VIF values greater than 10. If not addressed, the modeling results may become unstable and increase errors, thereby reducing predictive accuracy (**Montgomery *et al.*, 2012**).

The results of the multicollinearity test for each oceanographic parameter are presented in Table (1). The analysis showed that all Variance Inflation Factor (VIF) values were below 5 in each observation month. This indicates that there were no significant multicollinearity issues among the variables, allowing all oceanographic parameters to be simultaneously used in the model analysis.

Table 1. Results of the multicollinearity test for each oceanographic parameter used in the modeling

Month	Variance Inflation Factor (VIF)			
	Current	Salinity	Sea Surface Height	Sea Surface Temperature
January	1.574	1.641	1.131	1.692
February	1.608	1.543	1.146	1.750
March	1.359	1.389	1.091	1.531
April	1.149	1.412	1.235	1.389
May	1.293	1.439	1.459	1.443
June	1.31	1.522	2.229	1.200
July	1.289	1.513	1.858	2.352
August	1.324	1.570	1.919	2.417
September	1.386	1.815	2.035	3.057
October	1.305	1.731	1.977	2.686
November	1.172	1.350	1.310	1.180
December	1.393	2.059	1.485	1.458

Model performance

The performance of the model was evaluated using two commonly applied metrics in ecological modeling: Area Under the Curve (AUC) and True Skill Statistics (TSS). AUC is used to assess the model's ability to distinguish between suitable (presence) and unsuitable (absence) locations, while TSS evaluates the balance between sensitivity and specificity. According to **Yati *et al.* (2024)**, an AUC value greater than 0.7 and a TSS value greater than 0.5 indicate that the model performs well and can be reliably used for further analysis.

Referring to Table (2), it can be observed that, in general, the average AUC values of all algorithms were above 0.7 and the TSS values were above 0.5, indicating good model performance. Only the GLM algorithm produced AUC values below 0.7 and TSS values below 0.5 in certain periods, suggesting that its performance was relatively lower compared to the other algorithms. In contrast, the MARS algorithm achieved the highest average AUC (0.870) and TSS (0.666), followed by GAM (AUC 0.845; TSS 0.660) and MAXENT (AUC 0.821; TSS 0.638).

Table 2. Model performance evaluation for each algorithm

Algorithm	AUC	AUC Average	TSS	TSS Average
MAXENT	0.7 - 0.93	0.821	0.47 - 0.78	0.638
GAM	0.76 - 0.92	0.845	0.54 - 0.77	0.660
GLM	0.62 - 0.85	0.702	0.18 - 0.68	0.428
MARS	0.86 - 0.92	0.870	0.45 - 0.77	0.666

Variable importance

Based on the results of the variable importance analysis across four modeling algorithms (MARS, GLM, GAM, and MaxEnt), each oceanographic parameter exhibited different contributions to the habitat model (Fig. 1). In the MARS algorithm, salinity (34.46%) and sea surface height (34.23%) had the greatest influence, while ocean current contributed only 7.63%. In GLM, ocean current was the dominant variable with 33.81%, followed by sea surface height (29.91%) and sea surface temperature (23.03%), whereas salinity contributed less (13.25%). In GAM, salinity (32.49%) and sea surface height (30.58%) were the most influential factors, followed by sea surface temperature (23.74%), while ocean current contributed only 13.20%.

Meanwhile, the MaxEnt algorithm showed a clear dominance of salinity with a very high contribution (47.47%), followed by sea surface height (25.07%) and sea surface temperature (16.65%), while ocean current had the smallest contribution (10.81%). These results highlight the percentage contribution of each oceanographic parameter to the model, where higher percentages indicate greater importance and influence of the parameter in shaping the model and supporting further analysis.

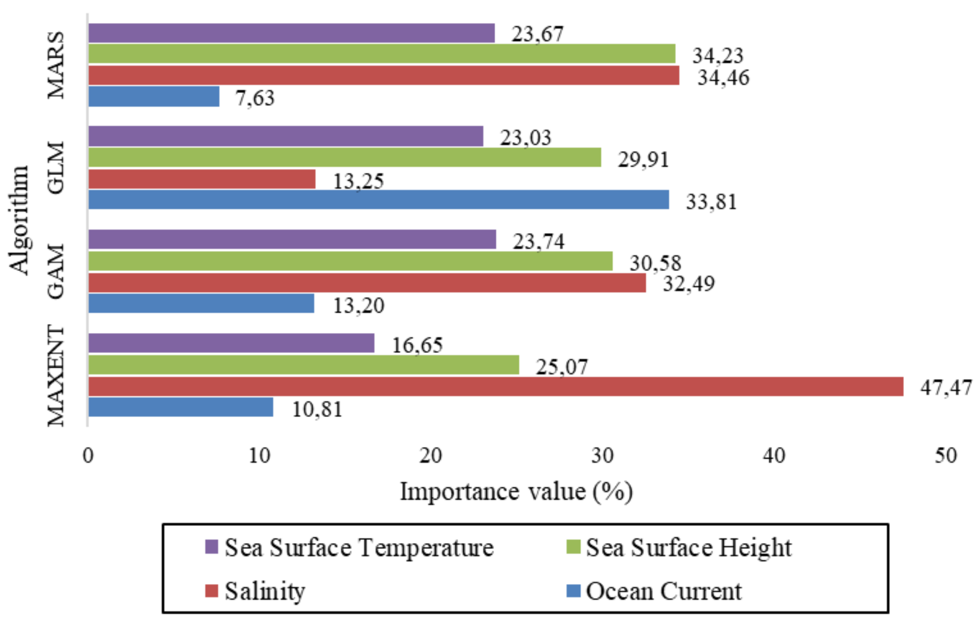

Fig. 1. The importance value of each parameter in model development

Suitable parameter ranges

The range of oceanographic parameters suitable to support habitat presence was obtained based on the results of the Response Curve analysis for each month, as presented in Table (3). Suitable ocean current values were found within the range of 0.1–0.75 m/s, with relatively stable monthly variations. Salinity was recorded within the range of 29–34 PSU, with minimum values generally occurring at the beginning of the year and maximum values of up to 34 PSU observed in September. The sea surface height parameter ranged between 0.45– 0.80m, with the lowest value recorded in October and the highest in December. Meanwhile, the suitable sea surface temperature ranged between 28– 31°C, with the minimum value of 28°C occurring in September and August, while the maximum of 31°C was recorded in February, July, and December. Overall, these ranges reflect oceanographic conditions that support habitat presence, with clear seasonal variations throughout the year.

Table 3. Optimal value ranges of each oceanographic parameter suitable to support habitat presence

	Ocean Current (m/s)		**Salinity (PSU)**		**Sea Surface Height (m)**		**Sea Surface Temperature (ºC)**	
	Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
January	0.1	0.6	29	33	0.6	0.75	29.5	30.5
February	0.2	0.7	30	31	0.65	0.75	29.5	31
March	0.3	0.7	30	33	0.6	0.75	29.5	30.5
April	0.2	0.3	31	34	0.65	0.72	29.5	30.5
May	0.1	0.4	31	33	0.6	0.72	29	31
June	0.1	0.6	29	33	0.6	0.75	29.5	30.5
July	0.2	0.7	29	33	0.6	0.75	29	30.5
August	0.25	0.75	32	33	0.5	0.7	28	30
September	0.1	0.75	32.5	34	0.6	0.7	28.5	30
October	0.1	0.3	32.5	33.5	0.45	0.7	29	30
November	0.1	0.3	32.5	33.5	0.55	0.70	29	30.5
December	0.2	0.5	31.5	34	0.6	0.8	30	31
Range	**0.1**	**0.75**	**29**	**34**	**0.45**	**0.8**	**28**	**31**

Overlay of habitat suitability index (HSI) from all algorithms

The habitat suitability index (HSI) is used as a measure to determine whether a marine area possesses environmental parameters that are suitable and optimal for a species, in this case, the skipjack tuna. The HSI value represents the probability of skipjack presence in an area that matches its habitat, ranging from 0 to 1. The higher the HSI value, the greater the likelihood of skipjack occurring or being found in that area (**Pratama *et al.*, 2022**). In this study, HSI values greater than 0.6 are considered highly suitable habitats, while values below 0.6 are categorized as less suitable habitats (**Hemery *et al.*, 2016**).

The overlay maps of HSI generated from four algorithms for each month throughout the year are presented in Fig. (2). Red shading indicates areas with high habitat suitability, representing regions consistently supported by all four algorithms. In general, suitable habitat distribution appears to be widespread across most of the study area throughout the year, although seasonal variations are observed. From January to March, highly suitable areas are concentrated in the central and western waters. From April to July, red areas expand, covering much of the region. Between August and October, suitable habitat distribution remains broad, but with some contraction in certain parts. Meanwhile, in November and December, highly suitable areas expand again, indicating stable habitat consistency during the year-end period.

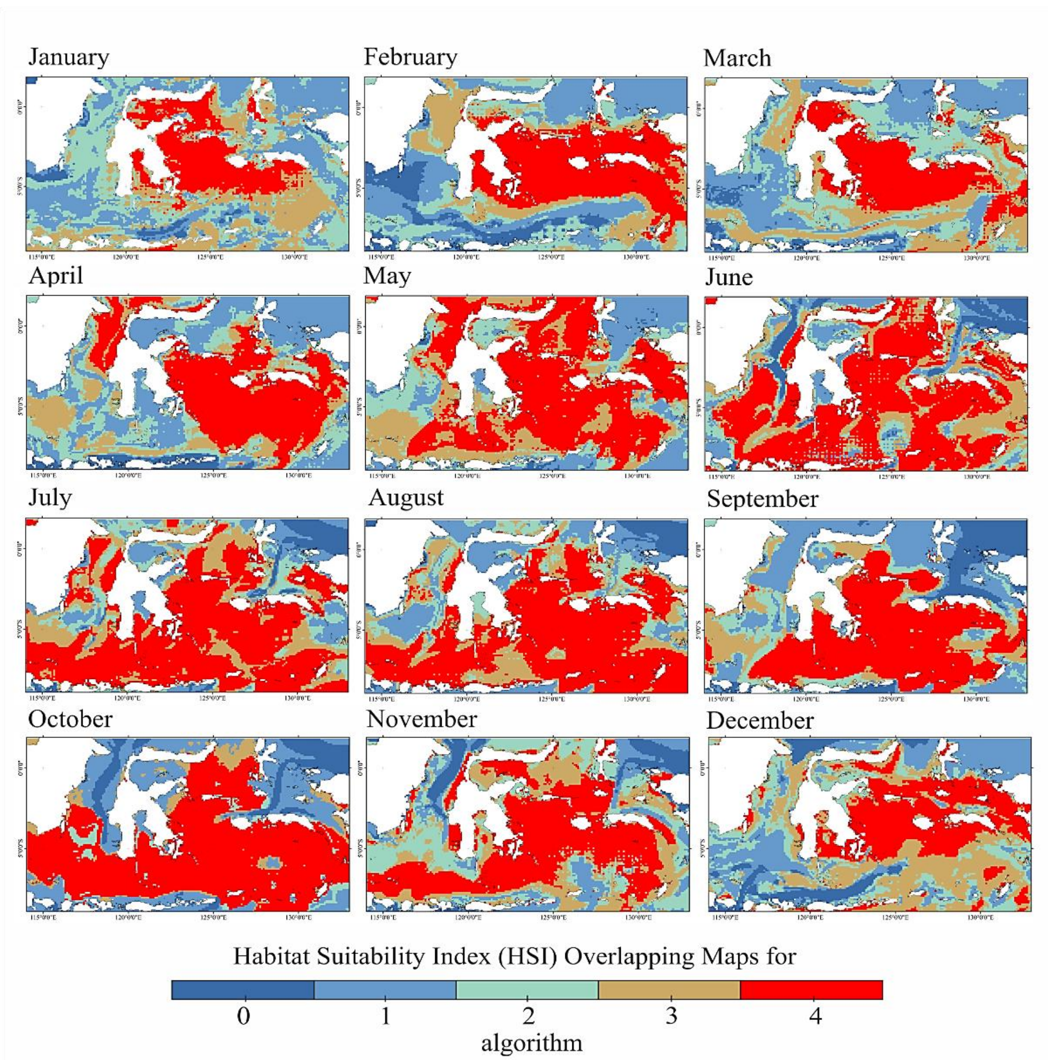

Fig. 2. Overlay map of skipjack tuna habitat distribution from all algorithms

DISCUSSION

The multicollinearity test results showed that all oceanographic parameters had VIF values below 5, indicating no issue of high correlation among variables. This condition is important because high multicollinearity can cause model instability and reduce prediction accuracy (**Montgomery *et al.*, 2012**). Therefore, the four oceanographic parameters; namely, current, salinity, sea surface height, and sea surface temperature, can be used simultaneously as predictors of skipjack tuna habitat in FMA 713 and 714. This finding is consistent with **Phillips *et al.* (2006)** and **Harrell (2015)**, who emphasized the importance of variable independence in ecological modeling to produce more reliable predictions.

Model performance evaluation showed that most algorithms performed well, with AUC values greater than 0.7 and TSS values greater than 0.5 (**Orue *et al.*, 2020; Yati *et al.*, 2024**). The MARS, MAXENT, and GAM algorithms recorded the highest accuracy compared to GLM, which in some periods still produced AUC values below 0.7 and TSS values below 0.5. Although model performance metrics indicated good predictive accuracy, some uncertainty remains due to potential sampling bias and oceanographic data errors. Nevertheless, the application of consistent resampling, controlled interpolation, and bootstrap replication helps minimize error propagation throughout the analysis. Therefore, although minor variations may still occur, this approach provides a reliable and methodologically robust representation of the environmental conditions required for skipjack tuna habitat modeling.

The relatively lower performance of the GLM algorithm can be attributed to its limited capacity to represent the non-linear and interactive effects of environmental variables, which are typical of dynamic pelagic ecosystems (**Anderson *et al.*, 2022; Perez *et al*., 2023**). As a result, linear models may underestimate habitat responses driven by complex oceanographic processes such as upwelling intensity, current variability, and mesoscale eddies (**Taylor *et al.*, 2025**). This finding highlights the advantage of non-linear and flexible modeling approaches in capturing the ecological complexity underlying skipjack tuna distribution (**Anderson *et al.*, 2022; Taylor *et al.*, 2025**). Nevertheless, the overall mean AUC and TSS values across all algorithms remained within the good performance category, confirming that all models are suitable for use in skipjack habitat suitability analysis as they adequately describe both species presence and absence.

Variable importance analysis showed that salinity and sea surface height were the dominant factors influencing habitat distribution. The dominance of salinity, particularly in the MAXENT algorithm (47.47%), highlights the crucial role of this parameter in defining the ecological boundaries of skipjack tuna habitat. This finding is reinforced by **Pratama *et al.* (2022)**, who showed that salinity was the most effective parameter in building habitat suitability models for pelagic fish in Palabuhanratu. Salinity is closely related to the osmoregulatory capacity and metabolism of fish (**Khalil *et al.*, 2015; Pamungkas *et al.*, 2020**), meaning that small changes within the optimal range can affect the spatial distribution of skipjack tuna. This study found that the optimal salinity range for skipjack tuna was 29 to 34 PSU.

In addition to salinity, sea surface height also proved to be a very important variable influencing skipjack tuna habitat distribution, which is consistent with the findings of **Yati *et al.* (2024)**. The optimal environmental parameter range for sea surface height was 0.45 to 0.80 meters. Sea surface height dynamics reflect oceanographic processes such as the presence of eddies and frontal zones, which serve as areas with high food concentrations for small fish prey. **Gregr *et al.* (2008)** found that regions with high frontal activity, measured from sea surface height variability, can attract prey fish including skipjack tuna. Meanwhile, eddies in the waters can transport plankton and small fish to the surface layer, thus attracting tuna, including skipjack, to aggregate (**Sabarros *et al.*, 2009**). Therefore, sea surface height not only functions as a physical indicator of the ocean surface but also represents biological processes that create nutrient-rich and prey-abundant areas, making it a key factor in determining the spatial distribution of skipjack tuna.

The role of sea surface temperature and currents, although not dominant, remains significant. This study showed that skipjack tuna tends to be found at a temperature range of 28 to 31 degrees Celsius, which is consistent with **Mujib *et al.* (2013)** and **Pratama *et al*. (2022)**, who reported an optimal range of 26 to 30 degrees Celsius for pelagic fish. Sea surface temperature affects metabolic processes, dissolved oxygen availability, and prey dynamics (**Laevastu & Hayes, 1981**). Therefore, the combination of sea surface temperature and salinity becomes the strongest environmental indicator in determining skipjack tuna distribution.

Ocean currents in this study contributed less compared to other parameters, yet they still play a role as a nutrient transport mechanism and influence fish swimming behavior. The suitable environmental parameter range for ocean currents was 0.1 to 0.75 meters per second. The waters of FMA 713 have distinct wind patterns that directly influence surface current patterns. These variations in current patterns subsequently affect water mass dynamics, which are suspected to cause changes in oceanographic characteristics including water productivity levels (**Gordon, 2005**). This aligns with the findings of **Pratama *et al.* (2022)**, who stated that currents provided greater training gain compared to chlorophyll-a and bathymetry when used partially in the model. Skipjack tuna and other pelagic groups generally use currents as natural migration routes (**Laevastu & Hayes, 1981**), so even though their relative contribution is smaller compared to sea surface temperature and salinity, currents remain ecologically important.

The habitat suitability index overlay analysis revealed that suitable skipjack tuna habitats were available throughout the year, although the extent fluctuated seasonally. The periods from April to July and November to December were characterized by more stable and broader habitat distribution, which implies the potential for increased catchability. This finding is consistent with the skipjack fishing season in FMA 713, where moderate to high fishing intensity was recorded from April to June and from October to December (**Fajrianti *et al.*, 2016**). The alignment between habitat dynamics and fishing seasons indicates that the habitat suitability index model can represent the ecological conditions underlying fluctuations in skipjack availability, thus providing a basis for planning more effective and sustainable fishing strategies. This shows that habitat modeling based on oceanographic parameters can not only explain the ecological preferences of skipjack tuna but also support ecosystem-based management strategies in identifying potential fishing zones that are adaptive to environmental variation.

Explicitly communicating spatial uncertainty is essential when translating HSI outputs into fisheries-management recommendations (**Beale *et al.*, 2013**). Regions with consistently low uncertainty (high inter-model agreement) represent more reliable candidates for decision support, for example prioritizing them in adaptive fishing calendars or as candidate priority fishing zones. Conversely, high-uncertainty areas should be treated cautiously: they are prime targets for further data collection and probabilistic decision-making frameworks that explicitly address model uncertainty (**Iturbide *et al*., 2018**). Methodologically, future work would benefit from implementing formal probabilistic ensemble approaches (e.g., Bayesian model averaging or quantile-based bootstrap intervals) to produce more robust, manager-friendly confidence metrics (**Chen *et al.*, 2019**). By providing explicit uncertainty maps, the study offers clearer guidance on where HSI predictions are actionable and where additional evidence is required.

CONCLUSION

Habitat distribution modeling of *Katsuwonus pelamis* using a multi-algorithm SDM approach (MARS, GLM, GAM, and MaxEnt) demonstrated robust performance (AUC > 0.7; TSS > 0.5), with salinity and sea surface height (SSH) identified as the dominant environmental factors shaping habitat suitability. The optimal habitat (HSI ≥ 0.6) showed a clear seasonal pattern, with the most extensive and stable distribution occurring from April to July and November to December, consistent with the main skipjack fishing season. These findings highlight the importance of adopting adaptive fishing calendars that align with environmental dynamics, integrating oceanographic data into decision-support systems for fishers, and designating priority fishing zones based on HSI values. Overall, this study provides a spatially explicit, data-driven framework to support sustainable and ecosystem-based management of skipjack tuna in Indonesia’s Fisheries Management Areas (FMAs), strengthening evidence-based policy formulation for resource sustainability.

ACKNOWLEDGEMENT

The authors would like to express their gratitude to the Ministry of Higher Education, Science, and Technology (KEMDIKTISAINTEK) of the Republic of Indonesia for funding this research through the novice lecturer research grant scheme in 2025, under contract number 460/II.3.AU/D/VII/2025. The authors also thank the Ministry of Marine Affairs and Fisheries of Indonesia for providing the fisheries data required for this study. Appreciation is also extended to the Study Program of Fisheries Product Technology, Institut Teknologi Sains dan Bisnis Muhammadiyah Selayar, and the Study Program of Fisheries, Universitas Padjadjaran, for their valuable support.

REFERENCES

Abdi, M.; Nazruddin, M.; Arifuddin, M., and Gunawan G.L. (2019). The implementation of fishing e-logbook for small-scale fisheries in Indonesia – Report of Enabling Transboundary Cooperation for Sustainable Management of the Indonesian Seas (ISLME project) GEF/FAO project No. GCP/RAS/289/GFF. Jakarta: FAO.

Allouche, O.; Tsoar, A. and Kadmon, R. (2006). Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, 43: 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Amir, F. and Mallawa, A. (2015). Parameter pertumbuhan dan tingkat eksploitasi ikan cakalang (*Katsuwonus pelamis*) di Selat Makassar. Jurnal IPTEKS PSP, 2(1): 1–10.

Anderson, S.C.; Ward, E.J. and O'Hara, R.B. (2022). *Non-linear models of species' responses to environmental and spatial gradients. Ecography*, 45(3), e06027. https://doi.org/10.1111/ecog.06027

Araújo, M.B. and New, M. (2007). Ensemble forecasting of species distributions. *Trends in Ecology & Evolution*, 22(1): 42–47. https://doi.org/10.1016/j.tree.2006.09.010

Chen, X., Dimitrov, N. B., Meyers, L. A., et al. (2019). *Uncertainty analysis of species distribution models.* PLOS ONE, 14 (5): e0214190. https://doi.org/10.1371/journal.pone.0214190

Dormann, C.F.; Calabrese, J.M.; Guillera-Arroita, G.; Matechou, E.; Bahn, V.; Bartoń, K.; Beale, C.M.; Ciuti, S.; Elith, J.; Gerstner, K.; Guelat, J.; Keil, P.; Lahoz-Monfort, J.J.; Pollock, L.J.; Reineking, B.; Roberts, D.R.; Schröder, B.; Thuiller, W.; Warton, D.I.; Wintle, B.A.; Wood, S.N.; Wüest, R.O. and Hartig, F. (2018). Model averaging in ecology: a review of Bayesian, information-theoretic, and tactical approaches for predictive inference. *Ecological Monographs*, 88(4): 485–504. https://doi.org/10.1002/ecm.1309

Dunn, D.C.; Maxwell, S.M.; Boustany, A.M. and Halpin, P.N. (2021). Dynamic ocean management increases the efficiency and efficacy of fisheries management. Nature Sustainability, 4(5): 381–390. https://doi.org/10.1038/s41893-021-00686-4

Elith, J. and Leathwick, J.R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics*, 40: 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Fajrianti, N.; Mallawa, A. and Arief, M. (2016). Analisis musim penangkapan ikan cakalang (*Katsuwonus pelamis*) di Teluk Bone Sulawesi Selatan. *Jurnal IPTEKS PSP*, 3(1): 42–50.

Ghozali, I. (2018**)**. Aplikasi Analisis Multivariate dengan Program IBM SPSS 25 (Edisi 9). Semarang: Badan Penerbit Universitas Diponegoro.

Gordon, A.L. (2005**)**. Oceanography of Indonesian Seas and Their Through flow. *Oceanography*, 18 (4): 14–27.

Gregr, E.J. and Triter, A.W. (2008**)**. A novel presence-only validation technique for improved Steller sea lion Eumetopias jubatus critical habitat descriptions. *Marine Ecology Progress Series*, 365: 247-261

Guillot, G.; Benoît, P.; Kinalis, S.; Bastardie, F. and Bartolino, V. (2017**)**. Enhancing and comparing methods for the detection of fishing activity from Vessel Monitoring System data. *arXiv preprint*. arXiv:1708.09663.

Guisan, A. and Thuiller, W. (2005**)**. Predicting species distribution: Offering more than simple habitat models. *Ecology Letters*, 8(9): 993–1009. https://doi.org/10.1111/j.1461-0248.2005.00792.x

Harrell, F.E. (2015**)**. Regression Modeling Strategies. Springer Series in Statistics. *Springer International Publishing, Cham*. https://doi.org/10.1007/978-3-319-19425-7.

Hemery, L.G.; Marion, S.R.; Romsos, C.G.; Kurapov, A.L. and Henkel, S.K. (2016**)**. Ecological niche and species distribution modelling of sea stars along the Pacific Northwest continental shelf. *Divers Distribution*. 22: 1314–1327. https://doi: 10.1111/ddi.12490

Hengl, T.; Heuvelink, G.B.M. and Stein, A. (2009**)**. A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma*, 140(4): 310–323. https://doi.org/10.1016/j.geoderma.2007.12.013

Iturbide, M., Bedia, J., & Gutiérrez, J. M. (2018). *Tackling uncertainties of species distribution model projections with the mopa package.* The R Journal, 10(2), 410-428.

Khalil, M.; Mardhiah, A. and Rusydi, R. (2015**)**. Pengaruh penurunan salinitas terhadap laju konsumsi oksigen dan pertumbuhan ikan kerapu lumpur (*Epinephelus tauvina*). *Acta Aquatica*, 2(2): 114-121.

Komori, T.; Suda, Y. and Yamaguchi, K. (2023**)**. Statistical learning for species distribution models in ecological studies. *Ecological Modelling*, 481: 110-128. https://doi.org/10.1016/j.ecolmodel.2022.110128

Kutner, M.H.; Nachtsheim, C.J.; Neter,J. and Li, W. (2005**)**. Applied Linear Statistical Models (5th ed.). McGraw-Hill Irwin.

Laevastu, T. and Hayes, M.L. (1981**)**. Fisheries Oceanography and Ecology. Farnham (UK): Fishing New Books.

Li, J. and Heap, A.D. (2014**)**. Spatial interpolation methods applied in the environmental sciences: A review. *Environmental Modelling & Software*, 53: 173–189. https://doi.org/10.1016/j.envsoft.2013.12.008

Montgomery, D.C.; Peck, E.A. and Vining, G.G. (2012**)**. Introduction to Linear Regression Analysis (5th ed.). Hoboken, NJ: John Wiley & Sons.

Mujib, Z.; Boesono, H. and Fitri, A.D.P. (2013**)**. Pemetaan sebaran ikan tongkol (*Euthynnus* sp.) Dengan data klorofil-a citra modis pada alat tangkap payang (danish-seine) di Perairan Teluk Palabuhanratu, Sukabumi, Jawa Barat. *Fisheries Resources Utilization Management and Technology*, 2 (2): 150-160.

Nguyen, M.H.; Le, Q.T. and Tran, T.L. (2023**)**. Improving small-scale fisheries through machine learning spatial analysis. *Marine Policy*, 151: 105847. https://doi.org/10.1016/j.marpol.2022.105847

Pamungkas, R.D.; Hariyadi, S. and Sulmartiwi, L. (2020**)**. Toleransi salinitas dan suhu terhadap kelangsungan hidup dan pertumbuhan ikan kerapu (*Epinephelus* sp.). *Jurnal Ilmu dan Teknologi Kelautan Tropis*, 12(1), 1–9. https://doi.org/10.29244/jitkt.v12i1.30462

Perez, M. A., Furey, N. B., & Fabrizio, M. C. (2023). Nonlinearity and spatial autocorrelation in species distribution modeling: an example based on Weakfish *(Cynoscion regalis). Fishes*, 8(1), 27. https://doi.org/10.3390/fishes8010027

Phillips, S.J.; Anderson, R.P. and Schapire, R.E. (2006**)**. Maximum entropy modeling of species geographic distributions. *Ecol. Model*, 190: 231–259. https://doi.org/ 10.1016/j.ecolmodel.2005.03.026.

Pratama, G.B.; Nurani, T.W.; Mustaruddin, and Herdiyeni, Y. (2022**)**. Modeling of habitat suitability of pelagic fish based on oceanographic conditions in Palabuhanratu Waters. *Bawal: Widya Riset Perikanan Tangkap*, 14(3): 161–171.

Precioso, D.; Navarro-García, M.; Gavira-O'Neill, K.; Torres-Barrán, A.; Gordo, D.; Gallego-Alcalá, V. and Gómez-Ullate, D. (2021**)**. Tuna-AI: tuna biomass estimation with Machine Learning models trained on oceanography and echosounder FAD data. *arXiv preprint*, arXiv:2109.06732. https://arxiv.org/abs/2109.06732

Putri, R. S. (2021**)**. Produksi dan potensi tangkap ikan cakalang (*Katsuwonus pelamis*) di WPP 713. *Jurnal Kelautan dan Perikanan Tropis*, 3(2): 45–54.

Sabarros, P.S.; Menard, F.; Levenez, J-J.; Tew-Kai, E. and Ternon, J-F. (2009**)**. Mesoscale eddies influence distribution and aggregation patterns of micronekton in the Mozambique Channel. *Marine Ecology Progress Series*, 395: 101-107

Santoso, S.; Firmansyah, A. and Abdullah, M. (2023**)**. Parameter populasi dan laju eksploitasi ikan cakalang di WPP 714. *Jurnal Sumberdaya Ikan dan Ilmu Perikanan*, 18(1): 13–21.

Syamsuddin, M.; Fahrul, F. and Rachmawati, A. (2020**)**. Pemanfaatan teknologi penginderaan jauh untuk menentukan daerah penangkapan ikan. *Jurnal Kelautan Tropis*, 23(1): 56–65. https://doi.org/10.14710/jkt.v23i1.8242

Taylor, P., Brodie, S., Maxwell, S. M., Dunn, D. C., & Halpin, P. N. (2025). *Applications of species distribution modeling and future needs to support marine resource management.* **ICES Journal of Marine Science**, 82(3), fsaf024. https://doi.org/10.1093/icesjms/fsaf024

Orue, B.; Lopez, J.; Pennino, M.G.; Moreno, G.; Santiago, J. and Murua, H. (2020**)**. Comparing the distribution of tropical tuna associated with drifting fish aggregating devices (DFADs) resulting from catch dependent and independent data. *Deep Sea Res 2 Top Stud Oceanogr*, 175. https://doi.org/10.1016/j.dsr2.2020.104747

O'Brien, R.M. (2007**)**. A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, 41: 673–690. https://doi.org/10.1007/s11135-006-9018-6

Yati, E.; Sadiyah, L.; Satria, F.; Alabia, I.D.; Sulma, S.; Prayogo, T.; Marpaung, S.; Harsa, H.; Kushardono, D.; Gaol, J.L.; Budiarto, A.; Efendi, D.S. and Patmiarsih, S. (2024**)**. Spatial distribution models for the four-commercial tuna in the sea of maritime continent using multi-sensor remote sensing and maximum entropy. *Marine Environmental Research*. 198**.**