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HOURLY DISCHARGE PREDICTION USING LONG SHORT-TERM MEMORY RECURRENT NEURAL NETWORK (LSTM-RNN) IN THE UPPER CITARUM RIVER

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ABSTRACT: The Upper Citarum River is Indonesia's most strategic river since it provides fresh water to West Java and DKI Jakarta, the capital of Indonesia. Flooding is a significant issue in the upstream Citarum River, particularly in the Bandung Basin. Flood problems have not been solved despite many implementations of structural improvements. As a result, further efforts must be made to mitigate the impact of any potential floods. In particular, a more advanced early warning system with a longer forecasting lead time is required. Data-driven models which take into account a variety of historical data inputs are an option for predicting discharge analysis. The Long Short Term Memory Recurrent Neural Network (LSTM RNN) model is utilized in this study to predict discharge at the Dayeuhkolot hydrological station in the Upper Citarum River, West Java, Indonesia. This study considers input data of hourly rainfall from 13 gauging stations and flows data from the relevant stations. Discharge predictions are generated for the following 2, 4, 6, 8, 10, 12, and 24 hours. Model performance is calculated using Nash–Sutcliffe efficiency (NSE), Root Mean Square Error (RMSE), Coefficient determination (R^2), and Relative Error (RE). The findings of the study indicate that the suggested LSTM-RNN model can precisely forecast the discharge for the next two and four hours with NSE and R^2 more than 0.9. Prediction of discharge in a longer period (4 to 24 hours ahead) shows a satisfactory prediction result (NSE and $R^2 > 0.5$).

Keywords: LSTM, Discharge prediction, Upper Citarum River, Data-driven model, Hourly rainfall

1. INTRODUCTION

The upper Citarum River serves as the freshwater supply not only for West Java but also for Jakarta City, the Capital of Indonesia. It has become the most strategic river in Indonesia where three cascade reservoirs have been developed since 1972 to meet the water management requirement [1–4]. These three cascade reservoirs, Jatiluhur, Saguling, and Cirata, were developed to balance the requirement of flood resiliency and the need for water supply. This balance applies not only to the downstream part of the Citarum River but also to Jakarta City [1–7]. The flood-prone area of the upper part of the Citarum River is a natural floodplain (lowland) area named Bandung Basin. That basin is located at the confluence of 13 tributaries of the Upstream Citarum River. Due to the regional development, increasing economic activity, and population growth in the Bandung Basin many areas are being converted into housing, commercial, and other business activities [1,2,5,8]. Several previous studies of the Upstream Citarum River have reported an increasing problem of sedimentation, water quality, and increased solid waste. Also, an increasing trend of peak discharge and flash flooding during the rainy season and a decreasing trend of dependable flow during the dry season has been reported [1–3,5,8]. All these phenomena obviously change the hydrologic, hydraulic, and flood characteristics of the upper part of the Citarum River. These problems are commonly found in the critical river catchment area of Indonesia where extreme land use change has occurred due to mining activity or uncontrolled urban area development [3,5,9–13].

Structural and non-structural mitigation is proposed by the most previous study as a compulsory measure to decrease the flood risk not only in Bandung Basin Area but also in three Cascades Reservoirs [1–4]. The increasing flood risk in Cascade Reservoir Area will increase the risk of its dam break which would potentially increase water-related disasters to the downstream part of the Citarum River [1-5,7,9–12,14]. Several structural flood mitigations such as river normalization, river dredging, and tunneling river cut-off are applied in the Upper Citarum River but the flood risk in Bandung Basin reminds the same [1–3,5]. Meanwhile, as one of the nonstructural measures, the flood early warning system is not yet well developed due to the lack of reliable data for supporting flood prediction models based on merely physical hydrologic-hydraulic parameters. Several previous studies concluded that Neural Network is one of the promising analytical tools to yield a good and or reasonable prediction of not only extreme discharges but also dependable flow, sedimentation rate, and other hydrologic-hydraulic parameters of a catchment area with fewer observation data [1–3][15–19].

Numerical modeling is used to construct a flood database system using hypothetical data, as well as a pattern recognition learning process for a neural network that will increase the speed and accuracy of flood prediction. The produced flood database has limitations in terms of the numerical model, particularly a DEM grid that is too large, hence more research must be conducted using a smaller DEM grid to build a more accurate flood database [19]. Hence, in this study, the prediction of flood discharge is conducted using a data-driven model technique by using real-time rainfall measurement data from rainfall stations dispersed across the Upstream Citarum watershed, as well as discharge data from the same measurement period.

The data-driven models seek to construct a mathematical model tying input factors to an output variable that might be utilized to estimate flood extent [20]. The Artificial Neural Network (ANN) model is one of the popular data-driven approaches. Artificial neural network (ANN) models are information processing systems that imitate the human brain's structure and function. It can simulate non-linear and complicated systems lacking specific physical justifications. In this system, ANNs are the major flow predicting technique [21].

Recurrent Neural Networks (RNN) are commonly used to build hydrological models. The Long Short Term Memory (LSTM) network, derived from RNN, is commonly utilized in flood prediction because it can handle lengthy length sequence data and has advantages in capturing long-term dependence and modeling nonlinear processes [22]. The capacity to analyze and forecast time series sequences without losing unnecessary information distinguishes LSTM from other typical Recurrent Neural Networks (RNNs) [23]. Simple RNN processes numerous recurrent data in a single-flow process, while LSTM-RNN processes them in a directed graph along the temporal sequence. LSTM RNN has "memory cells", which Simple RNN doesn't. [16].

The LSTM model has been widely applied to various water resource analyses including for discharge and water level prediction [16,24,25]. and rainfall-runoff modeling [26,27].

This study aims to construct a discharge forecast model using the LSTM model at the Dayeuhkolot station on the Citarum River. Using input data from thirteen rainfall stations and discharge data from the Dayeuhkolot station, the LSTM model was developed to predict discharge 2, 4, 6, 8, 12, and 24 hours into the future. This discharge prediction model was developed to aid in the early warning of flooding. This methodology is expected to increase the lead time so that the government has sufficient time to issue flood warnings to the public.

2. RESEARCH SIGNIFICANCE

This study focused on the use of data-driven methods to flood prediction models based on real-time rainfall data as an input, and discharge as an output. This method can be considered for forecasting discharge on watersheds with limited physical data and has advantages in terms of faster computation. The LSTM RNN, one of the most recent data-driven models utilized in this research, can predict discharge accurately. Furthermore, the development of a flood model prediction based on LSTM RNN could be a part of a non-structural flood risk reduction in the Bandung Basin which is a flood-prone area.

3. METHODOLOGY

3.1 Study Area

The study area is in Bandung Basin, the natural floodplain area of the Upper Citarum River, West Java, Indonesia, as described in the above discussion. The Upper Citarum River has ± 37 Km length and approximately 1771 km^2 watershed area (Fig. 1). The Dayeuhkolot Automatic Water Level Recorder (AWLR) station is one of the discharge measurement locations on the Citarum River located in the Dayeuhkolot District. Dayeuhkolot and the surrounding area are sub-districts that frequently experience flooding.

As with other tropical Indonesian areas, the Upper Citarum river basin has only a rainy season from October to April and a dry season from May to September with the average annual rainfall and annual maximum daily rainfall in the Upper Citarum river basin is about 2071 mm/year and 81 mm/day, respectively. However, the recorded data in the last three decades have shown an increasing trend of maximum daily rainfall during the rainy season and a decreasing trend of minimum daily rainfall during the dry season [1–3,28].

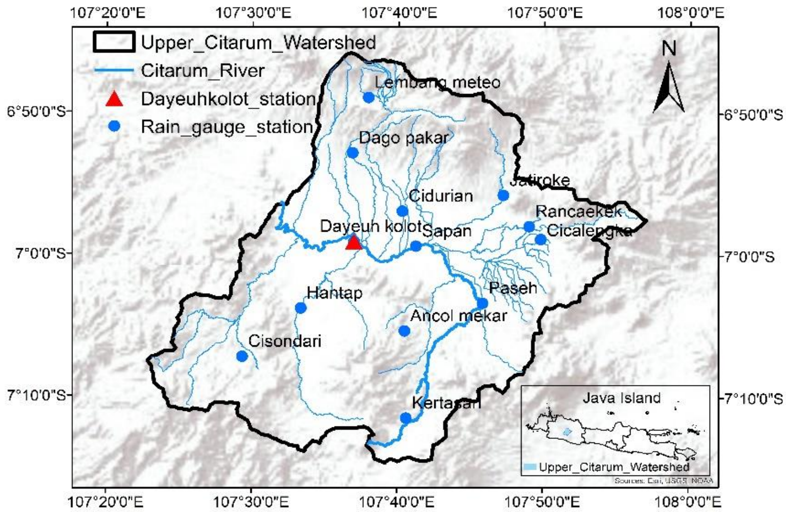


Fig.1 Location of the study area and hydro-meteorological station

3.2 Data Description

In this study, hourly rainfall data from 13 rain gauge stations in the Upper Citarum river basin and hourly discharge at the Dayeuhkolot hydrology station were utilized. The location of the rainfall station and water level station is shown in Fig. 1. Data on rainfall and water levels are derived from BBWS Citarum, which can be reached at http://103.110.9.91/ [29].

3.3 LSTM Model

The LSTM is an artificial RNN presented by Sepp Hochreiter et al. in 1997. The RNN with an internal hidden state ('memory') enabling data to sequence over the network is more efficient and reliable in dealing with non-linear long-range time-varying issues than traditional methods. The LSTM is composed of a cell memory that stores a summary of the preceding input sequence and a gating mechanism that regulates the flow of information between the input, output, and cell memory [30]. An LSTM network has three layers: input, memory, and output. The schematic model of LSTM utilized in this study is shown in Fig.2.

The number of explanatory variables equals the number of input layer neurons. The hidden layer of LSTM networks contains memory cells, which are its distinguishing feature. Forget gate (***ft***), input gate (***it***), and output gate (***ot***) are the three gates that each memory cell possesses to maintain and change its cell state [23]. The formula for the sequential update is as follows:

Input node:

$$g^{(t)} = \tanh(W_{gx}X^{(t)} + W_{gh}h^{(t-1)} + b_g) \quad (1)$$

Input gate:

$$i^{(t)} = \sigma(W_{ix}X^{(t)} + W_{ih}h^{(t-1)} + b_i) \quad (2)$$

Forget gate:

$$f^{(t)} = \sigma(W_{fx}X^{(t)} + W_{fh}h^{(t-1)} + b_f) \quad (3)$$

Output gate:

$$o^{(t)} = \sigma(W_{ox}X^{(t)} + W_{oh}h^{(t-1)} + b_o) \quad (4)$$

Cell state:

$$s^{(t)} = g^t + \odot\, i^t + s^{(t-1)} \odot o^{(t)} \quad (5)$$

Hidden gate:

$$h^{(t)} = \tanh(s^{(t)}) \odot o^{(t)} \quad (6)$$

Output layer:

$$y^{(t)} = \left(W_{hy}h^{(t)} + b_y\right) \quad (7)$$

Where ***X (t)*** is the input vector (forcing and static characteristics) at the time step ***t***, ***Ws*** is the network weights, ***bs*** is bias parameters, ***y*** is the output to be compared to observations, ***h*** is the hidden state, ***σ*** is the sigmoid function, ⊙ is element-wise multiplication, and ***s*** is the cell state of memory cells, which is specific to LSTM.

3.4 Model Design

In the neural network technique, screening relevant data for model inputs is a crucial step in determining the best model architecture. Precipitation, evaporation, and temperature are some of the causative factors in the rainfall-runoff connection. The number of various variables is determined by the availability of data and the study's purpose [31]. According to other studies, using potential evapotranspiration estimates in the inputs did not improve computation results, but did result in a modest degradation when compared to utilizing just precipitation data [32]. In this study, a discharge prediction model was created for flood early warning purposes, therefore it must be able to analyze data fast and have a limited number of input data variables. Therefore, observed rainfall and previous flow variables were selected as input data.

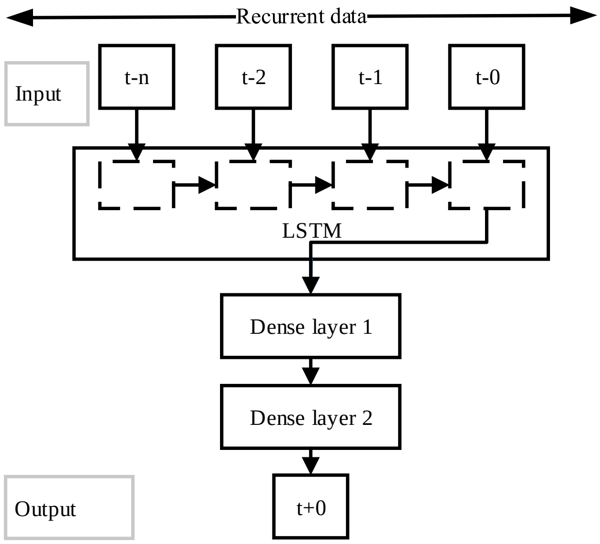


Fig.2 Schematic model LSTM [16]

After selecting relevant input variables, the following step is to determine the proper parameter for each variable to build model inputs. Table 1 summarizes the parameter settings utilized in this study.

Table 1 Parameter setting

Recurrent time (hours)	6	8	12	24
Epoch		15, 20, 25		

As mentioned above, hourly rainfall data from thirteen rain gauge stations and previous flow data at Dayeuhkolot hydrology station as input data, the target output is discharge at time interval level t+1. The input and output data are normalized to the range [0-1] prior to further processing. The data normalization process uses the Min Max scalar method. Then the next step is to restructure the existing dataset. The existing dataset will be shifted backward for input data and forward for output data (in the "to supervised" function's code).

The following step is to split the dataset into training and testing sets while learning a dependency from the data. The previous study demonstrates that using 20-30% of data for testing and 70-80% for training produces the greatest outcomes [33]. In this study, the dataset was performed by splitting the training and testing data by 75% and 25%, respectively. While the loss in the training phase was calculated using the MSE function.

The programming language used in this study is Python. Several python packages are used in modeling including NumPy which is used as the main package for performing numerical calculations, Matplotlib for visualization and plotting work, Pandas for tabular data manipulation, and a deep learning framework that makes use of the keras framework's built-in LSTM layer components.

Model performance was analyzed by the statistical parameter approach. NSE, RMSE, and R^2 are statistical approaches that are frequently used to compare projected and actual values in domains connected to hydrology to calculate the effectiveness of predicting models. The NSE calculates the fraction of the initial variance accounted for by the model and examines its ability to predict variables other than the mean. Based on the relative range of the data, the RMSE is typically used to assess how well the predicted values match the observed values [34].

4. RESULT AND DISCUSSION

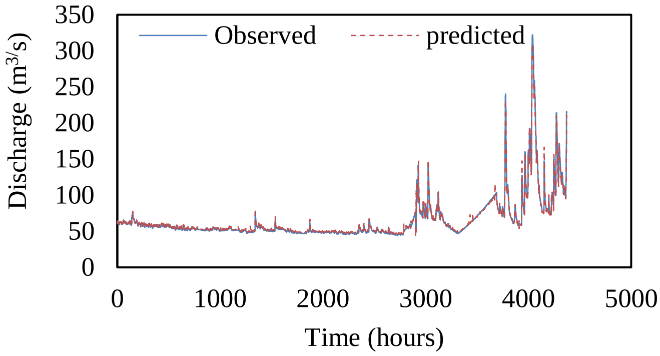
4.1 Modeling Parameter Optimization in Hourly Predicted Discharge

As indicated in Table 1, a selection of LSTM modeling with distinct parameters (recurrent time, and maximum epoch number) has been constructed. Table 2 shows the model performance for various parameters used in the LSTM model. Meanwhile, hourly hydrographs and scatter plots at Dayeuhkolot hydrology station in one-hour ahead prediction utilizing optimum parameters are shown in Fig.3.

In all instances, the NSE values indicate a very excellent performance (NSE > 0.9) in estimating the discharge over the following hour. According to the NSE and RMSE values, the best performance is achieved with a recurrent time of 24 hours and a maximum epoch of 20. The values of NSE and R2 indicate a slightly increasing trend as the maximum epoch number rises. In contrast, the RMSE value drops as the maximum epoch number increases.

Table 2 Model performance of parameter optimization based on NSE, RMSE, and R^2 value

Recurrent time	NSE			RMSE			R^2		
(hours)	Epoch 15	Epoch 20	Epoch 25	Epoch 15	Epoch 20	Epoch 25	Epoch 15	Epoch 20	Epoch 25
6	0.992	0.993	0.993	2.817	2.678	2.591	0.995	0.996	0.996
8	0.993	0.993	0.993	2.653	2.673	2.611	0.995	0.995	0.996
12	0.994	0.994	0.993	2.539	2.503	2.615	0.995	0.996	0.996
24	0.993	0.994	0.994	2.640	2.414	2.456	0.995	0.996	0.996



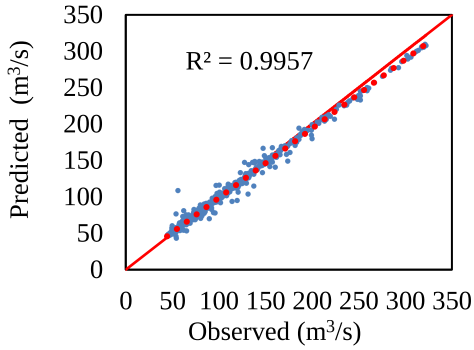


Fig.3 Comparison of forecasting and observed hourly discharge using the optimal parameter

It denotes that the maximum epoch number can improve model performance. According to Fig.3, it should be noticed that the predicted flow agrees well with the observed flow. The scatter plot provides performance data as pairs of data. Closer data pairings near the 45 line indicate more accurate prediction findings. The scatter plot for one-hour flow forecasting in the testing phase shows that predicted and observed discharge is comparable.

4.2 Multi-Hour-a Head Discharge Prediction

For a more efficient and practical flood warning system, it is important to determine the discharge with a lead time of more than one hour ahead. In this study, the optimum parameter was evaluated for 2, 4, 6, 8, 12, and 24 hours ahead of forecasting discharge. By comparing observed and predicted flow created throughout the testing process, the NSE, R^2, and RMSE values are used to evaluate the model's performance. The model performance of the testing process is summarized in Table. 3.

In general, the developed LSTM model has the ability to predict discharge for the next 2 to 24 hours quite well. This can be seen from the RMSE, NSE, and R^2 values which are in the range of 18.918-4.533; 0.642-0.979, and 0.643-0.984, respectively. The best performance was obtained for 2 and 4-hour discharge predictions with NSE values of 0.979 and 0.926, respectively. As the prediction time increases, the model performance decreases, with an average decrease in the NSE and R^2 value of 6% for the 2-hour prediction time interval. While the change in the NSE value for 12-hour to 24-hour discharge predictions drop by 12% for NSE and 15% for R^2 value. Similarly, the trend of changes in the RMSE value demonstrates a growth in the error value of the predicted discharge to the observation. The forecast time is added, resulting in a higher inaccuracy with an average error rate of 21% for each increase in prediction time.

Table 3 The model performance of the testing process for discharge prediction

Time forecasting (hours)	RMSE	NSE	R^2
2	4.533	0.979	0.984
4	8.547	0.927	0.939
6	11.690	0.863	0.879
8	13.441	0.819	0.830
10	15.325	0.765	0.776
12	16.691	0.721	0.741
24	18.918	0.642	0.643

The hydrographs for various discharge time forecasts are shown in Fig.4 and 5. Overall, the hydrograph shows a good agreement between the predicted and measurement discharge for the next 2, 4, 6, 8, 10, 12, and 24 hours of forecasting. In addition, the effect of forecast time on low and high flows can be illustrated in the Flow Duration Curve (FDC) (Fig.6). For all prediction periods, the high flow with a probability of less than 30% (Q30), the resulting predicted discharge is smaller than the measured flow (underestimate). On the other hand, at low flow (discharge with a probability of more than 30%), the estimated discharge is greater than the actual discharge (overestimated). The developed LSTM model predicts high flow better than low flow (Fig.7).

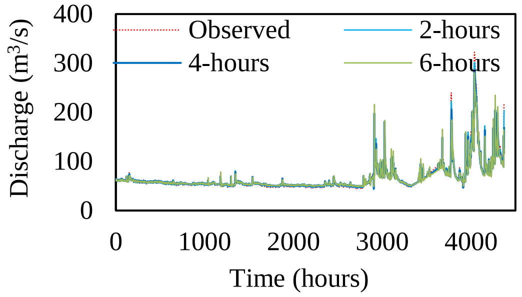


Fig.4 Comparison of the observed and forecasted hourly discharge for the next 2, 4, and 6 hour

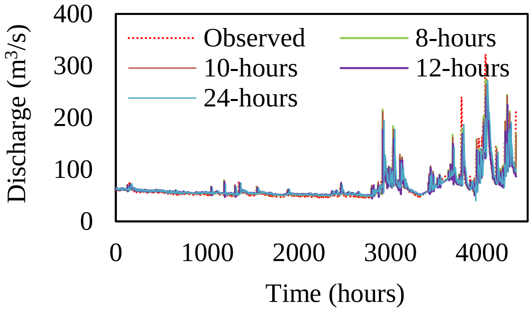


Fig.5 Comparison of the observed and forecasted hourly discharge for the next 8, 10, 12, and 24 hour

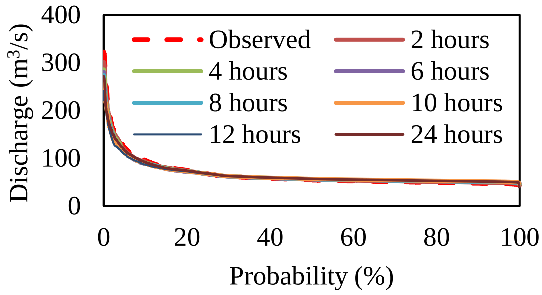


Fig.6 Flow duration curve for observed and predicted discharge across a range of time forecasts

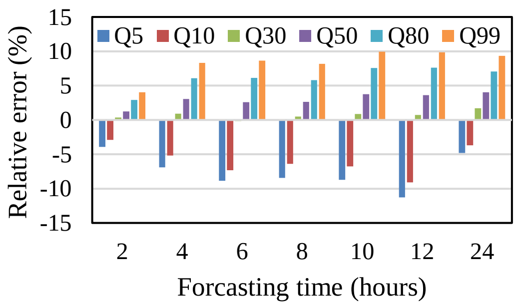


Fig.7 Relative error for high flow and low flow prediction

4.3 Peak Discharge Prediction

For flood forecasting purposes, the next step is to compare the predicted peak discharge with measurement data from test data. The peak discharge from the observations is 322.3 m3/s on 18th December 2019. Predicted peak discharge for 2, 4, 6, 8, 10, 12, and 24 ahead and Relative Error (RE) as shown in Table 4. Predicted peak discharge for various forecasting times (2 to 24 hours ahead) as shown in Table 4 is found underestimate compared to the observed discharge.

Table 4 Peak discharge error for varied time forecasting

Time forecasting (hours)	Peak Discharge (m^3/s) Observed	Predicted	RE %
2		301.3	-6
4		285.9	-11
6		280.2	-13
8	322.3	274.4	-15
10		264.1	-18
12		241.4	-25
24		271.2	-16

According to the RE parameter, the performance of the model can be classified as “Very good” when the difference between observed and simulated values is less than 10%, “Good” is between 10% and 15%, and “satisfactory” is between 15% and 25% [34]. The magnitude of RE for the prediction discharge for the next 2 hours indicates a “Very good” performance in peak discharge prediction. Meanwhile, the RE indicates “Good” for 4, 6, and 8 hours-ahead forecastings, and the next 10 to 24-hour peak discharge prediction indicate satisfaction.

As the forecasting time lengthens, several factors lead to less accurate discharge estimates. Due to a lack of study data, for instance. The data used in this study comes from two years of observations (2018-2019). The chosen model parameters are also a consideration. More parameters in the machine learning model's design are required to perform deeper "abstraction" of data features or to improve the present LSTM layer.

5. CONCLUSION

The LSTM model was used in this study to forecast the discharge 2, 4, 6, 8, 10, 12, and 24 hours ahead at the Dayeuhkolot hydrological station. Hourly rainfall data from 13 rainfall stations and river flow data at the interest station are used as inputs. The most optimal parameters obtained based on the performance of the model for predicting discharge for the next 1 hour is a time lag of 24 hours and a maximum epoch of 20.

The research findings indicate that based on model performance criteria such as NSE, R^2, and RMSE values, the LSTM model can accurately forecast Dayeuhkolot discharge in the following two and four hours with the NSE and R^2 values higher than 0.9 which indicates "Excellent" performance. Meanwhile, for the predicted discharge for time forecasting exceeds four hours, the LSTM model is quite accurately forecasting the discharge according to the NSE, $R^{2,}$ and RMSE values (NSE and $R^2 > 0.5$). The model becomes less accurate in expected discharge when the forecast time is increased from 2 to 24 hours. This is because, even if the software "understands" the trend extremely well, a model that forecasts further into the future is more uncertain. The longer the duration of the prediction, the less accurate the resulting prediction will be. Future development of a more accurate prediction model with a longer lead time than 24 hours and a higher level of precision will be a challenge.

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