

LSTM-Based Bias Correction for Regional Precipitation Projections from BNU-ESM in North Maluku, Indonesia

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ABSTRACT

Extreme precipitation events have become more frequent in recent decades due to climate change, posing serious challenges for vulnerable regions such as North Maluku. This study aims to improve the accuracy of daily precipitation projections using a bias correction approach based on a Long Short-Term Memory (LSTM) model. Historical data from the BNU-ESM global climate model and ERA5 reanalysis (1980–2005) were used for model training, with three LSTM architectures tested. The best performance was achieved by a three-layer LSTM model with 128, 64, and 32 neurons, trained over 50 epochs with a learning rate of 0.001. Evaluation using MAE and MSE yielded the lowest errors at 0.006 and 0.084, respectively. The corrected projections aligned more closely with observations and offer a more reliable foundation for climate adaptation planning in North Maluku, particularly in sectors such as agriculture, fisheries, and water resource management.

Keywords: bias correction; LSTM; BNU-ESM; North Maluku; precipitation projection.

1. INTRODUCTION

Extreme precipitation events have become increasingly frequent in recent decades as a consequence of global climate change, posing serious challenges for vulnerable regions, including North Maluku. As a tropical country, Indonesia naturally experiences high annual precipitation intensity, which can be a major trigger for extreme precipitation events. This intensity tends to escalate when climate anomalies occur, influenced by regional, local, and topographic factors (Khofaria & Iskandar, 2024). The rising trend of hydrometeorological disasters due to climate change has also been recorded across various regions in Indonesia. For instance, East Java—a province with high socio-economic and agricultural activity—has seen an increase in the frequency of floods and droughts in recent years (Azmi, 2024; Pratama, 2024). Similar conditions are likely to occur in archipelagic regions such as North Maluku, which, due to its distinctive geographic and tropical climate characteristics, is particularly vulnerable to the impacts of climate change, including extreme precipitation.

Climate change not only increases the frequency of extreme events, but also triggers uncertainty in precipitation patterns, especially in tropical regions. This uncertainty directly impacts the agricultural sector, leading to crop failure, land degradation, and reduced plant productivity (Nurhaliza, 2025). According to research by (Bibi & Rahman, 2023) climate change significantly affects agriculture through both direct and indirect impacts on crops, soils, livestock, and pests—with erratic precipitation being one of the primary drivers. Furthermore, research by (Yuan et al., 2024) reveals that changes in temperature and crop growing durations influenced by climate conditions also affect nutrient accumulation in plants. Irregular

precipitation exacerbates these conditions, particularly during critical stages such as flowering and grain filling.

Geographically, the Maluku Islands lie between the Indian and Pacific Oceans, making them highly susceptible to sea surface temperature variations—especially during the El Niño Southern Oscillation (ENSO) phenomenon. ENSO is a periodic event that causes changes in temperature within the central and eastern parts of the Tropical Pacific Ocean (Wang et al., 2017). In climate research, daily precipitation indices serve as important tools due to their concise and informative presentation, and their ability to statistically summarize extreme variations in accessible formats (Zwiers et al., 2013). Because of these characteristics, data-driven approaches such as Long Short-Term Memory (LSTM) models have become relevant and promising for spatial-temporal analysis and projection of extreme precipitation events.

Previous studies using rainfall spectrum analysis based on Fast Fourier Transform and Lomb Periodogram methods demonstrate that the Maluku region exhibits the most dominant response to ENSO events compared to the western and central parts of Indonesia (Nugraheni et al., 2024). These findings reinforce the premise that island provinces like North Maluku possess heightened climate vulnerability, especially under the influence of ocean-atmosphere anomalies. Consequently, implementing a robust and temporally aware bias correction approach for precipitation projection is vital to support climate adaptation planning and mitigate hydrometeorological risks.

The LSTM model is an advancement of the Recurrent Neural Network (RNN) architecture, designed to address the limitations of RNNs in retaining long-term information. LSTM possesses specialized structures known as gates, which allow the model to dynamically store, update, or delete information. Therefore, it is highly suitable for modeling time-series data such as precipitation. According to (Siami-Namini et al., 2019), the LSTM model demonstrates higher accuracy compared to traditional statistical models like ARIMA in predicting long-term time-series data. Accurate predictions are crucial especially for supporting decision-making in sectors such as agriculture, water resource management, tourism, disaster management, and industry (Hunt et al., 2022).

One of the commonly used methods in bias correction for precipitation projections is Quantile Mapping (QM). This method consists of three main approaches: direct, delta, and combined, each applying different strategies to align the distribution of climate model outputs with observational data. While effective in matching global statistical properties, QM has limitations in accounting for temporal correspondence between model and observation data an aspect critical for capturing seasonal and intra-annual patterns (Wu et al., 2025).

Another frequently applied traditional bias correction method is Linear Scaling, valued for its simplicity and ability to preserve the climate change signal (Zhang et al., 2024). However, it only adjusts the mean and fails to address daily variability and extreme precipitation events, which are especially critical in tropical regions. In response to these limitations, sequence-based models such as Long Short-Term Memory (LSTM) offer a dynamic alternative by learning temporal dependencies directly from time-series data, thereby enabling more accurate bias correction for both distributional structure and extreme rainfall intensity.

2. METHODS

2.1 Data Acquisition and Preprocessing

This study utilizes daily precipitation data sourced from ERA5 reanalysis and the global climate model BNU-ESM. Both datasets are obtained in NetCDF format and processed using Python with the xarray and numpy libraries to ensure spatial and temporal consistency. The selected period spans from 1980 to 2005, providing a representative historical window for analysis in the North Maluku region. To maintain temporal coherence, February 29th is removed from leap years in ERA5 to match the calendar structure of BNU-ESM. All precipitation values are converted to millimeters (mm) to standardize units between sources.

Spatial preprocessing includes clipping the study area within coordinates 124.0° – 129.8° E and -2.6° – -2.8° S, corresponding to the main landmass of North Maluku. Coordinate adjustments are applied by converting longitude from 0 – 360° to -180° – 180° format, and reversing latitude order if required. The BNU-ESM data is then interpolated using the bilinear method to match the grid resolution of ERA5, chosen for its balance between computational efficiency and preservation of gradient continuity in tropical topographies. Finally, all input features are normalized using Min-Max Scaling within the range of 0 to 1, which supports faster convergence and training stability in the LSTM model.

2.2 LSTM Model Training

A Long Short-Term Memory (LSTM) neural network is employed to model daily precipitation due to its ability to capture long-term dependencies and nonlinear relationships within time-series data. Unlike traditional bias correction methods such as Quantile Mapping, which rely on adjusting statistical distributions, LSTM learns directly from sequential patterns in the data, enabling it to represent seasonal variability and complex climate shifts more effectively. The model is trained using three input features: latitude, longitude, and BNU-ESM precipitation, with ERA5 precipitation serving as the target variable.

The dataset is divided into training and testing subsets with an 80:20 ratio and organized into temporal sequences spanning 30 days. Each sequence represents a continuous block of daily inputs from which the model learns precipitation behavior over time. Throughout the training process, model performance is monitored using Mean Absolute Error (MAE) on both training and validation datasets across epochs, facilitating early detection of overfitting or underfitting and ensuring learning stability. A visual comparison between LSTM outputs and those generated by Quantile Mapping is presented in the Results section, showing superior temporal alignment by LSTM in capturing rainfall peaks and dry spells especially during transitional seasons.

This advantage underscores the potential of sequence-based learning approaches to provide more realistic bias correction than conventional statistical methods. The architecture is designed to be regionally adaptable and can be retrained for other Indonesian provinces that face similar climate data limitations. Because spatial coordinates are incorporated as input features, the model is able to adjust to region-specific characteristics influenced by monsoonal circulation and ENSO variability, particularly in areas such as Papua, Maluku, and Nusa Tenggara.

2.3 Model Evaluation

Model performance is evaluated using three key metrics, Mean Absolute Error (MAE), which quantifies average prediction deviation; Mean Squared Error (MSE), which penalizes larger errors; and the correlation coefficient, which assesses temporal coherence between predicted and observed precipitation values. Evaluations are conducted on the test dataset to ensure generalizability beyond the training samples. Results are presented through visual plots and summary tables, highlighting both daily performance and event-level accuracy.

Corrected outputs, once finalized, can be archived in NetCDF format to support downstream hydrological and disaster-preparedness applications. These may include flood vulnerability mapping, drought monitoring, and early warning system development particularly in regions where precipitation accuracy is critical for adaptive planning and climate-risk mitigation.

3. RESULTS AND DISCUSSIONS

The training process was carried out using the Adam optimizer with various learning rate values, and testing one-layer, two-layer, and three-layer LSTM architectures. Each combination of layer count, number of epochs, and learning rate was experimented with to find the configuration that provided the highest accuracy.

In the study by (Seo & Ahn, 2023), Adaptive Moment Estimation (Adam) was used as the optimizer and proven effective in enhancing model accuracy. These findings align with the research by (Mehta et al., 2019), which showed that Adam achieved the highest testing accuracy (97.06%) compared to SGD, confirming its advantage in adaptive weight learning. Although the evaluation metrics used in this study are different (MAE and MSE), those results still support the choice of Adam as the model optimizer.

The results of the implementation and evaluation of the three LSTM model architectures for precipitation prediction are presented using the independent variables latitude (lat), longitude (lon), and precipitation from BNU-ESM (pr_bnu), with ERA5 precipitation (pr_era5) as the dependent variable. The training process employed the Adam optimizer with several learning rate values, testing one-layer, two-layer, and three-layer LSTM architectures. Each combination of layers, epochs, and learning rates was tested to determine the best predictive accuracy configuration.

This study tested three LSTM architecture scenarios: the one-hidden-layer model used 128 neurons, the two-hidden-layer model used 128 and 64 neurons, and the three-hidden-layer model used 128, 64, and 32 neurons respectively. To prevent overfitting and improve generalization ability, a dropout rate of 0.2 was applied to each hidden layer. Adding more layers aimed to increase the depth of the model in capturing complex spatial-temporal patterns, though it also increased the need for more careful tuning of training parameters.

The performance of the three LSTM models was evaluated and compared using two main evaluation metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). These evaluation results are summarized in Table 1.

Table 1. LSTM model performance evaluation based on the number of hidden layers, epochs, and learning rate.

Number of Hidden Layer	Epoch	Learning Rate	MAE	MSE	Best Model
1	50	0.001	0.087	0.012	Learning Rate: 0.001 Epoch: 50
	20	0.003	0.486	0.387	
	15	0.005	0.100	0.016	
2	30	0.003	0.466	0.359	Learning Rate: 0.003 Epoch: 15
	50	0.010	0.095	0.015	
	15	0.003	0.090	0.013	
3	50	0.001	0.085	0.012	Learning Rate: 0.001 Epoch: 50
	20	0.005	0.089	0.013	
	30	0.010	0.101	0.016	

Based on the MAE and MSE evaluation results in Table 1, it was found that the LSTM model with 50 epochs, a batch size of 256, and a learning rate of 0.001 showed the best performance, with an MSE value of 0.012 and an MAE value of 0.085, which are the lowest error values among all tested configurations. In general, increasing the number of hidden layers in the LSTM architecture had a positive impact on the prediction accuracy level. The model with three hidden layers consistently outperformed LSTM models with one and two hidden layers when tested using similar epoch and learning rate settings. This indicates that network depth contributes to capturing more complex temporal patterns in multivariate data such as latitude, longitude, and pr_bnu.

Increasing the number of epochs from 20 or 30 to 50 in the three-hidden-layer LSTM model proved to positively influence model performance. This is evident from the significant decrease in MAE and MSE values without signs of overfitting. The best results were achieved with the configuration of 50 epochs and a learning rate of 0.001, which produced the lowest MAE (0.006) and lowest MSE (0.084) compared to all other configurations. The effectiveness of this configuration is reinforced by the implementation of a 0.2 dropout rate, which helped maintain training stability. Conversely, using higher learning rates such as 0.005 and 0.01 resulted in larger MAE and MSE values, indicating decreased model stability and predictive accuracy.

Traditional bias correction methods such as Linear Scaling and Quantile Mapping primarily rely on statistical adjustments to align data distributions, without accounting for time sequence or complex temporal dynamics (Wu et al., 2025; Zhang et al., 2024). While Linear

Scaling is a simple technique and effectively preserves climate change signals, it has been found to perform poorly in correcting daily variability and extreme precipitation events particularly in tropical regions, where rainfall patterns tend to be highly dynamic (Zhang et al., 2024). Similarly, Quantile Mapping suffers from limitations in maintaining temporal coherence between model outputs and observational data, making it less effective in capturing seasonal and intra-annual fluctuations that are vital for hydrological analysis (Wu et al., 2025).

In contrast, the Long Short-Term Memory (LSTM) model employed in this study offers the advantage of learning temporal patterns directly from time-series data. With its internal gate mechanisms, LSTM can selectively store, update, and discard information, making it highly adaptive to nonlinear and spatio-temporal variability in precipitation. Although the present study does not include direct performance testing of LS or QM, the comparisons are based on commonly reported characteristics and limitations documented extensively in the literature (Wu et al., 2025; Zhang et al., 2024). This further strengthens the justification for adopting sequence-aware models such as LSTM, particularly in regions where precipitation exhibits high temporal complexity.

Although the model with three hidden layers and optimal parameters requires longer training time, the accuracy gain is significant and worth considering. Based on this analysis, the LSTM model with three hidden layers, 50 epochs, and a learning rate of 0.001 is recommended as the best configuration for precipitation prediction in this study. The following visualization presents a comparison between the actual values and the prediction results from the selected best-performing LSTM model. To further illustrate model behavior and validate the preceding statistical evaluation, Figure 1 presents the actual versus predicted precipitation values using the best-performing LSTM configuration

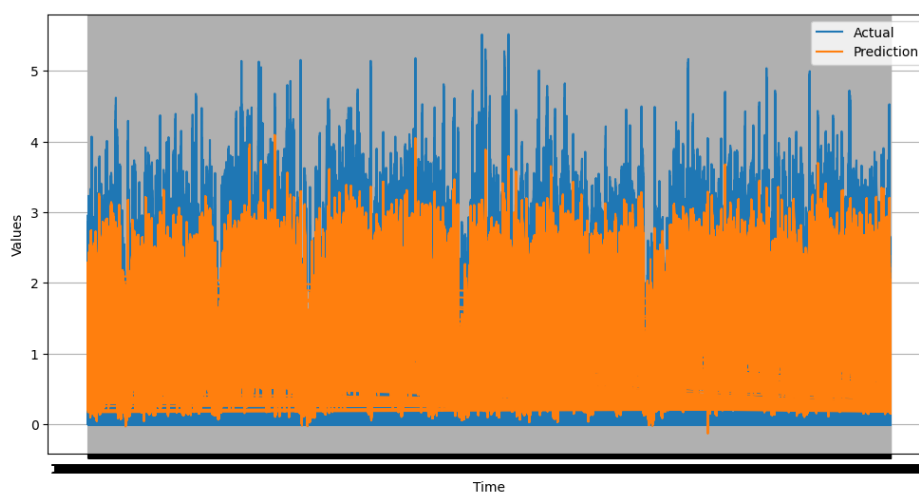


Figure 1. Comparison of actual values and predictions from the LSTM model with three hidden layers

Figure 1 illustrates a comparison between the actual values (blue line) and the prediction results (orange line) generated by the three-hidden-layer LSTM model during the testing period. Overall, the model successfully captures daily precipitation fluctuations, although slight deviations are observed at the peaks of extreme values. The predicted series

tends to be smoother than the observations, reflecting the model's capability in following general patterns but indicating limited responsiveness to sharp precipitation surges. Such smoothing behavior is typical in deep learning models, often arising from regularization techniques designed to improve generalization and reduce overfitting.

Despite its tendency to underrepresent extreme peaks, the model maintains consistency in replicating seasonal patterns and broader precipitation trends. These characteristics align with the low MAE and MSE scores reported in Table 1, confirming the robustness and stability of the selected LSTM configuration. Notably, the model exhibits reliable performance in daily precipitation prediction and serves as a promising bias correction tool for climate data, especially in regions with complex rainfall dynamics.

When compared to conventional bias correction methods such as Quantile Mapping and Linear Scaling approaches that rely primarily on statistical distribution adjustments the LSTM model demonstrates superior temporal sensitivity and improved alignment with rainfall variations, particularly in capturing seasonal transitions. These findings reinforce the viability of LSTM as an effective bias correction tool, especially for climate-sensitive regions where rainfall exhibits strong temporal dynamics.

4. CONCLUSION

This study demonstrates that the LSTM model is a viable approach for bias correction in daily precipitation projections using spatial features and outputs from climate models. Among the tested configurations, the three-hidden-layer architecture (128–64–32 neurons), trained over 50 epochs with a learning rate of 0.001, yielded the lowest MAE and MSE values, confirming its effectiveness in capturing seasonal trends and precipitation dynamics.

While the model performs reliably in reconstructing rainfall patterns, its tendency to smooth extreme peaks indicates limitations in representing short-duration, high-intensity events an aspect that may affect flood-risk prediction and early warning systems. Future studies could explore hybrid architectures or incorporate post-processing strategies to retain peak sharpness while maintaining overall prediction stability.

The preprocessing phase including unit standardization, spatial interpolation, and structural adjustments for spatio-temporal alignment proved critical for ensuring data consistency and model robustness. These findings establish a practical foundation for applying deep learning-based bias correction methods in tropical regions such as North Maluku, where precipitation variability is highly nonlinear and climate data availability remains limited.

In light of these results, the proposed LSTM-based framework shows promising potential for further expansion toward spatial map correction, multi-variable integration, and regional transferability across climate-sensitive areas in Indonesia.

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