



Ecological Modelling of Potential Habitats for Indian Mackerel (*Rastrelliger* spp.) in the Western of Banda Sea using an Artificial Neural Network Approach

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HIGHLIGHTS

- The study identified November as the peak fishing season for Indian mackerel, with the highest catch per unit effort (220 kg per trip). This peak season is supported by stable salinity, heavy rainfall and upwelling currents that enhance nutrient availability and reproduction.
- The results showed that salinity and ocean currents are the most influential oceanographic factors, contributing 16% and 14%, respectively, to catch productivity. These conditions play a vital role in determining the distribution and abundance of Indian mackerel.
- The application of an Artificial Neural Network (ANN) model demonstrated high accuracy with only a 1.12% error rate in predicting potential fishing zones. By integrating the Fishing Season Index (FSI) and ANN.



Ecological Modelling of Potential Habitats for Indian Mackerel (*Rastrelliger* spp.) in the Western of Banda Sea using an Artificial Neural Network Approach

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Abstract: Indian mackerel (*Rastrelliger* spp.) is a species with high catch volumes, amounting to approximately 451.750 tonnes over five years. This substantial yield holds significant potential for local communities, making sustainable utilisation crucial. This study focuses on the fishing season of Indian mackerel (*Rastrelliger* spp.) and the development of a habitat suitability model in the waters of the western of Banda Sea, Indonesia. The Fishing Season Index (FSI) method identified November as the peak fishing season, with the highest CPUE recorded at 220 kg trip⁻¹. During this period, stable salinity levels were observed, which supported the reproductive processes of Indian mackerel. Additionally, high rainfall and strong winds facilitated local upwelling, influencing currents and bringing nutrients to the surface, which were consumed by mackerel larvae. The ANN (Artificial Neural Network) models used to estimate potential fishing zones for Indian mackerel demonstrated high accuracy, with an error rate of just 1.12%. The analysis revealed that salinity and currents were the most influential environmental parameters, contributing 16% and 14% to catch success during the peak fishing season with salinity levels at 34.2 psu and current velocity at 3.29 cm s⁻¹. The implementation of this model in analysing Indian mackerel habitats and their relationship with environmental factors supports data and technology-driven fisheries management. This study also introduces a novel integration of the Fishing Season Index (FSI) method and ANN modelling to simultaneously identify peak fishing seasons and predict potential fishing zones based on dynamic oceanographic parameters. The application of machine learning in this model enables the identification of non-linear relationships between environmental variables and fish distribution with high accuracy, representing a significant advancement in predictive habitat modelling for Indian mackerel in Indonesian waters. This approach contributes to sustainable fisheries resource management and aligns with the achievement of SDG 14 in Indonesia.

Keyword: Indian Mackerel, ANN Algorithm, Spatial Modelling, Remote Sensing, Oceanographic Condition

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Abstrak: Ikan kembung (*Rastrelliger spp.*) merupakan spesies dengan jumlah tangkapan yang tinggi yaitu sekitar 451.750 tan dalam tempoh lima tahun. Jumlah ini berpotensi besar untuk masyarakat setempat, menjadikan penggunaan yang mampan sangat penting. Kajian ini menumpukan kepada musim penangkapan ikan kembung (*Rastrelliger spp.*) dan pembangunan model kesesuaian habitat di perairan barat Laut Banda, Indonesia. Kaedah Indeks Musim Penangkapan (Fishing Season Index/FSI) mengenal pasti bulan November sebagai musim puncak penangkapan dengan nilai CPUE tertinggi sebanyak 220 kg trip⁻¹. Pada tempoh tersebut, paras saliniti yang stabil telah diperhatikan, menyokong proses pembiakan ikan kembung. Selain itu, hujan lebat dan angin kencang membolehkan berlakunya fenomena “upwelling” tempatan yang mempengaruhi arus dan membawa nutrien ke permukaan laut untuk dimakan oleh larva ikan kembung. Model ANN (Artificial Neural Network) yang digunakan untuk menganggar zon penangkapan ikan kembung menunjukkan ketepatan yang tinggi dengan kadar ralat hanya 1.12%. Analisis mendapati saliniti dan arus merupakan parameter persekitaran yang paling mempengaruhi kejayaan tangkapan menyumbang masing-masing 16% dan 14% semasa musim puncak dengan paras saliniti pada 34.2 psu dan kelajuan arus pada 3.29 cm s⁻¹. Pelaksanaan model ini dalam menganalisis habitat ikan kembung dan hubungannya dengan faktor persekitaran menyokong pengurusan perikanan berasaskan data dan teknologi. Kajian ini juga memperkenalkan integrasi baru kaedah Indeks Musim Memancing (FSI) dan pemodelan ANN untuk mengenal pasti musim penangkapan kemuncak secara serentak dan meramalkan zon penangkapan ikan yang berpotensi berdasarkan parameter oseanografi dinamik. Aplikasi pembelajaran mesin dalam model ini membolehkan pengenalpastian hubungan bukan linear antara pembolehubah persekitaran dan taburan ikan dengan ketepatan yang tinggi, mewakili kemajuan yang ketara dalam pemodelan habitat ramalan untuk ikan kembung di perairan Indonesia. Pendekatan ini menyumbang kepada pengurusan sumber perikanan yang mampan dan sejajar dengan pencapaian SDG 14 di Indonesia.

Kata Kunci: Ikan Kembung, Algoritma ANN, Pemodelan Spasial, Penderiaan Jauh, Kondisi Oseanografi

INTRODUCTION

Capture fisheries play a pivotal role in bolstering food security and the economy of coastal communities in Indonesia (Fuadi & Wiryawan 2018). Among the fish species with significant economic value, mackerel (*Rastrelliger spp.*) stands out as a primary commodity in the small pelagic fisheries sector (Nurdin *et al.* 2015; Kamaruzzaman *et al.* 2021). The high demand for mackerel highlights the urgency of implementing sustainable fisheries management, particularly due to evidence of stock fluctuations and localised population declines in several regions (Shaari & Mustapha 2018; Lakhnigie *et al.* 2019; Srioktoviana *et al.* 2024). Recent studies have shown that mackerel populations, including *Rastrelliger spp.*, are increasingly vulnerable to overfishing and environmental variability, which may threaten long-term availability if not properly managed (Putri & Zainuddin 2019a; Huang *et al.* 2022; Nair *et al.* 2023). Therefore, integrating scientific approaches to enhance fishing efficiency while protecting critical habitats is essential to ensure the sustainability of mackerel fisheries.

The identification of an appropriate fishing season is a critical determinant in the success of fishing operations (Ben-Hasan *et al.* 2019; Putri & Zainuddin 2019b). Traditional methods of determining fishing seasons (Kurniawati *et al.* 2015) often rely on local knowledge and the experiential wisdom of fishers, which may prove inadequate in addressing the complexities and variability of fish stocks caused by oceanographic phenomena such as the El Nino Southern Oscillation (ENSO) and global climate change (Zainuddin *et al.* 2020; Mukherjee *et al.* 2023). Consequently, technology-driven and data-centric approaches are increasingly relevant to support more precise and informed decision-making (Nuno *et al.* 2005; Wang *et al.* 2016). Artificial Neural Networks (ANNs) have become increasingly prominent in ecological and fisheries modelling due to their ability to capture complex, non-linear relationships among multiple environmental variables (Guisan & Zimmermann 2000; Pradana 2023; Salem *et al.* 2023). Unlike traditional statistical methods such as linear or multiple regression, which assume linearity and independence among predictors, ANNs can handle large, heterogeneous datasets and identify intricate patterns in variables such as sea surface temperature (SST), chlorophyll-a concentration, salinity, and ocean currents (Zainuddin 2011; Yuniar *et al.* 2024; Wang *et al.* 2025). These advantages make ANNs particularly well-suited for modelling dynamic and spatially heterogeneous marine ecosystems, where fish behaviour is strongly influenced by the interplay of various environmental factors.

In addition, ANN-based models have demonstrated superior predictive accuracy and resilience under uncertain and variable conditions when compared to conventional approaches (Zhang & Zimba 2017; Prasad *et al.* 2023). Their application in fisheries not only enhances the precision of fish distribution and fishing season forecasts but also contributes to sustainability by informing more adaptive harvesting strategies and reducing the risk of overexploitation (Torri *et al.* 2018; Ibrahim *et al.* 2023). This study aims to develop a predictive model for the fishing season of Indian mackerel (*Rastrelliger* spp.) in the western part of the Banda Sea using an ANN algorithm. By incorporating dynamic oceanographic parameters into the modelling framework, this research seeks to contribute to data-driven fisheries management and support the implementation of sustainable fishing policies aligned with SDG 14 in Indonesia. Therefore, this study represents a strategic effort to enhance both the productivity and sustainability of the capture fisheries sector in the region.

MATERIALS AND METHODS

Study Area

This study was conducted in the western part of the Banda Sea, located within the geographical coordinates of 120°E to 126°E and 2°S to 5°S (Fig. 1). This area is an integral part of Indonesia's marine ecosystem and is globally recognised as one of the regions with the highest marine biodiversity (Aryanti *et al.* 2018; Ministry of Environment and Forestry 2021). The Banda Sea lies within the Coral Triangle, which is widely known as the epicentre of global marine biodiversity (Veron *et al.* 2009). The western Banda Sea also serves as a critical fishing ground for small pelagic species, particularly Indian mackerel (*Rastrelliger* spp.), which have historically contributed significantly to both local and national fisheries economies (Zainuddin *et al.* 2013; Kementerian Kelautan dan Perikanan [KKP] 2022). According to data from the Ministry of Marine Affairs and Fisheries, this region consistently records high catch volumes of Indian mackerel, making it a strategic site for studying fishing season patterns and habitat suitability (Nurdin *et al.* 2017; Harahap *et al.* 2020). The area's dynamic oceanographic conditions—characterised by seasonal upwelling, current variability and nutrient availability—further highlight its ecological relevance for analysing the spatial and temporal distribution of mackerel.

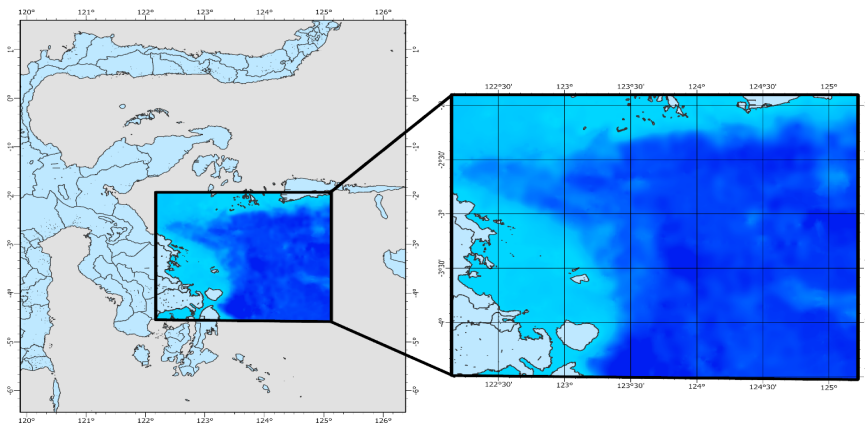


FIGURE 1: The research location is in the western of Banda Sea which is included in the Coral Triangle area, Indonesia.

Fisheries Data

Monthly data on Indian mackerel fishing and production were collected between 2019–2022. The total production of mackerel catches amounted to 451.750 tonnes with approximately 16.833 fishing trips conducted using purse seine gear. The catch results were standardised using Catch Per Unit Effort (CPUE), calculated with the following mathematical formula:

CPUE= Catch / Effort

Where, Catch = Indian mackerel catch (Kg) and Effort = Number of fishing attempts (Trips).

The application of CPUE in this study is critical not only as a measure of fishing efficiency, but also as an indirect indicator of fish stock dynamics in the western Banda Sea. A high CPUE value reflects effective fishing performance and suggests a sufficient stock availability, while a declining CPUE may signal early signs of overfishing pressure or changes in environmental conditions (Andrade & Garcia 1999; Liu et al. 2020; Canales et al. 2024). In addition, CPUE was used to identify the most productive fishing season by analysing monthly trends. This temporal analysis allows researchers to determine peak mackerel fishing periods and better understand their spatial distribution. Furthermore, CPUE served as a target variable in the development of the ANN model, enabling the integration of catch data with environmental parameters such as sea surface temperature, salinity and ocean currents.

Oceanographic Parameter Data

This study utilised oceanographic parameters (SST, CHL-a, SSS, Current) obtained through insitu methods or direct field observations, as well as *ex situ* methods in the form of satellite imagery from various data providers (Table 1).

TABLE 1. Oceanographic parameter data processed through satellite imagery.

No.	Parameter	Data source
1.	Sea Surface Temperature/SST (°C)	https://oceancolor.gsfc.nasa.gov/
2.	Chlorophyl-a/CHL-a (mg/m³)	https://oceancolor.gsfc.nasa.gov/
3.	Current (m/s)	https://data.marine.copernicus.eu/
4.	Sea Surface Salinity/SSS (psu)	https://data.marine.copernicus.eu/

Analysing the relationship between oceanographic parameters is a key factor in understanding fish catch dynamics, particularly for small pelagic species such as Indian mackerel (*Rastrelliger* spp.) (Hidayat *et al.* 2021; Srioktoviana *et al.* 2024). Previous studies have demonstrated significant correlations between marine environmental parameters and mackerel landing patterns. For instance, seasonal variations in mackerel catches have been shown to correlate positively with chlorophyll-a concentration (CHL-a) and negatively with sea surface temperature (SST), with a one-month lag (Sekadende *et al.* 2020). In addition, to chlorophyll-a and SST, other oceanographic parameters such as sea surface salinity (SSS) and ocean current also play essential roles in influencing the distribution and abundance of Indian mackerel (Yang *et al.* 2024). Variability in SSS can affect water stratification and nutrient availability, indirectly influencing primary productivity and subsequently fish distribution (Lima Bomfim *et al.* 2023). Moreover, ocean currents are key in larval transport and migration patterns, shaping spatial dynamics of pelagic fish species (Safruddin *et al.* 2014; 2018). Ignoring these factors may overlook important ecological drivers of fish aggregation and movement. Therefore, incorporating SSS and current data provides a more comprehensive understanding of the biophysical environment that governs mackerel dynamics.

To ensure the accuracy and consistency of the satellite imagery used in this study, a statistical validation process was conducted by comparing satellite-derived data with in situ measurements. The comparison employed correlation analysis, Root Mean Square Error (RMSE) and Mean Square Error (MSE) methods. The results confirmed that the satellite data used in this study were sufficiently accurate and representative to support the spatio-temporal analysis of Indian mackerel distribution in the western Banda Sea.

Data Analysis

The analysis of seasonal data in this study employs the FSI (Fishing Season Index) calculation to determine the fishing season based on the CPUE, using the following calculations:

The subsequent FSI analysis is utilised to ascertain the Fishing Season Index (FSI) (Dajan 1986) for Indian mackerel in western of Banda Sea:

Series of CPUE within 5 years period:

$$CPUE_i = n_i$$

Moving Average CPUE (MA):

$$MA_i = \frac{1}{12} \left(\sum_{i=i-6}^{i+5} CPUE_i \right)$$

Centred CPUE moving average (CMA):

$$CMA_i = \frac{1}{2} \left(\sum_{i=i-6}^{i=1} CPUE_i \right)$$

Formula AM for Monthly Average ratio:

$$AM_i = \frac{CPUE_i}{CMA_i}$$

Average ratio for monthly i (AAM):

$$AAM_i = \frac{1}{n} \left(\sum_{j=1}^n AM_{ij} \right)$$

The total monthly ratio (TAM):

$$TAM = \sum_{i=1}^{12} AAM_i$$

$$CF = \frac{1200}{TAM}$$

Fishing Season Index:

$$FSI_i = AAM_i \times CF$$

Where, n_i = CPUE of the i -th order; AM_i = 12-month moving average of the i -th order; CMA_i = centred moving average of CPUE in month i ; AM_i = monthly average ratio in month i ; AAM_i = average for i -th month ($i = 1, 2, 3, \dots, 12$ and $j = 1, 2, 3, \dots, n$); TAM = total of monthly average ratios; CF = Correction factor and FSI_i = Fishing Season Index in month i .

In addition, this study employed statistical forecasting analysis to generalise monthly predictions of variable X, which was derived from catch point data. To improve prediction accuracy, an ANN model with a backpropagation learning algorithm was utilised. ANN is one of the most widely used artificial intelligence-based models due to its ability to model complex nonlinear relationships with high accuracy (Wu *et al.* 2020; Kenny *et al.* 2024). The ANN model architecture in this study consisted of three layers: one input layer, one hidden layer and one output layer. The input layer received predictor variables extracted from oceanographic and catch data. The hidden layer comprised 10 neurons, determined through a trial-and-error process to achieve optimal model performance. The sigmoid activation function was used in the hidden layer, while a linear

activation function was applied in the output layer, which is appropriate for continuous variable prediction tasks. The dataset was divided into two parts: 70% for training data and 30% for testing data, using a random sampling method. This partitioning aimed to objectively evaluate the model's performance on unseen data. To evaluate the performance of the ANN model, two statistical error metrics were used: MSE and RMSE.

MSE is a commonly used metric to measure the average of the squared differences between the predicted values and the actual values. It is calculated as:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Where Y_i = actual value and n = number of observation/rows.

A lower MSE value indicates that the model's predictions are closer to the actual data. However, since MSE produces values in squared units, RMSE is also used to bring the error back to the same unit as the original data. RMSE is the square root of MSE, formulated as:

$$RMSE = \sqrt{\sum \frac{(y_i - y_p)^2}{n}}$$

Where y_i = actual value, y_p = predicted value and n = number of observation/rows.

RMSE provides a more interpretable scale for the error, making it easier to assess the predictive performance of the model in real-world units. Both metrics are sensitive to large errors, which makes them suitable for identifying models with poor generalisation. These error metrics are widely adopted in machine learning and time-series forecasting studies to ensure the reliability and robustness of predictive models (Datta & Faroughi 2023; Nicolas *et al.* 2023).

RESULTS

Fishing Season

Based on the analysis and processing of mackerel production data from 2019–2023 (see Fig. 2), it was determined that the mackerel fishing season (*Rastrelliger* spp.) occurs in November.

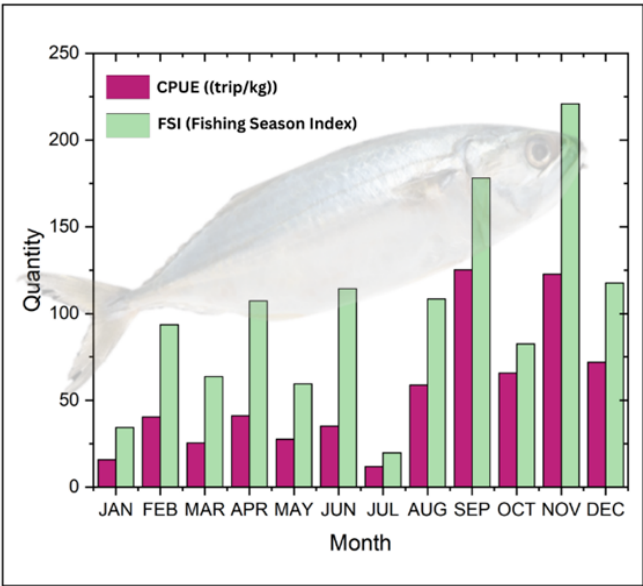


FIGURE 2: The study’s experimental setup in a greenhouse.

In Fig. 2, the highest CPUE and FSI values are November which has the highest number of catches and intensity. Other details can be seen in Table 2.

TABLE 2. Intensity of the annual mackerel fishing season on 2019 to 2023 (five years) in western of Banda Sea.

No	Month	CPUE (kg/trip)	FSI (%)	± std. dev	Result
1	January	15.868	34.334	18.486	Regular season
2	February	40.353	93.609	61.259	Regular season
3	March	25.39	63.797	47.704	Regular season
4	April	41.148	107.242	66.15	Fishing season
5	May	27.536	59.427	24.521	Regular season
6	June	35.179	114.364	51.69	Fishing season
7	July	11.904	19.695	16.786	Lean season
8	August	58.849	108.364	54.022	Fishing season
9	September	125.25	178.093	110.056	Fishing season
10	October	65.76	82.51	63.014	Regular season
11	November	122.764	220.897	159.942	Peak season
12	December	71.883	117.667	93.508	Fishing season

The low fishing season occurs from January to May, characterised by low CPUE and FSI values, indicating that this period is less productive for fishing. Conversely, higher CPUE values in certain months suggest that fish populations are more abundant or easier to catch during those periods, while FSI values reflect that fishermen are actively capitalising on this time as the primary fishing season. As for August, September, November and December, these months represent the harvesting period.

Mackerel fishing efforts in the research area over the past 3 to 4 years have shown a minimal level of activity (Fig. 3). This indicates that the fishing efforts are relatively limited, with indications that fishermen are concentrating their efforts at the same location during this period.

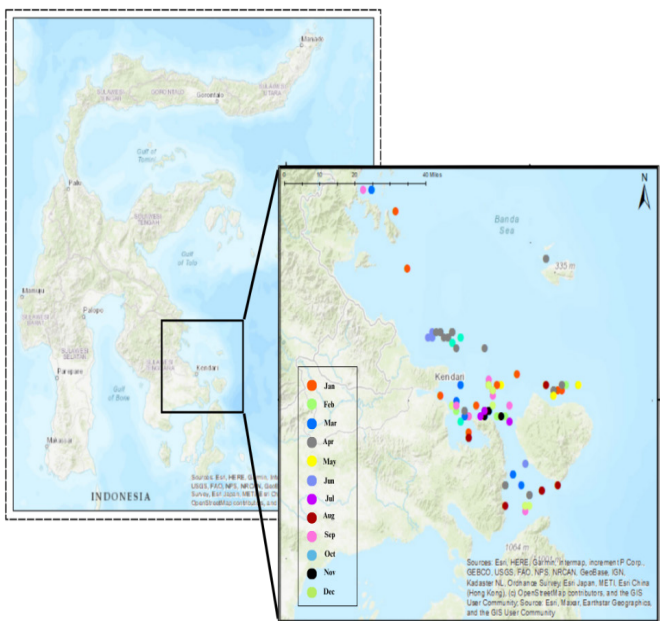


FIGURE 3: Coordinate points for mackerel fishing (*Rastrelliger* spp.) from 2019 to 2023 (five years) in the Northwest of Banda Sea.

Relationship between Oceanographic Parameters and CPUE

The results of data processing from the catchment points, linked to environmental conditions (oceanographic parameters), reveal the relationship between the X and Y variables as illustrated in Fig. 4.

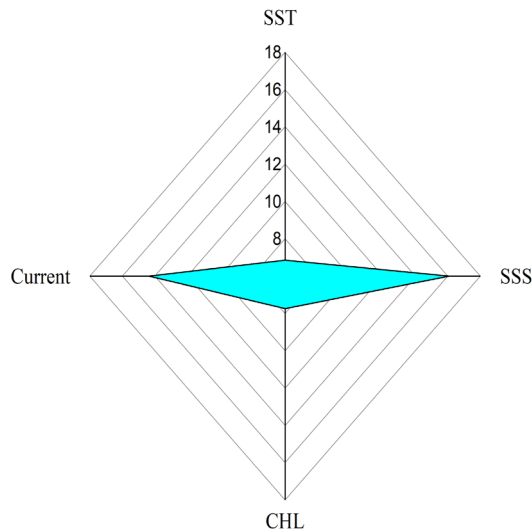


FIGURE 4: Percentage contribution of Sea Surface Temperature (SST), Chlorophyll-a Concentration (CHL-a), Sea Surface Salinity (SSS) and Current(s) relationship to mackerel catch.

The results of the data visualisation indicated that salinity and currents were the parameters most significantly influencing mackerel catches contributing 16% and 14%, respectively (Fig. 4). Conversely, the parameters of sea surface temperature (SST) and chlorophyll-a (chl-a) exhibited lower contribution values. This aligns with the findings of Nugraha *et al.* (2020), which demonstrated that while SST is a critical factor in determining the presence of fish, it does not significantly influence the quantity or size of fish catches in the western part of the Banda Sea.

These findings are further contextualised by the peak fishing season (Fig. 2), which corresponds to the transitional period between the eastern and western monsoon seasons. During the period, increased rainfall leads to a significant decrease in salinity levels, stabilising surface salinity within the range of 30 psu–34 psu. This stability supports the reproductive activities of mackerel. Furthermore, transitional months such as November often experience shifts in currents and winds, potentially triggering upwelling in certain regions. This upwelling brings nutrient-rich, high-salinity water from deeper layers to the surface, enhancing primary productivity. The resulting abundance of nutrients serves as a critical food source for fish and mackerel larvae (*Rastrelliger* spp.).

Prediction of Potential Mackerel Fishing Areas (*Rastrelliger* spp.) Based on ANN-Backpropagation

Fig. 5 shows a comparison between observed data (blue lines) and model-predicted data (red lines) for four key oceanographic parameters: sea surface temperature (SST), chlorophyll-a concentration, sea surface salinity (SSS), and ocean current speed over a one-year period (January–December).

In general, the four graphs illustrate that the model can represent the seasonal patterns of each parameter well. The fluctuation patterns of temperature, chlorophyll-a, salinity, and ocean currents shown by the predicted data follow the observed data trends, although there are slight differences in values in certain months, particularly during extreme conditions (maximum or minimum values).

This confirms that the prediction model has sufficient accuracy in depicting monthly oceanographic dynamics, making it suitable for understanding and projecting broader marine environmental conditions.

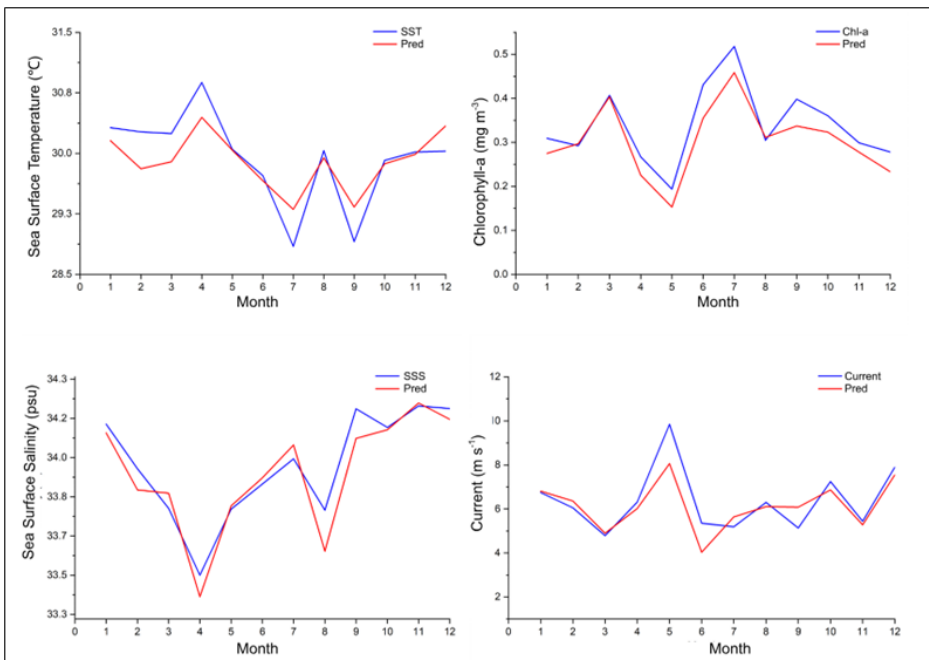


FIGURE 5: Comparative observation of model and actual data using MSE (Mean Squared Error) and RMSE (Root Mean Squared Error).

In determining the potential fishing zones based on predictions, additional variables, including longitude, latitude and CPUE (Catch Per Unit Effort) predictions, were incorporated using the developed model. The results of the visualisation of the predicted potential mackerel fishing zones indicated that the parameters associated with the highest CPUE (343 kg trip⁻¹) were observed at a sea surface temperature (SST) of 31.4°C, a chlorophyll-a concentration (CHL-a) ranging from 0.18 to 1.5 mg/m³, a current velocity of 3.29 cm/s and salinity (SSS) level of 34.2 psu (Fig. 6).

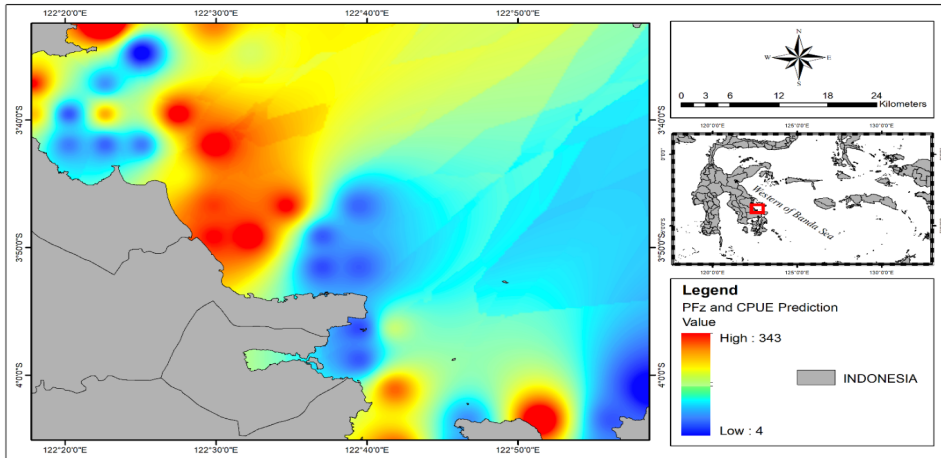


FIGURE 6: Prediction of potential mackerel fishing zones (*Rastrelliger* spp.) is based on the peak season (November 2020–2023) using the implementation of the Artificial Neural Network (ANN-Backpropagation) model.

DISCUSSION

The findings of this study demonstrate that the modelling of seasonal patterns and mackerel fishing grounds (*Rastrelliger* spp.) using the ANN algorithm in the western of Banda Sea provides valuable insights into the management of fishery resources. Data analysis from 2019 to 2023 revealed that November marks the peak of the fishing season, characterised by the highest CPUE and FSI values. These findings align with previous research, which established that seasonal variations in mackerel landings are positively correlated with chlorophyll-a concentrations (CHL-a) and negatively associated with SST.

Further analysis indicated that salinity (SSS) and ocean currents were the most significant oceanographic parameters affecting mackerel catches during this period, contributing 16% and 14%, respectively. This underscores the critical role of environmental conditions in determining the distribution and productivity of fish populations, including reproduction,

which is often significantly influenced by salinity. Moreover, applying an ANN algorithm in this study proved to be highly effective, achieving a model accuracy exceeding 90%. The model successfully predicted fishing potential zones based on oceanographic parameters.

The integration of seasonal fishing index with ANN-based habitat suitability modelling offers a novel approach to identifying both temporal and spatial hotspots of mackerel abundance. By leveraging satellite-derived environmental data, this study provides a dynamic tool to guide fishers and policymakers in optimising fishing efforts while ensuring long-term sustainability. The combination of high-resolution CPUE data with oceanographic variability reinforces the model's robustness in simulating real-world fishery dynamics. In addition, the results of this study provide a scientific basis for developing adaptive and ecosystem-based fisheries management strategies for Indian mackerel in the Banda Sea. To ensure the sustainable exploitation, several concrete policy recommendations are proposed: implementation of seasonal fishing regulations aligned with peak fishing months identified by the model to prevent overfishing during spawning seasons, establish dynamic catch limits that reflect seasonal variability in mackerel abundance as predicted by the model and designate marine protected areas in critical habitats such as spawning and nursery grounds to safeguard population regeneration. These measures align with the principles of sustainable fisheries and support the achievement of SDG 14 in Indonesia.

Furthermore, while the model was developed specifically for the western part of the Banda Sea, its high predictive accuracy and flexibility demonstrate its potential applicability to other fisheries in Indonesia and globally. The ANN approach can be adapted to model the habitat suitability of other species sensitive to oceanographic parameters, such as skipjack tuna, *Sardinella lemuru* and scad fish. Previous applications in different oceanographic contexts confirm the ANN's versatility in supporting broader spatial fisheries planning. However, site-specific model recalibration and input parameter adjustment remain necessary to maintain accuracy and relevance across different ecological and geographic settings.

CONCLUSION

This study developed a predictive model for the fishing season and potential fishing zones of Indian mackerel (*Rastrelliger* spp.) in the western of Banda Sea using an ANN approach. Based on analysis of catch data from 2019 to 2023, the peak fishing season for Indian mackerel occurs in November with the highest CPUE recorded at 220 kg/trip.

This high catch rate signifies the aggregation of fish schooling during a biologically favourable period, likely linked to spawning activity and nutrient availability. As such, it represents a crucial temporal for optimising fishing efficiency while minimising pressure on the stock. This finding supports the development of seasonal management measures tailored to the biological rhythms of the species. Oceanographic parameters, such as salinity (34.2 psu) and current velocity (3.29 cm/s) were identified as the most influential factors, contributing 16% and 14%, respectively to the success of the catch.

The ANN model demonstrated a high level of accuracy (error rate of 1.12%) in predicting potential fishing zones based on oceanographic parameters. These zones were characterised by a sea surface temperature of 31.4°C, chlorophyll-a concentrations ranging from 0.18 to 1.5 mg/m³ and stable salinity conditions.

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AUTHORS' CONTRIBUTIONS

Alfira Yuniar: Developed conceptual ideas, prepared, executed and supervised the research process and write up of manuscript, collected data, data analysis.

Mukti Zainuddin: Contributed to developing conceptual ideas, monitoring and supervising the research process, and critically revising the manuscript.

Safruddin: Developing conceptual ideas, supervising the research process, and critically revising the manuscript.

Muzzneena Ahmad Mustapha: Developing conceptual ideas, supervising the research process and critically revising the manuscript.

Rachmat Hidayat: Analyse data, monitor the research process, and critically revise the manuscript.

Siti Khadijah Sriktoviana: Download oceanographic parameters data and data collection.

REFERENCES

- Andrade H A and Garcia C A E. (1999). Skipjack tuna fishery in relation to sea surface temperature off the southern Brazilian coast. *Fisheries Oceanography* 8(4): 245–254. <https://doi.org/10.1046/j.1365-2419.1999.00107.x>
- Aryanti N L N, Hendrawan I G and Suteja Y. (2018). Studi variabilitas produktivitas primer bersih serta hubungannya dengan El-Nino Southern Oscillation (ENSO) dan Indian Ocean Dipole (IOD) di Laut Banda berdasarkan data satelit Aqua MODIS. *Journal of Marine and Aquatic Sciences* 5(1): 64. <https://doi.org/10.24843/jmas.2019.v05.i01.p08>
- Ben-Hasan A, Walters C and Rashid Sumaila U. (2019). Effects of management on the profitability of seasonal fisheries. *Frontiers in Marine Science* 6: 1–8. <https://doi.org/10.3389/fmars.2019.00310>
- Canales C M, Olea G, Jurado V and Espíndola M. (2024). Management Strategies Evaluation (MSE) in a mixed and multi-specific fishery based on indicator species: An example of small pelagic fish in Ecuador. *Marine Policy* 162: 106044. <https://doi.org/10.1016/j.marpol.2024.106044>
- Dajan A. (1986). *Pengantar metode statistik*. Indonesia: LP3ES.
- Datta P and Faroughi S A. (2023). A multihead LSTM technique for prognostic prediction of soil moisture. *Geoderma* 433: 116452. <https://doi.org/10.1016/j.geoderma.2023.116452>
- Fuadi A and Wiryawan B. (2018). Pendugaan daerah penangkapan ikan lyang dengan citra satelit di perairan Aceh sekitar Pidie Jaya. *Jurnal Teknologi Perikanan dan Kelautan* 9(2): 149–161. <https://doi.org/10.24319/jtpk.9.149-161>
- Guisan A and Zimmermann N E. (2000). Predictive habitat distribution models in ecology. *Ecological Modelling* 135(2–3): 147–186. [https://doi.org/10.1016/S0304-3800\(00\)00354-9](https://doi.org/10.1016/S0304-3800(00)00354-9)
- Harahap Z A, Nasution H K and Leidonald R. (2020). Relationship of spatial and temporal characteristics of water conditions and *Rastrelliger kanagurta* production in the Malacca Strait using satellite imagery. *IOP Conference Series: Earth and Environmental Science* 454: 012126. <https://doi.org/10.1088/1755-1315/454/1/012126>
- Hidayat R, Zainuddin M, Mallawa A, Mustapha M A and Putri A R S. (2021). Mapping spatial-temporal skipjack tuna habitat as a reference for fish aggregating devices (Fads) settings in Makassar Strait, Indonesia. *Biodiversitas* 22(9): 3637–3647. <https://doi.org/10.13057/biodiv/d220905>
- Huang Y, Liu B, Zhao H and Yang X. (2022). Spatial and temporal variation of droughts in the Mongolian plateau during 1959–2018 Based on the gridded self-calibrating palmer drought severity index. *Water (Switzerland)* 14(2): 230. <https://doi.org/10.3390/w14020230>
- Ibrahim L A, Abu-Hashim M, Shaghaleh H, Elsadek E, Hamad A A A and Alhaj Hamoud Y. (2023). A comprehensive review of the multiple uses of water in aquaculture-integrated agriculture based on international and national experiences. *Water (Switzerland)* 15(2): 367. <https://doi.org/10.3390/w15020367>
- Kamaruzzaman Y N, Mustapha M A and Ghaffar M A. (2021). Impacts of sea temperature rise on *Rastrelliger kanagurta* potential fishing grounds in the Exclusive Economic Zone (EEZ) off South China Sea. *Sains Malaysiana* 50(12): 3467–3479. <https://doi.org/10.17576/jsm-2021-5012-01>
- Kenny E M, Ruelle E, Keane M T and Shalloo L. (2024). A hybrid model that combines machine learning and mechanistic models for useful grass growth prediction. *Computers and Electronics in Agriculture* 219: 108805. <https://doi.org/10.1016/j.compag.2024.108805>

- Kementerian Kelautan dan Perikanan (KKP) (2022). *Fisheries statistic*. <https://kkp.go.id/publikasi/akuntabilitas-kinerja/pelaporan-kinerja/detail/laporan-kinerja-kkp-2022664ea5c2405a8.html>
- Kurniawati F, Sanjoto T B and Geografi J J. (2015). Estimation of potential zones for catching small pelagic fish in Java Sea waters in the west and east seasons using AQUA MODIS imagery, geoimage (Spatial-Ecological-Regional). *Geo Image (Spatial-Ecological-Regional)* 4(2): 9. <https://doi.org/https://doi.org/10.15294/geoimage.v4i2.7278>
- Lakhnigie A, Tandstad M, Fuller J, Sambe B and Caramelo A M. (2019). More than fifteen years of collaboration on the assessment of small pelagic fish off Northwest Africa: Lessons learned and future perspectives. *Deep-Sea Research Part II* 159: 92–102. <https://doi.org/10.1016/j.dsr2.2018.12.004>
- Lima Bomfim J R A, da Costa Cunha G, Botero W G and Romão L P C. (2023). Use of shrimp farming waste in the production of biomaterials for sustainable agriculture and mitigation of environmental damage. *JSFA Reports* 3(12): 622–632. <https://doi.org/10.1002/jsf2.165>
- Liu S, Liu Y, Alabia I D, Tian Y, Ye Z, Yu H, Li J and Cheng J. (2020). Impact of climate change on wintering ground of Japanese anchovy (*Engraulis japonicus*) using marine geospatial statistics. *Frontiers in Marine Science* 7: 1–15. <https://doi.org/10.3389/fmars.2020.00604>
- Ministry of Environment and Forestry. (2021). *Climate change vulnerability profile of Indonesian Coral Triangle Region*. Jakarta: Ministry of Environment and Forestry of the Republic of Indonesia.
- Mukherjee S, Pal J, Manna S, Saha A and Das D. (2023). El-Niño Southern Oscillation and its effects. In A Srivastav, A Dubey, A Kumar, S K Narang and M A Khan (eds.), *Visualization techniques for climate change with machine learning and artificial intelligence*. Elsevier, 207–228. <https://doi.org/10.1016/b978-0-323-99714-0.00013-3>
- Nair P G, Joseph S, Pillai N and Abdulla M H A. (2023). Is there a significant long-term shift in phytoplankton in small pelagic fish diets along India's southwest coast? *Oceanologia* 65(2): 297–309. <https://doi.org/10.1016/j.oceano.2022.07.001>
- Nicolas F, Kamai T, Ben Gal A, Ochoa-Brito J, Daccache A, Ogunmokun F and Kisekka I. (2023). Assessing salinity impacts on crop yield and economic returns in the Central Valley. *Agricultural Water Management* 287: 108463. <https://doi.org/10.1016/j.agwat.2023.108463>
- Nugraha E, Gunawan R, Danapraja S, Yusrizal, Kusdinar A, Waluyo A S, Hutajulu J, Prayitno H, Halim S and Sutisna D H. (2020). The sea surface temperature effect on the length and size of skipjack tuna (*Katsuwonus pelamis*) catches in the Banda Sea, Indonesia. *AACL Bioflux* 13(1): 1–18.
- Nuno A I, Arcay B, Cotos J M and Varela J. (2005). Optimisation of fishing predictions by means of artificial neural networks, anfis, functional networks and remote sensing images. *Expert Systems with Applications* 29(2): 356–363. <https://doi.org/10.1016/j.eswa.2005.04.008>
- Nurdin S, Mustapha M A, Lihan T and Abd Ghaffar M. (2015). Determination of potential fishing grounds of *Rastrelliger kanagurta* using satellite remote sensing and GIS technique. *Sains Malaysiana* 44(2): 225–232. <https://doi.org/10.17576/jsm-2015-4402-09>
- Nurdin S, Mustapha M A, Lihan T and Abd Ghaffar M. (2017). Applicability of remote sensing oceanographic data in the detection of potential fishing grounds of *Rastrelliger kanagurta* in the archipelagic waters of Spermonde, Indonesia. *Fisherika Research* 196: 1–12. <https://doi.org/10.1016/j.fishres.2017.07.029>

- Pradana G A. (2023). A study of prediction model for capture fisheries production in Indonesian sea waters using machine learning. *JISA Jurnal Informatika dan Sains* 6(01): 17–23. <https://doi.org/10.31326/jisa.v6i1.1553>
- Prasad P V V, Bhatnagar N, Bhandari V, Jacob G, Narayan K, Echeverría R, Beintema N, Farah Cox P and Compton J. (2023). Patterns of investment in agricultural research and innovation for the Global South, with a focus on sustainable agricultural intensification. *Frontiers in Sustainable Food Systems* 7: 1108949. <https://doi.org/10.3389/fsufs.2023.1108949>
- Putri A R S and Zainuddin M. (2019a). Application of remotely sensed satellite data to identify Skipjack tuna distributions and abundance in the coastal waters of Bone Gulf. *IOP Conference Series: Earth and Environmental Science* 241(1): 012012. <https://doi.org/10.1088/1755-1315/241/1/012012>
- Putri A R S and Zainuddin M. (2019b). Impact of climate changes on Skipjack tuna (*Katsuwonus pelamis*) catch during May–July in the Makassar Strait. *IOP Conference Series: Earth and Environmental Science* 253(1): 1–7. <https://doi.org/10.1088/1755-1315/253/1/012046>
- Safruddin, Zainuddin M and Rani C. (2014). Predicting potential fishing zones of large Pelagic fish in Mamuju Regency Waters. *Jurnal IPTEKS PSP* 1(2): 185–195.
- Safruddin, Dewi Y K, Hidayat R, Umar M T and Zainuddin M. (2018). *Studi kondisi oseanografi pada daerah penangkapan ikan pelagis besar dengan menggunakan pole and line di Perairan Teluk Bone [Study of the oceanographic conditions of fishing grounds of large pelagic fish using pole and line in the Gulf of Bone Waters]* [Paper presentation]. Prosiding Simposium Nasional Kelautan dan Perikanan V, Universitas Hasanuddin, Makassar, 5 May.
- Salem S B H, Gaagai A, Ben Slimene I, Moussa A B, Zouari K, Yadav K K, Eid M H, Abukhadra M R, El-Sherbeeney A M, Gad M, et al. (2023). Applying multivariate analysis and machine learning approaches to evaluating groundwater quality on the Kairouan Plain, Tunisia. *Water (Switzerland)* 15(19): 3495. <https://doi.org/10.3390/w15193495>
- Sekadende B, Scott L, Anderson J, Aswani S, Francis J, Jacobs Z and Jebri F. (2020). The small pelagic fishery of the Pemba Channel, Tanzania: What we know and what we need to know for management under climate change. *Ocean and Coastal Management* 197: 105322. <https://doi.org/10.1016/j.ocecoaman.2020.105322>
- Shaari N R and Mustapha M A. (2018). Predicting potential Rastrelliger kanagurta fish habitat using MODIS satellite data and GIS modeling: A case study of exclusive economic zone, Malaysia. *Sains Malaysiana* 47(7): 1369–1378. <https://doi.org/10.17576/jsm-2018-4707-03>
- Srioktoviana S K, Zainuddin M, Hidayat R, Yuniar A, Mustapha M A, Farhum S A and Safruddin. (2024). Exploring the relationship between salinity front and the distribution and abundance of Yellowfin Tuna (*Thunnus albacares*) in the Western Banda Sea, Center of Indonesia Coral Triangle. *IOP Conference Series: Earth and Environmental Science* 1410(1): 012040. <https://doi.org/10.1088/1755-1315/1410/1/012040>
- Torri M, Corrado R, Falcini F, Cuttitta A, Palatella L, Lacorata G and Patti B. (2018). Planktonic stages of small pelagic fishes (*Sardinella aurita* and *Engraulis encrasicolus*) in the central Mediterranean Sea: The key role of physical forcings and implications for fisheries management. *Progress in Oceanography* 162: 25–39. <https://doi.org/10.1016/j.pocean.2018.02.009>
- Veron J E N, Devantier L M, Turak E, Green A L, Kininmonth S, Stafford-Smith M and Peterson N. (2009). Delineating the Coral Triangle. *Galaxea, Journal of Coral Reef Studies* 11(2): 91–100. <https://doi.org/10.3755/galaxea.11.91>

- Wang C, Wang L, Ma G and Zhu L. (2025). CSF-YOLO: A lightweight model for detecting grape leafhopper damage levels. *Agronomy* 15(3): 741. <https://doi.org/10.3390/agronomy15030741>
- Wang J, Chen X and Chen Y. (2016). Spatio-temporal distribution of skipjack in relation to oceanographic conditions in the west-central Pacific Ocean. *International Journal of Remote Sensing* 37(24): 6149–6164. <https://doi.org/10.1080/01431161.2016.1256509>
- Wu L, Huang G, Fan J, Ma X, Zhou H and Zeng W. (2020). Hybrid extreme learning machine with meta-heuristic algorithms for monthly pan evaporation prediction. *Computers and Electronics in Agriculture* 168: 105115. <https://doi.org/10.1016/j.compag.2019.105115>
- Yang Z, Chen W, Wang X, Liu B, Dong J and Deng Y. (2024). Suitable habitat of the scad fish (*Decanthers* spp.) in Northern South China Sea predicted by MaxEnt model. *Regional Studies in Marine Science* 69(1): 103315. <https://doi.org/10.1016/j.rsma.2023.103315>
- Yuniar A, Zainuddin M, Hidayat R, Srioktoviana S K, Safruddin, Mustapha M A and Farhum S A. (2024). Review: The effect of climate change on the distribution pattern of small pelagic fish around the world. *Biodiversitas* 25(8): 3325–3341. <https://doi.org/10.13057/biodiv/d250804>
- Zainuddin M. (2011). Preliminary findings on distribution and abundance of flying fish in relation to oceanographic conditions of Flores Sea observed from multi-spectrum satellite images. *Asian Fisheries Science* 24(1): 20–30. <https://doi.org/10.33997/j.afs.2011.24.1.003>
- Zainuddin M, Mallawa A, Safruddin, Farhum S A, Hidayat R, Sahni Putri A R and Ridwan M. (2020). Spatio-temporal thermal fronts distribution during January–December 2018 in the Makassar Strait: An important implication for pelagic fisheries. *SPERMONDE: Jurnal Ilmu Kelautan* 6(1): 11. <https://doi.org/10.20956/jiks.v6i1.9899>
- Zainuddin M, Nelwan A, Farhum S A, Najamuddin, Hajar M A I, Kurnia M and Sudirman. (2013). Characterizing potential fishing zone of skipjack tuna during the southeast monsoon in the Bone Bay–Flores Sea using remotely sensed oceanographic data. *International Journal of Geosciences* 04(01): 259–266. <https://doi.org/10.4236/ijg.2013.41a023>
- Zhang H and Zimba P V. (2017). Analyzing the effects of estuarine freshwater fluxes on fish abundance using artificial neural network ensembles. *Ecological Modelling* 359: 103–116. <https://doi.org/10.1016/j.ecolmodel.2017.05.010>