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# Application of LSTM and MODIS Satellite Imagery for Forecasting Oceanographic Dynamics and Identifying Potential Fishing Zones in the Sunda Strait

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**Abstract**. This study integrates AQUA-MODIS satellite imagery with the Long Short-Term Memory (LSTM) model to forecast oceanographic dynamics and identify Potential Fishing Zones (PFZ) in the Sunda Strait. The dataset spanning from January 2014 to December 2024 was used for model training, while forecasts for January–August 2025 were validated using in-situ observations from six sampling stations. The model predicted sea surface temperature (SST), chlorophyll-a concentration, and ocean current speed, with SST reaching 31°C, chlorophyll-a at 3.5 mg/L, and peak current speeds of 0.4 m/s. The performance metrics for SST (MSE: 1.107, RMSE: 0.994, MAD: 0.794), chlorophyll-a (MSE: 1.609, RMSE: 1.011, MAD: 0.5739), and current speed (MSE: 0.0183, RMSE: 0.1223, MAD: 0.0959) confirmed model accuracy. The PFZ detection algorithm, based on SST, chlorophyll-a, and ocean current data, demonstrated strong spatial agreement with in-situ data, validated using metrics such as MSE and RMSE. This validation approach, employing direct in-situ comparison, supports effective fisheries management by identifying productive fishing areas under varying seasonal and climate conditions. These results underline the operational potential of the LSTM-based forecasting framework for adaptive fisheries decision-making in the Sunda Strait.

**Keywords**: Deep learning, LSTM, time-series forecasting, PFZ mapping, AQUA-MODIS, in-situ validation.

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## 1. Introduction

The Sunda Strait, a strategic maritime corridor connecting the Java Sea with the Indian Ocean, exhibits complex oceanographic dynamics [1,2] The interaction between tides, the Indonesian Throughflow, and monsoon winds influences oceanographic conditions such as Sea Surface Temperature (SST), Chlorophyll-a (Chl-a) concentration, as well as the direction and speed of ocean currents. These dynamic processes create significant spatial-temporal variability that impacts primary productivity and the distribution of marine organisms, emphasizing the need for continuous monitoring to support data-driven fisheries management and adaptation to environmental changes [3–5].

Intraseasonal fluctuations in Sea Surface Temperature (SST), Chlorophyll-a (Chl-a), and ocean currents play a significant role in the ecosystem dynamics of the Sunda Strait [6,7]. Monitoring these non-stationary and fluctuating patterns on seasonal and intraseasonal scales is essential for understanding marine environmental dynamics. Specifically, tracking parameters such as SST and Chl-a is crucial for assessing ocean productivity, which is foundational to the marine food web. A significant process influencing these parameters is upwelling, which transports cold, nutrient-rich waters from deeper layers to the surface, reducing local SST and increasing Chl-a concentrations. This enhanced nutrient supply supports primary productivity, which in turn shapes marine ecosystems and influences pelagic fish distributions, whose survival and migration depend on food availability influenced by SST and Chl-a dynamics [7,8].

MODIS imagery provides high temporal resolution data for monitoring sea surface temperature anomalies and primary productivity [9,10]. This satellite data, when integrated with hydrodynamic models, can be used to forecast the direction and speed of ocean currents, which in turn affect nutrient distribution and marine organisms. The use of MODIS for mapping SST and Chl-a has been extensively applied in Indonesia. However, forecasting ocean current direction and speed in the Sunda Strait remains a challenge, primarily due to non-linearity in the data and noise interference. To address these limitations, deep learning approaches are necessary to improve the accuracy of these forecasts [11,12].

Long Short-Term Memory (LSTM) as an architecture of artificial neural networks for time series data can capture non-linear temporal patterns and long-term relationships [31],[32]. The integration of LSTM with MODIS imagery enables more accurate forecasting of Sea Surface Temperature (SST), Chlorophyll-a (Chl-a), and ocean current parameters, as well as supporting the dynamic identification of Potential Fishing Zones (PFZ) [13,14]. Oceanographic phenomena such as thermal fronts and water mass convergence influence the distribution of plankton and pelagic fish habitats [15–17]. The Sunda Strait's unique characteristics, influenced by the interaction of the Java Sea and Indian Ocean currents, underscore the importance of combining satellite data with forecasting models for adaptive fisheries management [18].

MODIS satellite data offers key spatial-temporal information, particularly regarding the distribution of Chl-a and SST [19,20], which is essential for forecasting oceanographic dynamics and mapping PFZs in the Sunda Strait [21]. This study develops and evaluates a framework that integrates MODIS imagery (SST and Chl-a) with the LSTM model to forecast oceanographic dynamics, including SST, Chl-a, current direction, and speed. The model is applied to intraseasonal to seasonal scales, with forecasts made for January to August 2025, and validated using actual MODIS data and field observations. This approach enhances oceanographic monitoring, providing critical insights for adaptive and sustainable fisheries management in the Sunda Strait.

Research on forecasting Sea Surface Temperature (SST) and chlorophyll-a has been extensively conducted, including a 2025 study [22] that developed a remote sensing and deep learning-based model to predict chlorophyll-a concentration. The ChlaPM model utilizes ConvLSTM with spatial-temporal feature extraction modules, periodic features, and denoising fusion to improve prediction accuracy. Results showed that ChlaPM reduced RMSE by 53.84% for one month, 53.58% for three months, and 49.70% for six months compared to the RSTFE model, demonstrating its capability to address short-term variability and periodic trends in chlorophyll-a predictions.

Another study from 2025 [23] proposed the Multi-Attention Collaborative Network (MACN) model for multi-horizon chlorophyll concentration prediction. The MACN model addresses two main challenges: reducing the impact of non-predictive variables and distinguishing the influence of target variables. It consists of NP-net, which minimizes the effect of irrelevant variables using variable-distillation attention, and T-net, which employs KeLSTM for chlorophyll prediction. Experimental results revealed that MACN outperformed baseline models such as MTSMFF, DA-RNN, and TPA-LSTM in prediction accuracy, while providing improved interpretation across various time horizons.

A comparative study [24] assessed the performance of ARIMA and LSTM models in forecasting Jakarta's sea levels, with ARIMA performing better in terms of MAE, MAPE, and RMSE. Despite ARIMA's higher accuracy for this dataset, LSTM demonstrated promise due to its ability to capture non-linear patterns, making it a potential tool for future applications with larger datasets. These findings provided valuable insights into flood risk management in Jakarta, highlighting the different advantages of both models in various forecasting scenarios.

In a study on fishing ground classification using satellite data, [25] compared Random Forest (RF) and Support Vector Machine (SVM) models. RF outperformed SVM in accuracy (99.90%) and recall (100%), with chlorophyll being a critical factor (77.14%) in determining fishing zones. These results underscore the potential of machine learning techniques to enhance fishing productivity by providing more accurate classification of fishing grounds based on satellite-derived oceanographic data.

## 2. Methods

This study applies MODIS Level-3 satellite data and Long Short-Term Memory (LSTM) modeling to forecast oceanographic dynamics in the Sunda Strait. The workflow includes data acquisition, preprocessing, spatial-temporal feature extraction, LSTM model training, thermal front detection, and validation using in-situ data, as illustrated in Figure 1. The integration of these methods ensures a comprehensive approach to forecasting and identifying Potential Fishing Zones (PFZs) in the region.

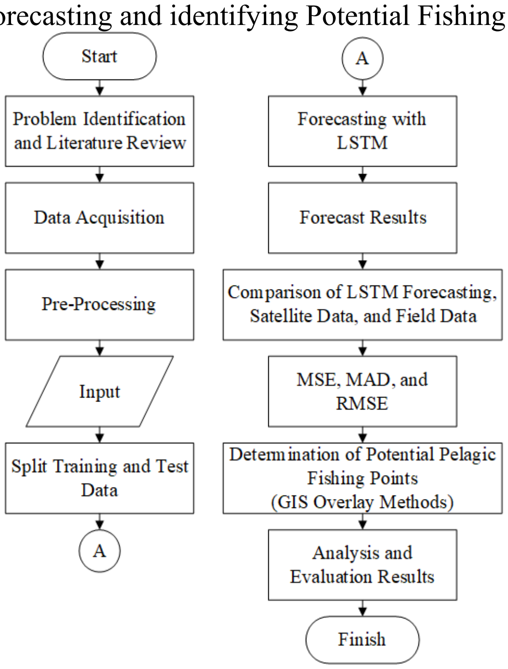



**Figure 1.** Research Flowchart

### *2.1. Data Acquisition*

This study utilized MODIS Level-3 satellite imagery from NASA's Ocean Color Web to monitor oceanographic dynamics, specifically Sea Surface Temperature (SST) and Chlorophyll-a, covering the period from January 2014 to December 2024 across the Sunda Strait region (5.8°–6.8° S; 104.8°–106.8° E). The Level-3 dataset, with a spatial resolution of 4 km, was selected to facilitate long-term temporal trend analysis and reduce spatial noise, thereby enhancing the reliability of the data for oceanographic forecasting. These oceanographic parameters were subsequently used to model Potential Fishing Areas (DPPI) for the January–August 2025 period, with field validation carried out in August 2025 to represent actual in situ conditions.

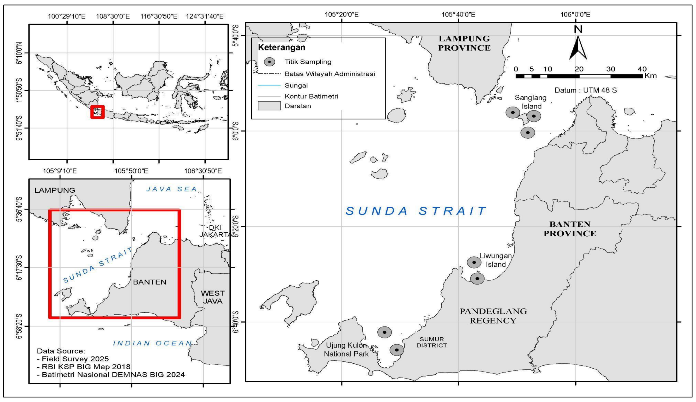



**Figure 2.** Map of the Sunda Strait Region Showing Sampling Points and Administrative Boundaries

In-situ data, including temperature and Chlorophyll-a (Chl-a) measurements, were used for model validation. The dataset, with a six-step time lag, used January–June data to predict the following month's parameters. The forecasted features included Sea Surface Temperature (SST), Chlorophyll-a, current direction, and speed. PFZ were identified based on these parameters. Data was collected from sampling points in the Sunda Strait in August 2025, with water samples tested for Chlorophyll-a in the lab, and temperature was measured using thermometers. The time difference between satellite overpasses and in-situ measurements was carefully accounted for to ensure accurate data alignment.

**Table 1.** Station Coordinates and Locations for Oceanographic Forecasting in the Sunda Strait

| No | Station | Longitude | Latitude | Location |
|---|---|---|---|---|
| 1 | 7 | 105.476768 | -6.776417 | Badul |
| 2 | 6 | 105.455802 | -6.719267 | |
| 3 | 5 | 105.708185 | -6.506539 | Liwungan Island |
| 4 | 4 | 105.713167 | -6.482674 | |
| 5 | 2 | 105.905604 | -6.019437 | Sangiang Island |
| 6 | 1 | 105.88406 | -5.88406 | |

### 2.2. *MODIS Data Pre-Processing*

The preprocessing of MODIS satellite imagery data involved several essential steps to ensure data quality. Initially, cloud masking was applied using the cloud mask function to exclude cloud-affected data, ensuring only cloud-free pixels were used. Atmospheric correction was applied to both Sea Surface Temperature (SST) and Chlorophyll-a (Chl-a) data to remove atmospheric interference, resulting in accurate surface measurements. The data was then reprojected to the WGS84 coordinate system to align with global geographic standards. Following this, the data was interpolated onto a fixed spatial grid that matched the study area in the Sunda Strait. To minimize gaps caused by cloud cover, daily data were composited into weekly averages, enhancing temporal consistency.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

The inverse scaling process to return the data to its original scale:

$$X_a = X_{norm}(X_{max} - X_{min}) + X_{min} \quad (2)$$

These preprocessing steps ensured that the data was accurate, consistent, and ready for further analysis and modeling.

## *2.3. Training and Test Data Sharing*

The dataset was divided into training (80%) and testing (20%) subsets to ensure reliable model evaluation. Data from January 2024 to June 2025 were used for training the model, while forecasts were generated for January to August 2025. This division enabled an effective assessment of the LSTM model's capability to predict oceanographic dynamics and identify Potential Fishing Zones (PFZ) in the Sunda Strait, ensuring the model's robustness.

## *2.4. Long Short-Term Memory (LSTM) Model Training*

Deep learning, a branch of artificial intelligence, is particularly effective for analyzing time series data with non-linear patterns that traditional methods struggle to handle. The use of layered artificial neural networks (ANNs) enables the learning of latent patterns, improving prediction accuracy. In this study, LSTM, a variant of Recurrent Neural Networks (RNN), was applied to forecast oceanographic dynamics in the Sunda Strait, including SST, chlorophyll-a, current direction, and speed, which are influenced by seasonal variability. LSTM is especially suited to handle the temporal dependencies and long-term trends present in oceanographic data.

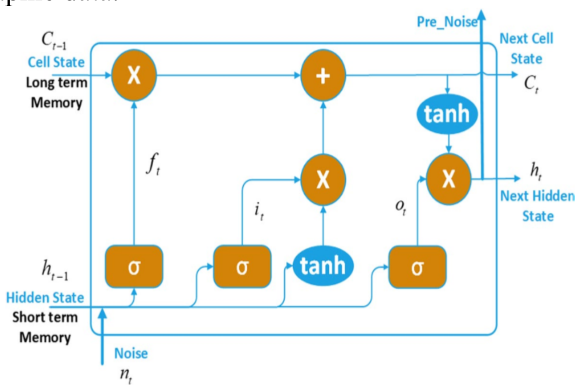



**Figure 3.** Long Short-Term Memory (LSTM) architecture [23]

LSTM addresses the vanishing and exploding gradient problems in RNNs using a cell state mechanism controlled by the forget, input, and output gates. This allows LSTM to retain long-term information and recognize complex temporal patterns [26,27]. The forget gate equation, used to decide what information to discard, is given by:

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \quad (3)$$

In this equation, $f_t$ represents the forget gate value, and $\sigma$ is the sigmoid activation function, $W_f$ is the weight of the forget gate, and $h_{t-1}$, $x_t$ are the concatenation of the output vector from the previous step with the input at the current step. $b_f$ is the bias value of the forget gate. Next, the information in the cell state (memory cell) is used to update the memory based on the results of the previous step. The decision to remember or forget long-term information is determined by the value of the forget gate. The mathematical equation for cell state updating is as follows:

$$\hat{C}_t = (W_c . [h_{t-1}, x_t] + b_c) \quad (4)$$

This equation shows that $\hat{C}_t$ is the value of the memory cell, $tan^{-1}$ is the hyperbolic tangent activation function, $W_c$ is the weight on the memory cell, and $b_c$ is the bias on the memory cell. The input gate then serves to select and control how much data will be entered into the memory cell. The equation for the input gate is as follows:

$$i_g = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (5)$$

In this equation, $i_g$ is the value of the gate input, $\sigma$ is the sigmoid activation function, $W_i$ is the weight of the gate input, and $b_i$ is the bias of the gate input. The output of the gate input is then used to generate a new memory cell, which is a linear combination of the candidate cell state and the output of the forget gate. The equation for updating the new cell state is as follows:

$$C_t = f_t.C_{t-1} + i_g.\tilde{C}_t \quad (6)$$

In this equation, $C_t$ is the new memory cell, while $C_{t-1}$ is the memory cell from the previous time step. The final output gate controls how much information will be output from the memory cell to the next time step. The equation for the output gate is as follows:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (7)$$

The Long Short-Term Memory (LSTM) model employed in this study adopts a single-layer architecture with 50 units, followed by a Dense output layer to predict oceanographic parameters including Sea Surface Temperature (SST), Chlorophyll-a (Chl-a), current direction, and current speed. The use of a single-layer LSTM is intended to capture temporal dependencies in the oceanographic time series while preventing unnecessary model complexity that could lead to overfitting. The choice of 50 units provides an effective balance between the model's capacity to learn long-term temporal patterns, which are influenced by seasonal and intraseasonal variability, and its computational efficiency.

The model was trained using historical data for 50 epochs with a batch size of 32, allowing stable parameter updates and facilitating faster convergence. The Adamax optimizer with a learning rate of 0.002 was selected to enhance convergence speed and improve forecasting accuracy. A batch size of 32 further helps maintain stable gradients during training, while early stopping was applied to halt training once the validation performance ceased to improve, thereby reducing the risk of overfitting and enhancing the model's generalization capability.

This overall architecture and training configuration were designed to ensure a computationally efficient yet robust model capable of accurately forecasting complex oceanographic dynamics in the Sunda Strait. The internal mechanism of the LSTM is reflected in the output gate equation,$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o)$, which regulates the information passed to the next time step, where $W_o$ represents the output-gate weight matrix and $b_o$ denotes the bias term [28].

## *2.5. Validation and Forecasting*

The LSTM model was validated using test data to predict SST, chlorophyll-a, current direction, and speed in the Sunda Strait for the period from January to August 2025. Model performance was evaluated using MSE, RMSE, and MAD. Forecasts were overlaid on the official PFZ map through GIS for spatial verification. Additional comparisons with MODIS imagery and in-situ data were conducted to assess accuracy and identify any model limitations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x_i})^2 \quad (8)$$

Where $n$ is the number of data points, $x_i$ is the actual value, and $\hat{x}_i$ is the forecasted value. In addition to MSE, the Root Mean Squared Error (RMSE) is used to measure the square root of MSE, which is formulated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2} \tag{9}$$

RMSE measures forecasting errors in the original data units, making it easier to interpret and more applicable than MSE, which uses squared units. Mean Absolute Deviation (MAD) represents the average absolute difference between predicted and observed values, ignoring direction and reflecting the consistency of forecasts. Mathematically, MAD is expressed as:

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |x_i - \hat{x}_i|^2 \tag{10}$$

Where $x_i$ is the actual value at time *i*, $\hat{x}_i$ is the predicted value at time *i*, and *n* is the total number of observations. MAD provides a clearer understanding of the average absolute deviation without being influenced by extreme fluctuations or the direction of the error, making it more robust for practical applications [29,30].

### *2.6. Potential Fishing Zone (PFZ)*

PFZ were determined through interpolation and overlay techniques using sea surface temperature, chlorophyll-a, and current data. The Natural Neighbor method was applied for interpolation to estimate values at unmeasured points based on their proximity to existing data points. The equation for Natural Neighbor interpolation is given by:

$$f(x) = \sum_{i=1}^{n} w_i f_i \tag{11}$$

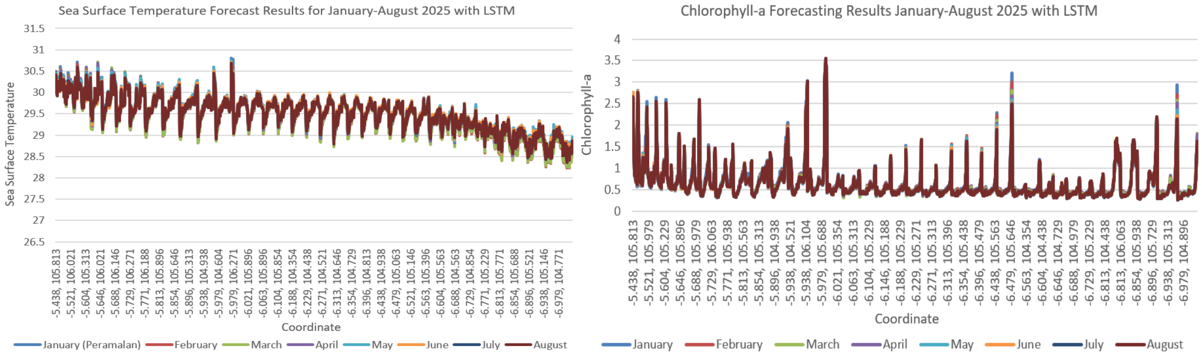
Where *f(x)* is the predicted value at point *x*, $f_i$ is the known value at neighboring point *i*, $w_i$ is the weight based on the proximity between *x* and *i*, and n is the number of nearest neighbors used in the interpolation. After interpolation, the overlay method was applied by combining the three variables. The overlay method, such as weighted summation or fuzzy overlay, assigned higher weights to combinations of conditions favorable for fishing, such as higher temperatures and chlorophyll levels. Threshold values were set for contour determination, specifically temperature = 0.5°C and chlorophyll-a = 0.2, to identify areas optimal for fishing activity. The result of this overlay produced a PFZ map that highlighted areas with the highest potential for fishing.

## 3. **Result and Discuss**

This section presents the application of LSTM for forecasting oceanographic dynamics in the Sunda Strait, focusing on Sea Surface Temperature (SST), chlorophyll-a, current direction, and current speed to support the identification of Potential Fishing Zones (PFZ). Model validation using test data, MODIS imagery, and field observations showed that LSTM could detect frontal zones through SST and chlorophyll-a gradients, confirming its effectiveness in adaptively identifying PFZ. The integration of LSTM with satellite data improves the accuracy of oceanographic forecasting and enhances decision-making for sustainable fisheries management.

### *3.1. Temporal Data on Sea Surface Temperature, Chlorophyll-a Concentration, Current Direction, and Current Velocity in the Sunda Strait*

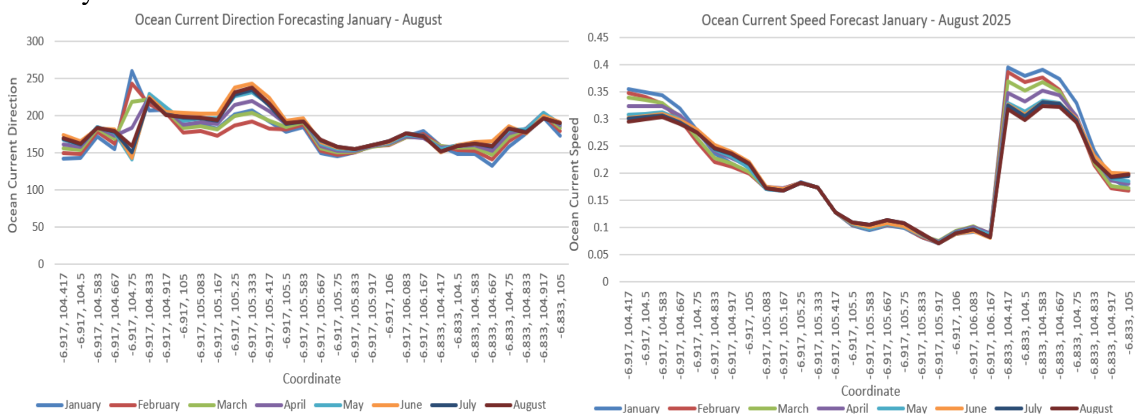
Temporal analysis was conducted to assess the LSTM model in capturing seasonal patterns of SST, chlorophyll-a, current direction, and speed in the Sunda Strait. Forecasts from January to August 2025 align with tropical seasonal dynamics, as shown in Figure 4, where SST and chlorophyll-a fluctuate consistently, with higher values in July–August and lower in January–February. These patterns are indicative of the monsoon influence, with SST and chlorophyll-a varying in response to nutrient dynamics and ocean circulation.




(a) (b)

**Figure 4.** Forecast Results for January–August 2025 Using the LSTM Model: (a) Sea Surface Temperature (SST), (b) Chlorophyll-a in the Sunda Strait

Figure 4(a) shows SST variation in the Sunda Strait, influenced by the monsoon cycle and water mass transport. The west monsoon brought colder waters from the Indian Ocean, while the east monsoon increased temperatures through current shifts and upwelling south of Java. Upwelling typically causes a decrease in SST due to the rise of cooler deep waters, which the LSTM model effectively captured, aiding in PFZ detection and supporting fisheries management. Figure 4(b) presents LSTM-based forecasts of chlorophyll-a (Chl-a) concentrations from January to August 2025, using MODIS imagery. Seasonal peaks occurred in July–August and lows in January–February, reflecting productivity driven by monsoon dynamics and nutrient supply from upwelling, which the model accurately captured to help identify productive habitats. Figure 5 shows the forecast of ocean current direction and speed in the Sunda Strait for January–August 2025 using LSTM, reflecting seasonal circulation variations critical for detecting potential fishing zones. Current dynamics, influenced by monsoons, tides, and the Indonesian Throughflow, affect the distribution of temperature, nutrients, and marine organisms. These currents play a crucial role in shaping nutrient distribution, directly influencing primary productivity and fishery resources.




(a) (b)

**Figure 5.** Forecast Results for January – August 2025: a. Ocean Current Direction, b. Ocean Current Speed

Figure 5(a) shows dominant current directions of 160°–230° with marked shifts during monsoon transitions, while Figure 5(b) indicates reduced speeds early in the year and sharp increases in June–July due to the Indonesian Throughflow. These dynamic changes in current direction and speed directly affect nutrient and plankton distribution, supporting pelagic fish abundance. The correlation of current surges with elevated chlorophyll-a and SST variation strengthens PFZ mapping, which is critical for adaptive fisheries management. Model accuracy was validated by comparing LSTM forecasts with MODIS imagery and field data, as presented in Figure 6.

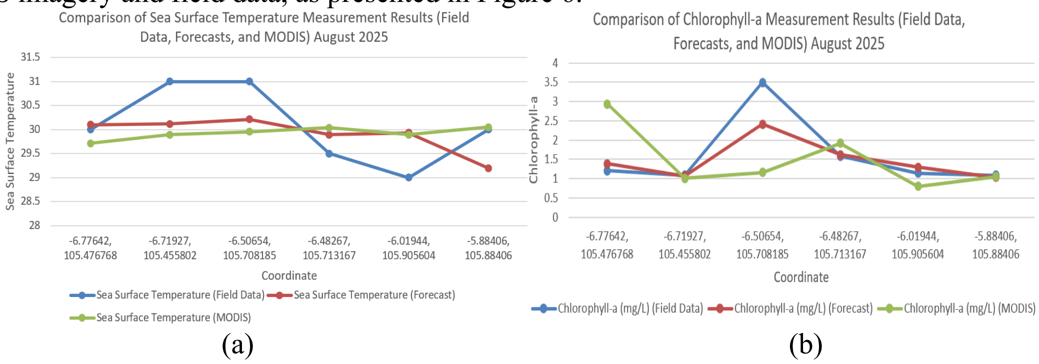



**Figure 6.** Comparison of Measurement Results in the Sunda Strait Region in August 2025: (a) Sea Surface Temperature (SST) between MODIS, LSTM, and Field Data; (b) Chlorophyll-a between MODIS, LSTM, and Field Data

Figure 6(a) shows a comparison of SST between field data, LSTM predictions, and MODIS imagery for August 2025, with LSTM showing high alignment, especially in areas with moderate temperatures. Figure 6(b) compares chlorophyll-a, where LSTM aligns well with field data, while MODIS shows lower values due to resolution limitations. The LSTM model's performance was evaluated using MSE, RMSE, and MAD to assess the accuracy of oceanographic parameter predictions, as shown in Figure 7.

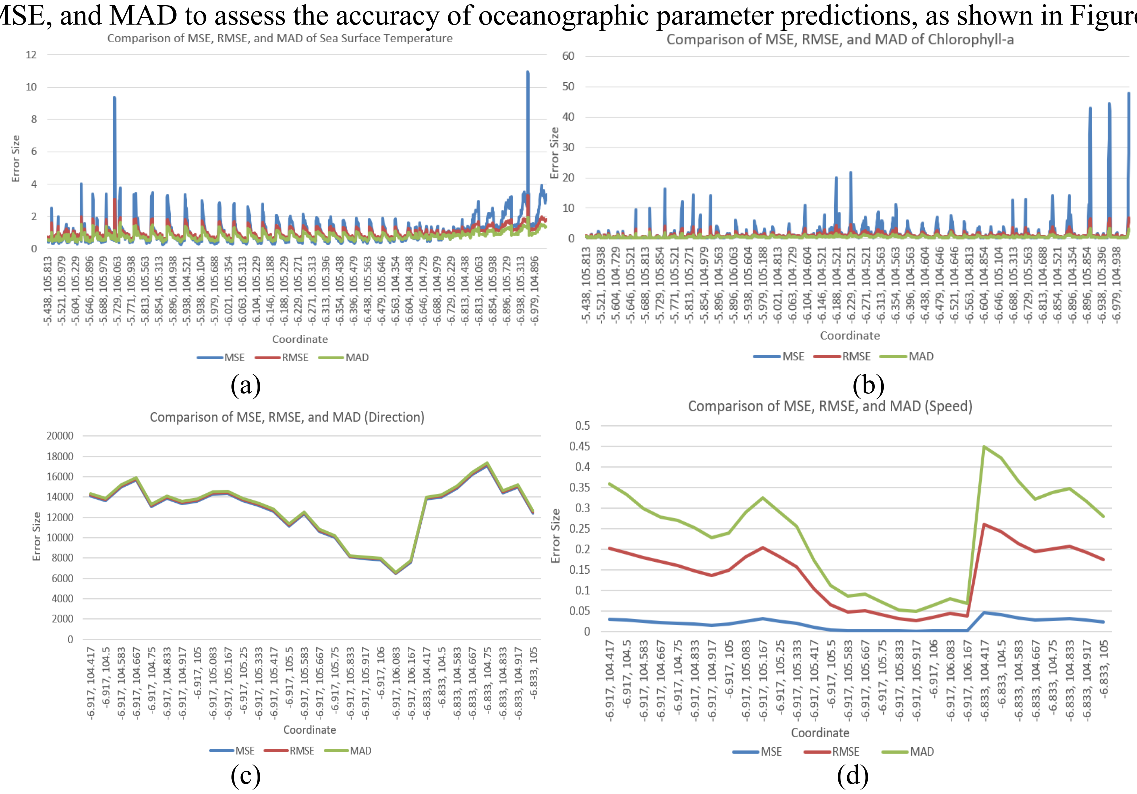
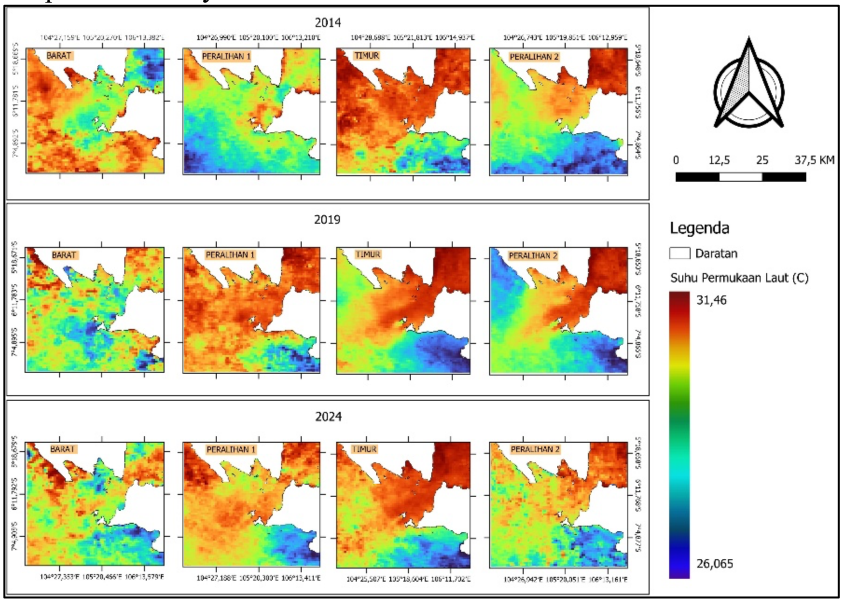
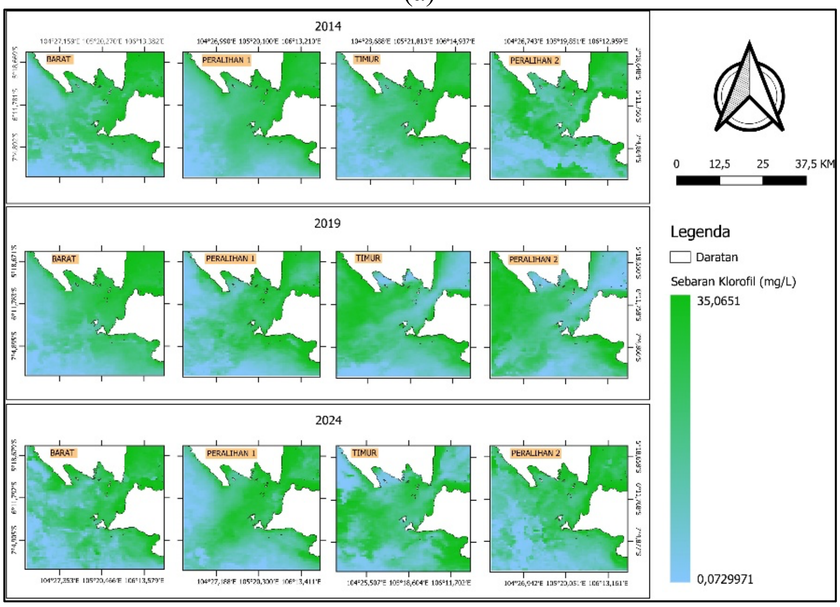



**Figure 7.** Comparison of MSE, RMSE, and MAD of LSTM Forecasting Results: a. Sea Surface Temperature, b. Chlorophyll-a, c. Ocean Current Direction, d. Ocean Current Speed

Figure 7(a) shows LSTM forecasts of SST in the Sunda Strait, with high MSE at certain points reflecting sensitivity to extreme fluctuations such as upwelling. RMSE highlights large errors, while MAD remains stable, indicating overall reliability. The model performs well but requires refinement during periods of extreme temperature changes critical for fisheries management. Figure 7(b) presents chlorophyll-a forecasts, where high MSE and RMSE in highly variable areas indicate limitations in capturing sudden fluctuations, though stable MAD supports ecosystem monitoring. Figure 7(c) shows current direction forecasts, with elevated errors at locations of sharp directional change, while low MAD reflects general reliability despite local inaccuracies. Figure 7(d) displays current speed forecasts, where high errors occur in strong currents, but stable MAD suggests good performance overall, with optimization needed under extreme conditions. Overall, LSTM effectively captures oceanographic dynamics but remains sensitive to extreme variability, requiring parameter and data refinement to improve spatio-temporal accuracy.




(a)




(b)

**Figure 8.** Distribution of Average Sea Surface Temperature (SST) and Seasonal Chlorophyll-a in the Sunda Strait in 2014, 2019, and 2024

Figure 8 illustrates seasonal SST and Chlorophyll-a distribution (2014, 2019, 2024), highlighting the influence of climate variability on primary productivity and environmental conditions in the Sunda Strait. Figure 8(a) shows the seasonal SST distribution in the Sunda Strait for 2014–2024. Higher temperatures in 2024, particularly during the West and Transition 2 monsoons, indicate regional sea warming influenced by climate change and circulation patterns. Monsoon-driven upwelling and vertical mixing regulated SST variability, impacting phytoplankton and pelagic fish habitats, fishery productivity, and PFZ detection. Long-term SST monitoring is crucial for assessing climate change impacts and supporting sustainable fisheries management.

Figure 8(b) presents the seasonal chlorophyll-a distribution in the Sunda Strait for 2014–2024. The increase in 2024 during the West and East monsoons indicated higher primary productivity driven by SST rise and nutrient enrichment, while the decline in Transition 2 of 2019 reflected interannual variability from monsoon shifts and upwelling. These patterns confirmed the strong link between oceanographic dynamics and productivity, where higher chlorophyll-a supported phytoplankton growth, pelagic fish abundance, and PFZ detection.

### *3.2 Identification of Potential Fishing Zones (PFZ) in the Sunda Strait Region*

The Sunda Strait, connecting the Java Sea and the Indian Ocean, is influenced by currents, tides, and monsoon winds that regulate SST, chlorophyll-a, and currents, impacting marine productivity. The LSTM model, combined with AQUA-MODIS imagery, successfully forecasted these parameters and identified Potential Fishing Zones (PFZ) for January–August 2025, showing patterns linked to SST variability, nutrient supply, and phytoplankton abundance. The results demonstrated that LSTM effectively captured spatio-temporal variability, supporting PFZ identification and ecosystem-based fisheries management.

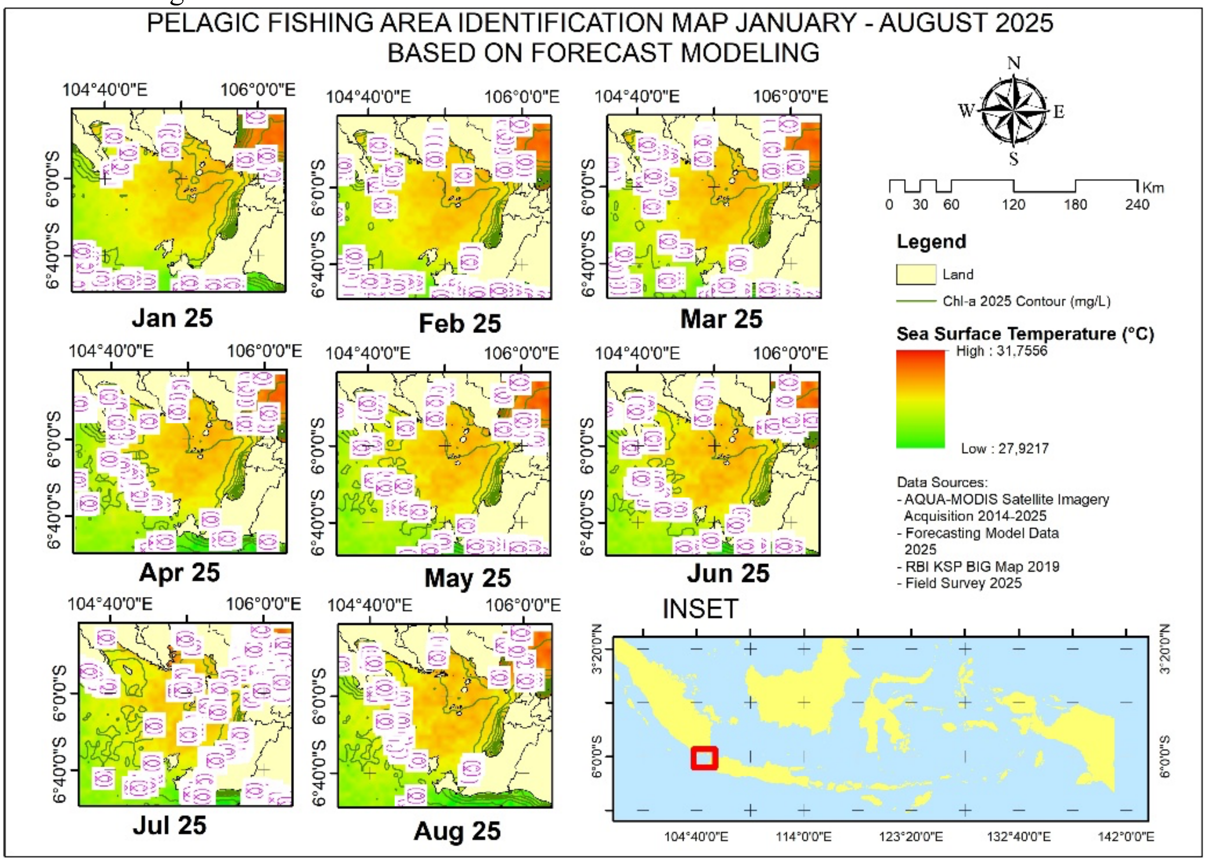


**Figure 10.** Map of Potential Fishing Zones (PFZ) for Pelagic Fish Identification Based on LSTM Forecasting Modeling for the Period January - August 2025

The PFZ mapping derived from AQUA-MODIS imagery (Figure 11) represents actual oceanographic conditions and serves as a benchmark for evaluating LSTM prediction accuracy. SST and chlorophyll-a data reflect seasonal variability influencing fish distribution, supporting fisheries management and climate adaptation. Figure 11 shows pelagic PFZ in the Sunda Strait for January–August 2025, with SST and chlorophyll-a distribution indicating primary productivity. The color gradient highlights zones with higher SST and chlorophyll-a concentrations, marking areas with greater pelagic fish catch potential.

The monthly spatial distribution of SST and chlorophyll-a reflected oceanographic seasonal dynamics in the Sunda Strait, influencing fish food accumulation locations. This satellite data complemented LSTM forecast results (Figure 10), where LSTM captured long-term trends and patterns, while satellite data provided real-time conditions for decision-making. The results showed that the seasonal variability of SST and chlorophyll-a in the Sunda Strait played a crucial role in shaping the presence and abundance of pelagic fish. During the dry season (July–August), elevated SST induced nutrient-rich upwelling, enhancing Chl-a concentrations and creating a productive zone for pelagic fish that rely on plankton. In contrast, during the early months of the year (January–February), lower SST and reduced Chl-a concentrations led to a less productive environment, limiting resources for pelagic fish populations.

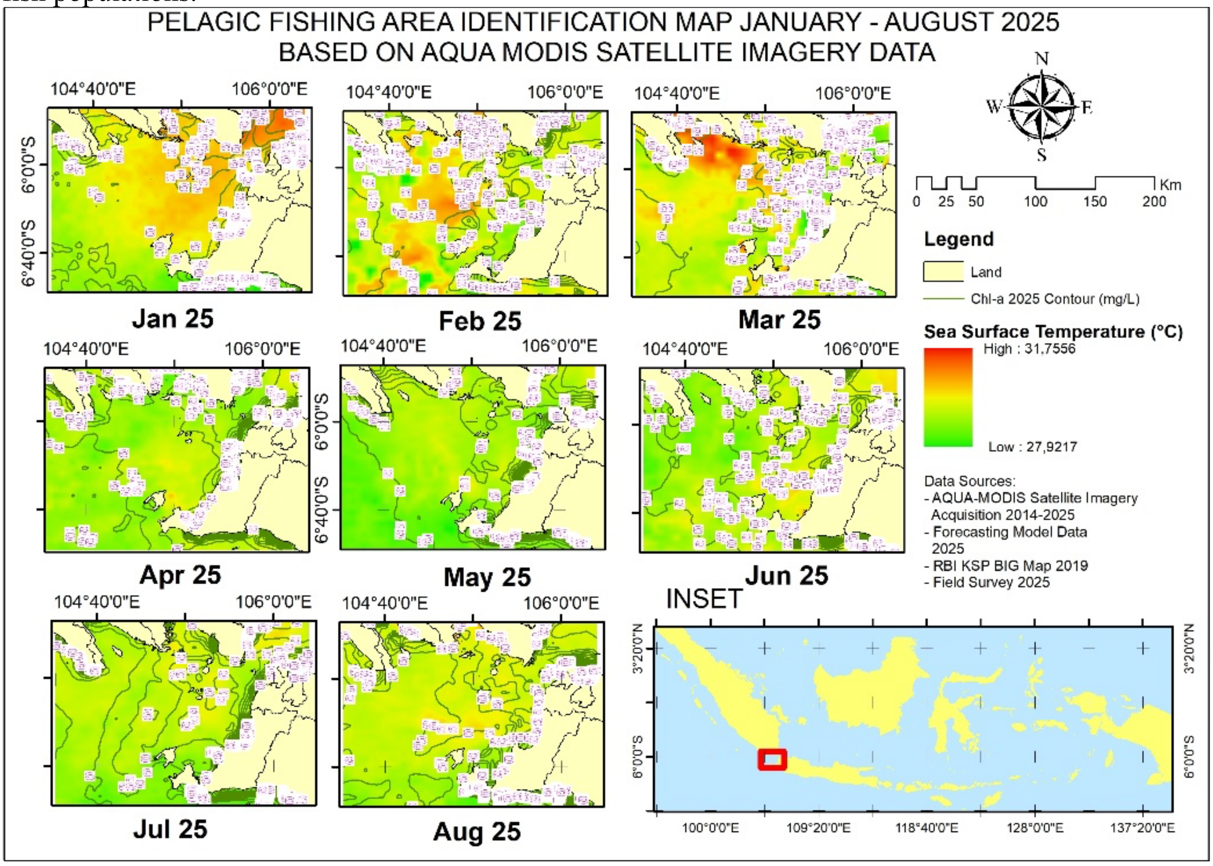



**Figure 11.** Map of Potential Fishing Zones (PFZ) for Pelagic Fish Identification Based on Aqua MODIS Imagery for the Period January - August 2025

Integrating LSTM modeling with satellite observations establishes a robust fisheries monitoring system, where predictions support strategic planning and satellite data inform daily management. This synergy improves PFZ detection, optimizes catch yields, and reinforces sustainable fisheries management in the Sunda Strait. The LSTM model effectively captured seasonal patterns but showed higher error under extreme conditions such as intense upwelling. Refinement is therefore needed to improve performance in handling extreme variability and to increase accuracy in delineating potential fishing zones under dynamic oceanographic conditions.

## 4. Conclusion

This study integrated AQUA-MODIS satellite imagery with a Long Short-Term Memory (LSTM) model to forecast oceanographic dynamics and identify Potential Fishing Zones (PFZs) in the Sunda Strait. The model was trained using data from January 2014 to December 2024 and used to predict Sea Surface Temperature (SST), chlorophyll-a concentration, and ocean currents for January–August 2025. The predicted SST peaked at 31°C, chlorophyll-a reached 3.5 mg/L, and current speed reached 0.4 m/s, reflecting seasonal dynamics influenced by monsoon cycles and upwelling. The model showed reliable performance for SST (MSE: 1.107; RMSE: 0.994; MAD: 0.794), chlorophyll-a (MSE: 1.609; RMSE: 1.011; MAD: 0.5739), and current speed (MSE: 0.0183; RMSE: 0.1223; MAD: 0.0959), with strong spatial agreement among in-situ data, MODIS imagery, and forecast outputs. These findings indicate that LSTM can effectively detect PFZs and support fisheries management by identifying productive zones shaped by seasonal and climatic factors. Moderate errors in highly variable oceanographic areas suggest that further refinement and additional validation are required before operational deployment. Future research should incorporate multi-sensor fusion, including VIIRS, Himawari-8, Sentinel-3 OLCI, and altimetry-based current estimates, as well as hydrodynamic or physics-informed models, ensemble modeling, uncertainty quantification, cross-seasonal validation, and ecological variables such as mixed layer depth and primary productivity indices. Overall, this study demonstrates that integrating satellite remote sensing with LSTM deep learning provides a robust foundation for real-time marine monitoring, PFZ identification, and sustainable fisheries decision-making in the Sunda Strait under climate-driven oceanographic variability.

### Declaration of AI and AI assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT to improve sentence structure, clarity, grammar, and language flow. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.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