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ASSESSING LSTM ALGORITHM PERFORMANCE FOR DAILY RUNOFF PREDICTION AT HOA DUYET HYDROLOGICAL STATION, VIETNAM

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Abstract. Accurate discharge forecasting is crucial for effective water resource management, flood risk mitigation, and hydrological planning, particularly in regions prone to extreme weather events. This study evaluates the performance of a Long Short-Term Memory (LSTM) network in predicting river discharge at the Hoa Duyet hydrology station. The prediction model is developed using rainfall data from the Ngan Sau river basin, collected over a 49-year period from 1975 to 2023. The model's accuracy was assessed across a range of lead times (1-day, 3-day, 5-day, and 7-day) and time lag length (365, 90, 30, 10, and 7 days). It was revealed that short-term forecasts (e.g., 1-day) consistently achieved high accuracy, with the time lag length 90-day yielding the best Nash-Sutcliffe Efficiency (NSE) of 0.864. Seasonal analysis indicated the reliability of the model for the rainy season (NSE = 0.863), but lower accuracy during the dry season (NSE = 0.582), reflecting the challenges of predicting low-flow dynamics. The model also demonstrated reasonable accuracy in predicting annual runoff peaks, with an average error of 91.75 m³/s, although discrepancies were observed in specific years. These findings highlight the LSTM model's capacity to adapt to diverse temporal configurations and hydrological conditions, making it a valuable tool for discharge prediction while emphasizing the need for further optimization in low-flow and extreme event scenarios.

Keywords: LSTM, Deep learning, Runoff prediction, Ngan Sau river basin.

1. INTRODUCTION

Research and forecasting of flow are of practical and scientific importance. The fundamental properties of flood flow (i.e. duration, intensity and peak module) are frequently associated with the prevailing meteorological and geographical characteristics of the basin. Rainfall-runoff simulation models have a long-established presence within the domain of hydrological science. The earliest studies that sought to predict the flow discharge from rainfall events through the utilisation of regression methods were conducted approximately 170 years ago [1]. Since then, modeling concepts have been continuously developed by gradually combining concepts based on (numerical) model formulations. These include the consideration of spatial variability of processes, boundary conditions and physical properties of the catchment. However, the development towards a combined, physical and spatial formulation of hydrological processes at the catchment scale often comes at the cost of high computational costs and very large input data requirements [2].

In Northern Vietnam, hydrological forecasting was virtually non-existent prior to 1954. There is a lack of observation data, with the exception of water level data at hydrological stations on Da River (Lai Chau, Hoa Binh), Thao River (Lao Cai, Yen Bai), Lo River (Tuyen Quang) and so on [3]. Following 1954, and particularly since 1981, the development of flow forecasting began to take place. The application of hydrological models in Vietnam, including SSAAR, TANK, NAM, and HEC-HMS, has yielded favourable outcomes in the context of flow forecasting for major river basins within the nation [4]. However, it should be noted that these models require a substantial number of input parameters, a considerable simulation time, and a high level of experience on the part of the forecaster.

Recently, Artificial Intelligence (AI) has made significant contributions to the fields of science and technology, particularly in the area of big data management, including hydrological forecasting. One of the earliest algorithms developed was the Artificial Neural Network (ANN) algorithm. Binh H.N. [5, 6] applied of ANN with Error backpropagation Networks (EBN) to predict the peak flow for the Hoang Long river in Ninh Binh province, Vietnam and the dry season discharge for the Ta Trach river in Thua Thien Hue province, Vietnam. These studies indicate that EBN has the capacity to predict daily discharge with a reasonable degree of reliability and lead times ranging from 1-day to 7-day. Cheng, M., et al. [7] applied ANN to forecast daily and monthly discharge scales for a long lead-time period for the Nan river in Thailand. It has been demonstrated that, under optimal parameter configuration, the model demonstrates the capacity to generate precise daily forecasts with lead time up to 20 days. Furthermore, machine learning algorithms such as Support Vector Regression (SVR), Decision Tree (DT), Random Forest (RF), Light Gradient Boosting Machine Regressor (LGBM), and Linear Regression (LR) have been employed to predict water levels. Hanh N. D., et al. [8] examined the effectiveness of various machine learning in predicting water levels with lead times of 1-day, 3-day, 5-day and 7-day. These algorithms are being used to forecast the water level at the Cao Lanh gauging station on the Tien river, located within the Vietnamese Mekong Delta. The findings of this study demonstrate that the SVR model exhibited consistent superiority over the other models in all scenarios, with RF, DT, and LGBM ranking second, third, and fourth, respectively.

Machine learning techniques, particularly deep learning models like Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for addressing the challenges of modeling non-linear and sequential data in hydrology [9, 10]. LSTM network is a special upgraded architecture of Recurrent Neural Networks (RNN) invented by Hochreiter and Schmidhuber in 1997 [11]. The LSTM method has been demonstrated to outperform the ANN model in the context of daily streamflow forecasting for a long lead time [7]. LSTM networks have been shown to be particularly effective in the retention of long-term dependencies and the management of temporal variability, rendering them highly suitable for the analysis of time series data, including rainfall, discharge, and water level records. Their ability to capture complex patterns and relationships has led to significant advancements in discharge prediction, flood forecasting, and water resource management. Recent studies have demonstrated the efficacy of LSTM models in enhancing forecast accuracy and reliability under various hydrological scenarios. The LSTM model has been identified as the optimal choice for predictions with short lead times, demonstrating superior performance in comparison to the bidirectional LSTM (BiLSTM) and the Gated Recurrent Unit (GRU) in some cases [12]. However, despite these achievements, further exploration of their performance under diverse temporal configurations and seasonal conditions is required to fully harness their potential and address specific challenges in hydrological forecasting.

The primary objective of this study is to evaluate the performance of LSTM algorithms in predicting river discharge based on rainfall data at Hoa Duyet hydrology station, Ngan Sau river in Ha Tinh province. The study focuses on assessing the model's accuracy across different lead times, including 1-day, 3-day, 5-day, and 7-day predictions, and varying time lag length, such as 365, 90, 30, 10, and 7 days, to determine the optimal look back period. Moreover, the research examines seasonal variations in model performance, analyzing predictions for the entire year, the rainy season, and the dry season to identify strengths and limitations under diverse hydrological conditions. The research results will contribute to the diversification of approaches in simulating and predicting rainfall flows as well as the potential of applying artificial intelligence in hydrological forecasting in Vietnam.

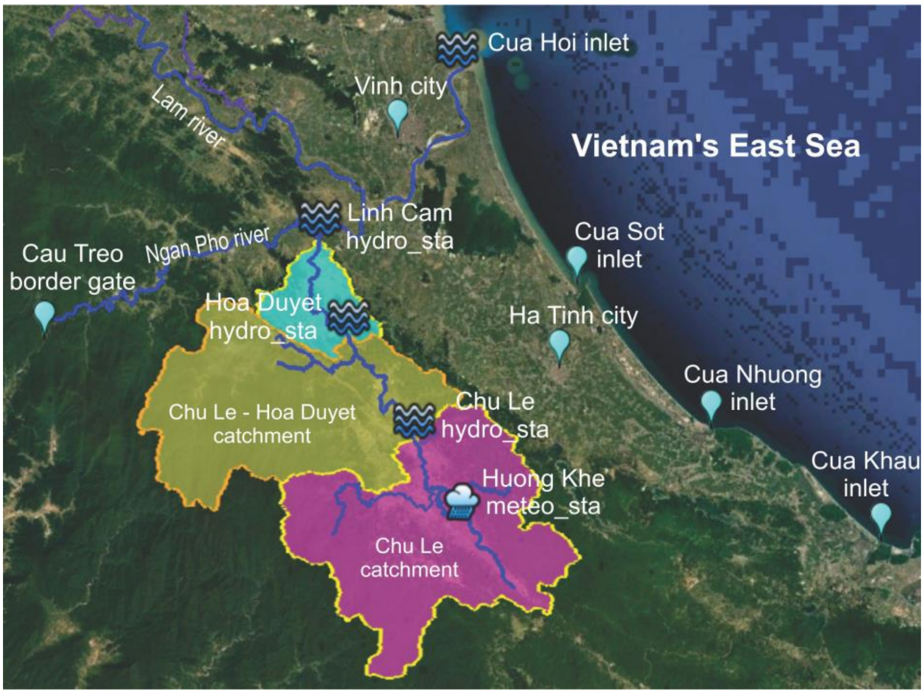

Figure 1. Study area with a background image sourced from Google Earth.

2. DATA AND METHODOLOGY

2.1. Study area and dataset

The Ngan Sau River constitutes one of the two primary tributaries of the La River basin. Its origins are situated within the Giang Man mountain range in the Huong Khe district of Ha Tinh province, Vietnam, and it converges with the Ngan Pho River at Linh Cam. The length of the main stream of Ngan Sau from spring to Linh Cam hydrological station is 102km. The catchment area of Chu Le, Hoa Duyet and Linh Cam hydrological stations is 970 km^2, 1880 km^2 and 2060 km^2 respectively (Figure 1). The primary course of the Ngan Sau River experiences a constriction at Hoa Duyet, impeding effective flood drainage.

The topography of the Ngan Sau River basin is characterized by two distinct terrains: midland hills and high mountains. The Midland region is characterized by a topographical range extending from an altitude of 20m to 200m. The topography of the area surrounding the Ngan Sau River is predominantly flat, with a pronounced main slope directed towards the riverbeds. It is evident that as one moves further away from the river, the terrain becomes increasingly complex. The topography of high mountain terrain is characterized by elevations ranging from 1200 to 1500m, steep slopes, and narrow valleys.

The input data for this study comprise daily time series extending over a period of 49 years (1975–2023) and include: (i) rainfall measurements from the Huong Khe meteorological station and Chu Le, Hoa Duyet hydrological stations; (ii) discharge and water level data from the Hoa Duyet hydrological station (Table 1). These variables are closely associated with flow formation in the Ngan Sau river basin and at the Hoa Duyet hydrological station. Each data series exhibits varying degrees of correlation. In the LSTM model, the correlation between input variables and the target forecast variable is critical for ensuring the model's relevance and predictive accuracy. Input data exhibiting strong correlations to the target variable provides more substantial information for predicting its behaviour [13] and are therefore prioritized for developing effective predictive models.

Table 1. Statistical characteristics of input data.

	Date	X_Chule	X_HuongKhe	X_HoaDuyet	H_HoaDuyet	Q_HoaDuyet
Count		17897	17897	17897	17897	17897
Mean		6.10	5.17	6.48	2.35	113.06
Min	01/01/1975	0	0	0	1.02	0.2
25%		0	0	0	1.75	34.4
50%		0	0	0	2	52.6
75%		2	1.3	2.4	2.44	94.5
Max	12/31/2023	548.2	492.6	681.5	12.62	3300
Std		22.78	20.89	23.70	1.21	232.80

The performance of forecasting models, such as the LSTM model used in this study, is highly dependent on the quality and quantity of the input time series data [14]. The dataset under consideration has been collected over a period of 49 years, resulting in a total of 17,897 data points. This extensive collection provides a robust foundation for the training and testing of the model. The long-term dataset encompasses a wide range of hydrometeorological conditions, thereby ensuring that the model is exposed to a substantial degree of variability, which enhances its ability to generalize and improve predictive accuracy. This extensive temporal coverage also facilitates a detailed analysis of patterns and relationships within the data, thereby supporting the development of a reliable forecasting framework.

All data were normalized to the range of 0 to 1 by formula (1) via the sklearn library in Python.

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where, z is the normalized value, x is the original data value.

2.2. Long Short-Term Memory algorithm

The structure of the LSTM network consists of many LSTM cells (LSTM memory cells) connected together (Figure 2). The LSTM network incorporates an internal cell state and three gates - namely, the forget gate, input gate, and output gate - that regulate the flow of information into and out of the cell. At each time step, the gates sequentially process an input value (representing an element in the input sequence) along with the output value from the cell's previous time step. The forget gate is designed to discard irrelevant information, the input gate selects and retains essential information, and the output gate determines which information from the cell state is propagated as the output. This gating mechanism enables the LSTM network to effectively manage long-term dependencies in sequential data.

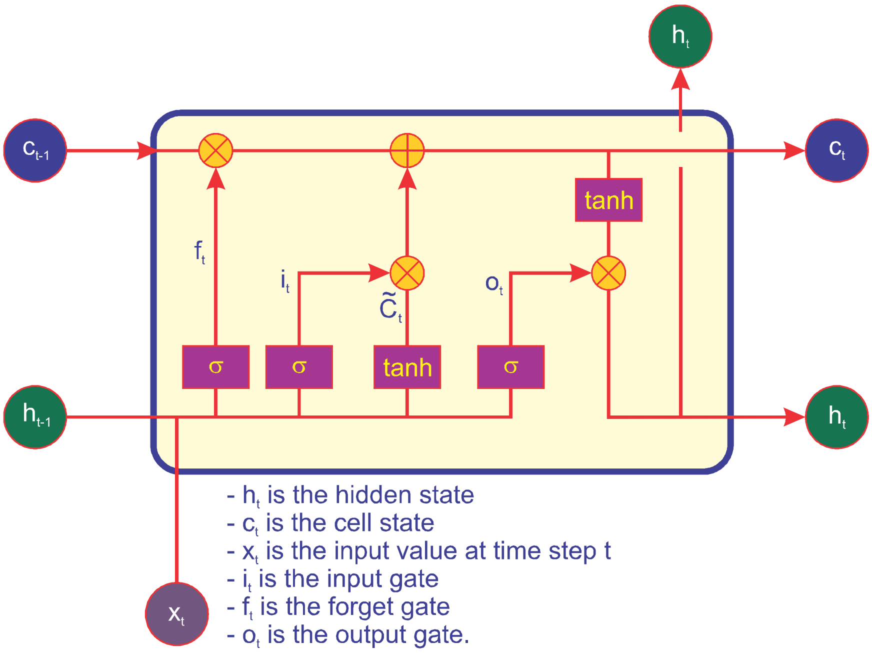

Figure 2. Illustration of the inner workings of LSTM.

The functions depicted in Figure 2 are determined as follows [15]:

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{2}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{3}$$

$$\tilde{C}_t = \tanh\left(W_{\tilde{C}} x_t + U_{\tilde{C}} h_{t-1} + b_{\tilde{C}}\right) \tag{4}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{C}_t \tag{5}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{6}$$

$$h_t = \tanh\left(c_t\right) \otimes o_t \tag{7}$$

where σ is the logistic sigmoid function, W is weight of the input value, U is weight of the hidden state, b is a bias, $\tilde{C}_t$ is a vector with values in the range (-1, 1), tanh is the hyperbolic tangent, and $\otimes$ denotes element-wise multiplication.

For the loss function, we defined the dimensional attributes of both input and output tensors and systematically investigate multiple loss functions, encompassing the custom nse_loss function. This facilitates a comprehensive assessment of the model's predictive proficiency utilizing diverse evaluation criteria, including the Nash-Sutcliffe efficiency metric. Regarding optimization algorithm, the Adam algorithm was employed during both the training and validation stages of the LSTM model due to its widespread application in real-world scenarios [16].

2.3. Model evaluation

The 49-year dataset was partitioned into two subsets: 38 years (1975 - 2012), constituting approximately 80% of the total data, were utilized for training, while 11 years (2013 - 2023) served for testing the LSTM model. The LSTM model was developed with varying data structures, defined by time lag and lead time. The time lag length is defined as the number of past days used to forecast the current time step. In this study, time lag of 365 days (1 year), 90 days (3 months), 30 days (1 month), 10 days (1/3 month), and 7 days (1 week) were employed, in alignment with the daily hydrometeorological series. The lead time represents the future days for which the model aims to forecast, with forecasts for 1 day, 3 days, 5 days, and 7 days utilized to assess the model's accuracy.

The model's performance was assessed using the Nash-Sutcliffe Efficiency (NSE) calculated as per Equation (8), the Root Mean Squared Error (RMSE) determined using Equation (9), (10), and the Mean Absolute Error (MAE) derived from Equation (11).

$$NSE = 1 - \frac{\sum_{t=1}^{n}\left(Q_t^{obs} - Q_t^{sim}\right)^2}{\sum_{t=1}^{n}\left(Q_t^{obs} - Q_{mean}^{obs}\right)^2} \tag{8}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Q_t^{obs} - Q_t^{sim}\right)^2 \tag{9}$$

$$RMSE = \sqrt{MSE} \tag{10}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Q_t^{obs} - Q_t^{sim}\right| \tag{11}$$

where n is the length of the data set, Q_t^{obs} is observed discharge at the time t, Q_t^{sim} is the predicted discharge at the time t and Q_{mean}^{obs} is the average value of observed timeseries discharge.

3. RESULTS AND DISCUSSION

3.1. Time lag and lead time

The results of the LSTM model for discharge prediction from rainfall demonstrate clear trends across different lead times (1-day, 3-day, 5-day, and 7-day) and time lag length (365, 90, 30, 10, and 7 days) (Table 2). For the NSE, the model achieves its best performance for short-term forecasts, particularly the 1-day forecast, with NSE values consistently high across all time lag length (0.856 - 0.864). The time lag length 90-day achieves the highest NSE (0.864) for the 1-day forecast, indicating that medium-term historical rainfall patterns provide the most useful information for short-term discharge prediction. As the lead time increases to 3, 5, and 7 days, NSE values decline steadily, reflecting the model's reduced predictive capability for longer horizons due to increasing uncertainty and compounding errors. The time lag length 7-day demonstrates a marginal enhancement in NSE performance for extended forecasts, underscoring the impact of recent rainfall events.

Table 2. Comparison of NSE, MSE and MAE corresponding to different time lag and lead times.

Metrics	Lead times	Time lag length (days)				
		365	90	30	10	7
NSE (-)	1 days	0.857	0.863	0.861	0.856	0.858
	3 days	0.591	0.599	0.583	0.589	0.596
	5 days	0.436	0.429	0.441	0.438	0.442
	7 days	0.301	0.352	0.346	0.349	0.356
RMSE (m^3/s)	1 days	82.68	82.71	91.24	98.66	97.95
	3 days	135.92	141.73	143.42	142.09	140.75
	5 days	159.73	169.11	166.13	166.15	165.48
	7 days	177.85	180.16	179.76	178.84	177.80
MAE (m^3/s)	1 days	27.77	29.85	31.58	27.71	27.65
	3 days	57.29	44.64	54.65	57.73	47.76
	5 days	61.57	63.98	54.72	55.45	54.54
	7 days	68.06	63.11	62.43	64.37	62.26

For RMSE, the errors remain low for the 1-day forecast across all time lag length, with the 365-day time lag achieving the smallest RMSE (82.68 m^3/s). However, as the lead times increases, RMSE increases significantly, indicating larger prediction errors over longer lead times. For example, RMSE for the 7-day forecast ranges between 177.80 and 180.16 m^3/s, with the 365-day lag still demonstrating the lowest error. This suggests that longer historical time windows may provide additional context for discharge prediction, particularly for longer forecasts. Despite the increase in RMSE over time, the relatively small variation between time lag length demonstrates that the LSTM model can adapt well to different temporal inputs, though with reduced accuracy for extended forecasts.

The MAE follows a similar trend, showing low values for the 1-day forecast and increasing progressively with longer lead times. For short-term predictions, the 7-day and 365-day lags perform best, achieving the lowest MAE (27.65 and 27.77 m^3/s, respectively).

As the forecast horizon extends to 3, 5, and 7 days, the errors increase, with MAE reaching up to 68.06 m³/s for the 7-day forecast under the 365-day lag. Interestingly, for 3-day forecasts, the 90-day lag achieves the lowest MAE (44.64 m³/s), suggesting that medium-term temporal windows are particularly useful for balancing short- and medium-term discharge predictions. Overall, the results show that shorter time lag length (e.g., 7 days) are more effective for longer forecasts, while medium-term lags (90 days) perform best for short-term predictions, reflecting the model's ability to capture different temporal dynamics depending on the forecast horizon.

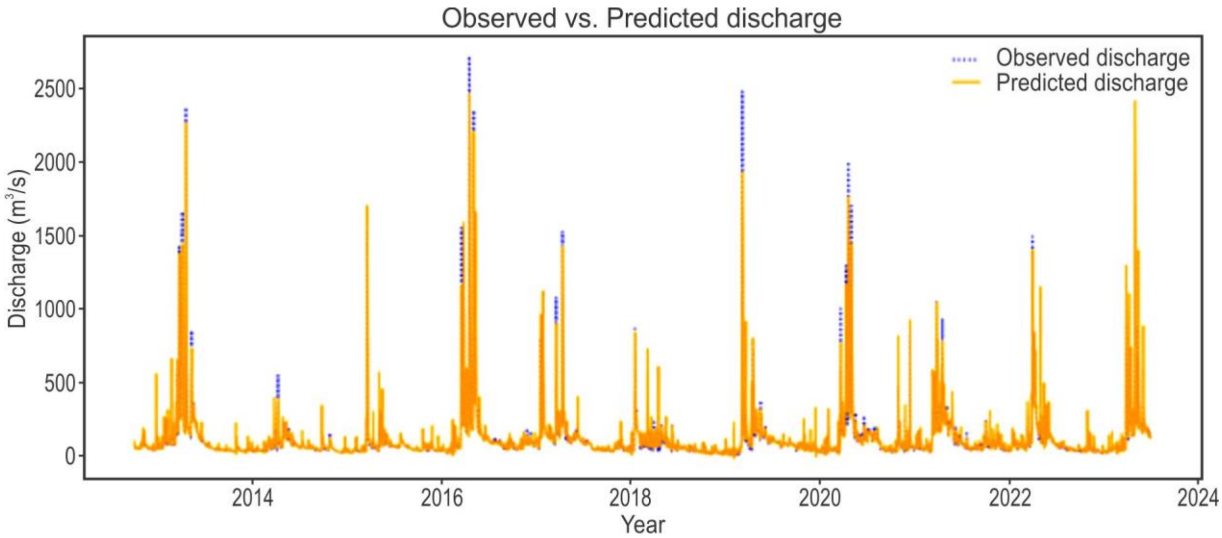

Figure 3. Comparison of observed and predicted discharge by LSTM with 1-day forecasting period.

Figure 3 presents a comparison of the predicted and observed discharge over the past 11 years at Hoa Duyet station, considering a time lag of 90 days and a lead time of 1 day. The results demonstrate that the LSTM model effectively captures the annual flow patterns, as well as discharge during both the dry and flood seasons. However, for major flood events characterised by peak discharges exceeding 2000 m³/s, the model tends to underestimate the flood peaks. This discrepancy can be attributed to the rarity of large floods, particularly extreme events exceeding 2500 m³/s, which have occurred only four times over a 49-year period. Such limited occurrences constrain the model's ability to learn and generalize these extreme events, leading to higher prediction errors for significant flood peaks.

3.2. Annual flood peak prediction ability

The comparison of annual runoff peaks between observed values and LSTM predictions (Table 3) shows that the LSTM model performs reasonably well but exhibits some discrepancies in certain years. The observed peak values range from 545 m³/s (2014) to 2720 m³/s (2016), with an overall average of 1695.27 m³/s. Concurrently, the LSTM model predicted an average of 1603.52 m³/s, which is comparable to the observed mean but has a tendency to underestimate or overestimate in individual years. For instance, in 2019, the LSTM model significantly underpredicted the observed peak (2480 m³/s) by 549.42 m³/s, while in 2023, it overestimated the peak by 356.05 m³/s. However, smaller errors were observed in years such as 2018 (25.46 m³/s) and 2021 (15.87 m³/s), indicating enhanced model performance. The mean error across all years is 91.75 m³/s, which demonstrates the model's overall reliability but also emphasises the necessity for further enhancements to address sporadic substantial deviations.

Table 3. Annual runoff peaks of observed values and LSTM predictions.

No	**Year**	**Q_{peak_Obs} (m^3/s)**	**Q_{peak_LSTM} (m^3/s)**	**Error**	
				(m^3/s)	**(%)**
1	2013	2370	2265.52	104.48	4.41
2	2014	545	393.69	151.31	27.76
3	2015	1530	1701.38	-171.38	-11.20
4	2016	2720	2464.15	255.85	9.41
5	2017	1530	1424.72	105.28	6.88
6	2018	863	837.54	25.46	2.95
7	2019	2480	1930.58	549.42	22.15
8	2020	2000	1759.85	240.15	12.01
9	2021	1060	1044.13	15.87	1.50
10	2022	1490	1401.09	88.91	5.97
11	2023	2060	2416.05	-356.05	-17.28
Average		1695.27	1603.52	91.75	5.41

3.3. Seasonal and annual performance evaluation

The performance of the LSTM model for runoff prediction shows varying accuracy across the whole year, the rainy season, and the dry season, as indicated at Table 4. Throughout the year, the overall NSE is high at 0.864, demonstrating reliable model performance. The MAE and RMSE are 28.66 and 82.38, respectively. Notably, years like 2016 and 2020 stand out with exceptional NSE of 0.907 and 0.925, respectively, indicating strong predictive accuracy.

Table 4. The seasonal and annual performance for testing period

Year	**Whole year**			**Rainy season**			**Dry season**		
	MAE	**RMSE**	**NSE**	**MAE**	**RMSE**	**NSE**	**MAE**	**RMSE**	**NSE**
2013	42.34	127.25	0.848	58.60	155.41	0.836	6.18	17.67	0.691
2014	14.93	30.85	0.654	22.61	39.04	0.692	8.38	19.25	0.575
2015	16.91	44.86	0.882	26.35	60.91	0.888	6.02	12.83	0.672
2016	34.62	119.47	0.907	63.20	168.44	0.898	11.11	19.28	0.656
2017	24.74	63.63	0.882	36.29	86.05	0.877	10.72	23.86	0.528
2018	26.36	70.19	0.725	41.47	96.92	0.714	11.79	20.03	0.626
2019	31.95	94.91	0.838	53.67	133.08	0.832	11.93	24.79	0.470
2020	33.20	77.14	0.925	51.73	105.32	0.926	24.60	58.19	0.510
2021	39.15	83.50	0.645	54.10	103.10	0.662	17.91	29.46	0.440
2022	27.93	81.05	0.721	40.02	110.84	0.718	10.91	23.33	0.528
2023	26.48	77.73	0.868	38.65	103.54	0.869	31.17	72.81	0.568
Overall	28.66	82.38	0.864	44.24	111.60	0.863	12.27	28.71	0.582

Conversely, years like 2021 and 2014 have lower NSE of 0.645 and 0.654 respectively, indicating reduced performance likely due to more complex hydrological dynamics or data limitations (Figure 4). Overall, the LSTM model performs well for annual predictions, with error values relatively stable across most years.

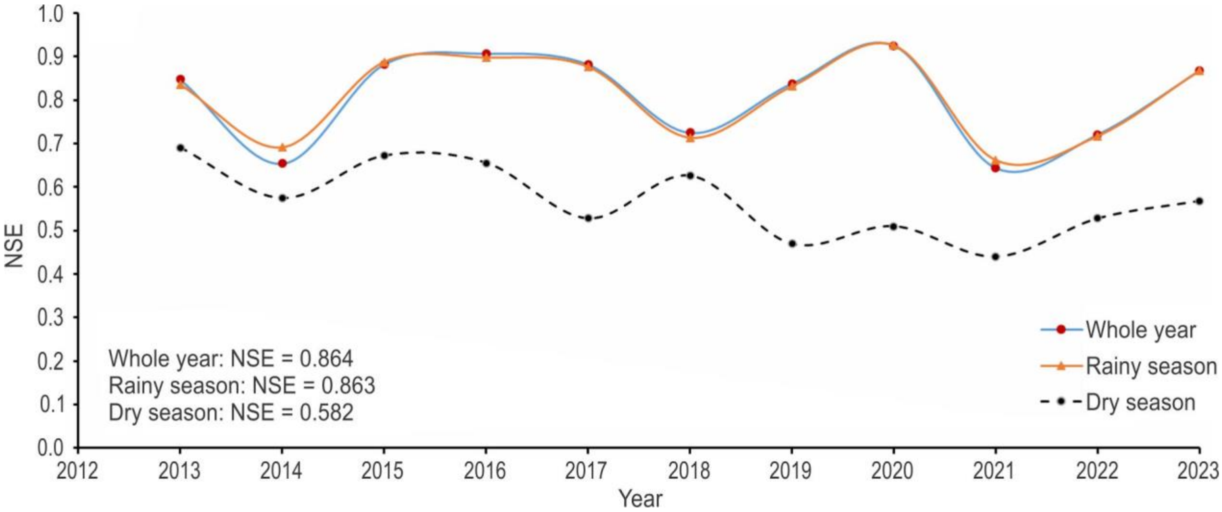

Figure 4. The NSE metric of whole year, rainy season and dry season.

During the rainy season, the LSTM model maintains high accuracy, with an overall NSE of 0.863, slightly lower than for the whole year but still reliable. The errors, however, increase, with MAE at 44.24 and RMSE at 111.60, which reflects the increased complexity of discharge prediction during high-flow periods. Years such as 2016 and 2020 again demonstrate excellent performance with NSE around 0.898 and 0.926, respectively, while years like 2018 and 2021 have lower NSE of 0.714 and 0.662. This suggests that the model struggles to predict extreme variations during heavy rainfall events in certain years. Larger errors during the rainy season are expected due to the influence of intense precipitation, leading to abrupt changes in runoff patterns that are harder to model.

For the dry season, the overall performance declines compared to the whole year and rainy season, with a NSE of 0.582, MAE of 12.27, and RMSE of 28.71. The lower NSE indicate that predicting discharge during the dry season is more challenging, likely due to smaller discharge variations and sensitivity to noise. For example, 2013 achieves the best NSE at 0.691, with a very low MAE of 6.18, while other years like 2021 and 2019 show poor performance with NSE of 0.440 and 0.470, respectively. Additionally, errors in years like 2023 are relatively high, with an MAE of 31.17 and RMSE of 72.81, indicating difficulty in capturing low-flow dynamics. These results suggest that while the LSTM model is effective for high-flow periods, additional calibration or alternative methods might be needed to improve predictions during dry seasons.

4. CONCLUSIONS

The results of this study demonstrate the effectiveness of the LSTM model for discharge prediction from rainfall, with varying levels of accuracy depending on the lead time, time lag length, and hydrological season. The model achieves its highest predictive performance for short-term forecasts, particularly for 1-day predictions, with NSE values consistently high across all time lag length, peaking at 0.864 for the 90-day lag. As the lead time extends, the accuracy diminishes, with increasing RMSE and MAE values reflecting greater uncertainty. The model's ability to capture different temporal dynamics is evident, as medium-term lag times (e.g., 90 days) excel in short-term forecasts, while shorter lags (e.g., 7 days) perform better for longer lead times. The medium-term lag times optimally balance short-term fluctuations and long-term trends, enhancing the model's ability to learn cyclic variations.

While shorter lags may fail to incorporate sufficient seasonal context, and longer lags (e.g., 365 days) obscure recent variations, the 90-day lag provides a suitable compromise, improving prediction performance. Analysis of annual runoff peaks reveals the model's general reliability, though discrepancies in certain years suggest the need for refinement to address extreme events.

Seasonal performance evaluation further highlights the model's strengths and limitations. The LSTM model performs well for annual and rainy-season predictions, achieving high NSE of 0.864 and 0.863, respectively. However, larger errors during the rainy season reflect the challenges of modelling abrupt runoff changes caused by intense precipitation. For dry-season predictions, performance declines with a NSE of 0.582, indicating difficulty in capturing low-flow dynamics. Notably, some years, such as 2016 and 2020, stand out with exceptional performance, while others, like 2021 and 2014, reveal reduced accuracy due to complex hydrological conditions. These findings underscore the LSTM model's potential for hydrological forecasting while highlighting areas for further optimization, particularly for dry-season and long-term forecasts.

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