



# Multivariate Time-Series Flood Prediction Using LSTM Networks and GIS-Based Visualization of Meteorological Data from BMKG

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**Abstract.** Accurate and timely flood forecasting is essential for reducing socio-economic losses in coastal urban areas. This study proposes a multivariate time-series forecasting framework for predicting short-term rainfall intensity as an indicator of potential flooding in Baubau City, Southeast Sulawesi. The research utilizes fifteen years (2009-2024) of local meteorological data obtained from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG). A deep learning approach based on Long Short-Term Memory (LSTM) and hybrid CNN-LSTM architectures is employed to capture temporal dependencies among multiple atmospheric variables, enabling 1-7 day ahead rainfall forecasts. The modeling process includes systematic data cleaning, normalization, and temporal feature extraction to enhance predictive accuracy. The performance of the proposed framework is evaluated against conventional statistical and machine-learning baselines using standard error metrics and efficiency coefficients. Furthermore, the forecasting results are spatially integrated within QGIS to generate flood-risk maps, facilitating visual interpretation and decision-making support for local disaster management authorities. Experimental results demonstrate that the LSTM-based model effectively captures complex temporal interactions in the meteorological dataset, outperforming baseline models in both accuracy and reliability. This integration of deep learning and GIS provides a practical, data-driven foundation for improving flood early-warning systems and strengthening adaptive planning in coastal regions.

**Keywords:** BMKG Meteorological Data, Deep Learning, Flood Forecasting, GIS Visualization, LSTM Networks.

## 1 Introduction

This Flooding is one of the most recurrent natural hazards in coastal urban areas, leading to substantial socio-economic losses, infrastructure damage, and environmental degradation. Indonesia, as an archipelagic country with extensive coastlines, experiences frequent flood events driven by complex interactions between rainfall variability, tidal influence, and land-use change [1, 2]. Baubau City, located in Southeast Sulawesi, is particularly vulnerable due to its coastal setting, river crossings, and rapid urban expansion, which increase surface runoff and flood exposure.

Traditional flood forecasting and early warning systems commonly rely on statistical models or threshold-based monitoring techniques. Although effective for basic analysis, these approaches often fail to capture non-linear dynamics and long-term temporal dependencies inherent in high-resolution hydrometeorological time-series data [3, 4]. The increasing availability of continuous observations from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) provides an opportunity to apply data-driven methods for more accurate flood-related predictions.

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Recent studies have demonstrated that deep learning models, especially Long Short-Term Memory (LSTM) networks, are highly effective in modeling temporal dynamics in hydrological and rainfall-runoff processes. Kratzert et al. showed that LSTM-based models significantly outperform traditional hydrological models in rainfall-runoff simulations by capturing long-term temporal dependencies [5]. Similarly, Xiang et al. proposed an LSTM sequence-to-sequence framework for runoff forecasting and reported improved prediction accuracy over conventional machine-learning methods [6].

In addition to pure LSTM architecture, hybrid deep learning models have gained increasing attention [7–11]. Studies combining neural networks with LSTM layers have demonstrated enhanced performance by leveraging both non-linear feature transformation and temporal memory mechanisms. Such hybrid approaches have been successfully applied in flood and water-level forecasting tasks, yielding lower prediction errors and improved model stability compared to standalone models [3].

Beyond prediction accuracy, spatial interpretation of flood forecasts is essential for operational decision-making. GIS-based flood visualization has been widely used to translate numerical predictions into spatial risk information. Chen et al. demonstrated that integrating machine learning outputs into GIS platforms enables intuitive flood-risk mapping and supports emergency planning and mitigation strategies [12]. However, the integration of deep learning-based time-series forecasting with open-source GIS platforms such as QGIS remains limited, particularly for localized flood monitoring in Indonesian coastal cities.

Therefore, developing a data-driven flood forecasting framework that integrates deep learning models with GIS-based visualization is crucial for improving early warning capabilities and supporting adaptive flood management in vulnerable coastal areas such as Baubau City.

## 2 Method

### 2.1 Dataset

This study employs water-level time-series data collected from three bridge monitoring locations in Baubau City, Southeast Sulawesi, namely Bridge Gantung, Bridge Tengah, and Bridge Beli. Each bridge provides 7,050 water-level observations recorded at 30-minute intervals over a four-month period. The dataset consists of timestamp information, including date and time, along with corresponding water-level measurements expressed in meters. These data are used to analyze temporal variations in water levels and to support the development of flood prediction models. A detailed description of the dataset attributes is presented in Table 1.

TABLE 1. Dataset Water-Level Baubau

Attribute	Data Type	Value	Description
ID	Integer	0, 1, 2, ...	Index records
Date	Datetime (YYYY-MM-DD HH:MM:SS)	2/1/2025 0:00	Date and time indicating when the water-level observation was recorded.
Time	Time (HH:MM:SS)	00:00:00, 00:30:00	Observation time recorded at fixed 30-minute intervals to ensure temporal consistency.
BRIDGE GT	Float	1.7, 0.155	Water-level measurement (in meters) recorded at Bridge Gantung.
BRIDGE TGH	Float	1.7, 0.20547	Water-level measurement (in meters) recorded at Bridge Tengah.
BRIDGE BELI	Float	1.7, 1.50245	Water-level measurement (in meters) recorded at Bridge Beli.

The dataset consists of several attributes that describe temporal information and water-level measurements at three monitoring locations in Baubau City. The ID attribute is an integer value used as a unique identifier for each observation record. The DATE attribute represents the combined date and time of observation in the format YYYY-MM-DD HH:MM:SS, providing a complete temporal reference for each measurement. To support consistent time-series processing, the Time attribute records the observation time in HH:MM:SS format at fixed 30-minute intervals.

Water-level measurements are represented by three floating-point attributes, each corresponding to a specific bridge location. The BRIDGE GT attribute indicates the water level (in meters) measured at Bridge Gantung, the BRIDGE TGH attribute represents water-level observations at Bridge Tengah, and the BRIDGE BELI attribute records water-level values at Bridge Beli. These continuous numerical attributes serve as the primary input variables for time-series forecasting and flood risk analysis. Together, the temporal and spatial attributes enable the modeling of water-level dynamics across multiple locations, supporting both predictive analysis and GIS-based visualization.

## 2.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a specialized variant of Recurrent Neural Networks (RNNs) designed to address the vanishing gradient problem and to effectively model long-term temporal dependencies in sequential data. LSTM introduces a memory cell regulated by three gating mechanisms input, forget, and output gates that control information flow and allow the network to selectively retain or discard past information over long time horizons [13]. This architecture makes LSTM particularly suitable for hydrological and meteorological time-series forecasting, where historical patterns strongly influence future conditions.

Beyond hydrological and meteorological applications, LSTM has been widely adopted in other time-series forecasting domains. A systematic literature review conducted by Dowlut and Gobin-Rahimbux in the hospitality and tourism sector demonstrated that LSTM is the most frequently used deep learning algorithm for occupancy rate forecasting [14]. Their review analyzed 50 international studies published between 2017 and 2022 and concluded that LSTM consistently outperformed traditional statistical models due to its superior ability to capture temporal trends, seasonality, and irregular demand fluctuations. These findings reinforce the robustness and generalizability of LSTM across diverse forecasting contexts.

In this study, the LSTM model is applied to predict water-level variations at three critical bridge locations in Baubau City, Southeast Sulawesi: Bridge Gantung, Bridge Tengah, and Bridge Beli. The model utilizes high-resolution water-level time-series data recorded at 30-minute intervals, enabling the network to learn temporal dynamics associated with rainfall response, runoff accumulation, and river discharge behavior. Previous studies have demonstrated that LSTM outperforms traditional statistical and machine-learning models in modeling non-linear and delayed hydrological responses[5].

The LSTM architecture employed in this research consists of stacked LSTM layers followed by dense output layers to generate water-level predictions. Prior to training, the dataset undergoes preprocessing steps including data cleaning, normalization using Min–Max scaling, and sequence generation through a sliding window approach. This preprocessing enhances training stability and improves convergence. The model is trained to perform short-term forecasting and evaluated using standard performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), consistent with established hydrological forecasting studies.

Overall, the ability of LSTM to capture complex temporal dependencies makes it a robust and reliable approach for water-level prediction and flood early-warning applications in coastal urban environments.

## 3 Result

### 3.1 Data Cleaning

The preprocessing stage plays a crucial role in ensuring data quality and model reliability. Raw water-level time-series data collected from the three bridges in Baubau City initially contained several inconsistencies that required systematic cleaning. First, inconsistent date and time formats were standardized by merging date (DATE) and time (TIME) attributes into a unified datetime index to preserve temporal continuity. Second, non-numeric and invalid entries were identified and filtered out to avoid bias and numerical instability during model training.

These cleaning procedures ensured that only valid, continuous, and reliable observations were retained. After preprocessing, a fixed and consistent dataset was obtained for each bridge location. The final cleaned dataset, used for model training and evaluation, is summarized in Table 2.

**TABLE 2.** Clean Dataset (a) Bridge Gantung, (b) Bridge Tengah, and (c) Bridge Beli

DATE	TIME	BRIDGE GT	DATE	TIME	BRIDGE TGH	DATE	TIME	BRIDGE BELI
2/1/2025 0:00	0:00:0 0	1.7	2/1/2025 0:00	0:00:00	1.7	2/1/2025 0:00	0:00:0 0	1.7
2/1/2025 0:00	0:30:0 0	0.155	2/1/2025 0:00	0:30:00	0.20547	2/1/2025 0:00	0:30:0 0	1.50245
2/1/2025 0:00	1:00:0 0	0.1	2/1/2025 0:00	1:00:00	0.109736	2/1/2025 0:00	1:00:0 0	1.50261
2/1/2025 0:00	1:30:0 0	0.175	2/1/2025 0:00	1:30:00	0.172796	2/1/2025 0:00	1:30:0 0	1.50261
2/1/2025 0:00	2:00:0 0	0.25	2/1/2025 0:00	2:00:00	0.249288	2/1/2025 0:00	2:00:0 0	1.50261

### 3.2 Model Training

After data preprocessing and normalization, the cleaned water-level time-series datasets were divided into training and testing subsets using an 80:20 ratio. The first 80% of the chronological data was used for model training, while the remaining 20% was reserved for testing. This temporal split ensures that the models are evaluated on unseen future observations, preserving the integrity of time-series forecasting and avoiding data leakage. Information can be found in Table 3, which provides a detailed overview.

**TABLE 3.** Number dataset

Model	Number
Training	5620
Test	1405

Time-series sequences were generated using a sliding window (look-back) approach, allowing the models to learn temporal patterns from historical water-level observations. Four predictive models were implemented and trained: Linear Regression, Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), and a Hybrid ANN–LSTM model. Linear Regression was used as a baseline statistical method, while ANN represented a non-linear feed-forward learning approach. The LSTM model was designed to capture long-term temporal dependencies in sequential data, and the hybrid ANN–LSTM architecture combined LSTM-based temporal feature extraction with dense neural layers for enhanced feature refinement and prediction accuracy.

All models were trained using the same training dataset to ensure fair comparison. Model performance was subsequently evaluated on the testing dataset using standard regression error metrics, enabling an objective assessment of generalization capability across the three bridge locations.

### 3.3 Model Evaluation and Performance Analysis

Model performance was evaluated using three standard error-based metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These metrics provide complementary perspectives on prediction accuracy, sensitivity to large errors, and overall deviation from observed values. Information can be found in Table 4, which provides a detailed overview.

**TABLE 4.** Performance Bridge Gantung

Model	MSE	RMSE	MAE
<b>Linier Regression</b>	0.017182	0.13108	0.06834
<b>ANN</b>	0.01171	0.108211	0.05053
<b>LSTM</b>	0.012039	0.109724	0.05083
<b>ANN-LSTM</b>	0.011268	0.106151	0.04321

For Bridge Gantung, Linear Regression exhibited the highest error values, indicating its limitation in modeling non-linear temporal dynamics. ANN and LSTM significantly improved prediction accuracy, while the hybrid ANN-LSTM model achieved the lowest error values across all metrics, demonstrating superior robustness and precision. Information can be found in the Table 5, which provides a detailed overview.

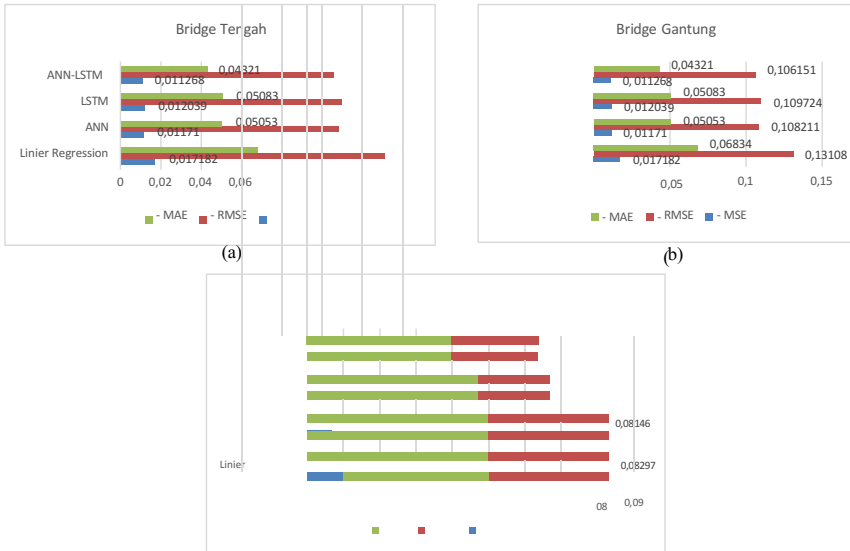
**TABLE 5.** Performance Bridge Tengah

Model	MSE	RMSE	MAE
<b>Linier Regression</b>	0.017182	0.13108	0.06834
<b>ANN</b>	0.01171	0.108211	0.05053
<b>LSTM</b>	0.012039	0.109724	0.05083
<b>ANN-LSTM</b>	0.011268	0.106151	0.04321

Similar trends were observed at Bridge Tengah. Linear Regression again performed poorly compared to deep learning approaches. While LSTM slightly outperformed ANN in terms of MSE and RMSE, the ANN-LSTM hybrid model consistently provided the most accurate predictions, particularly in reducing MAE. Information can be found in the Table 6 and Figure 1, which provides a detailed overview.

**TABLE 6.** Performance Bridge Beli

Model	MSE	RMSE	MAE
<b>Linier Regression</b>	0.006884	0.08297	0.05255
<b>ANN</b>	0.006636	0.08146	0.05493
<b>LSTM</b>	0.004488	0.06699	0.04725
<b>ANN-LSTM</b>	0.004043	0.06358	0.03884



**FIGURE 1.** Performance Model at (a) Bridge Gantung, (b) Bridge Tengah, and (c) Bridge Beli

At Bridge Beli, all models achieved lower error values compared to the other two locations, indicating relatively smoother water-level variations. Nevertheless, the ANN–LSTM model still demonstrated the best performance, achieving the lowest MSE, RMSE, and MAE. This highlights its ability to capture subtle temporal patterns and reduce both large and small prediction errors. Comparison of the model can be seen at Figure 1.

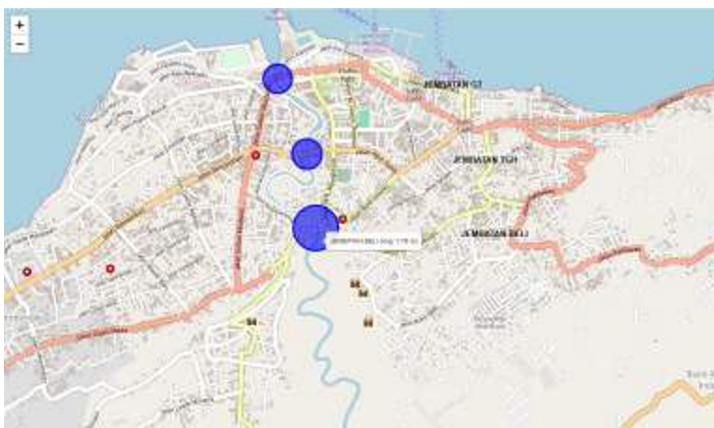
The experimental results indicate that the Hybrid ANN–LSTM model is the most recommended approach, as it consistently achieves the highest prediction accuracy and the lowest error values across all monitoring locations, namely Bridge Gantung, Bridge Tengah, and Bridge Beli. This superior performance demonstrates the effectiveness of combining temporal feature extraction with advanced non-linear learning. The standalone LSTM model also exhibits strong and reliable predictive capability, particularly in scenarios where reduced model complexity and computational efficiency are prioritized. However, the hybrid architecture further enhances forecasting performance by integrating LSTM’s ability to capture sequential and long-term dependencies with ANN’s strength in non-linear feature mapping and output refinement. This synergy allows the hybrid model to better represent the complex temporal behavior of water-level fluctuations, making it the most effective and robust architecture for the multivariate time-series dataset used in this study.

### 3.4 GIS-Based Visualization Results

The spatial visualization of water-level prediction results was successfully implemented using QGIS, providing a clear geographic representation of flood-related indicators across Baubau City. Figure X illustrates the distribution of predicted average water levels at three critical monitoring locations: Bridge Gantung, Bridge Tengah, and Bridge Beli. Each bridge location is represented using circular markers positioned according to its geographic coordinates, overlaid on an OpenStreetMap basemap to ensure spatial accuracy and contextual clarity.

The size of each circular marker corresponds to the magnitude of the predicted water level, enabling rapid visual comparison among locations. Larger markers indicate higher average water levels and thus a potentially greater flood risk. Permanent labels were added to each marker to display the bridge name and its associated average predicted water level, enhancing map readability and interpretability without requiring additional interaction.

The visualization reveals that Bridge Beli exhibits the highest average predicted water level, followed by Bridge Tengah and Bridge Gantung. This spatial pattern aligns with the quantitative model evaluation results, where Bridge Beli also demonstrated stronger temporal variability and higher sensitivity to hydrological changes. The integration of prediction outputs into QGIS allows temporal forecasting results to be transformed into actionable spatial information, supporting intuitive identification of high-risk locations.



Source: Google Maps

**FIGURE 2.** GIS-Based Visualization of Predicted Water Levels at Three Bridge Locations in Baubau City

Overall, the GIS-based representation effectively bridges the gap between numerical model outputs and spatial decision support, demonstrating the practical value of integrating deep learning-based forecasting with geospatial visualization for flood monitoring and early warning applications in coastal urban areas.

#### 4 Conclusion

This study proposes a deep learning-based framework for short term water level forecasting and spatial flood visualization in Baubau City, Southeast Sulawesi. Time series data recorded at 30-minute intervals from three strategic bridge locations, namely Bridge Gantung, Bridge Tengah, and Bridge Beli, were processed through systematic data cleaning, normalization, and model training to support flood risk analysis and early warning efforts.

The experimental results show that deep learning models consistently outperform traditional Linear Regression in predicting water level fluctuations. Artificial Neural Networks provide improved accuracy but remain limited in modeling temporal dependencies. In contrast, LSTM demonstrates strong capability in capturing long term temporal patterns within water level time series data. The hybrid ANN LSTM model achieves the best overall performance across all bridge locations, producing the lowest prediction errors and the most stable forecasting results. This indicates that combining sequence learning with non linear feature mapping is highly effective for hydrological time series forecasting.

In addition, integrating prediction outputs into QGIS enables clear spatial representation of water level conditions across Baubau City. The resulting maps allow flood prone locations to be easily identified and support practical decision making for flood monitoring and mitigation. Overall, the proposed integration of deep learning models and GIS visualization provides a reliable and scalable approach for strengthening flood early warning systems in coastal urban environments. Future research may incorporate additional environmental variables and longer prediction horizons to further enhance forecasting performance and spatial analysis.

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