Journal of Science and Technology – Smart Systems and Devices
Volume xx, Issue x, Month 202x, 000-000

An Autoencoder Approach to Water Level Forecasting

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Abstract

Climate change exacerbates the frequency and intensity of flood events, presenting substantial threats to human lives and infrastructure. Consequently, accurate and timely water level forecasting systems are critical for effective early warning dissemination and rapid disaster response. While numerous studies in Vietnam have focused on river water level prediction, a notable gap exists in the specific area of continuous, multi-hour time series forecasting. The study addresses this gap by proposing a novel modeling approach for forecasting future water levels at the Le Thuy station on the Kien Giang river in Quang Tri province. The proposed models leverage historical hydrological observations from multiple upstream stations to predict water level sequences at the Le Thuy station over continuous horizons of 6, 12, and 24 hours. The methodology employs advanced deep learning techniques, specifically Autoencoder, Long Short-Term Memory (LSTM) networks, and Attention mechanism, with each forecast horizon being modeled independently. Experimental results demonstrate the models' robust capability to accurately capture both rising and falling water level trends. The forecasted sequences exhibit strong alignment with observed values, even during periods of rapid fluctuation. Point-wise prediction errors are consistently low, indicating high forecasting precision. Crucially, the models maintain their effectiveness during extreme flood events, successfully predicting both the magnitude and timing of flood peaks.

Keywords: Attention, LSTM Autoencoder, time series, water level sequence forecasting.

1. Introduction

Due to climate change, floods are becoming more frequent and more dangerous, posing a serious threat to human life and property. Recent studies in Vietnam have shown that both the intensity and frequency of typhoon-induced rainfall have significantly increased in the Central Coastal Region, with average increases of about 27 %, and the probability of daily rainfall exceeding 100 mm/day projected to rise by up to 20% under the RCP8.5 scenario [1]. Developing an accurate water level forecasting system is essential for providing early flood warnings. It helps people respond to floods quickly and effectively. Forecasting water levels is crucial during rainy and flood days when water levels are high.

Numerous studies have demonstrated the effectiveness of machine learning methods in hydrological forecasting. For example, Shamseldin [2] employed Artificial Neural Networks (ANN) to forecast flows of the Blue Nile River in Sudan. Chen *et al.* utilized the Cuckoo Search algorithm to optimize a Feedforward Neural Network for predicting the 10-day total inflows of the Hoa Binh Reservoir in Vietnam [3]. In 2017, Sung *et al.* developed ANN models to forecast hourly water levels in the Anyangcheon Stream, a tributary of the Han River in South Korea [4]. Futhermore, Guo *et al.* compared the performance of several machine learning algorithms - Support Vector Regression, Random Forest Regression, Multi-Layer Perceptron Regression, and Light Gradient Boosting Machine Regression (LGBMR) - for forecasting the 1–6-hour river stages in the tidal section of the Lan-Yang River in Taiwan [5]. Nevo *et al.* integrated Long Short-Term Memory (LSTM) networks and linear models to develop a real-time operational flood forecasting system for river systems in India and Bangladesh [6]. Vizi *et al.* employed LSTM models to forecast water levels in the Tisza River in Central Europe, with lead times of up to 7 days [7]. Their results demonstrated that LSTM models provided the best results in all time horizons and gave more precise predictions than the Discrete Linear Cascade Model and baseline models (Linear, Multilayer Perceptron Model). Kao *et al.* [8] proposed SAE-RNN (Stacked AutoEncoder - Recurrent Neural Network) model which uses SAE to compress (encode) the high-dimensional flood inundation depths over a wide region into a low-dimensional latent space representation (flood features), uses RNN to forecast multistep-ahead flood features based on regional rainfall patterns, and finally uses SAE to reconstruct (decode)

p-ISSN 3093-3285
e-ISSN 3093-3315
https://doi.org/10.51316/jst.xxx.ssad.202x.xx.x.xx
Received: Aug 5, 2025; Revised: Nov 3, 2025;
Accepted: Nov 16, 2025; Online: Dec 20, 2025

the multistep-ahead forecasts of flood features into regional flood inundation depths. More recently, the study of Azad *et al.* [9] provided a comprehensive overview of advancements and challenges in water level forecasting and prediction from 2011 to 2024, based on approximately 200 published studies. According to this study, machine learning methods applied to water level prediction include: Artificial Neural Networks, Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System, AutoRegressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Support Vector Regression, deep learning (RNN, LSTM), hybrid models and advanced deep learning techniques.

In Vietnam, the application of machine learning models in hydrological forecasting has also gained momentum. Do *et al.* [10] applied a hybrid approach combining Singular Value Decomposition with Support Vector Machines to estimate daily maximum and minimum water levels. Dinh *et al.* [11] compared the performance of Linear Regression, Random Forest Regression, and LGBMR models for daily water level prediction in the Kien Giang river using historical data from 1977 to 2020. The results confirmed the effectiveness of data-driven regression techniques in capturing flood-related dynamics. In 2024, Ta *et al.* [12] investigated and assessed the performance of several machine learning methods, including Linear Regression, Support Vector Regression, Random Forest Regression, Multi-Layer Perceptron Regression and Gradient-Enhanced Machine Learning Regression, for water level forecasting on the Kien Giang river. Luong *et al.* [13] applied advanced machine learning techniques, specifically the XGBoost algorithm, to identify large floods in the Da River Basin, demonstrating the potential of artificial intelligence for improving flood prediction and disaster management in Vietnam. Furthermore, Ngo *et al.* [14] developed a deep learning model based on a Multilayer Perceptron (MLP) neural network to forecast flood characteristics at the Yen Bai hydrological station on the Thao River, using flood recession flow data and 5-day accumulated rainfall from the Sa Pa, Van Chan, and Yen Bai stations. In these studies, models have shown considerable success in short-term forecasting, typically focusing on one-step-ahead predictions.

Although numerous studies have investigated water level forecasting for rivers in Vietnam, to the best of our knowledge, there has been no research focusing on the prediction of continuous water level time series over several consecutive future hours. Therefore, in this paper, we propose a modeling approach to forecast water level time series over multiple consecutive future hours at the Le Thuy station on the Kien Giang river in Quang Tri province, Vietnam.

The remainder of the paper is organized as follows. Section 2 presents the dataset. Section 3 outlines the problem under study. Section 4 details the development of the water level forecasting model. Section 5 discusses the experimental results. Section 6 concludes the paper.

2. Dataset Description

The Kien Giang river, approximately 58 km in length, is one of the two main tributaries of the Nhat Le river system. It flows through Le Thuy district in Quang Tri province. This basin is recognized as one of the most flood-prone regions in Vietnam.

We use native hourly observations from September–December of 2015–2024 at Kien Giang, Le Thuy, and Dong Hoi stations, and hourly tidal level at the Nhat Le estuary (all timestamps in UTC+7). Prior to windowing, we applied a uniform QC pipeline: duplicate timestamps were removed; implausible values (e.g., negative rainfall) were flagged. Short gaps (≤ 2 consecutive hours) in water level and tide series were linearly interpolated in time; gaps in rainfall were not imputed and any sample window intersecting a rainfall gap was discarded. Longer gaps (> 2 hours) led to exclusion of the affected windows. All variables were then aligned on a common hourly index: rainfall represents the accumulated total over the previous hour, while water level and tide are instantaneous hourly readings.

The dataset used in this study includes hourly rainfall and water level data during the rainy season (from September to December) from 2015 to 2024 at the Kien Giang, Le Thuy, Dong Hoi meteorological and hydrological stations and the tidal water level at the Nhat Le estuary in Dong Hoi city. Table. 1 displays a detailed description of the features of the dataset. Table. 2 provides a subset of the collected dataset.

Table 1. Features of the dataset.

Feature	Description	Note
WL_LeThuy (m)	Water level at the Le Thuy station	Target
WL_KienGiang (m)	Water level at the Kien Giang station	
WL_DongHoi (m)	Water level at the Dong Hoi station	
RF_LeThuy (mm)	Rainfall at the Le Thuy station	
RF_KienGiang (mm)	Rainfall at the Kien Giang station	
RF_DongHoi (mm)	Rainfall at the Dong Hoi station	
Tide_NhatLe (m)	Tidal water level at the Nhat Le estuary	

The water level of rivers is a critical parameter in flood monitoring and is directly associated with official flood warning levels. These warning levels consist of three ascending stages. Specifically, flood alert level 1 indicates a potential flood risk, while flood alert level 3 denotes a highly dangerous flood situation. Each alert level corresponds to specific threshold values of water levels, which are measured at designated hydrological stations along rivers and streams. Therefore, accurate and timely forecasting of river water levels plays an essential role in predicting flood alert stages, enabling

Table 2. Subset of the collected dataset

Time	WL_KienGiang (m)	RF_KienGiang (mm)	WL_LeThuy (m)	RF_LeThuy (mm)	WL_DongHoi (m)	RF_DongHoi (mm)	Tide_NhatLe (m)
2020-10-15 06:00	7.01	1.00	1.81	1.20	0.29	0.00	-0.45
2020-10-15 07:00	7.00	0.40	1.79	1.20	0.37	0.20	-0.29
2020-10-15 08:00	6.99	0.20	1.77	0.20	0.56	2.40	-0.10
2020-10-15 09:00	6.98	0.00	1.76	0.00	0.66	0.40	0,09
2020-10-15 10:00	6.96	0.00	1.74	0.00	0.84	0.00	0.25

Table 3. Flood warning levels at the Le Thuy station and corresponding sample distribution in the training dataset.

Flood Warning Level	Water Level Threshold	Training Samples
0	< 1.2m	6,907
1	≥ 1.2m and < 2.2m	4,297
2	≥ 2.2m and < 2.7m	746
3	≥ 2.7m	557

communities to implement preventive measures and mitigate potential damage. The flood warning levels of the Le Thuy station, their corresponding water level thresholds, and the distribution of training samples across these levels, are summarized in Table. 3.

This study focuses on developing models of forecasting water level prediction at the Le Thuy station, with the water level at this station designated as the prediction target. To train and evaluate models, the dataset is divided into two subsets:

- Training set: data collected from 2015 to 2021.
- Test set: data collected from 2022 to 2024.

3. Problem Statement

This study develops water level forecasting models that utilize a continuous sequence of observations over the past t hours, including water level and rainfall data from the hydrological and meteorological stations at Kien Giang, Le Thuy, Dong Hoi, and the tidal water level at the Nhat Le estuary, to forecast a continuous sequence of water levels over the next k hours at the Le Thuy station. Specifically, the project builds and evaluates forecasting models with forecast horizons of 6, 12, and 24 consecutive hours. Each forecast horizon corresponds to a separate forecasting model.

The water level forecasting models are trained on the training set, which consists of data collected from 2015 to 2021. The test set, which includes data collected from 2022 to 2024, is used to evaluate the forecasting performance of the models.

4. Development of the Water Level Forecasting Model

4.1. Overview of the Model Development Process

Essentially, this is a time series problem characterized by temporal dependencies, where the water level at a given time is directly influenced by the water levels at previous time steps. Therefore, forecasting methods must be capable of capturing and utilizing long-term dependencies within the data. Among deep learning models, the LSTM recurrent neural network [15] is chosen for its effectiveness in handling time-dependent sequences, as well as its ability to overcome the vanishing and exploding gradient problems commonly encountered in traditional neural networks.

In addition, we apply an Autoencoder architecture [16] combined with LSTM for the sequence-to-sequence forecasting task. This approach allows the model to encode the entire historical water level sequence and decode it to predict the future water level sequence. It is a suitable method for forecasting water levels over multiple consecutive hours.

Moreover, the movement of water in the river basin is also influenced by topography, secondary flows, and tidal fluctuations, which cause the impact of input factors to vary over time. To enable the model to automatically identify and adjust its focus on the most relevant factors at each time step, an Attention mechanism [17] is integrated into the Autoencoder architecture. The incorporation of Attention enhances the model's ability to learn complex relationships between influencing factors and water level changes, thereby improving forecasting accuracy, especially over long prediction horizons and during periods of hydrological anomalies.

The model development forecasting water levels at Le Thuy station consists of three steps (Fig. 1):

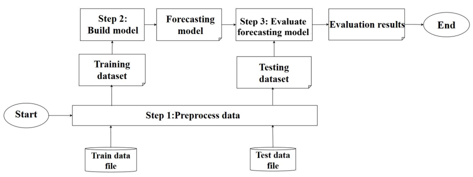

Fig. 1. Workflow for developing a water level forecasting model

- Step 1. Data Preprocessing

  Transform the data from the original file into a set of samples and corresponding labels based on t (the past time window) and k (the future forecasting horizon).

- Step 2. Designing and Training the Model
  - Define the Autoencoder architecture (including LSTM, Attention, and fully connected layers) and set training parameters.
  - Train the model (optimize the model's weight parameters).
- Step 3. Model Evaluation

Use the model developed in Step 2 to forecast the targets in the test set. The predicted targets are compared with the actual ones using evaluation metrics commonly employed in time-series forecasting tasks. Among them, Nash–Sutcliffe Efficiency (NSE) evaluates the predictive skill of the model compared to the mean of the observed data, Coefficient of Determination (R^2) measures how well the predicted values fit the observed data, Mean Absolute Error (MAE) quantifies the average magnitude of the errors between predicted and observed values (without considering their direction), Root Mean Square Error (RMSE) measures the square root of the average squared differences between predicted and observed values, and Dynamic Time Warping (DTW) assesses the temporal similarity between two time series by measuring the minimal distance required to align them. High NSE and R^2 values (close to 1), along with low MAE, RMSE and DTW values, indicate that the predicted targets closely match the actual ones, which means that the model achieves good forecasting performance.

4.2. Detailed Steps for Model Development

4.2.1. Data preprocessing

The data file is segmented into samples and corresponding targets. Each sample is a time series consisting of data form the stations over t consecutive hours, and its target is a time series of water levels at the Le Thuy station over the next k hours. A simulation of the data preprocessing step is illustrated in Fig. 2

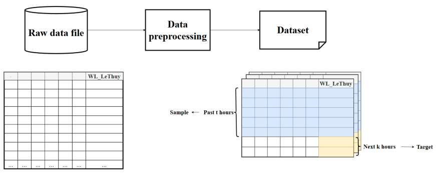

Fig. 2. A simulation of the data preprocessing

4.2.2. Designing and training the model

The model is built upon an Autoencoder architecture, incorporating LSTM and Attention mechanisms to enhance its ability to capture long-term dependencies and relationships between time steps in a time series. Specifically, a Multi-Head Attention layer is inserted between the Encoder and Decoder. This mechanism allows the model to attend to information from different representation subspaces at multiple positions simultaneously, enabling it to learn diverse temporal dependencies and interaction patterns from hidden states of the encoder. As a result, the model can better capture complex relationships in the input sample and improve the accuracy of future predictions.

Within the decoder block, a self-attention mechanism is also employed to model the dependencies among previously generated outputs. By enabling each decoding step to attend to all prior outputs, the model is able to leverage contextual information throughout the output sequence. This enhances its ability to generate accurate forecasts, particularly in the case of long and complex time series.

The model is trained using the Mean Squared Error (MSE) loss function and the Adam optimizer. Additionally, the Early Stopping technique is applied during training to prevent overfitting, ensuring model stability and generalization capability.

The model design and training parameters as shown in Fig. 3 and Table. 4.

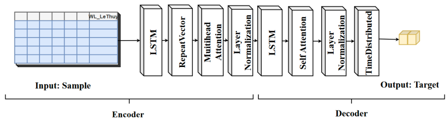

Fig. 3. Architecture of the water level forecasting model

Table 4. Detailed configuration of the water level forecasting model

Encoder
LSTM (352, activation = tanh, return_sequence =Flase, return_state=True)
RepeatVector()
MultiHeadAttention (num_heads = 4, key_dim = 32)
Add()
LayerNormalization()
Decoder
LSTM (352, return_sequence = True, activation = tanh)
Attention(use_scale=True)
Add()
LayerNormalization()
TimeDistributed(Dense(1))
Parameters
Batch size = 32
Loss = MSE
Optimizer = Adam
Epochs = 50
Earlystopping = 15

4.2.3. Model evaluation

The models are evaluated using five metrics in time series regression tasks, including R^2, NSE, RMSE, MAE and DTW. Table 5 summarizes the evaluation results of the models across different forecasting time horizons.

According to the Hydrometeorological Forecasting Center, the allowable forecast error thresholds at Le Thuy station are 0.14 m for 6-hour forecasts, 0.18 m for 12-hour forecasts, and 0.22 m for 24-hour forecasts. The experimental results show that all models perform well, with R^2 and NSE values above 0.9, and average errors lower than the allowed thresholds. The R^2 and NSE values indicate that the LSTM Autoencoder model integrated with Attention achieves higher and more stable forecasting performance compared to the standard LSTM Autoencoder, especially as the forecast horizon increases. Furthermore, the models achieved NSE values above 0.9, indicating that the predicted water level series almost perfectly match the observed data and that the models effectively captures both

Table 5. Performance evaluation of the models.

Forecasting time	Model	NSE	R2	MAE (m)	RMSE (m)	DTW (m)
6 hours	LSTM Autoencoder	0.982	0.982	0.032	0.084	0.179
	LSTM Autoencoder + Attention	**0.986**	**0.986**	**0.027**	**0.073**	**0.149**
12 hours	LSTM Autoencoder	0.961	0.956	0.061	0.131	0.655
	LSTM Autoencoder + Attention	**0.970**	**0.970**	**0.041**	**0.108**	**0.431**
24 hours	LSTM Autoencoder	0.910	0.908	0.091	0.188	1.982
	LSTM Autoencoder + Attention	**0.929**	**0.928**	**0.075**	**0.166**	**1.567**

the amplitude and temporal variations of hydrological responses. Additionally, DTW values, ranging from 0.149 to 1.567 demonstrate only a very small temporal misalignment between the predicted and observed hydrographs, confirming that the models successfully reproduces the timing and shape of flood peaks.

Specifically, for the 6-hour forecast horizon, the model with Attention achieves $R^2 = 0.986$ and NSE = 0.986, outperforming the version without Attention. In addition, the error metrics (MAE, RMSE and DTW) are all lower (MAE decreased from 0.032 m to 0.027 m; RMSE from 0.084 m to 0.073 m; and DTW from 0.1787 m to 0.1491 m), indicating that the Attention-enhanced model provides forecasts that better align with actual water level time series.

At the 12-hour forecast horizon, the Attention-integrated model continues to hold an advantage, with higher R^2 and NSE values, and improved MAE, RMSE, and DTW metrics. This demonstrates the effectiveness of the Attention mechanism in extracting relevant information from long input sequences.

Notably, for the extended 24-hour forecast horizon, the Attention-integrated model shows a clear advantage: the goodness-of-fit metrics (NSE and R^2) increased by approximately 0.2, while the forecast error metrics (RMSE and MAE) decreased by about 0.02m. This confirms the Attention mechanism's ability to maintain high forecasting accuracy even over long prediction intervals.

The paired *t*-tests ware conducted to statistically evaluate whether the improvements achieved by the Attention mechanism are significant rather than coincidental. The results show that the *p*-values are extremely small ($p = 4.750 \times 10^{-163}$ for the 6-hour forecast horizon, $p = 3.526 \times 10^{-1437}$ for the 12-hour forecast horizon, and $p = 8.11 \times 10^{-1105}$ for the 24-hour forecast horizon), indicating that the improvements brought by the Attention mechanism are statistically significant.

Overall, the analysis results demonstrate that the LSTM Autoencoder combined with Attention is both feasible and effective for multi-step water level forecasting tasks.

5. Empirical Evaluation

5.1. Experimental Analysis on the Test Set

This section analyzes the forecasting results of the models corresponding to forecast horizons of 6, 12, and 24 consecutive hours. In the following figures, the black line represents the actual observed water level at the Le Thuy station, the blue line shows the forecast generated by the LSTM AutoEncoder model, and the red line depicts the forecast produced by the LSTM AutoEncoder model with an Attention mechanism. The red and blue lines are plotted only within the forecast horizon, while the black line spans both the historical period and the forecast horizon. This visualization allows readers to observe how past water level variations influence the forecasted values. The orange, red, and purple dashed lines correspond to the flood warning levels 1, 2, and 3, respectively, at the Le Thuy station.

For each forecast horizon, three representative plots were generated to compare the forecasted water level series with the actual observations at different forecasting time points (Fig. 4, Fig. 5, Fig. 6). These visual comparisons show that the LSTM AutoEncoder model with Attention produces predictions that align more closely with the actual observations compared to the LSTM AutoEncoder model. The forecast results generated by the Attention-based models exhibit the following characteristics:

- The forecasted sequences closely resemble the actual ones in terms of shape, accurately capturing the upward and downward trends of water level fluctuations.
- The point-wise errors between predicted and observed values are generally small, indicating high forecasting precision across most time steps.
- The predicted and observed water levels reach the thresholds of warning levels 1 and 2 at nearly the same time. However, for warning level 3, the predicted series tends to reach the threshold slightly later than the actual observations.
- For the 6-hour and 12-hour forecast horizons, the predicted and actual water levels consistently fall within the same flood warning levels at each forecast time point (Fig. 4, Fig. 5). However, under the 24-hour forecast horizon, the predicted and observed

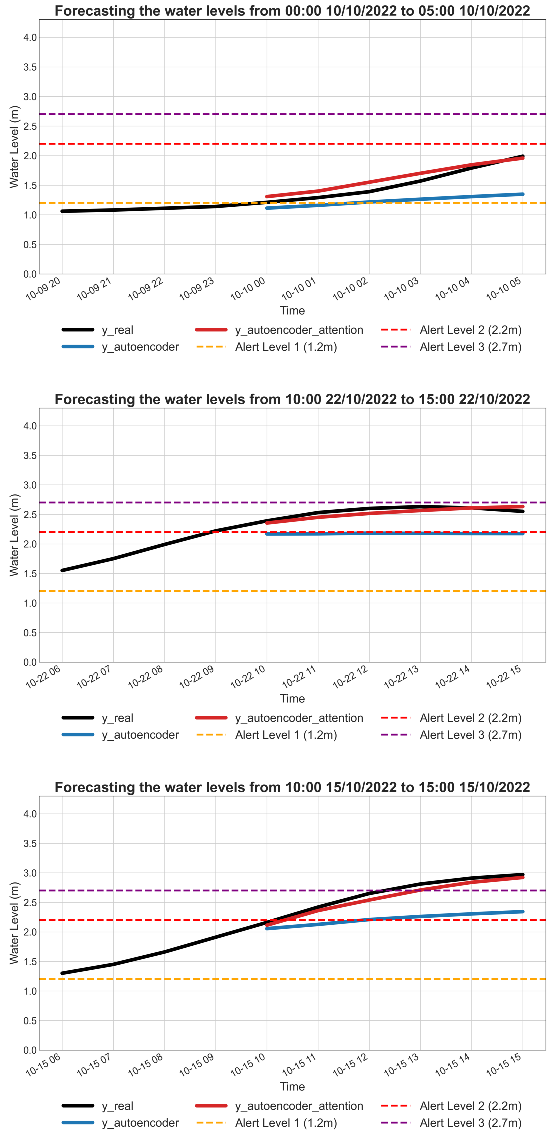

Fig. 4. Comparison between forecasted and observed water levels with a 6-hour forecast horizon.

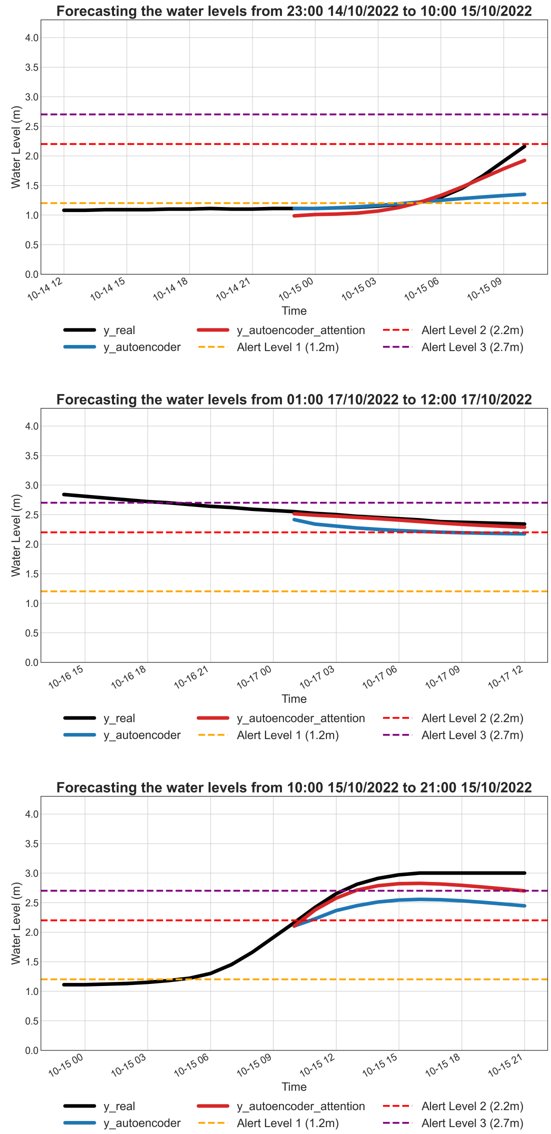

Fig. 5. Comparison between forecasted and observed water levels with a 12-hour forecast horizon.

water level series may reach the thresholds for flood warning levels 2 and 3 at different times (Fig. 6). These results indicate that the forecasts at the 6-hour and 12-hour horizons are more accurate compared to those at the 24-hour horizon.

- The model shows consistent performance across different time points and forecast horizons, suggesting its stability and reliability for short- to medium-term water level forecasting tasks.

The analysis results not only provide further evidence of Attention's effectiveness in reducing cumulative errors and enhancing model accuracy and stability but also demonstrate the model's practical applicability in real-time water level warning systems, where forecast charts can be directly used to monitor water level dynamics and detect threshold exceedances.

5.2. Experimental Analysis of the Extreme Flood Event in 2024

According to hydrological monitoring data, the most significant flood peak in 2024 in Quang Tri province occurred in October. The flood crest exceeded flood warning level 3 by approximately 1.60 meters and was 1.29 meters higher than the historical flood record set in 1979. This event is considered the most severe flood since the catastrophic flood of 2020. During this event, the peak water level at the Le Thuy hydrological station reached 4.16 meters at 00:00 on October 29, 2024. Due to its exceptional magnitude, this flood serves as a critical test case for evaluating the performance of hydrological forecasting models under extreme conditions.

From the comparison between forecasted and observed values in Fig. 7, several key observations can be drawn as follows:

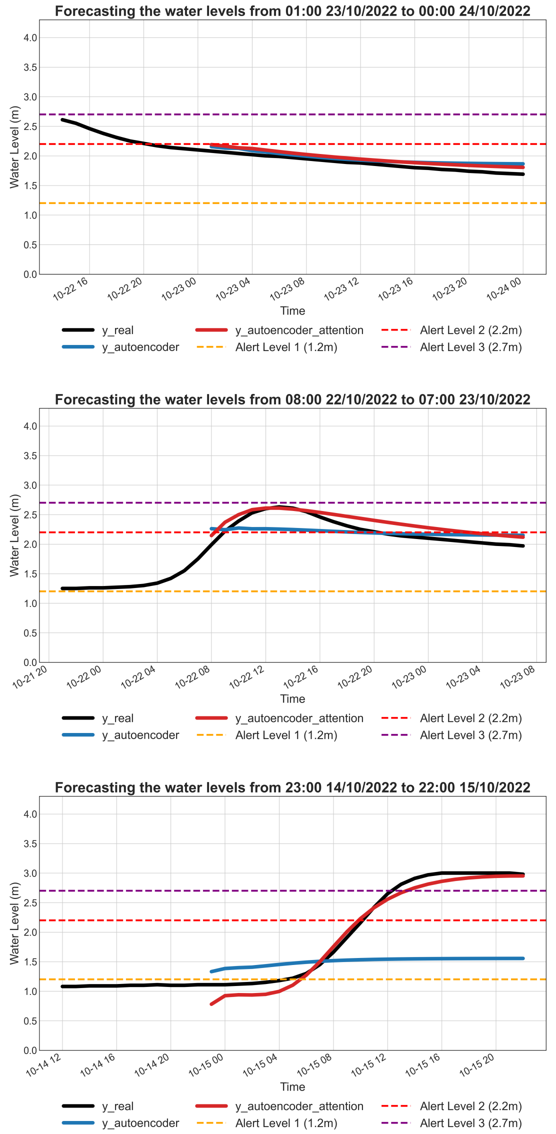

Fig. 6. Comparison between forecasted and observed water levels with a 24-hour forecast horizon.

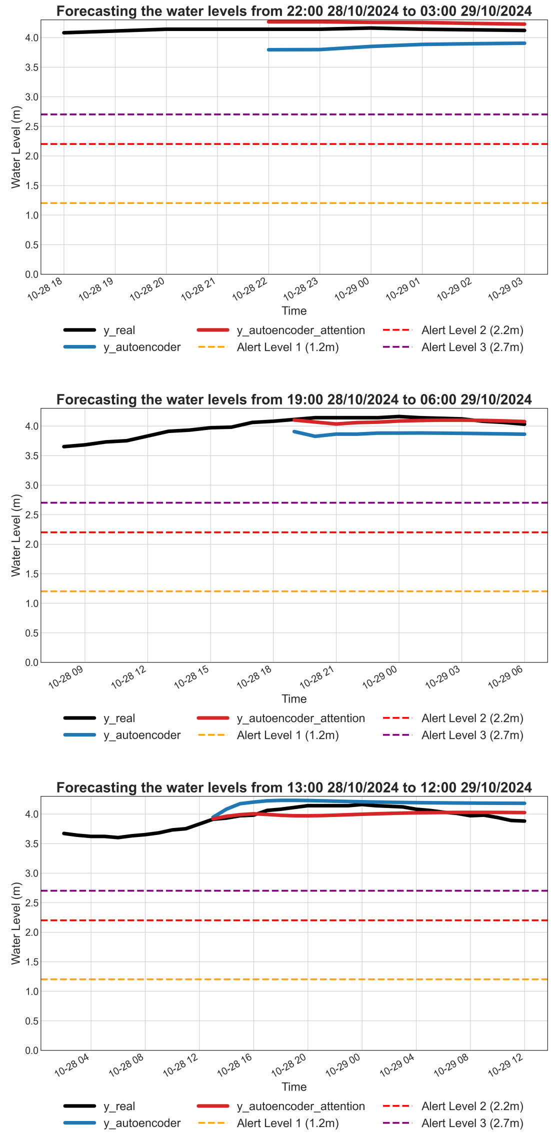

Fig. 7. Comparison of forecasted and observed water levels during the extreme flood event at Le Thuy Station in 2024.

- The LSTM Autoencoder model enhanced with an Attention mechanism demonstrated superior forecasting performance compared to the baseline LSTM Autoencoder model. Notably, the prediction error at the flood peak was approximately 0.2 meters, remaining well below the allowable error threshold of 0.4 meters, thereby confirming the model's high precision during critical stages.
- Even in the context of an extreme flood event, characterized by water levels rarely observed in historical records, the LSTM Autoencoder models with Attention showed strong generalization capability. With 6-hour and 12-hour forecast horizons, the models ware able to accurately reproduce the dynamic changes in water levels, including the timing and magnitude of the peak. The 24-hour forecast horizon model exhibits minor phase shifts at the beginning or end of stages corresponding to warning levels 2 and 3.
- While all models yielded relatively low forecasting errors of an extreme flood event, the results suggest that in scenarios involving rapid and large-scale water level fluctuations, it is advisable to adopt forecasting models with short forecast horizons (6 hours, 12 hours) to ensure more timely and accurate flood warnings.

From the experimental results discussed above, several conclusions can be summarized as follow:

- The LSTM Autoencoder models enhanced with an Attention mechanism have demonstrated strong suitability for forecasting future water level sequences based on past observed data.

- Despite achieving low overall prediction errors, the 24-hour forecast horizon model exhibits minor phase shifts when forecasting water levels associated with warning level 3.
- In the context of extreme flood events, the use of shorter forecast horizons (6-hour or 12-hour) is recommended, as these configurations offer higher predictive accuracy and more effectively capture the dynamic fluctuations in water levels under rapidly changing conditions.

6. Conclusions

In this study, we developed and presented a novel methodology for forecasting water levels at the Le Thuy hydrological station, situated on the Kien Giang river in Quang Tri province. The models leverage historical time series data from multiple hydrological stations to accurately predict water level sequences at the Le Thuy station over continuous horizons. Our model design incorporates advanced deep learning techniques, specifically Autoencoder, Long Short-Term Memory networks, and the Attention mechanism. Experimental validation across three distinct forecast horizons (6, 12, and 24 hours) consistently demonstrated the models' capacity to generate high-quality predictions. Notably, the integration of the Attention mechanism significantly enhanced forecasting performance, enabling the models to more precisely align with observed water levels, even during highly dynamic periods such as extreme flood events. These robust models empower hydrologists with the capability to anticipate water level fluctuations several hours in advance, thereby facilitating more timely and effective flood response planning and mitigation strategies.

Although the models generally produced forecasts that closely aligned with observed measurements, the 24-hour forecast horizon exhibited minor phase shifts when forecasting water levels associated with warning level 3. A promising direction for future research is to explore alternative machine learning approaches to further improve the performance of flood forecasting models.

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