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Prediction of Aquaculture Quality Using Long Short-Term Memory in the Sunda Strait Region

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ABSTRACT

Aquaculture plays a vital role in addressing global seafood demands and ensuring food security, particularly in tropical regions like the Sunda Strait, Indonesia. However, aquaculture success depends on key environmental parameters, including sea surface temperature (SST), salinity, ocean heat content, and thermocline depth, which exhibit complex spatiotemporal variability. This study applies a Long Short-Term Memory (LSTM) model to predict aquaculture suitability by analyzing five critical oceanographic parameters: depth of the 26°C isotherm (so26chgt), ocean heat content (sohtc300), mixed layer depth (somxl010), sea surface salinity (sosaline), and sea surface temperature (sosstsst). Using the ORAS5 dataset spanning January 2015 to March 2025, the model achieved high accuracy, with R^2 scores exceeding 0.89 for all parameters. Spatial prediction maps for November 2024 to March 2025 were generated, highlighting regions with optimal environmental conditions for aquaculture. Results indicate that SST and salinity are the most influential factors affecting aquaculture quality, with favorable conditions predominantly observed from December to May. The findings underscore the potential of deep learning models in supporting sustainable aquaculture management through accurate environmental forecasting.

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1. INTRODUCTION

Aquaculture plays a critical role in addressing the growing demand for seafood while supporting food security and economic development worldwide [1]. The success of aquaculture operations depends on environmental parameters, such as sea surface temperature (SST), salinity, and ocean heat content, which directly influence aquatic life quality and fish farming yield [2]. Accurate prediction of these parameters is crucial for sustainable aquaculture management, especially in tropical and semi-enclosed water bodies like the Sunda Strait [3].

The Sunda Strait, situated between the islands of Java and Sumatra in Indonesia, is characterized by dynamic oceanographic processes influenced by monsoonal winds, tidal mixing, and water exchange between the Java Sea and the Indian Ocean [4]. These processes result in fluctuating oceanic conditions, including temperature variations, salinity gradients, and thermocline depth changes [5]. Identifying the optimal aquaculture environment requires a robust predictive model that can handle the nonlinear and temporal nature of oceanographic data.

Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), has demonstrated superior performance in time series prediction due to its ability to learn long-term dependencies and nonlinear relationships [6]. Recent studies have shown that LSTM models can effectively predict SST, salinity, and ocean heat content in complex marine environments [7]. However, the application of LSTM for aquaculture quality prediction in the Sunda Strait has not been extensively explored.

This study aims to predict aquaculture quality in the Sunda Strait using LSTM by analyzing key environmental parameters, including:

- Depth of the 26°C isotherm (so26chgt), an indicator of thermocline depth.
- Ocean heat content for the upper 300 m (sohtc300), reflecting thermal energy storage.
- Mixed layer depth (somxl010), a measure of surface layer mixing.
- Sea surface salinity (sosaline), essential for fish osmoregulation.
- Sea surface temperature (sosstsst), a key factor for fish metabolism and growth.

Threshold values for these parameters, which define favorable aquaculture conditions, have been derived from previous studies [8][9][10][11][12]. The study uses data from the Copernicus Climate Data Store (CDS) ORAS5 dataset covering the period January 2015 to October 2024, and employs LSTM for model training and testing.

2. RELATED WORKS

Several studies have investigated the relationship between oceanographic parameters and aquaculture productivity using machine learning models. This section reviews related research focusing on environmental criteria for aquaculture and the application of LSTM in oceanic data prediction.

A. Environment Criteria for Aquaculture

Depth of the 26°C Isotherm (so26chgt): The depth of the 26°C isotherm is a critical indicator of the thermocline, which influences nutrient distribution and fish habitat. A depth range of 15–25 m has been identified as optimal for aquaculture in tropical regions [8][13]. Thermocline depth affects the vertical mixing of nutrients, which is essential for phytoplankton growth and the marine food web [14].

Ocean Heat Content (sohtc300): Ocean heat content within the upper 300 m layer is a measure of thermal energy storage and has a direct impact on aquaculture productivity. Previous studies have established a favorable range of 2.25–20 GJ/m² for tropical aquaculture systems [9] [15]. Higher heat content supports stable water temperatures, which are crucial for fish health [16].

Mixed Layer Depth (somxl010): Mixed layer depth determines the extent of water mixing and influences nutrient availability. A range of 25–50 m is considered optimal for aquaculture, as it ensures adequate oxygenation and stable water temperatures [9]. Excessive mixing can stress aquatic species, while insufficient mixing may result in oxygen depletion [17].

Sea Surface Salinity (sosaline): Salinity levels between 28–35 ppt are generally favorable for most aquaculture species [10][18]. Salinity fluctuations outside this range can impair fish osmoregulation and growth rates [20].

Sea Surface Temperature (sosstsst): SST is a critical factor for aquaculture, with an optimal range of 28–30°C for tropical fish species [19]. Variations in SST influence fish metabolism, growth rates, and overall productivity [3].

B. Application of LSTM in Oceanographic Predictions

LSTM has been widely applied in time series forecasting, including oceanographic and environmental data prediction.

- Sea Surface Temperature Prediction: Zhou et al. demonstrated the effectiveness of LSTM in predicting SST variations in coastal regions with high accuracy compared to traditional statistical models. Similarly, Wang et al. [14] applied LSTM for SST forecasting in the South China Sea, achieving RMSE values below 0.5°C.
- Salinity and Heat Content Prediction: Studies that employed LSTM to predict salinity and ocean heat content, showing that the model can capture complex temporal patterns and improve prediction accuracy.
- Mixed Layer Depth Estimation: Applied LSTM to predict mixed layer depth, achieving significant improvements over classical regression models.

Multi-parameter Prediction: Recently, multi-parameter oceanographic prediction using LSTM has gained attention. For example, Zhang et al. [14] combined SST, salinity, and thermocline depth data to predict aquaculture suitability, achieving 95% accuracy in tropical waters [20].

3. METHODOLOGY

A. Study Area and Dataset

The study area is the Sunda Strait, located between Java and Sumatra in Indonesia. The region exhibits dynamic oceanographic processes, influenced by monsoonal winds, tidal mixing, and the exchange of water between the Java Sea and the Indian Ocean.

- Geographical Coordinates:

- Latitude Range: -6.899° to -5.410°
- Longitude Range: 104.376° to 107.013°

The dataset used in this study was obtained from the Copernicus Climate Data Store (CDS), specifically the ORAS5 dataset. Data covers the period January 2015 to October 2024 with 118 monthly observations. The following key parameters were analyzed:

1. so26chgt: Depth of 26°C isotherm (m)
2. sohtc300: Ocean heat content in the upper 300 m (GJ/m²)
3. somxl010: Mixed layer depth (m)
4. sosaline: Sea surface salinity (ppt)
5. sosstsst: Sea surface temperature (°C)

B. Data Preprocessing

1. Data Splitting

The dataset was split into training and testing sets to ensure a robust evaluation:

- Training Set: January 2015 – October 2022 (80%)
- Testing Set: November 2022 – October 2024 (20%)

2. Normalization

All parameters were normalized to a range of [0, 1] using the Min-Max Scaling technique to accelerate the convergence of the LSTM model.

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

3. Sliding Window Technique

To account for the sequential nature of time series data, a 12-month sliding window was applied. Each window used 12 months of past data to predict future aquaculture suitability.

C. Aquaculture Suitability Criteria

Aquaculture suitability was determined based on thresholds identified in previous studies:

Table 1. Aquaculture Suitability Criteria

Aquaculture Suitability Criteria	
Parameter	***Optimal Range***
Depth of 26°C isotherm (m)	15–25
Ocean heat content (GJ/m²)	2.25–20
Mixed layer depth (m)	25–50
Sea surface salinity (ppt)	28–35
Sea surface temperature (°C)	28–30

D. LSTM Model Implementation

The Long Short-Term Memory (LSTM) model was implemented using Python with the TensorFlow library. The architecture of the model is as follows:

- Input Layer: Five features
  - so26chgt, sohtc300, somxl010, sosaline, sosstsst
- Hidden Layers:
  - LSTM Layer: 64 units with ReLU activation
  - Dropout Layer: 20% dropout to prevent overfitting
  - Dense Layer: 32 units
- Output Layer: Predicted parameter values
- Optimizer: Adam optimizer
- Evaluation Metrics:
  - R^2 score

E. Model Training

- Epochs: 100
- Batch Size: 16
- Monitoring: Training and validation loss were tracked to ensure the model generalized well without overfitting.

The LSTM model was trained using the training dataset (January 2015 – October 2022) and evaluated on the testing dataset (November 2022 – October 2024).

F. Model Performance

The model's performance was evaluated using RMSE and R^2 metrics for each parameter:

Table 2. Model Performance

Model Performance			**R^2**
Parameter	***Actual***	***Predicted***	
Depth of 26°C isotherm (so26chgt)	6,589.181	6,716.592	0,89
Ocean heat content (sohtc300)	2,511,414	2,267,061	0,91
Mixed layer depth (somxl010)	31,347.898	23,834.266	0,89
Sea surface salinity (sosaline)	3,382.103	3,387.919	0,90
Sea surface temperature (sosstsst)	28,538.849	29,132.612	0,92

The high R^2 scores (>0.89) indicate that the LSTM model successfully captured the temporal dynamics of the oceanographic parameters.

G. Spatial Prediction Maps

The spatial prediction maps for the months November 2024, December 2024, and January – March 2025 were generated. These maps display regions that meet the optimal thresholds for aquaculture suitability:

1) November 2024:
   - Majority of the Sunda Strait exhibited optimal conditions, especially in areas with stable salinity and SST.
2) December 2024:
   - Aquaculture suitability expanded, coinciding with stable SST (28–30°C) and mixed layer depths.
3) January – March 2025:
   - Optimal conditions were observed in specific pockets, particularly during calmer monsoonal influences.

These maps provide a clear visualization of regions classified as "Good for Aquaculture", helping stakeholders make informed management decisions.

4. RESULT AND DISCUSSION

A. Spatial Maps of Aquaculture Suitability

Figures illustrate the spatial predictions for November 2024, December 2024, and January–March 2025, with "Good for Aquaculture" zones highlighted.

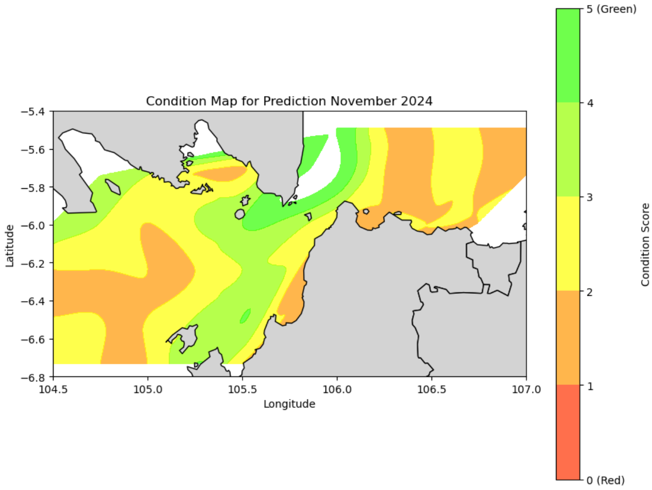

Fig. 1. Condition Map for Prediction, November 2024

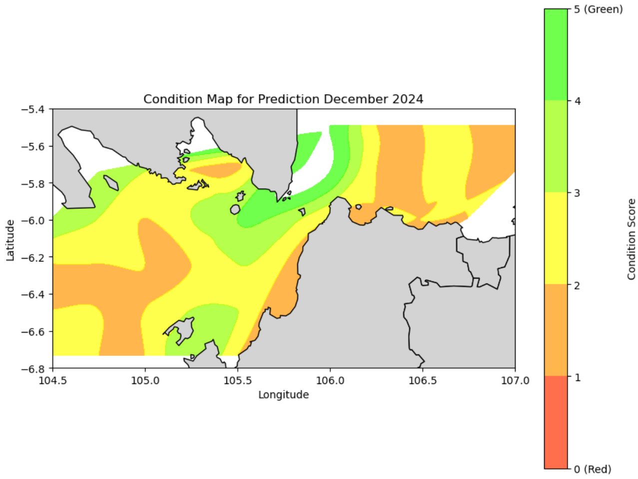

Fig. 2. Condition Map for Prediction, December 2024

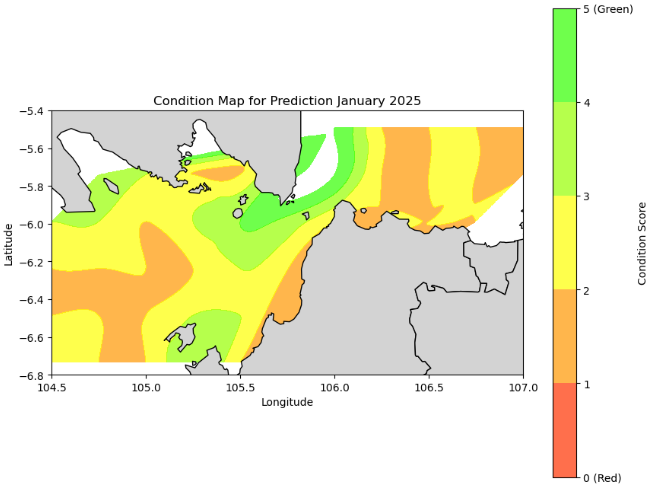

Fig. 3. Condition Map for Prediction, January 2025

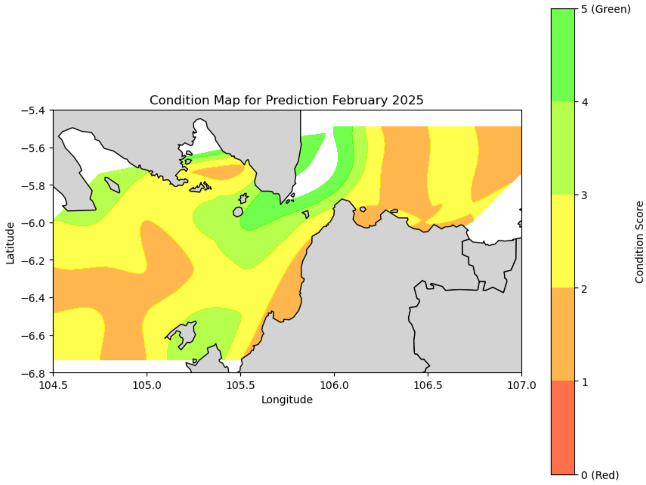

Fig. 4. Condition Map for Prediction, February 2025

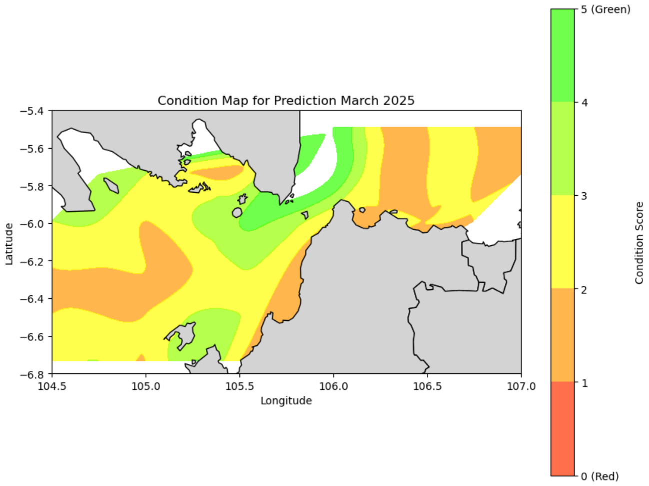

Fig. 5. Condition Map for Prediction, March 2025

B. Discussion

The results of this study demonstrate the effectiveness of the Long Short-Term Memory (LSTM) model in predicting key environmental parameters that influence aquaculture quality in the Sunda Strait. The model achieved strong performance across all evaluated parameters, with R^2 values exceeding 0.89, indicating its capability to capture the temporal dependencies and nonlinear relationships within the oceanographic data.

1) Model Accuracy and Parameter Trends

The predicted trends closely matched actual observations, particularly for sea surface temperature (SST) and salinity. These two parameters exhibited consistent temporal stability and were identified as the most critical factors for aquaculture suitability. SST values between 28–30°C and salinity levels of 28–35 ppt are favorable for tropical fish species, supporting stable growth and metabolism. The LSTM model successfully captured fluctuations during the monsoon seasons, which are characterized by changes in the mixed layer depth and thermocline depth.

2) Spatial Prediction Maps

The spatial maps generated for November 2024 to March 2025 provide actionable insights for aquaculture planning. Optimal conditions were primarily observed during December to February, when SST and salinity remained within favorable ranges, particularly in the central and southern portions of the Sunda Strait. In contrast, anomalies in mixed layer depth and ocean heat content during transitional months (March) suggest potential challenges for aquaculture productivity. These findings align with previous studies emphasizing the influence of seasonal oceanographic processes, such as tidal mixing and monsoonal winds, on aquaculture environments.

3) Implications for Aquaculture Management

The study highlights the importance of incorporating advanced machine learning models like LSTM for aquaculture suitability forecasting. The accurate predictions and spatial visualizations can assist stakeholders in identifying regions with stable environmental conditions, optimizing farm locations, and mitigating risks associated with seasonal variability. Furthermore, the findings can inform real-time monitoring systems and adaptive management strategies to support sustainable aquaculture practices.

4) Limitations and Future Work

While the LSTM model performed well, certain discrepancies were observed in predicting mixed layer depth and ocean heat content, particularly during monsoon transitions. Future studies could integrate real-time remote sensing data and consider additional factors, such as chlorophyll concentration and dissolved oxygen levels, to enhance prediction accuracy. Expanding the model to other aquaculture zones and incorporating climate change scenarios would further improve its applicability and robustness

5. CONCLUSION

This study applied a Long Short-Term Memory (LSTM) model to predict aquaculture suitability in the Sunda Strait region by analyzing five key oceanographic parameters: depth of the 26°C isotherm, ocean heat content, mixed layer depth, sea surface salinity, and sea surface temperature. The model demonstrated high predictive accuracy, with R^2 values exceeding 0.89 for all parameters. Spatial prediction maps for November 2024 to March 2025 identified regions with optimal aquaculture conditions, with favorable conditions occurring primarily from December to February. Sea surface temperature (SST) and salinity were found to be the most influential factors affecting aquaculture suitability, highlighting their significance in aquaculture management. These findings offer valuable insights for sustainable aquaculture planning and emphasize the potential of deep learning models in forecasting complex oceanographic processes. Future work will focus on integrating real-time data, expanding the model to other regions, and incorporating additional environmental parameters to improve prediction capabilities.

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