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Original Article

Long short-term memory (LSTM) neural networks for short-term water level prediction in Mekong river estuaries

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Abstract

This study firstly adopts a state-of-the-art deep learning approach based on a Long Short-Term Memory (LSTM) neural network for predicting the hourly water level of Mekong estuaries in Vietnam. The LSTM models were developed from around 8,760 hourly data points within 2018 and were evaluated using the Nash-Sutcliffe efficiency coefficient (NSE), mean absolute error (MAE), and root mean square error (RMSE). The results showed that the NSE values for the training and testing steps were both above 0.98, which can be regarded as very good performance. Furthermore, the RMSE were between 0.09 and 0.11 m for the training and between 0.10 and 0.12 m for the testing, while MAE for the training ranged from 0.07 to 0.08 m and varied from 0.08 to 0.10 m for the testing. The LSTM networks appear to enable high precision and robustness in water level time series prediction. The outcomes of this research have crucial implications in river water level predictions, especially from the viewpoint of employing deep learning algorithms.

Keywords: long short-term memory *(*LSTM*)*, neural network, water level, Mekong river estuary

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1. Introduction

Water level, the elevation of the free surface of a water body relative to a vertical datum, may be used for flow forecasting, flood hazard zoning, hydraulic engineering design, and computation of water discharge or storage (World Meteorological Organization [WMO], 2008). Its fluctuations can take place on various spatial and temporal scales due to natural cycles as well as anthropogenic forcings (Leira & Cantonati, 2008) whereby 57 percent of the variability occurs in dammed reservoirs and other bodies of water managed by people (Cooley, Ryan, & Smit, 2021). In turn, the variations of water level affect a series of chemical, physical, and biological processes in basins (Ning *et al.*, 2018). It is thus essential to predict water level fluctuations in water bodies.

Physics-based and data-driven approaches have been used to forecast water levels in streams and lakes. Possessing the ability to fully describe the nature of physical phenomena, physics-based models are widely applied to predict the variations of water levels in inland and coastal zones (Liu, Wang, & Lei, 2021). Nevertheless, these models are not always reasonable because they are complicated, data demanding, and time-intensive (Le, Ho, & Lee, 2019). To overcome the above limitations, data-driven models are a powerful alternative for real-time water level forecasting in rivers or lakes since they require less input data and computational time (Phan & Nguyen, 2020). Data-driven models can be built using machine learning techniques that learn nonlinear relationships in hydraulic and hydrological processes (Nguyen & Le, 2019). Among the machine learning techniques, Long Short-Term Memory (LSTM) is an enhanced Recurrent Neural Network (RNN) with a strong ability to capture and store information (Zou *et al.*, 2020) and it has been broadly applied to predict time-series data, such as water level (Tu *et al.*, 2021) and water quality (Zou *et al.*, 2020).

Vietnam has a rich variety of inland waters, including about 3,450 rivers and streams with length of at least ten kilometers each (Nguyen, Dang, & Nguyen, 2021), and 9,149 reservoirs (Directorate of Water Resources [DWR], 2021). Due to the sparse hydrological monitoring network with 354 existing stations (Decision No. 90/QD-TTg on Approval of a Master Plan for National Natural Resources and Environment Monitoring Networks for 2016 – 2025, with a Vision to 2030, 2016) and data sharing barriers, forecasting levels and flow of surface water in ungauged basins has been a major challenge in water resources management. A great deal of work was conducted to understand this issue by using different approaches, such as hydrologic model (Nguyen, Dang, & Nguyen, 2021), hydraulic model (Lam, 2019), Wavelet-Artificial Neural Network and Time Series (Dat, Thi, Solanki, Le An, 2020), Support Vector Regression (Nguyen & Le, 2019), Ensemble Learning Regression (Kim *et al.*, 2019), LSTM (Le, Ho, Lee, & Jung, 2019), and hybrid model (Phan & Nguyen, 2020).

Mekong Delta (MKD) is one of the most important bases of agriculture and aquaculture in Vietnam. Fluctuations of water levels in this flood plain resulting from climate change and anthropogenic interventions (e.g. upstream hydro-infrastructure developments, instream sand mining, and downstream sluices) affect water availability for farming, livestock, freshwater and brackish water culture, and biological protection purposes. During the high-flow season, flood pulses and frequency have cumulatively reduced along the entire Mekong due to reservoir operations (Binh *et al.*, 2020). In the low-flow season, water levels in the MKD have decreased because of increased riverbed incision which outweighs the effect of early emergency water release from upstream dams (Binh *et al.*, 2020), spring–neap cycles, and wind-generated offshore surges (Eslami *et al.*, 2019). This study aims to forecast water levels at one-hour lead time in the Mekong river estuaries of Vietnam. This was done by applying the LSTM model with input data of water level observed at hydrological stations during 2018.

2. Materials and Methods

2.1. Study area

The Mekong river basin, the tenth-largest river in the world, is located in Southeast Asia with an approximately 795,000 square kilometer area and 4,900 kilometer length. The Mekong entering MKD of Vietnam divides into the Mekong (or Tien) and Bassac (or Hau) rivers before draining into the East Sea via eight estuaries (Figure 1). The Tien and Hau rivers transport approximately 80% and 20% of the total flow of MKD, respectively (Binh *et al.*, 2020).

Thanks to its location, MKD has a vast plain area, a highly braided network of rivers, two sides bordering the sea, and over 732 kilometers long coastline (Anh *et al.*, 2021) which is favorable for agricultural diversification based on the three key sectors of rice cultivation, aquaculture, and fruit production. MKD is the largest agricultural production center in Vietnam, contributing 50% of rice, 65% of seafood, and 70% of fruit (Resolution on Sustainable and Climate-Resilient Development of the Mekong Delta, 2017).

MKD receives a large amount of fresh water, approximately 450-475 billion cubic meters per year, accounting for more than half of the total surface water of Vietnam. However, heavy rains and high flows usually concentrate in the wet season from May to October, causing annual flooding in this region with nearly 50% of the area being inundated for 2-4 months. In contrast, during the dry season that lasts from November to April rainfall is negligible, and the amount of water flowing from the Mekong River into the delta is low, so saltwater penetrates inland and groundwater resources have been significantly reduced. The above significant changes in streamflow between the wet and dry seasons have been challenges to securing the water supply for household and production uses by the coastal residents (Anh *et al.*, 2021).

2.2. Data acquisition and preprocessing

Due to data availability, this study focused on the Cua Tieu, Cua Dai, Ham Luong, and Co Chien estuaries. We collected water level data at 4 hydrological stations (Figure 1): Vam Kenh, Binh Dai, An Thuan, and Ben Trai near the estuaries. At each station, water level measurement was made hourly from January to December in 2018 for a total of 8,760 data points. Southern Regional Hydro-Meteorological Centre, an institute of Vietnam's Ministry of Natural Resources and Environment, provided the data.

Regarding time series data, the data quality has a great effect on the accuracy of the predictive models. As a

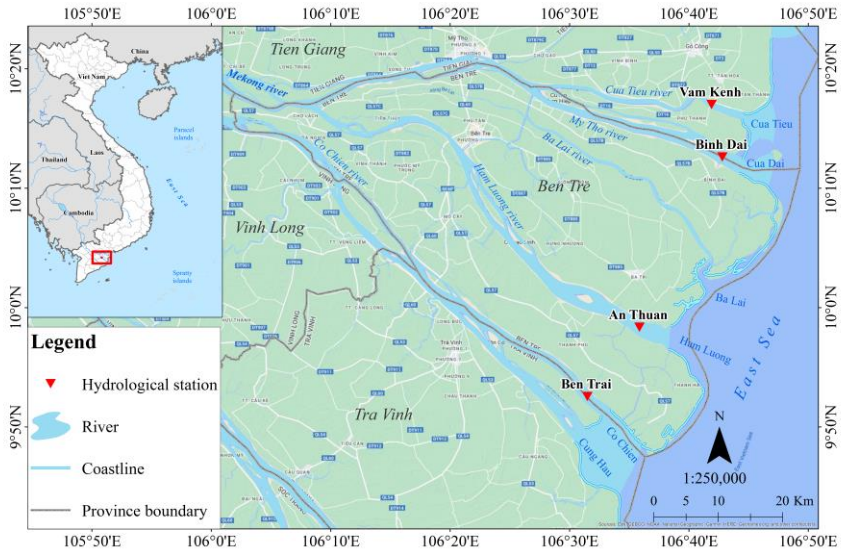

Figure 1. Locations of the study area and hydrological stations

result, depending on characteristics of the water level dataset, two-step preprocessing is performed before training.

1) Abnormal outliers in the dataset can be detected and replaced by the average values of the four points around them. The box plot is a convenient way of illustrating the distribution of data based on the five number indices: minimum, first quartile (Q1), median, third quartile (Q3), and maximum. In order to detect outliers, the box plot procedure is used with the upper limit of Q3 + 1.5 * Interquartile Range (IQR) and the lower limit of Q1 - 1.5 * IQR. Values that are more extreme than these limits can be classified as outliers or suspected outliers.

2) All water level data were scaled to within the interval (0, 1) by normalization performed using the scikit-learn preprocessing library in Python language. This step prevents dramatic changes in gradient and smooths the convergence (Barzegar, Aalami, & Adamowski, 2020). Moreover, it can increase the speed of neural network training and allow reducing the sample size without considerably influential prediction accuracy (Yang, Wu, & Hsieh, 2020).

2.3. LSTM neural networks

A recurrent neural network (RNN) is an improved multi-layer perception, which includes the input layer, hidden layer, and output layer (Figure 2a). In general, the basic principle of RNN is as follows: the status at time t (h_t) is determined by the previous state (h_{t-1}) and the current input (x_t). Since the output (y_t) is determined by the state (h_t), it reflects the sequential dependency of the data. W, U, and V are hyperparameters of different layers. They are able to predict the future unseen sequential data with respect to the earlier steps observed in the sequence. However, the major challenge with traditional RNNs is that these networks remember only a few time steps due to vanishing and exploding gradient problems during the back-propagation calculations; in other words, the RNNs are not suitable to go back over longer sequences of data (Hochreiter, 1998).

This challenging problem can be solved using the structure of LSTM. The critical component of the LSTM is composed of many linked memory cells and the architecture of each cell is shown in Figure 2b. Each repeating module of LSTM contains a memory cell state regulated by the three gates (forget, input, and output gates). The specific process of LSTM can be summarized as follows.

1. The forget gate (f_t) determines whether to accept the previous state (h_{t-1}) and a new input value (x_t) in the cell and maintain or remove the information (Equations 1, 2):

$$f_t = \sigma(W_t[h_{t-1}, x_t]) \tag{1}$$

$$\sigma\,(x) = \frac{1}{1+e^{-x}} \tag{2}$$

where σ is the sigmoid function and W_t is the weight of the forget gate.

2. The input gate (i_t) determines whether or not to save certain information in the cell (Equation 3). The input gate has two active function layers: a sigmoid and a tanh. The value to be updated using the sigmoid function and the vector value of the candidate cell ($\tilde{C}_t$) that can be added to the long-term memory in the tanh layer are generated. Then, these two values are multiplied to update the data state (Equations 4, 5):

$$i_t = \sigma(Wi[h_{t-1}, x_t]) \tag{3}$$

$$\tilde{C}_t = \tanh(W_c.\ [h_{t-1}, X_t]) \tag{4}$$

$$tanh\,(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

where W_i is the weight of the input gate and W_c is the weight of the candidate cell.

3. Update the cell state of the present time step C_t, which combines the candidate memory $\tilde{C}_t$ and the long-term memory C_{t-1} (Equation 6):

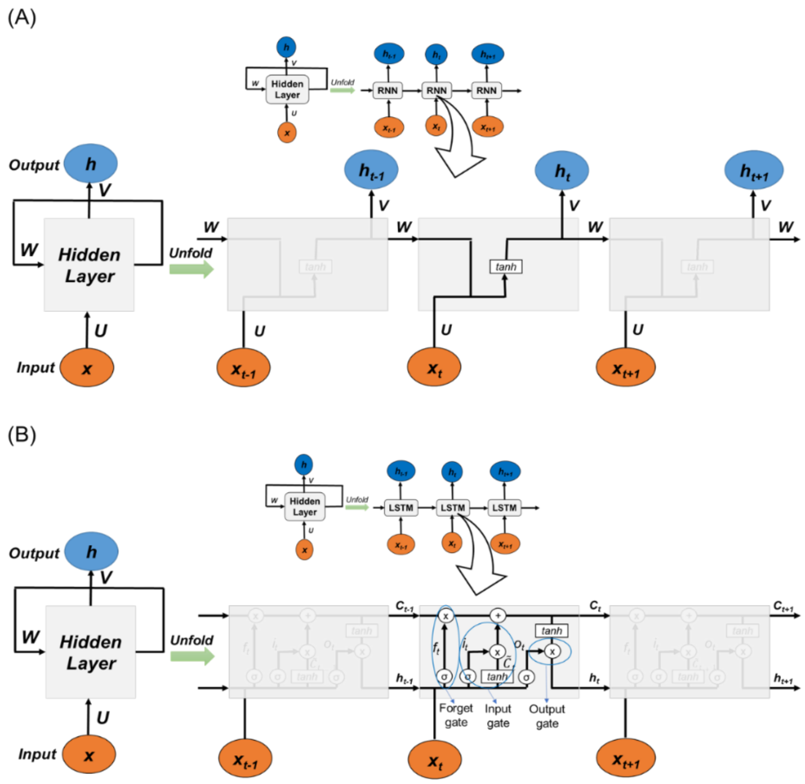

Figure 2. The internal structures of RNN (A) and LSTM (B)

$Ct = f_t.C_{t-1} + i_t.\tilde{C}_t$ (6)

4. The output gate (O_t) determines which part of the cell state to output using the sigmoid function as in Equation (7). Finally, it updates the state of a specific time (h_t) by multiplication with the tanh of the active cell state (C_t) (Equation 8):

$$O_t = \sigma(W_o.[h_{t-1}, X_t]) \quad (7)$$

$$h_t = O_t.tanh(C_t) \quad (8)$$

where W_o is the weight of the output gate.

2.4. Model architecture

In this study, the input data were divided into two parts for training and testing the LSTM model. The training dataset accounted for 70% of the data, and the remaining observed samples (30%) were used to assess the forecasting model. The complete network model structure is displayed in Figure 3.

The LSTM structures consist of an LSTM layer with a tangent function with four neurons, which was used in the hidden layer. A fully connected layer, termed "dense", with one neuron and a tangent activation function, was used. Subsequently, the models were compiled with a mean squared error loss function and an Adam optimizer with a learning rate of 0.001. Figure 4 presents the loss function plots for the models. The presented models were adapted in the open-source scikit-learn and Keras libraries in Python 3.6.

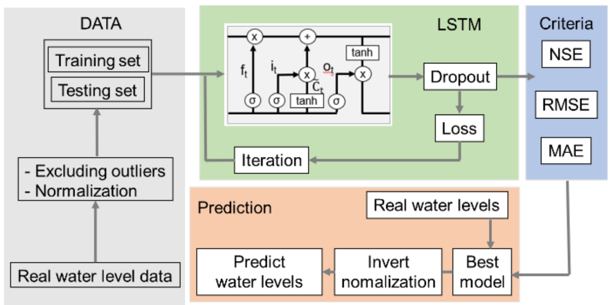

Figure 3. Flowchart of the LSTM networks

2.5. Performance criteria

Nash-Sutcliffe efficiency coefficient (NSE, Equation 9), Root Mean Squared Error (RMSE, Equation 10), and Mean Absolute Error (MAE, Equation 11) were used to evaluate model performance.

$$\text{NSE}=1- \frac{\sum_{i=1}^{n}(\hat{y}i - yi)^2}{\sum_{i=1}^{n}(\bar{y} - yi)^2} \quad (9)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}i - yi)^2} \quad (10)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}i - yi| \quad (11)$$

where n represents the number of samples and $\hat{y}i$, yi, and $\bar{y}$ denote the predicted value, the observed value, and the mean of observations, respectively.

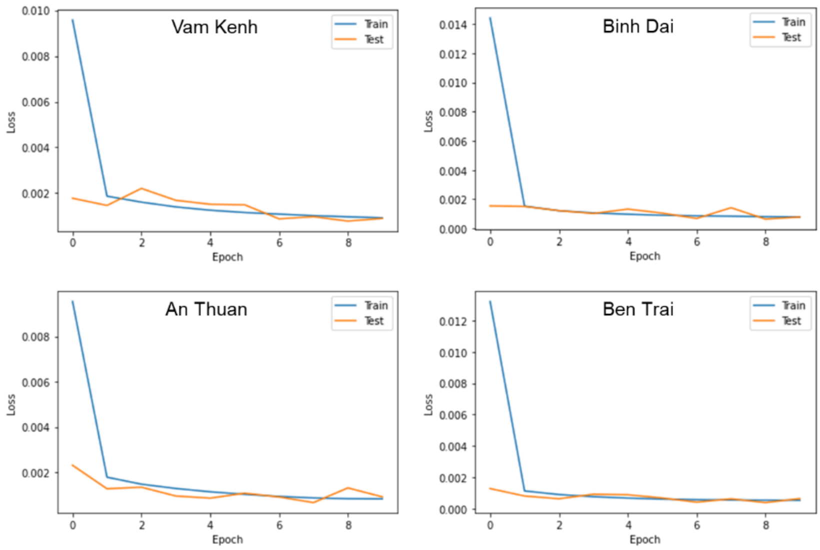

Figure 4. Loss function curve of LSTM model with different hydrological stations

The performance of the model based on NSE is categorized as very good, good, satisfactory or unsatisfactory when NSE > 0.80, 0.7 < NSE ≤ 0.8, 0.50 < NSE ≤ 0.70, or NSE ≤ 0.50, respectively (Moriasi, Gitau, Pai, & Daggupati, 2015).

3. Results and Discussion

3.1. Water level prediction

Table 1 shows the values of the validation error of forecasting water level for up to 5 hours ahead. The R^2 demonstrated that the ordering of the sizes of the lead times was as follows, from largest to smallest: 1, 2, 3, 4, and 5. In terms of RMSE and MAE, the ordering of the values for the lead times was as follows, from smallest to largest: 1, 2, 3, 4, and 5. With regard to accuracy, the LSTM model provided good accuracy for a short time horizon forecast. However, when the forecasting horizons were longer (e.g. t + 4, t + 5), the performance of LSTM model was insignificant.

Figure 5 illustrates a comparison between the observed and predicted water levels over the four estuaries for lead time of 1 h. Overall, the predicted water levels by the LSTM neural networks presented a good agreement with the observed water levels. The simulated and observed values were both reverted to their original scale, the NSE, RMSE and MAE were then calculated to evaluate the model. The LSTM performances did not vary much across the four estuaries. The results showed NSE values ranging from 0.98 to 0.99 for the training step and 0.98 for the testing step in all stations, which is within the "very good" performance range from 0.80 to 1.00. In addition, the RMSE were between 0.09 and 0.11 (m) for the training and between 0.10 and 0.12 (m) for the testing, while MAE for the training ranged from 0.07 to 0.08 (m), and from 0.08 to 0.10 (m) for the testing (Table 2). These indicate very high precision and robustness of the LSTM networks in water level time series prediction.

The scatter plots of the observed and simulated water levels in the training and testing steps (Figures 6 and 7) show

Table 1. Validation error of forecast water level for up to 5 hours ahead

Criteria	Lead time	Vam Kenh	Binh Dai	An Thuan	Ben Trai
R^2	t + 1	0.986	0.988	0.984	0.989
	t + 2	0.933	0.936	0.943	0.944
	t + 3	0.824	0.808	0.867	0.844
	t + 4	0.643	0.575	0.734	0.689
	t + 5	0.422	0.258	0.556	0.496
RMSE (m)	t + 1	0.097	0.089	0.103	0.083
	t + 2	0.208	0.207	0.193	0.188
	t + 3	0.340	0.358	0.295	0.313
	t + 4	0.484	0.533	0.418	0.443
	t + 5	0.616	0.704	0.539	0.563
MAE (m)	t + 1	0.074	0.072	0.080	0.066
	t + 2	0.161	0.165	0.151	0.151
	t + 3	0.262	0.287	0.237	0.253
	t + 4	0.375	0.432	0.337	0.356
	t + 5	0.477	0.572	0.437	0.450

Table 2. The results of LSTM neural networks for the training and testing datasets at hydrological stations for lead time of 1 h

Stations	Training period			Testing period		
	NSE	RMSE (m)	MAE (m)	NSE	RMSE (m)	MAE (m)
Vam Kenh	0.98	0.11	0.08	0.98	0.12	0.09
Binh Dai	0.98	0.11	0.08	0.98	0.11	0.09
An Thuan	0.98	0.11	0.08	0.98	0.12	0.10
Ben Trai	0.99	0.09	0.07	0.98	0.10	0.08

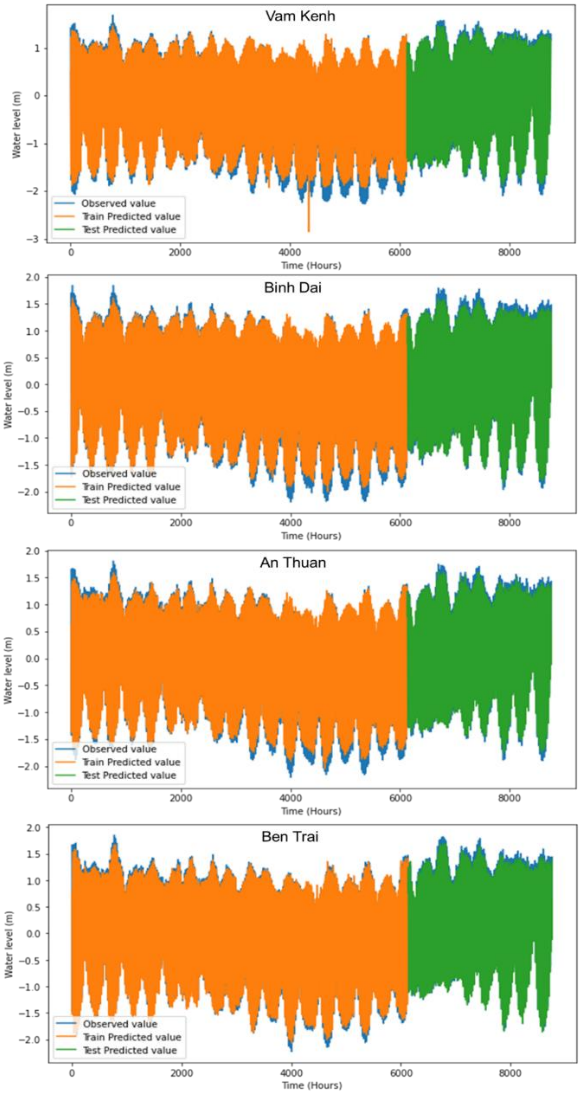

Figure 5. Observed and predicted water level in 2018 at hydrological stations for lead time of 1 h

that the LSTM neural networks gave highly accurate prediction. They had high r values (0.99 in all cases) and were well fit by linear regression.

Water level prediction plays an important role in Mekong Delta as water level relates to flooding and riverbank erosion in the wet season; and drought and saline intrusion in the dry season. Most people in this area are working in agriculture and aquaculture, and accurate predictions of water level would assist them in appropriate planning to protect their crops. Currently, the responsible institute for water level prediction in the area still prefers to use physically-based models such as MIKE21 for predicting water level. This study proposed a new approach using deep learning with less input data and higher accuracy, and can offer an alternative to that traditional approach. In the future, this approach can be developed for longer lead times such as one week, and that would be more useful for inhabitant activities regarding agriculture and aquaculture planning.

3.2. Comparison with state-of-the-art methods

Due to influences of different surrounding flows, the tidal schemes in the Mekong estuaries can be considered complex (Dang *et al.*, 2019). Therefore, many approaches have been tested for the water level simulations in Mekong River's mouths, such as machine learning algorithms, remote sensing techniques (He, Fok, Chen, & Chun, 2018), and process-based models (i.e., MIKE) (Nhan, 2016). Here, the study compares the accuracy of these different methods applied to water level prediction in the Mekong estuaries. However, the comparison becomes difficult, mainly because of differences in principles-based approaches and used datasets. In general, these models developed for water level prediction have had good performances, especially both the deep learning algorithms and the process-based models. Table 3 lists the prediction accuracies of these different state-of-the-art techniques for water level prediction in Mekong estuaries.

Although generally accurate results have been obtained from the process-based models, which showed a very high precision in water level time series prediction, the deep learning approach (i.e., LSTM) has still received more attention because of the following three aspects. First, physically-based hydrodynamic models are highly complex in general, needing lots of parameter data as model inputs, while the development of machine learning algorithms requires minor data as inputs (Zhu, Hrnjica, Ptak, Choiński, & Sivakumar, 2020). Second, the water level is a typical time series data (Ren, Liu, Niu, Lei, & Zhang, 2020). LSTM is able to keep the information gained from earlier parts of a long data sample in the memory cells and move it to the later parts of the same data sample. Moreover, the forget gate in LSTM can effectively filter out meaningless information from the input data, improving the model accuracy (Goodfellow, Bengio, & Courville, 2016). This makes LSTM suitable for modelling sequential or time series data (Yang *et al.*, 2020). Third, because the water level is certainly affected by the adjacent terrain characteristics, while LSTM algorithms not only considers the hidden information in water level time series they also captures local spatial factors from a specific sequence (Fang, Wang, Peng, & Hong, 2021).

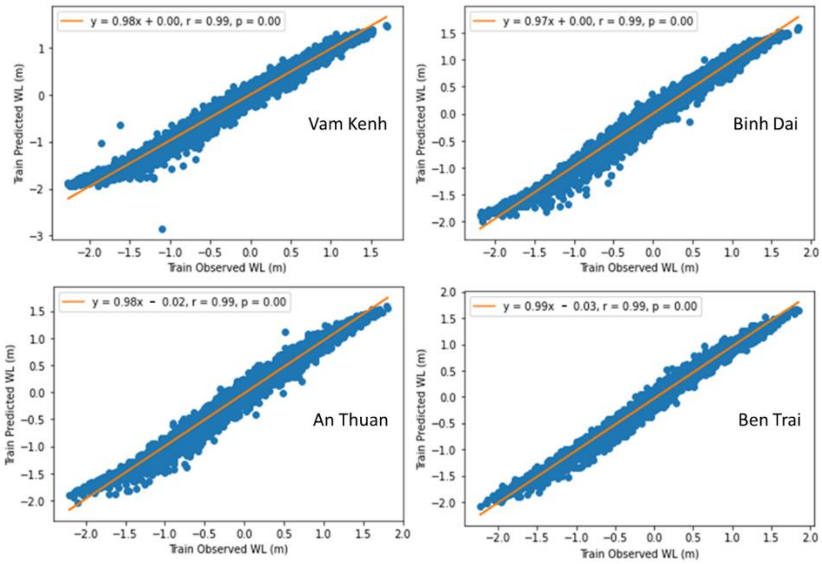

Figure 6. Comparisons between observed and predicted water levels for the training dataset at hydrological stations for lead time of 1 h

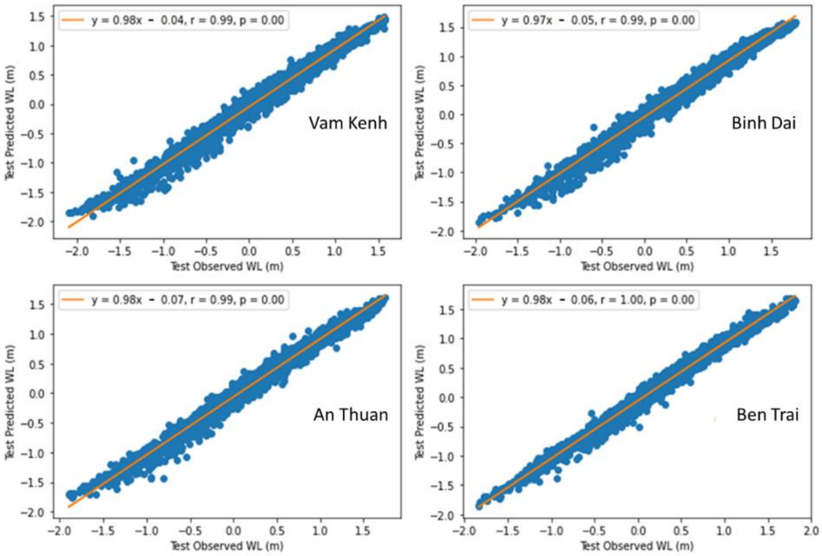

Figure 7. Comparisons between observed and predicted water levels for the testing dataset at hydrological stations for lead time of 1 h

Table 3. The performance of various methods in predicting water levels at Mekong river estuaries

Mekong river estuaries	Performance	Techniques	Datasets	References
Vam Kenh	NSE: 0.98, RMSE: 0.11-0.12 m, MAE: 0.08-0.09 m	LSTM	Hourly, 2018	Our study
	NSE: 0.70-0.78, RMSE: 0.41-0.47 m	Remote sensing	Daily, 1992 - 2006	He, Fok, Chen, and Chun (2018)
	NSE: 0.76-0.95, RMSE: 0.19-0.38 m	Drought indices	Daily, 1992 - 2007	He, Fok, Chen, and Chun (2018)
	RMSE: 0.042 m, R^2: 0.97	MIKE	Hourly, 1984-2016	Nhan (2016)
Binh Dai	NSE: 0.98, RMSE: 0.11 m, MAE: 0.08-0.09 m	LSTM	Hourly, 2018	Our study
	RMSE: 0.043 m, R^2: 0.97	MIKE	Hourly, 1984-2016	Nhan (2016)
An Thuan	NSE: 0.98, RMSE: 0.11-0.11 m, MAE: 0.08-0.10 m	LSTM	Hourly, 2018	Our study
	RMSE: 0.041 m, R^2: 0.98	MIKE	Hourly, 1984-2016	Nhan (2016)
Ben Trai	NSE: 0.98-0.99, RMSE: 0.09-0.10 m, MAE: 0.07-0.08 m	LSTM	Hourly, 2018	Our study
	RMSE: 0.042 m, R^2: 0.98	MIKE	Hourly, 1984-2016	Nhan (2016)

In fact, several researchers have tried to apply LSTM to time series forecasting and compared their results to other process-based models. Kratzert *et al.* (2018) proposed an LSTM model for daily runoff prediction using meteorological observations. The results showed that the LSTM performed better than the Sacramento Soil Moisture Accounting Model SAC-SMA + Snow-17. Damavandi *et al.,* (2019) applied an LSTM model to watershed predicting, which included the current day's streamflow and climate data, and obtained results better than the physical model, which was calibrated SAC-SMA and CaMa Flood.

4. Conclusions

This paper presents the first application of the LSTM neural networks for modelling and predicting hourly water levels in Mekong estuaries in Vietnam. The key research conclusions can be summarized: (i) The LSTM models achieved outstanding performance in river water level prediction of Mekong estuaries, indicating the successful application of the LSTM algorithms for times series forecasting. (ii) For river water level prediction, using the deep learning models may be sufficient when such models are provided with good data and they are well trained. This research suggests that deep learning approaches (i.e., LSTM) have promise as potential tools in accurately forecasting the water level and thus these techniques can contribute to building effective strategies for better water management and sustainability on the Mekong River and other river basins in Vietnam.

Acknowledgements

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