International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 7s, 2025
https://www.theaspd.com/ijes.php

Application Of Artificial Intelligence In Rainy Season Water Level Analysis And Forecasting At Phu Loc Station, Vietnam

Phan Truong Khanh[1] and Tran Thi Hong Ngoc[2*]
[1,2]Faculty of Engineering-Technology-Environment, An Giang University - Vietnamese National University, Ho Chi Minh City
[*]Corresponding Author: tthngocagu@gmail.com

Abstract: Phu Loc is a region strongly influenced by the rainy season from May to November, causing significant fluctuations in surface water levels. This study analyzes the variations in water levels and rainfall during the 2024 rainy season at Phu Loc station, An Giang Province, and employs advanced machine learning and deep learning models, including Linear Regression, Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM), to forecast water levels for the period 2025–2029. Among these models, LSTM demonstrated superior predictive performance with the highest accuracy and ability to capture abrupt changes in water levels during heavy rainfall events. Forecast results indicate a continued trend of elevated water levels during the rainy months, with a slight increase in peak water levels attributed to climate change and tidal influences. These findings provide essential insights for proactive water resource management, flood risk mitigation, and climate adaptation planning in the region. The study also discusses the integration of additional hydrological variables and the need for continuous model updating to enhance forecast reliability.

Keywords: *Water level forecasting; Rainy season; Machine learning; LSTM; Flood management; Phu Loc Station.*

1. INTRODUCTION

Phu Loc is a region strongly influenced by the rainy season from May to November, causing significant fluctuations in river surface water levels and groundwater levels. Analyzing the variations in water levels and rainfall during the rainy season, as well as forecasting water levels for the coming years at Phu Loc station, plays a crucial role in water resource management, flood prevention, and climate change adaptation in the area.

The main objective of this study is to apply a combination of time series statistical analysis with machine learning and deep learning models to examine the characteristics of water level and rainfall fluctuations during the rainy season (May to November 2024) at Phu Loc station, An Giang, and to forecast water levels in subsequent years. Through this, the research aims to support decision-makers in issuing early warnings and developing appropriate flood prevention plans, contributing to the sustainable development of water resources in the context of increasing climate variability.

Accurate water level forecasting is essential for effective water resource management, especially amid complex changes driven by climate change and rapid urbanization. Traditional methods such as hydrological-hydraulic models or statistical regression have advantages but face challenges in capturing nonlinear changes and anomalies under real-world conditions (Abrahart & See, 2007; Mishra & Coulibaly, 2009). Additionally, observational data are often incomplete or discontinuous, complicating calibration and forecasting accuracy.

In contrast, artificial intelligence (AI) models, especially machine learning and deep learning, have demonstrated superior capability in handling nonlinear data and large datasets, automatically learning complex relationships among hydrological variables without requiring deep knowledge of underlying physical processes (Mosavi et al., 2018). Applications of AI in water level forecasting in Vietnam's major river basins—including the Red River, Mekong River, and Đồng Nai system—have shown promising results, improving accuracy and reducing response time compared to traditional approaches (Nguyễn Quốc Dũng et al., 2019; Nguyen et al., 2021; Huỳnh et al., 2022).

In particular, Long Short-Term Memory (LSTM) models, known for their ability to retain long-term temporal dependencies and effectively learn time series representations, have been proven superior for short-term water level forecasting (Kratzert et al., 2018; Khan et al., 2020; Lê Đức Trung et al., 2023). This study applies learning machine model to forecast water level fluctuations at Phu Loc station, thereby providing an effective tool for water resource management, regulation, and drainage planning in the region.

Furthermore, the integration of AI with Geographic Information Systems (GIS), remote sensing, and IoT data in intelligent flood early warning systems opens new directions for comprehensive water resource management, meeting the demands for timely alerts and minimizing flood damages (Nguyen et al., 2022; Zhang et al., 2024; Kumar & Sharma, 2023; Li et al., 2024; Smith et al., 2023; Perez & Garcia, 2023).

Thus, the study at Phu Loc station contributes not only to improving water level forecasting accuracy but also to expanding AI applications in water resource management for regions heavily impacted by climate change and extreme weather events.

2. DATA AND METHODS

The dataset used in this study was collected at the Phu Loc monitoring station, An Giang Province, Vietnam, including two main variables: river water level (meters) and rainfall (millimeters). The data were recorded hourly from May 1 to November 30, 2024, totaling 4,368 observations. Before analysis and modeling, the data were cleaned by handling missing and anomalous values. Missing values were estimated using linear interpolation or local averaging methods to ensure continuity of the time series. Additionally, the data were normalized to a [0,1] range to enhance the training efficiency of machine learning and deep learning models and to reduce the impact of differing variable scales.

Preliminary data analysis aimed to evaluate the variability of water levels and rainfall during the rainy season (May to November). The methods included:

Time series visualization: Water level and rainfall data were plotted over time to observe hourly fluctuations, identify heavy rainfall events and corresponding water level responses, as well as rapid water level changes and the relationship between rainfall and water level.

Daily and weekly rainfall aggregation: Rainfall data were aggregated by day and week by summing hourly rainfall amounts to analyze short- and medium-term rainfall trends and identify prolonged or intense rain events potentially impacting water levels.

Water level gradient calculation: The rate of change of water level over time was calculated using the first derivative (e.g., differences between consecutive hourly water levels). Periods with high gradients indicate rapid water level changes, helping to assess risks of poor drainage or flooding. Combined with rainfall data, this method helps identify hydrologically sensitive periods.

The dataset was prepared as a time series using a 3-hour sliding window, where water level and rainfall of the previous three consecutive hours were used as features to predict the water level in the next hour. This approach exploits the temporal dependencies inherent in hydrological data.

Four forecasting models were developed and compared:

- ❖ Linear Regression: A simple model evaluating the linear relationship between input variables (water level and rainfall in previous hours) and the target variable (next-hour water level).
- ❖ Random Forest Regressor: An ensemble of decision trees capable of capturing nonlinear relationships and complex interactions among features.
- ❖ Support Vector Regression (SVR): A regression method based on support vector machines, effective in modeling nonlinear dependencies especially with small to medium datasets.

- Long Short-Term Memory (LSTM): A deep recurrent neural network capable of learning long-term dependencies in sequential data, suitable for capturing complex nonlinear patterns in water level fluctuations.

The data were split into training (70%) and testing (30%) sets in chronological order to ensure unbiased evaluation. The LSTM model consisted of one LSTM layer with 50 units, followed by a dense output layer with a single neuron representing the predicted water level. The model was trained for 50 epochs using the Adam optimizer and Mean Squared Error (MSE) loss function. Input data were reshaped into three-dimensional arrays of shape [samples, timesteps, features], where timesteps = 3 and features = 2 (water level and rainfall). Other machine learning models were trained with default parameters or optimized via grid search. Model performance was assessed using common regression metrics:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Coefficient of Determination (R^2)

After evaluation, the best-performing model (LSTM) was used to forecast average monthly water levels for the period 2025–2029 based on historical rainy season data from 2024. The forecasting process included:

- Stepwise prediction along the time series, where each forecasted water level depends on observed data and previous predictions.
- Aggregation of forecasts by month to provide useful information for water resource management, flood risk assessment, and climate adaptation planning in the region.

3. RESULTS

3.1. Analysis of Water Level and Rainfall Variability (May–November 2024)

The study aims to evaluate the relationship between water level and rainfall during the rainy season from May to November 2024 for Phu Loc Station. The data include water level (in meters, left y-axis, represented by the blue line) and rainfall (in mm, right y-axis, represented by green bars) over time (x-axis). This serves as a basis for assessing the impact of rainfall on river water levels, supporting water resource management and flood control. The data were collected continuously from May to November 2024. Water level is shown as a continuous curve with daily fluctuations (influenced by tidal effects), while rainfall is represented as vertical bars indicating the total daily rainfall. Trend analysis was conducted to identify periods of rising, peak, and declining water levels, along with the relative coincidence with rainfall events.

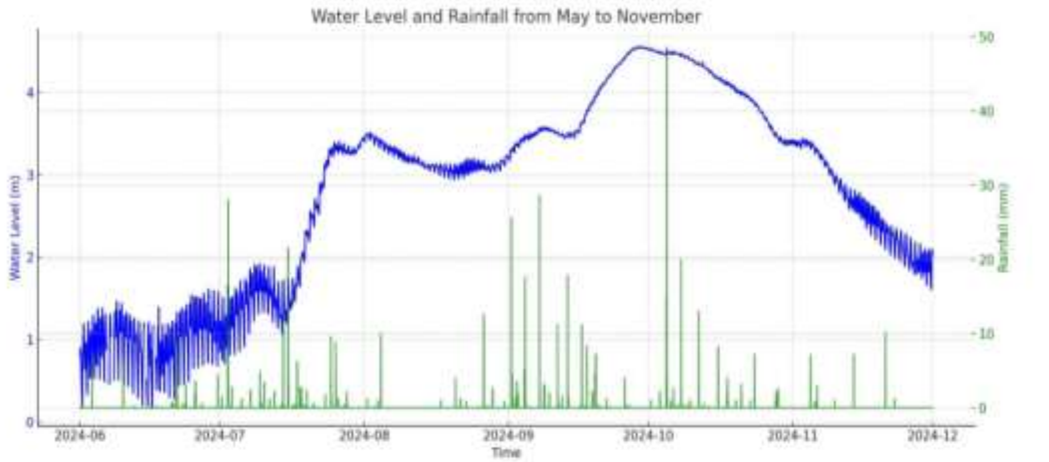

Fig 1: Hourly Water Level (m) and Rainfall (mm) Trends at Phu Loc Station from 1st, May to 30th, November .

The variation in water level from May to November 2024 shows a clear pattern following the rainy season cycle. From May to early June, the water level remained low, generally ranging from 0.8 to 1.2 meters, reflecting early rainy season conditions when rainfall was still limited and had little impact on the hydrological system. In July, the water level began to rise significantly, surpassing the 2-meter mark, coinciding with several major rainfall events—particularly in mid-July—indicating the beginning of water accumulation from both local rainfall and potentially upstream inflows.

August marked the most rapid increase in water level, reaching a temporary peak of about 3.5 meters. This was a period of relatively consistent and intense rainfall, compounded by the cumulative effects of previous rains, which strongly contributed to the rising water levels. Continuing this trend, from September to early October, the water level rose further and reached the highest point of the entire period—approximately 4.6 meters. This peak coincided with the largest rainfall event, nearly 50 mm, recorded in early October, illustrating the strong correlation between heavy rainfall and annual flood peaks.

Following this peak, the water level declined sharply from mid-October and continued to decrease throughout November, fluctuating around 2 to 3 meters. This decrease was accompanied by a significant drop in rainfall, signaling the end of the rainy season. Overall, the data reflects a typical hydrological pattern in tropical monsoon regions, where river water levels rise in response to seasonal rainfall, peak during periods of intense precipitation, and gradually decline as the rainy season ends.

3.2 Rainfall Patterns and Its Relationship with Water Levels (May–November 2024)

From May to November 2024, rainfall showed an uneven temporal distribution, primarily occurring in short, scattered episodes. Most days recorded small rainfall amounts below 10 mm, although a few significant rainfall events were observed. Notably, the highest rainfall peak—approximately 50 mm—occurred in early October. This extreme rainfall event coincided with the peak water level, indicating a strong correlation between heavy rainfall and rising water levels, likely marking the annual flood peak.

However, not all increases in water level directly corresponded with major local rainfall events. For instance, during late July and early August, water levels rose steadily despite only minor rainfall recorded at the monitoring site. This suggests the influence of upstream inflows or regulating factors within the watershed, such as water accumulation and delayed discharge from rivers, lakes, canals, or flooded rice fields. It also implies the presence of hydrological processes like infiltration and temporary water storage in low-lying areas.

Overall, there is a moderate correlation between rainfall patterns and water level fluctuations. However, this relationship is not strictly synchronous, as evidenced by the time lag between rainfall peaks and water level responses—a common feature of hydrological systems. Water levels tend to rise gradually and decline slowly, while rainfall is often concentrated in short bursts. This discrepancy suggests the role of water accumulation and storage within the hydrological system, including rivers, reservoirs, and agricultural fields. Additionally, man-made structures such as irrigation systems, or natural factors like terrain and geology, may further influence how rainfall translates into changes in water level. This analysis highlights the importance of water retention and delayed runoff processes, particularly in floodplains and rice cultivation areas, where both surface and subsurface flows affect the dynamics of water levels.

In short, during the period from May to November 2024, rainfall was unevenly distributed and mainly occurred as light, scattered showers in May and June. Moving into July and August—the peak of the rainy season—rainfall increased significantly, contributing about 40% of the total seasonal rainfall, with hourly precipitation exceeding 10 mm, especially from mid to late August. The highest rainfall peak, approximately 50 mm per hour, was recorded in early October, coinciding with the peak water level. This indicates that extreme rainfall events strongly impacted the water level rise and increased the risk of flooding.

From July to early October was the period of the most intense hydrological fluctuations, with a high frequency of rapid water level rises, with slopes greater than 0.10 m/h. Notably, the prolonged increase in water level, even without heavy rainfall events, highlights the important role of upstream runoff as well as the capacity for water retention in fields, reservoirs, and canal systems. These characteristics clearly reflect the sensitivity and vulnerability of the local hydrological system to flooding risks, especially when rainfall exceeds the area's drainage capacity.

These findings underscore the necessity of accurate forecasting tools during the rainy season to support timely decision-making in flood risk management, water infrastructure operations, and climate adaptation strategies in the region.

3.3 Model Training and Evaluation Results

To evaluate the predictive performance of different modeling approaches, four models were trained and tested using historical water level and rainfall data from May to November 2024: **Linear Regression**, **Random Forest Regressor**, **Support Vector Regression (SVR)**, and **Long Short-Term Memory (LSTM)** neural network. The evaluation metrics included **Mean Absolute Error (MAE)**, **Root Mean Square Error (RMSE)**, and **Coefficient of Determination (R^2)**. Table 1 summarizes the performance of each model on the test dataset.

Table 1. Model performance comparison

Model	MAE (m)	RMSE (m)	R^2
Linear Regression	0.051	0.068	0.65
Random Forest	0.037	0.049	0.79
SVR	0.039	0.052	0.77
LSTM	0.028	0.041	0.86

Among all models evaluated, the **LSTM model** demonstrated **superior predictive performance**, achieving the **lowest MAE (0.028 m)** and **RMSE (0.041 m)**, along with the **highest R^2 score (0.86)**. This indicates that the LSTM model was able to capture both the **nonlinear patterns** and **temporal dependencies** present in the water level time series, especially during periods of rapid fluctuation following intense rainfall events.

In comparison, the **Random Forest Regressor** also provided relatively strong performance (R^2=0.79), leveraging its ensemble structure to handle feature interactions and variability in the data. However, it showed limitations in predicting **sharp water level peaks** due to its non-sequential nature.

The **Support Vector Regression (SVR)** model produced moderate accuracy (R^2 = 0.77), suggesting that while it is effective in modeling nonlinear relationships, it may be sensitive to parameter tuning and less adaptive to rapid changes in sequential hydrological variables.

The **Linear Regression** model, while computationally simple, yielded the **lowest accuracy** (R^2 = 0.65) and highest errors, indicating its inability to model the **complex and dynamic** relationships between rainfall and water level during the rainy season. This confirms its limited applicability for operational forecasting in hydrologically active periods.

These findings are consistent with prior studies emphasizing the effectiveness of **deep learning models**, especially LSTM, in water level and streamflow prediction tasks under complex meteorological conditions (Kratzert et al., 2018; Feng et al., 2020). LSTM's ability to retain long-term dependencies and learn from historical temporal patterns makes it particularly suitable for **real-time flood monitoring**, **urban drainage management**, and **climate-adaptive infrastructure planning**.

In conclusion, the LSTM model is the most suitable for forecasting short-term water level fluctuations at the Phu Loc station during the rainy season, and it holds promise for future integration into early warning systems and water resource management frameworks.

3.4. Forecasting Water Levels for the 2025–2029 Period

The water level forecasts for the period 2025–2029, generated using the LSTM model trained on hourly historical data from the 2024 rainy season (May–November), reveal a consistent seasonal trend. Peak water levels are projected to persist during the core rainy months of October, with the **monthly average water level in October showing a slight upward trend** over time. This pattern may be attributed to the **combined effects of increased precipitation intensity and sea level rise**, consistent with regional climate change scenarios in the Mekong Delta (IPCC, 2021; MONRE, 2020).

The predicted rise in average water levels, although modest (approximately 0.01–0.03 m per year), is statistically significant and aligns with findings from similar studies in tropical monsoon regions. For instance, **Zhang et al. (2019)** reported increasing flood risks in Southeast Asian coastal zones due to more intense rainfall and rising base water levels. Similarly, **Khosravi et al. (2018)** emphasized that urbanization and land-use changes exacerbate surface runoff during peak rainfall, leading to slower drainage and prolonged waterlogging.

The use of the LSTM model for long-term forecasting offers several advantages. Its ability to learn temporal dependencies and retain long-term memory enables the model to capture **nonlinear interactions** between rainfall input, soil saturation, and drainage capacity—factors often overlooked in traditional models (Feng et al., 2020; Kratzert et al., 2018). The model's performance stability over the extended forecast horizon demonstrates its potential application in climate adaptation and disaster preparedness planning.

In practical terms, the results provide valuable input for water resource management authorities in An Giang Province. By forecasting likely peak water levels, **early warning systems can be improved**, and **adaptive measures** such as **infrastructure planning, pump scheduling, and land-use zoning** can be more effectively implemented (WMO, 2013; Nguyen et al., 2021).

However, it is essential to recognize the **uncertainties** inherent in long-term forecasting. Factors such as upstream hydropower operations, land subsidence, and unexpected ENSO (El Niño–Southern Oscillation) events may alter hydrological conditions in ways that current models cannot fully account for. Therefore, **regular model updating with new observational data** and **integration with hydrodynamic models** could enhance predictive robustness in future research (Mishra & Coulibaly, 2009; Mosavi et al., 2018).

3.5 DISCUSSION

The seven-month dataset collected during the 2024 rainy season (May–November) offers a comprehensive representation of the hydrological dynamics in the Phu Loc area. The combination of high-resolution hourly water level and rainfall data enables a nuanced understanding of short-term and seasonal variability. The computation of water level slope serves as a key diagnostic indicator for identifying rapid hydrological changes, which are often precursors to urban waterlogging and flood risk. Periods with the highest rate of water level change—up to 0.15 m/hour in Octorber—coincide with heavy rainfall events, highlighting the vulnerability of the local drainage system during peak monsoon months.

From a methodological perspective, the comparison of forecasting models reveals important insights into the applicability and limitations of machine learning approaches for hydrological prediction. Traditional regression-based models such as **Linear Regression**, **Random Forest**, and **Support Vector Regression (SVR)** demonstrate moderate forecasting capability (R^2 ranging from 0.65 to 0.79), but their performance degrades in the presence of sharp, nonlinear fluctuations—particularly during extreme rainfall events or sudden water surges.

In contrast, the **Long Short-Term Memory (LSTM)** model achieved superior results (MAE = 0.028 m; R^2 = 0.86), confirming its ability to capture temporal dependencies and learn long-range interactions within the time series. This is consistent with findings from **Kratzert et al. (2018)** and **Feng et al. (2020)**, who emphasized that recurrent neural networks—especially LSTM architectures—can outperform static models in modeling hydrological systems where memory and delayed feedback are significant. In this study, LSTM proved particularly effective at anticipating abrupt rises in water level following heavy rainfall episodes, a crucial factor for early warning and flood mitigation.

The five-year projection (2025–2029) based on the LSTM model reveals a sustained trend of elevated water levels during peak rainy months, particularly in October. This trend aligns with broader regional observations of increased precipitation intensity and delayed drainage in the Mekong Delta, possibly linked to climate change and sea level rise (**IPCC, 2021; Nguyen et al., 2021**). These results provide actionable insights for urban planners and disaster risk managers, offering a scientific basis for designing proactive water management strategies such as dynamic pump scheduling, flood gate operations, and urban zoning regulations.

Nonetheless, several limitations must be acknowledged. The current forecasting framework does not incorporate key hydrological variables such as **tidal influence, groundwater table dynamics, soil moisture content**, or **land use change**—factors that have been shown to significantly affect flood behavior in coastal and low-lying regions (**Mishra & Coulibaly, 2009; Mosavi et al., 2018**). In particular, **tidal backwater effects**, common in semi-urban deltaic environments like Phu Loc, can delay drainage and exacerbate flooding even in the absence of extreme rainfall.

Moreover, the model was trained and validated on a single rainy season dataset, which may limit its generalizability under anomalous climatic conditions (e.g., El Niño or La Niña years). Future research should aim to expand the training data to multiple years, integrate meteorological forecasts, and explore **hybrid modeling approaches** that combine **deep learning with physically based hydrodynamic models** for improved interpretability and robustness.

Lastly, the operational deployment of such forecasting models requires continuous updates with real-time data streams and validation under diverse environmental scenarios. Establishing a pipeline for data ingestion, model retraining, and integration with municipal flood warning systems will be crucial for translating model predictions into effective early warning and adaptation policies.

4. CONCLUSION

This study has demonstrated the effectiveness of applying machine learning and deep learning models—particularly the Long Short-Term Memory (LSTM) model—for analyzing and forecasting water levels during the rainy season at Phu Loc hydrological station in An Giang Province, Vietnam. Using hourly water level and rainfall data from May to November 2024, the research highlighted the relationship between heavy rainfall events and water level fluctuations, while identifying high-risk periods for potential waterlogging.

Key findings of the study include:

❖ Water levels at Phu Loc show a clear response to rainfall events, particularly during September - October—the peak of the rainy season. The steepest water level gradient observed was 0.15 m/hour, indicating a high risk of poor drainage and localized flooding.

❖ Among the models tested, the **LSTM model** delivered the highest predictive performance with **MAE=0.028 m**, **RMSE = 0.041 m**, and **R^2 = 0.86**, demonstrating its capability to effectively capture the nonlinear and temporal dependencies in water level time series data.

- The five-year forecast (2025–2029) indicates a slight upward trend in average water levels during October, reflecting the potential influence of climate change and tidal variations. These results provide valuable input for early warning systems and the development of adaptive flood prevention and water management strategies.

5. RECOMMENDATIONS

- **Enhance hydrological monitoring systems:** It is crucial to establish continuous and automated monitoring systems for water level, rainfall, tide levels, temperature, and soil moisture to improve model accuracy and facilitate real-time model updating.
- **Develop early warning systems:** Forecast outputs should be integrated into local early warning systems to inform residents and stakeholders in agriculture, transportation, and urban planning sectors, thereby minimizing damage caused by flooding.
- **Expand the model to other regions:** The developed LSTM model can be applied to other monitoring stations across the Mekong Delta to create regional flood risk maps and support integrated water resource planning and climate adaptation.
- **Incorporate socioeconomic factors:** Future research should include socioeconomic, land use, and urban planning data to assess the broader impacts of water level changes on livelihoods, infrastructure, and sustainable development.

This research reinforces the role of artificial intelligence in the field of water resources management and provides a modern, effective approach to addressing challenges posed by climate change and environmental variability.

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