International Journal of Simulation, Optimization & Modelling
ISSN: 3083-967X

Journal homepage: https://e-journal.scholar-publishing.org/index.php/ijsom

Development and Evaluation of an LSTM-Based Rainfall Prediction System at the Class I Sultan Iskandar Muda Meteorological Station, Banda Aceh

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Abstract

Rainfall is a key meteorological variable that influences agriculture, water resource management, transportation, and hydrometeorological disaster risk reduction. This study analyses historical rainfall patterns and evaluates the performance of a Long Short-Term Memory (LSTM) model for monthly rainfall prediction at the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. Meteorological observation data were processed through several stages, including data cleaning, missing-value treatment, normalisation, model training, and performance evaluation. Model accuracy was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results show that the LSTM model captures the general temporal pattern of rainfall but produces substantial deviations during periods of exceptionally low or high rainfall. A web-based dashboard was also developed to support meteorological data management, analysis, visualisation, and the presentation of prediction results. The dashboard provides statistical summaries, monthly rainfall trends, rainfall-intensity distributions, and other supporting features that enable efficient monitoring and interpretation of rainfall conditions. These findings contribute to the development of data-driven rainfall prediction systems and provide a basis for supporting meteorological decision-making and hydrometeorological disaster risk reduction in Banda Aceh.

Article Info
Received: 15 June 2026
Revised: 14 July 2026
Accepted: 18 July 2026
Available online: 19 July 2026

Keywords
Rainfall prediction
Long Short-Term Memory
Meteorological data
Web-based dashboard
Hydrometeorological disaster mitigation

1. Introduction

Rainfall is a fundamental component of the hydrological cycle and a major meteorological variable affecting environmental processes and socioeconomic activities. Its amount, intensity, duration, and temporal distribution influence agricultural production, freshwater availability, reservoir operation, transportation, urban drainage, hydroelectric power generation, and ecosystem functioning. Prolonged rainfall deficits may cause drought and water scarcity, whereas intense rainfall can trigger flooding, landslides, infrastructure disruption, and other hydrometeorological hazards. Reliable rainfall information is therefore needed not only for

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routine weather monitoring but also for resource allocation, early warning, disaster preparedness, and climate-resilient development. The increasing impacts of climate-related hazards across Asia have strengthened the need for observation-based forecasting systems that can translate meteorological records into accessible, decision-relevant information (World Meteorological Organisation [WMO], 2021, 2025).

Rainfall prediction in Indonesia is particularly challenging because the country is located within the Maritime Continent, where atmospheric and oceanic processes interact across multiple spatial and temporal scales. Indonesian rainfall is influenced by the Asian–Australian monsoon, seasonal migration of tropical convection, the El Niño–Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), and intraseasonal variability associated with the Madden–Julian Oscillation (MJO). These large-scale mechanisms interact with complex coastlines, mountainous terrain, land–sea thermal contrasts, and local wind circulation, producing substantial differences in rainfall seasonality among regions (Aldrian & Susanto, 2003; Chang et al., 2005; Hamada et al., 2002; Hendon, 2003; Qian, 2008). ENSO and IOD can alter seasonal rainfall totals and the occurrence of rainfall extremes, while the MJO can modulate short-term precipitation intensity and frequency across western and central Indonesia (Kurniadi et al., 2021; McPhaden et al., 2006; Muhammad et al., 2021; Saji et al., 1999). The combined effects of these processes create nonlinear, nonstationary, and highly variable rainfall time series that are difficult to represent using simple predictive relationships.

Banda Aceh and the surrounding Aceh Besar region experience rainfall variability due to their position at the northern end of Sumatra and their proximity to the Indian Ocean, the Strait of Malacca, and the surrounding regional seas. The Class I Sultan Iskandar Muda Meteorological Station provides an important long-term observational record representing the climatic conditions of Banda Aceh and northern Aceh Besar. Previous studies have identified temporal changes in local rainfall patterns, dry spells, and temperature characteristics, as well as varying responses to ENSO and IOD events (Ferijal & Fauzi, 2024; Ilhamsyah et al., 2019; Jannah et al., 2024). Research conducted in Aceh has also shown that satellite-derived rainfall estimates do not consistently reproduce station observations across seasons and elevations, reinforcing the importance of quality-controlled ground measurements for local analysis (Sahlan et al., 2024). Intraseasonal atmospheric variability may also increase the probability of extreme rainfall and flooding in parts of Aceh (Qalbi et al., 2024). These findings indicate that rainfall prediction models developed for other climatic regions may not be directly transferable to Banda Aceh without site-specific training and evaluation.

Conventional statistical forecasting methods remain useful when rainfall time series exhibit relatively stable trends, seasonality, and linear relationships. Their performance may, however, decline when the data contain nonlinear interactions, abrupt fluctuations, long-term temporal dependencies, and extreme observations. Machine-learning and deep-learning methods offer an alternative because they can identify complex relationships directly from historical data without requiring explicit representation of all atmospheric processes. Long Short-Term Memory (LSTM), a recurrent neural network architecture introduced by Hochreiter and Schmidhuber (1997), uses memory cells and gating mechanisms to retain or discard information over sequential observations. This structure reduces the vanishing-gradient problem commonly encountered in conventional recurrent neural networks and allows the model to learn both short- and long-term dependencies. LSTM-based approaches have subsequently been applied to precipitation nowcasting, rainfall–runoff modeling, and meteorological time-series forecasting (Barrera-Animas et al., 2022; Kratzert et al., 2018; Shi et al., 2015).

Recent studies have demonstrated that LSTM and its modified architectures can produce useful monthly and short-term precipitation forecasts. Multiscale decomposition, attention

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mechanisms, bidirectional structures, and hybrid forecasting models have been introduced to improve the representation of seasonal patterns and nonlinear rainfall fluctuations (Barrera-Animas et al., 2022; Jiang, 2023; Tao et al., 2021). Despite these advances, rainfall prediction remains sensitive to the length and quality of the historical record, preprocessing procedures, predictor selection, temporal resolution, model configuration, and the frequency of extreme events. Models that reproduce average seasonal behaviour may still underestimate major rainfall peaks or overestimate rainfall during dry periods. These limitations are particularly relevant to station-scale prediction in tropical regions, where rainfall distributions are often highly skewed and contain many observations near zero. A locally trained and transparently evaluated model is therefore needed to determine whether LSTM can adequately represent monthly rainfall variability at the Sultan Iskandar Muda Meteorological Station.

Predictive accuracy should be assessed using complementary performance measures because no single statistic fully captures model error. Mean Absolute Error (MAE) expresses the average magnitude of deviations in the original measurement unit, whereas Root Mean Square Error (RMSE) assigns greater weight to large errors and is useful for identifying substantial departures between observed and predicted rainfall. Mean Absolute Percentage Error (MAPE) provides a relative measure that is easier to interpret across scales, although it can become unstable when observed rainfall values are zero or close to zero. The simultaneous interpretation of these metrics provides a more balanced assessment than reliance on a single indicator (Chai & Draxler, 2014; Hyndman & Koehler, 2006). From an applied perspective, numerical predictions also need to be organised in a form that supports data inspection and interpretation. Integrating the forecasting model with a web-based dashboard can consolidate data management, statistical summaries, historical trend visualisation, prediction results, and model evaluation into a single platform.

This study specifically aims to analyse historical monthly rainfall patterns, develop an LSTM-based rainfall prediction model, and evaluate its predictive performance using MAE, RMSE, and MAPE at the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. It also aims to implement the model within a web-based dashboard that supports meteorological data management, rainfall visualisation, prediction generation, and communication of model performance. The novelty of the study does not lie in proposing a new LSTM architecture; rather, it lies in developing a location-specific, end-to-end prediction framework that integrates data preprocessing, temporal modelling, multi-metric performance evaluation, and interactive web-based visualisation for a meteorological station in northern Sumatra. This integration provides a practical link between predictive modelling and local rainfall monitoring, with potential applications in environmental planning, water resource management, and hydrometeorological disaster risk reduction in Banda Aceh.

2. Methodology

2.1 Research Design and Workflow

This study employed a quantitative time-series modelling approach to develop and evaluate a Long Short-Term Memory (LSTM)-based system for monthly rainfall prediction at the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. The research framework comprised five interconnected stages: meteorological data collection, data preprocessing and exploratory analysis, LSTM model development, predictive performance evaluation, and implementation of the model within a web-based dashboard. This framework was designed to integrate rainfall forecasting, model assessment, data management, and interactive visualisation within a unified system.

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2.2 Data Collection and Preliminary Analysis

The primary dataset consisted of historical meteorological observations from the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. Monthly rainfall was defined as the target variable, while available supporting meteorological variables relevant to rainfall formation were included according to their completeness and consistency. Before model development, the observations were arranged chronologically and examined to identify duplicate records, missing values, inconsistent timestamps, implausible measurements, and potential recording errors. Descriptive statistical analysis and time-series visualisation were also performed to examine rainfall distribution, seasonal variation, temporal fluctuations, and the occurrence of exceptionally low or high rainfall.

2.3 Data Preprocessing

Data preprocessing involved data cleaning, handling missing values, normalisation, and transforming the observations into sequential input–output samples. Duplicate and inconsistent records were corrected or removed, while missing observations were treated using an interpolation procedure to maintain the continuity of the time series. Potentially anomalous values were examined by comparing them with temporally adjacent observations before correction or exclusion, to avoid removing valid extreme rainfall events.

Because the meteorological variables were recorded on different numerical scales, Min–Max normalisation was applied to transform each continuous variable to a range from 0 to 1. The normalisation procedure was expressed as follows:

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}},$$

where x_{norm} represents the normalised value, x is the original observation, and x_{min} and x_{max} denote the minimum and maximum values of the corresponding variable. The normalisation parameters derived from the training dataset were subsequently applied to the testing dataset to prevent information from the testing period from influencing model development. Following normalisation, the chronologically ordered observations were transformed into time-sequence samples in which rainfall conditions from preceding periods were used to predict rainfall for the subsequent month.

2.4 Dataset Partitioning

The processed dataset was divided chronologically into training and testing subsets to preserve the temporal structure of the rainfall series. The training subset was used to estimate the model parameters and learn temporal relationships within the historical observations. The testing subset was reserved for evaluating the model's ability to predict rainfall values that were not included during training. Chronological partitioning was preferred over random sampling because time-series forecasting must preserve the natural order of observations and prevent future information from entering the model training process. This procedure provides a more realistic assessment of model performance under operational forecasting conditions.

2.5 LSTM Model Development

The rainfall prediction model was developed using the LSTM architecture, a recurrent neural network designed to process sequential and time-dependent data. Unlike conventional recurrent neural networks, LSTM uses memory cells and three primary gating mechanisms—the input, forget, and output gates—to regulate the retention, removal, and transmission of information across consecutive time steps. These mechanisms enable the model to learn both

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short-term fluctuations and longer-term temporal dependencies in historical rainfall records while mitigating vanishing-gradient problems.

The input layer received sequences of normalised historical meteorological observations, while the output layer generated a one-step-ahead prediction of monthly rainfall. During training, the model parameters were iteratively adjusted to minimise the difference between the observed and predicted rainfall values. Model configuration involved determining the input sequence length, the number of LSTM layers and units, activation functions, learning rate, batch size, number of training epochs, and regularisation settings. The selected configuration was retained during final testing to ensure that the evaluation represented the model's performance on previously unseen observations.

2.6 Model Performance Evaluation

The predictive performance of the LSTM model was evaluated by comparing predicted monthly rainfall with the corresponding observed values. Three complementary error metrics were employed: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were calculated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|,$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2},$$

and

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|,$$

where y_i denotes the observed rainfall value, $y\hat{}_i$ represents the predicted rainfall value, and n is the number of observations in the testing dataset. MAE was used to measure the average absolute magnitude of prediction errors, while RMSE assigned greater weight to large deviations between observed and predicted rainfall. MAPE expressed the prediction error as a percentage of the observed value. Because MAPE can become unstable when actual rainfall values approach zero, its results were interpreted together with MAE and RMSE rather than as an independent measure of model accuracy. Graphical comparisons between observed and predicted rainfall were also used to assess the model's ability to reproduce seasonal patterns, rainfall peaks, and low-rainfall periods.

2.7 Web-Based System Implementation

Following model development and evaluation, the trained LSTM model was integrated into a web-based rainfall prediction system. The dashboard was designed to support meteorological data uploading, database management, historical rainfall analysis, prediction generation, and visualisation of model outputs. It presented statistical summaries, monthly rainfall trends, rainfall-intensity distributions, and comparisons between observed and predicted rainfall. The system also provided supporting modules for managing observation locations, environmental parameters, graphical outputs, and administrative functions. Integrating the prediction model with the dashboard enabled users to access rainfall information and interpret model performance through a single interface, thereby supporting meteorological monitoring and hydrometeorological risk-management activities in Banda Aceh.

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3. Result & Discussion

This section presents and discusses the performance of the developed LSTM-based rainfall prediction system, evaluated on historical meteorological data from the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. The analysis focuses on the system's ability to reproduce monthly rainfall patterns, the agreement between observed and predicted rainfall values, and model accuracy based on MAE, RMSE, and MAPE. The functionality of the web-based dashboard is also evaluated in terms of its capacity to manage meteorological data, display statistical summaries, visualise rainfall trends and intensity distributions, and communicate prediction results. The findings are interpreted by considering the temporal variability of rainfall and the model's ability to represent moderate conditions and extreme rainfall events, thereby providing an assessment of its practical value and current limitations for rainfall monitoring and hydrometeorological risk management in Banda Aceh.
Fig. 1 presents the administrator dashboard of the developed rainfall prediction system, which integrates meteorological data management, analysis, prediction, and visualisation within a single web-based interface. The dashboard provides access to several functional modules, including data uploading, rainfall analysis, prediction generation, gallery management, user profiles, and spatial mapping. Four summary indicators show that the system contains six uploaded datasets, 4,213 meteorological records, 27 available parameters, and six observation locations. These indicators allow administrators to assess the availability and completeness of the data before conducting further analysis or generating rainfall predictions. The integrated design improves operational efficiency by reducing the need to use separate applications for data storage, statistical analysis, and visualisation.

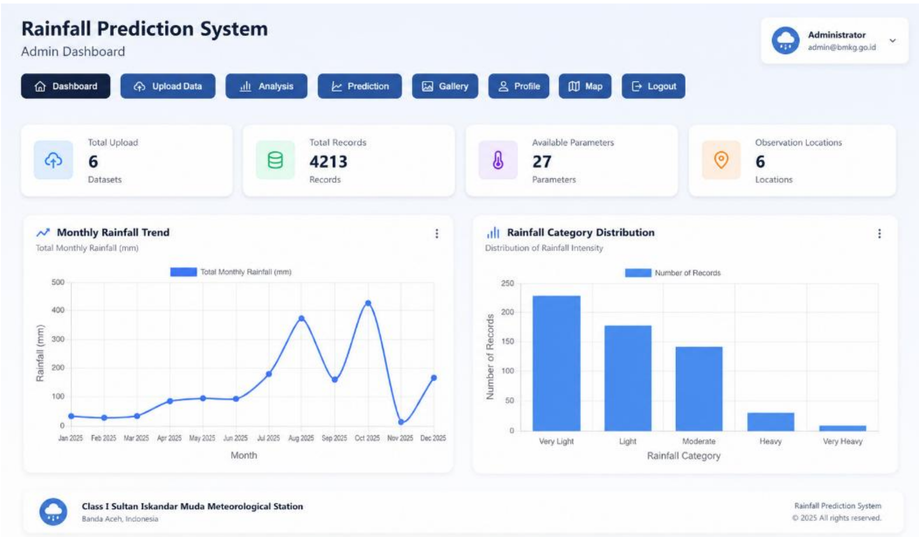

Fig. 1. Administrator Dashboard of the Rainfall Prediction System

The graphical components provide an overview of temporal rainfall variation and the frequency distribution of rainfall-intensity categories. The monthly rainfall trend indicates relatively low rainfall during the first months of 2025, followed by a gradual increase and pronounced peaks around August and October. A sharp decline is observed in November, followed by an increase in rainfall in December, demonstrating substantial monthly variability at the Class I Sultan Iskandar Muda Meteorological Station. The rainfall-category distribution shows that very light and light rainfall events dominate the observation records, while heavy and very heavy rainfall occur less frequently. Although extreme rainfall events represent a smaller proportion of the dataset, their potential hydrometeorological impacts remain substantial. Therefore, the

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dashboard provides a practical tool for identifying seasonal rainfall patterns, monitoring rainfall intensity, and interpreting prediction results to support environmental management and disaster-risk reduction.

Table 1. Comparison of Actual and Predicted Rainfall

Period	Actual Rainfall (mm)	Predicted Rainfall (mm)
2026-01	44.0	77.80
2026-02	36.8	89.60
2026-03	15.6	64.53
2026-04	50.0	32.13
2026-05	167.0	34.13
2026-06	58.6	77.53
2026-07	127.2	91.87

Table 1 compares the observed and predicted monthly rainfall from January to July 2026. The results show that the model reproduces the general month-to-month variation but does not consistently match the magnitude of the observed rainfall. Rainfall was overestimated in January, February, and March by 33.80, 52.80, and 48.93 mm, respectively. The model also overestimated rainfall in June by 18.93 mm. In contrast, rainfall was underestimated in April, May, and July. The smallest absolute difference occurred in April, when the observed rainfall was 50.0 mm, and the predicted value was 32.13 mm, whereas June also showed relatively close agreement between the observed and predicted values. These results suggest that the model performs more consistently during months with moderate rainfall.
The largest prediction error occurred in May, when the observed rainfall increased sharply to 167.0 mm, while the model predicted only 34.13 mm, resulting in an underestimation of 132.87 mm. A substantial difference was also observed in July, when the predicted rainfall was 91.87 mm compared with an actual value of 127.2 mm. Overall, the predicted values varied within a narrower range than the observed rainfall, indicating that the model tended to smooth temporal fluctuations, overestimate relatively dry periods, and underestimate high-rainfall events. This pattern suggests that the LSTM model captured the central tendency of the rainfall series more effectively than sudden or extreme changes. Improving its performance may require a longer historical dataset, additional meteorological predictors, and further optimisation of the model architecture and training parameters.

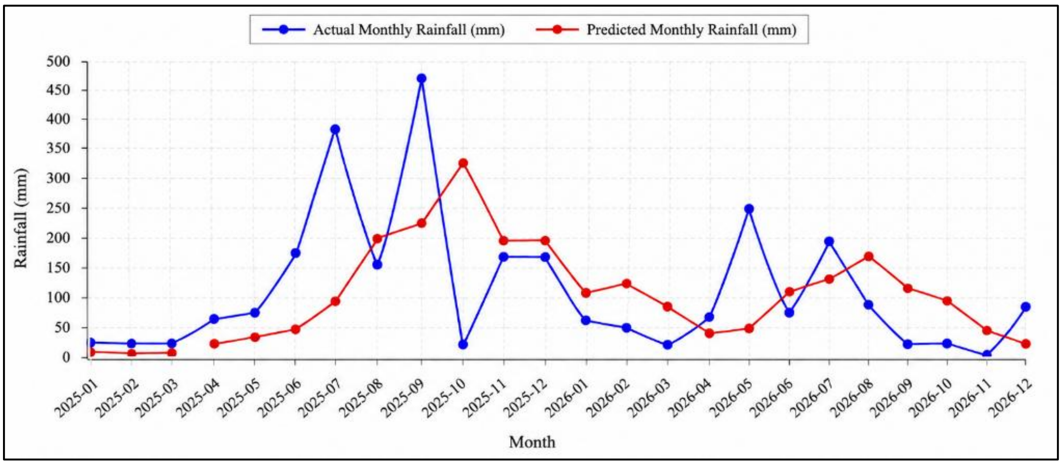

Fig 2. Comparison of Actual and Predicted Monthly Rainfall

Fig. 2 compares the observed monthly rainfall with the values predicted by the LSTM model from January 2025 to December 2026. The observed series exhibits pronounced temporal variability, with relatively low rainfall during the first quarter of 2025, followed by a gradual increase from April to June. Rainfall then rises sharply to approximately 380 mm in July 2025, decreases to about 155 mm in August, and reaches the highest observed value of approximately 470 mm in September. This peak is

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followed by an abrupt decline to around 20 mm in October before rainfall stabilises at approximately 170 mm in November and December. During 2026, the observed rainfall generally remains lower but continues to fluctuate considerably, including a marked increase to approximately 250 mm in May and another peak of nearly 200 mm in July. Rainfall subsequently declines, reaching its lowest level in November 2026, before increasing again in December. These variations demonstrate the irregular and highly dynamic character of monthly rainfall at the Class I Sultan Iskandar Muda Meteorological Station.

The predicted rainfall series follows some of the broader temporal changes but is considerably smoother than the observed series. The model generally reproduces the increase in rainfall in mid-2025 and predicts its peak in October 2025 at approximately 325 mm. However, the predicted peak occurs one month later than the largest observed peak in September, indicating a possible temporal lag in the model response. The model also substantially underestimates the extreme rainfall recorded in July and September 2025, while overestimating rainfall during the sharp decline in October. A similar pattern is evident in 2026: the model underestimates the observed rainfall peaks in May and July but overestimates rainfall during several relatively dry months, particularly January–March and September–November. The narrower range of predicted values suggests that the LSTM model tends to regress toward average rainfall conditions rather than reproduce abrupt extremes. Although the model captures the general seasonal movement of the rainfall series, its limited ability to represent sudden peaks and rapid declines suggests that additional meteorological predictors, longer input sequences, model architecture optimisation, or greater weighting of extreme events may be required to improve predictive accuracy.

Table 2. Performance Evaluation Metrics of the Proposed LSTM Model

Evaluation Metric	Value	Unit	Description
MAE (Mean Absolute Error)	59.67	mm	Measures the average absolute deviation between the predicted and observed rainfall values.
RMSE (Root Mean Square Error)	79.47	mm	Assigns greater weight to larger prediction errors, making it sensitive to significant deviations.
MAPE (Mean Absolute Percentage Error)	126.05	%	Measures the prediction error as a percentage of the observed rainfall values.

Table 2 summarises the predictive performance of the proposed LSTM model, as measured by MAE, RMSE, and MAPE. The MAE value of 59.67 mm indicates that the predicted monthly rainfall differed from the corresponding observed values by an average of approximately 59.67 mm. This magnitude of error suggests that the model can represent the general temporal behaviour of rainfall but does not consistently reproduce observed rainfall amounts with high precision. The RMSE value of 79.47 mm is substantially higher than the MAE, indicating that several prediction errors were considerably larger than the average deviation. Because RMSE assigns greater weight to large residuals, the difference between these two metrics indicates that the model struggled during months with abrupt increases or decreases in rainfall. This result is consistent with the comparison between the actual and predicted series, in which extreme rainfall peaks were generally underestimated, while rainfall during several relatively dry periods was overestimated.

The MAPE value of 126.05% further indicates a high relative prediction error and limited forecasting accuracy across the evaluation period. A percentage error exceeding 100% means that, on average, the absolute prediction error was greater than the magnitude of the observed rainfall values. However, this result should be interpreted with caution because MAPE is highly sensitive to observations with very low or near-zero rainfall, where even moderate absolute differences can yield extremely large percentage errors. Taken together, the three evaluation metrics show that the LSTM model is more effective at identifying broad rainfall trends than at accurately estimating monthly rainfall magnitudes, particularly under extreme or low-rainfall conditions. Model performance could be improved by expanding the training dataset, incorporating additional predictors such as temperature, humidity, atmospheric pressure, wind speed, ENSO, and IOD indices, and optimising the sequence length, network architecture, loss function, and hyperparameters. Future evaluations should also consider

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additional metrics, such as the coefficient of determination, Nash–Sutcliffe efficiency, or symmetric MAPE, to provide a more balanced assessment of predictive performance.

The novelty of this study lies in the development of a location-specific, end-to-end rainfall prediction system that integrates historical meteorological data processing, LSTM-based monthly rainfall forecasting, multi-metric performance evaluation, and web-based visualisation for the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. Unlike studies that focus solely on predictive accuracy or model development, this research integrates data management, temporal rainfall analysis, prediction generation, and interactive presentation into a single operational platform. The system also provides a practical assessment of the model's ability to capture rainfall variability under moderate and extreme conditions using MAE, RMSE, and MAPE. This integrated approach offers a more applicable framework for station-scale rainfall monitoring and supports local decision-making in water resource management, environmental planning, and hydrometeorological disaster risk reduction.

4. Conclusion

This study developed a location-specific, web-based rainfall prediction system that integrates meteorological data management, monthly rainfall forecasting, model evaluation, and interactive visualisation within a unified platform. The system employed a Long Short-Term Memory (LSTM) model trained using historical meteorological observations from the Class I Sultan Iskandar Muda Meteorological Station in Banda Aceh. By combining data processing, temporal modelling, and visualisation, the developed system provides an integrated framework for examining historical rainfall variability and presenting prediction results in an accessible format. The findings indicate that the LSTM model reproduced the general temporal pattern and seasonal movement of monthly rainfall. However, substantial discrepancies remained between the observed and predicted values, particularly during periods of exceptionally high or low rainfall. The model tended to smooth abrupt temporal fluctuations, underestimate major rainfall peaks, and overestimate rainfall during several relatively dry periods. The recorded MAE of 59.67 mm and RMSE of 79.47 mm indicate considerable differences between the predicted and observed rainfall values, while the MAPE of 126.05% reflects a high relative prediction error. The MAPE result should nevertheless be interpreted with caution, as this metric is sensitive to observed rainfall values near zero. Overall, the model was more effective in representing broad rainfall trends than in accurately estimating the magnitude of extreme rainfall events.

The web-based dashboard complements the prediction model by providing statistical summaries, monthly rainfall trends, rainfall-intensity distributions, and comparisons between observed and predicted values. Its integrated structure facilitates meteorological data organisation, model assessment, and interpretation of rainfall conditions without requiring separate analytical applications. The main contribution of this study is therefore the development of an end-to-end, station-scale framework that connects LSTM-based rainfall prediction with data management and interactive visualisation. Although the system requires further validation before operational use, it has the potential to support BMKG, local government institutions, disaster management agencies, and other stakeholders involved in water resource planning, agricultural management, flood preparedness, and hydrometeorological risk reduction in Banda Aceh. Several limitations should be considered when interpreting the findings. The model relied primarily on historical rainfall observations, although atmospheric, oceanic, and regional climatic processes also govern rainfall variability. The absence or limited inclusion of variables such as air temperature, relative humidity, atmospheric pressure, wind speed and direction, sea surface temperature, ENSO, IOD, and the Madden–Julian Oscillation may have constrained the model's ability to represent complex rainfall-generating mechanisms. Model performance may also have been affected by the dataset's length and distribution, the limited occurrence of extreme events in the training data, and the selected LSTM architecture and hyperparameters.

Future research should expand the dataset's temporal coverage, incorporate additional meteorological and climate predictors, and compare the LSTM model with alternative machine-learning, deep-learning, and hybrid forecasting approaches. Greater attention should also be given to hyperparameter optimisation, uncertainty quantification, extreme-event prediction, and evaluation metrics that are less sensitive to near-zero observations. Further development of the dashboard could include automatic

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synchronisation with observation stations, real-time data processing, geospatial rainfall mapping, probabilistic forecasts, early-warning functions, and mobile access. These improvements could strengthen the system's accuracy, operational relevance, and transferability to other regions with similar tropical rainfall characteristics.

Acknowledgement

The authors gratefully acknowledge the Class I Sultan Iskandar Muda Meteorological Station, Banda Aceh, for providing the meteorological data used in this study. The authors also extend their appreciation to all individuals and institutions whose support and contributions facilitated the completion of this research.

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