

LSTM-Based Regional Sea Surface Temperature Prediction Model for Climate Projection in North Maluku

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ABSTRACT

North Maluku Province, as an archipelagic region, is highly vulnerable to the impacts of climate change, particularly the increasing frequency of extreme precipitation events, while facing limitations in observational data. This study aims to develop a regional sea surface temperature (SST) prediction model using a Long Short-Term Memory (LSTM) neural network to generate more accurate SST projections by applying bias correction to outputs from the BNU-ESM global climate model. The model was trained using daily SST data from 1980 to 2005, with ERA5 reanalysis data as the reference and BNU-ESM outputs as predictors. Evaluation on the test data showed strong performance, with the best model (1-layer LSTM, 80 epochs, batch size 1024, learning rate 0.003) achieving a Mean Absolute Error (MAE) of 0.56°C, Mean Squared Error (MSE) of 0.57, and Mean Absolute Percentage Error (MAPE) of 2.09%. These results demonstrate the model's reliability in capturing SST patterns and its potential use for precipitation modeling, early warning systems, and climate adaptation strategies in data-scarce regions.

Keywords: sea surface temperature; LSTM; BNU-ESM; ERA5; North Maluku

1. INTRODUCTION

Global warming has led to a notable rise in Sea Surface Temperature (SST), which serves as a primary indicator of climate change. This rise in SST is not only instigating severe weather events but also endangering fragile marine ecosystems, such as coral reefs, while altering the distribution patterns of fisheries resources that are vital to the livelihoods of millions (Hughes et al., 2017). For an island country like Indonesia, especially North Maluku Province, situated in the core of the Coral Reef Triangle, the consequences of increasing SST present a significant danger to food security and the local economy.

Geographically, North Maluku lies at the intersection of the Indian and Pacific Oceans, rendering it especially susceptible to fluctuations in sea surface temperatures. This susceptibility is intensified by occurrences like the El Niño-Southern Oscillation (ENSO), a cyclical event that induces temperature shifts in the Tropical Pacific Ocean and leads to severe climate anomalies in Indonesia (Schilling et al., 2019).

The selection of North Maluku as the study location is therefore critical due to its ecological sensitivity and socio-economic reliance on marine resources, making accurate regional climate projections indispensable for local adaptation and resilience strategies.

Accurate climate forecasts at a regional level are crucial to reduce the impacts of climate change in areas like North Maluku. Nonetheless, Global Climate Models (GCMs) frequently exhibit insufficient spatial resolution, rendering them ineffective for local adaptation strategies. To remedy this issue, downscaling techniques are necessary to produce climate data that is both higher in resolution and relevant to local conditions (Giorgi & Gutowski, 2015). The historical

daily SST data from 1980 to 2005 were chosen for model training to establish a robust baseline representative of past climate conditions. While climate change symptoms have intensified significantly after 2005, this historical period provides a stable dataset for the initial development and validation of the bias correction model. Future research will focus on extending this analysis to more recent periods to capture evolving climate dynamics.

In order to transcend the limitations inherent in General Circulation Models (GCM), a statistical downscaling approach driven by machine learning has been identified as a feasible resolution. A notably efficacious methodology is the Long Short-Term Memory (LSTM) network, a subtype of Recurrent Neural Network (RNN) that is meticulously designed to scrutinize time series data while retaining long-term dependencies through the implementation of gating mechanisms. This methodology enables more precise forecasts for climate variables like sea surface temperature compared to traditional statistical approaches (Scher, 2018).

Research indicates that the LSTM model is capable of generating precise forecasts for climate time series data, including sea surface temperature, owing to its proficiency in capturing intricate patterns and long-term dependencies within oceanographic data (Zhao et al., 2024).

2. METHODS

In this study, a Long Short-Term Memory (LSTM) model was applied as a bias correction method for meteorological time series data. The LSTM architecture was chosen for its ability to overcome the vanishing gradient issue found in traditional Recurrent Neural Networks (RNNs) and its effectiveness in preserving long-term dependencies within sequential data. LSTM networks demonstrate superior capability in modeling complex and dynamic systems, such as those found in climatology and hydrology. By effectively recognizing non-linear patterns and temporal dependencies in time series data, the application of LSTM has been shown to significantly enhance prediction accuracy, an advancement well-documented in various studies (Kratzert et al., 2018; Shen, 2018)

The model was trained using daily historical data from 1980–2005, derived from two primary sources: ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) served as the reference (ground truth), while outputs from the Beijing Normal University Earth System Model (BNU-ESM) climate simulation were used as predictors. ERA5 data were chosen for their high spatial and temporal resolution, whereas BNU-ESM was selected for its validation as a reliable global climate projection mode (Hersbach et al., 2020). Within the LSTM model framework, ERA5 data were used as the target (dependent) variable, representing observational climate conditions, while BNU-ESM outputs served as the predictor (independent) variables, representing climate simulation results. With this approach, the model was trained to learn the relationship between simulation projections and observational conditions, thereby enabling more accurate bias correction.

The integration of these two sources through a bias correction approach using LSTM allows for a significant improvement in prediction accuracy compared to conventional methods (Flores et al., 2020) The methodology in this study consists of several main stages: data

preprocessing, LSTM model training and testing, the prediction process, and the analysis and evaluation of prediction results. All these stages are systematically arranged and visualized in the process flowchart in Figure 1.



Figure 1. Flowchart of the LSTM model development stages for sea surface temperature prediction.

2.1. Data Acquisition and Synchronization

This study utilizes two primary sources of climate data for the North Maluku region, covering the period from 1980 to 2005. ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) were used as the reference or ground truth (Hersbach et al., 2020), while the predictor data were the sea surface temperature outputs from the BNU-ESM model. To temporally align the two datasets, all records for February 29th were removed to eliminate inconsistencies from leap years. Additionally, the temperature unit was converted from Kelvin to degrees Celsius to better align with standard climate analysis practices.

2.2. Spatial Alignment and Interpolation

The two datasets used have different spatial resolutions or grid systems, necessitating a spatial alignment process. In this process, the BNU-ESM data were interpolated to match the ERA5 grid using the nearest neighbor method. This process allows each ERA5 grid point to acquire a temperature value from the nearest BNU-ESM point, thereby forming an integrated dataset with consistent spatial coordinates. This integrated dataset can then be used to compare observed and simulated temperatures at the same geographical locations.

2.3. Data Preprocessing

Following spatial and temporal alignment, the next stage was data cleaning and transformation. Incomplete data rows were discarded to maintain the quality and integrity of the time sequence. Next, temporal information in the form of months was converted into two cyclical features using sine and cosine functions to represent annual seasonal patterns. This transformation aims to enable the model to recognize the periodic characteristics of the climate data. All features, including the temperature from BNU-ESM and the temporal features, as well as the target variable (temperature from ERA5), were then normalized using the RobustScaler. This technique was chosen for its effectiveness in stabilizing the scale between variables and its resistance to outliers frequently found in climate data..

The cleaned and normalized data were subsequently converted into a time series format using a sliding window technique. In this method, the data were arranged into sequences of 28 days, which were used to predict the temperature on the 29th day. This process was applied separately to each location point (grid) to preserve the temporal order of each location. The result is a collection of thousands of data sequences ready for model training and testing. This format allows the LSTM to more effectively recognize temporal patterns and daily temperature dynamics.

2.4. Model Training (LSTM Architecture)

In this modeling framework, the dependent variable targeted for prediction is the sea surface temperature (SST) data from the ERA5 reanalysis, which is considered the ground truth. Meanwhile, the independent variables used as predictors include SST data from the BNU-ESM model and the cyclical time features (sine and cosine of the month). To train and evaluate the model, the entire dataset was divided chronologically to maintain the integrity of the time series. Seventy percent of the initial data was used for the training set, the next 15% was allocated for the validation set to monitor model performance during training, and the remaining 15% was used as the testing set for final model evaluation.

Using this partitioned dataset, the Long Short-Term Memory (LSTM) model was then trained. The model architecture was designed to capture temporal dependencies in the time series data, utilizing the independent variables to predict the dependent variable. This architecture includes an LSTM layer that processes input sequentially, followed by a Dropout layer to reduce the risk of overfitting by randomly deactivating a portion of neurons during training. The optimization process was performed using the Adam optimizer algorithm, known for its ability to adaptively adjust the learning rate to accelerate convergence. During the training process, two additional control mechanisms were used: Early Stopping, which halts training if there is no significant improvement in the validation loss, and ReduceLROnPlateau, which dynamically reduces the learning rate when the model's performance stagnates.

2.5. Prediction and Evaluation

After training was complete, the LSTM model was reloaded and used to generate sea surface temperature predictions based on the test data. The model's output was then returned to its original scale by applying the inverse transform of the RobustScaler. These prediction results were compared with the ERA5 observation values to assess the model's accuracy. The evaluation was conducted using several statistical metrics, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics provide a quantitative overview of how well the model can reconstruct climate conditions based on the predictor data from BNU-ESM.

3. RESULTS AND DISCUSSIONS

This section presents the evaluation of the LSTM model's performance in predicting Sea Surface Temperature (SST). The evaluation was conducted quantitatively using statistical metrics such as MAE, MSE, and MAPE, and qualitatively through time series plots of the prediction results to understand the temporal dynamics captured by the model. An initial visualization used was a boxplot (Figure 2) to compare the distribution of SST values from both data sources before the bias correction process was performed. Figure 2 shows that although both datasets have relatively similar distributions, there are differences in the median and the number of outliers, indicating a systematic discrepancy that needs to be corrected to improve the prediction accuracy of the simulation-based climate model.

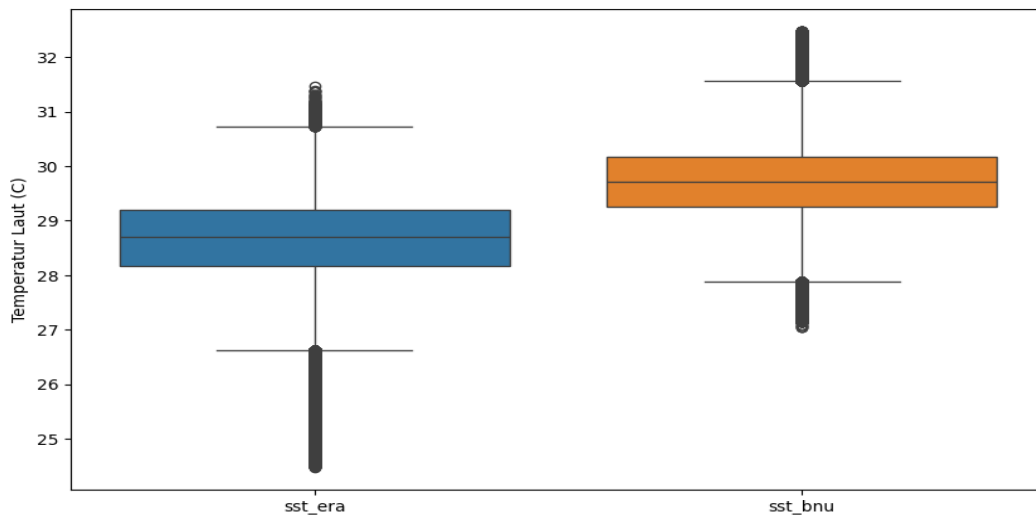


Figure 2. Boxplot SST from ERA5 and BNU-ESM data in North Maluku before bias correction with LSTM.

The use of RobustScaler to standardize the independent variable `sst_bnu` was an appropriate step in the context of sea surface temperature modeling. This method relies on the median and interquartile range (IQR) to transform the data, thereby reducing the influence of extreme values or outliers often found in climate data. Thus, the original distribution characteristics of the data are preserved, allowing the model to learn from more representative patterns. Furthermore, this standardization helps to accelerate the training process and improve the stability of the LSTM model in recognizing temporal patterns in the sea temperature time series.

The model's performance was evaluated using MAE, MSE, and MAPE on the test dataset, as summarized in Table 1. The best-performing model, a single-layer LSTM with 80 epochs, a batch size of 1024, and a learning rate of 0.003, achieved an MAE of 0.56°C, an MSE of 0.57, and a MAPE of 2.09%. The MAE of 0.56°C indicates that the model's predictions deviate, on average, by only 0.56°C from the ERA5 reference data. This is competitive with other studies, such as (Akbar et al., 2023), who reported an MAE of 0.65°C and a MAPE of 2.3% for air temperature prediction using LSTM in Semarang, Indonesia, suggesting that an MAE of 0.56°C and a MAPE of 2.09% are relatively small in the context of tropical climate predictions. Similarly, (Tanto, 2020) reported an RMSE of 0.74°C for satellite-based SST estimations in Indonesian waters, indicating that the LSTM model's MAE is lower than typical errors in remote sensing methods. The MAPE of 2.09% is also notably low, closely aligning with the MAPE of 1.93%–2.51% reported for temperature predictions in Ternate, Maluku Utara, using LSTM (Andre & Handhayani, 2024), and slightly higher than the MAPE of 1.9499% reported by (Tita Lattifia, Putu Wira Buana, 2022) for weather predictions, reinforcing that this error level is small in the regional context.

Table 1. LSTM Model Evaluation Results on Test Data

Model	MAE	MSE	MAPE
LSTM 1 Layer (epochs=80, batch_size=1024 learning_rate=0.003)	0.56	0.57	2.09%
LSTM 1 Layer (epochs=40, batch_size=512 learning_rate=0.001)	0.60	0.58	2.10%
LSTM 2 Layer (epochs=80, batch_size=1024 learning_rate=0.003)	0.60	0.59	2.10%
LSTM 2 Layer (epochs=40, batch_size=512 learning_rate=0.001)	0.60	0.60	2.12%

Note: MAE = Mean Absolute Error, MSE = Mean Squared Error, MAPE = Mean Absolute Percentage Error.

In practical terms, the sea surface temperature prediction model demonstrates good accuracy, with a Mean Absolute Error (MAE) of only about 0.56°C. This means the average deviation of the predictions from the actual values is very small. Interestingly, using a more complex model architecture, such as two LSTM layers, didn't lead to significant performance improvements. In fact, these more complex models tended to perform slightly worse. This suggests that a simpler architecture is likely easier to train and less prone to overfitting in this context.

Another crucial point is that optimal model performance is heavily influenced by a balanced combination of hyperparameters. The best model utilized a higher number of epochs for deep learning, a large batch size for gradient stability, and a sufficiently aggressive learning rate to accelerate convergence. These findings are consistent with previous research, like (Tita Lattifia, Putu Wira Buana, 2022), who lofound that LSTM models with optimized batch sizes and epochs (e.g., batch size 50, epoch 100) achieved high accuracy (MAPE 1.9499%) for

weather predictions. All of this underscores the critical importance of the hyperparameter tuning process in building reliable and stable predictive models.

The training process, monitored through the loss (MSE) plot in Figure 3, shows a steady decrease in training loss and stable validation loss, indicating effective learning without overfitting. The use of callbacks such as EarlyStopping and ReduceLROnPlateau ensured model generalization, as supported by (Akbar et al., 2023), who noted that LSTM's ability to handle time series data is enhanced by such techniques in tropical climate applications.

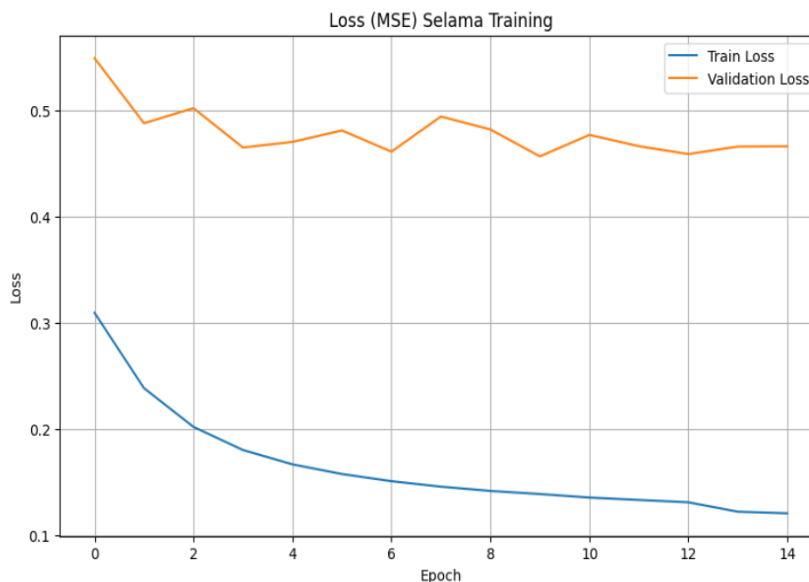


Figure 3. Time Plot of Loss (MSE) during LSTM Model Training on Training and Validation Data.

The time series plot in Figure 4 compares the LSTM model's predictions with ERA5 SST values from 1980 to 2005, demonstrating the model's ability to capture seasonal patterns and long-term fluctuations. This stability in mapping temporal relationships is consistent with findings from a study in Ternate, Maluku Utara (Andre & Handhayani, 2024), which reported that LSTM effectively captured consistent temperature trends with MAPE values around 2%. Similarly, (Akbar et al., 2023) highlighted LSTM's ability to model seasonal and long-term trends in air temperature data, reinforcing the robustness of the model in this study. However, some studies suggest that LSTM models may face challenges with abrupt changes in weather data (Tita Lattifia, Putu Wira Buana, 2022), though the inclusion of cyclical time features in this study likely mitigated such issues by enhancing the model's ability to model seasonal variations..

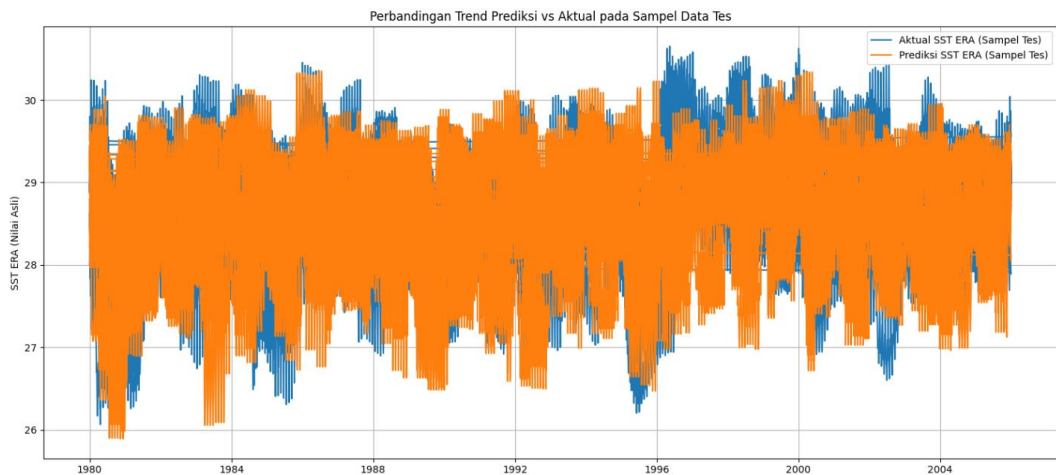


Figure 4. Time series plot of actual SST and LSTM model predictions on test data (1980–2005).

While the model performs well, its reliance on a single predictor variable (BNU-ESM SST) is a limitation. Incorporating additional variables, such as sea level pressure or wind speed, could improve accuracy, as suggested (Akbar et al., 2023), who used multiple meteorological parameters to enhance LSTM predictions. Future research could also explore hybrid architectures, such as CNN-LSTM, to further improve performance in data-scarce tropical regions.

In conclusion, the LSTM model provides accurate and stable SST predictions for North Maluku, with error metrics (MAE 0.56°C, MAPE 2.09%) that are competitive with or better than those reported in similar studies. These results highlight the potential of LSTM-based bias correction for regional climate projections and its applicability in early warning systems and climate adaptation strategies.

4. CONCLUSION

This study successfully developed a Long Short-Term Memory (LSTM)-based model for predicting sea surface temperature (SST) in the North Maluku region, utilizing ERA5 reanalysis data as the reference and BNU-ESM climate model outputs as predictors to perform bias correction. The best-performing model, a single-layer LSTM with 80 epochs, a batch size of 1024, and a learning rate of 0.003, achieved a Mean Absolute Error (MAE) of 0.56°C, a Mean Squared Error (MSE) of 0.57, and a Mean Absolute Percentage Error (MAPE) of 2.09%. These results demonstrate high accuracy and stability in capturing SST temporal patterns, as evidenced by the model's ability to closely follow seasonal and long-term fluctuations in ERA5 data (Figure 4).

The significance of these findings lies in their potential to enhance climate resilience in North Maluku, a critical region within the Coral Reef Triangle vulnerable to climate-driven SST changes. The MAE of 0.56°C and MAPE of 2.09% are notably low, closely aligning with similar studies, such as (Wei et al., 2020), which reported an RMSE of 0.5°C for SST predictions in the China Seas, including tropical regions like the South China Sea. These

comparisons highlight the model's high precision, enabling its integration into early warning systems for climate-related events, such as extreme precipitation or ENSO-driven anomalies, which are critical for fisheries and marine ecosystems in Maluku Utara. For instance, accurate SST predictions can guide fishing communities in optimizing harvest schedules and support conservation efforts to mitigate coral bleaching risks, addressing urgent needs for food security and economic stability. Additionally, the model's bias correction approach enhances the usability of global climate model outputs, which often lack the resolution needed for local applications, as evidenced by its alignment of BNU-ESM data with high-resolution ERA5 observations (Tanto, 2020).

The potential for applying this LSTM-based bias correction method to other locations is promising, particularly in tropical coastal regions with similar oceanic and climatic characteristics. The model's success in North Maluku suggests its applicability to other parts of Indonesia or the Coral Reef Triangle, as supported by (Wei et al., 2020), who demonstrated consistent SST prediction accuracy across tropical and temperate zones in the China Seas. Similarly, (Tita Lattifia, Putu Wira Buana, 2022) reported a MAPE of 1.9499% for weather predictions in a tropical context, and (Andre & Handhayani, 2024) achieved a MAPE of 1.93%–2.51% for temperature predictions in Ternate, Maluku Utara, indicating that LSTM models can effectively capture temporal patterns in data-scarce tropical regions. (Akbar et al., 2023) further reinforce this by achieving an MAE of 0.65°C and MAPE of 2.3% for air temperature predictions in Semarang, suggesting generalizability within Indonesia's tropical climate. However, applying the method to non-tropical regions, such as temperate or polar areas, may require adjustments due to differing SST variability patterns. (Tanto, 2020) noted that SST estimation errors (e.g., RMSE 0.74°C) vary with regional oceanographic conditions like upwelling or currents, which differ from those in Maluku Utara. Moreover, the model's reliance on a single predictor (BNU-ESM SST) may limit its performance in regions with complex climatic drivers, necessitating the inclusion of additional variables like sea level pressure or wind speed, as recommended by (Akbar et al., 2023). Future research could validate the model's performance in diverse geographic contexts and explore hybrid architectures, such as CNN-LSTM, to enhance robustness across varied climatic conditions.

In summary, this study delivers a highly accurate and stable SST prediction model for North Maluku, with significant implications for climate adaptation in fisheries, marine conservation, and early warning systems. Its potential for application in other tropical regions underscores its value for data-scarce areas, provided that regional variations are addressed through tailored data inputs and model configurations.

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